Short and Long Horizon Behavioral Factors

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Abstract

Recent theories suggest that both risk and mispricing are associated with commonality in security returns, and that the loadings on characteristic-based factors can be used to predict future returns. We offer a parsimonious model which features: (1) a factor motivated by limited attention that is dominant in explaining short-horizon anomalies, and (2) a factor motivated by overconfidence that is dominant in explaining long-horizon anomalies. Our three-factor risk-and-behavioral composite model outperforms both standard models and recent prominent factor models in explaining a large set of robust return anomalies.

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Introduction

In his 2011 Presidential Address to the American Finance Association, John Cochrane asks three questions about what he describes as the "zoo" of new anomalies:

> First, which characteristics really provide independent information about average returns? Second, does each new anomaly variable also correspond to a new factor formed on those same anomalies? Third, how many of these new factors are really important (and can account for many characteristics)?

This paper addresses these questions, and also explores what factors are important for explaining *short-horizon* anomalies (those for which the average returns become statistically insignificant within 1 year after portfolio formation) versus *long-horizon* anomalies (those that earn statistically significant positive abnormal returns for at least 1 year after portfolio formation).

Building on past literature, we propose a factor model that augments the CAPM with two behaviorally-motivated factors. These factors are constructed using firm characteristics that have been hypothesized to capture misvaluation resulting from psychological biases. The two behavioral factors are complementary, in that they capture distinct short- and long-term components of mispricing. The resulting three-factor model provides a parsimonious description of the return predictability associated with a large set of well-known return anomalies, and provides a better description of the cross-section of expected returns than other factor models proposed in the literature.[1]

Existing behavioral models motivate the use of factor exposures as proxies for security mispricing. Intuitively, when investors are imperfectly rational and make similar errors about related stocks, the commonality in stock mispricing can be associated with return comovement. For example, in the model of Barberis and Shleifer (2003), investors categorize risky assets into different 'styles,' and allocate funds at the style level rather than at individual asset level. If these investors are subject to correlated sentiment shocks which result in their moving funds from one style to another, their correlated demand can result in return comovement of assets that share the same style, even when shocks to these assets' cash flows are uncorrelated.

Alternatively, return comovement can result from investors' mistakes in interpreting signals

[1] A tempting but fallacious way to evaluate parsimony is by the number of factors. Our model is parsimonious by this measure as well, but it is well known that any pattern of returns can be 'explained' by a single-factor model in which the factor is the ex post mean-variance efficient portfolio. In other words, radical overfitting is entirely compatible with having a small number of factors.

about fundamental economic factors. In the model of Daniel, Hirshleifer, and Subrahmanyam (2001), overconfident investors overestimate the precision of signals they receive, and accordingly overreact to private information and underreact to public information about genuine economic factors that influence firms' profits. Thus, sets of stocks with similar exposures to any given economic factor tend to have incremental mispricing-driven comovement associated with updates in investor beliefs about fundamental values.

In general we expect both risk and mispricing to be associated with commonality in returns. In consequence, behavioral factors can potentially be used to construct a factor model that improves on our ability to describe the cross-section of expected returns.[2] Firms which are exposed to systematic risk factors earn an associated risk premium; similarly, the prices of firms which are exposed to behavioral factors move with shocks to common mispricing (and correction) and earn a premium that results from the average correction of this mispricing. Fama and French (1993) construct risk factors based on firm characteristics that they argue are correlated with risk exposure; similarly, we use behavioral factors based on characteristics that are likely to be misvalued by investors because of their psychological biases.

Of course, the observed premia of the behavioral factors we propose can be interpreted as rational risk premia, just as traditional factor models are themselves subject to alternative interpretations in terms of mispricing. However, we motivate the two factors (other than the market) that we employ based upon behavioral/mispricing arguments. We do not hypothesize that *all* investors are biased, just that there is factor mispricing, as occurs in settings with commonality in returns, investors with biased expectations, and rational risk-averse arbitrageurs (Daniel, Hirshleifer, and Subrahmanyam, 2001; Kozak, Nagel, and Santosh, 2015). Our purpose is to use behaviorally-motivated factors to provide a new factor model that gives a more parsimonious description of return anomalies and insight into long- and short-horizon anomalies.

Our long-horizon factor is based upon security issuance and repurchase. The new issues puzzle, the finding of poor returns after firms issue equity or debt, is well documented, as is the

[2]Several other studies also suggest that behavioral biases could affect asset prices systematically. For example, Goetzmann and Massa (2008) construct a behavioral factor from trades of disposition-prone investors and find that exposure to this disposition factor seems to be priced. Similarly, Baker and Wurgler (2006) suggest including investor sentiment in models of prices and expected returns, and Kumar and Lee (2006) show that retail investor sentiment leads to stock return comovement beyond risk factors.

complementary repurchase puzzle in which repurchases positively predict future returns.[3] There are two prominent behavioral explanations for the issuance anomaly, based on either market timing or earnings management on the part of the managers of issuing firms.[4]

Under the market timing hypothesis, managers possess inside information about the true value of their firms and undertake equity (or debt) issuance or repurchase to exploit pre-existing mispricing (Stein, 1996). Instead of correcting mispricing instantly based on observation of the new issue or repurchase, investors hold stubbornly to their mistaken beliefs, perhaps owing to overconfidence (Daniel, Hirshleifer, and Subrahmanyam, 1998). Alternatively, under the earnings management hypothesis, managers adjust earnings upward as a way of inducing overpricing prior to share issuance, or manage earnings downward to induce underpricing before repurchase. If investors have limited attention about such manipulation, or again if investors are overconfident about their mistaken beliefs, they will not adequately correct for the manipulation of earnings even when accounting adjustments are publicly observable (Hirshleifer, Lim, and Teoh, 2011). Both hypotheses imply that firms undertaking share issues will generally be overpriced and repurchasing firms underpriced. Furthermore, under the timing hypothesis, issuance and repurchase should be powerful indicators of mispricing, because firms can benefit from trading against mispricing that derives from many possible sources.

Building on this intuition, Hirshleifer and Jiang (2010) provide an overconfidence-based model of market timing by firms when there is commonality in misvaluation. In this setting, the loadings on the mispricing factor are proxies for stock-level mispricing. They therefore propose a behavioral factor, the underpriced-minus-overpriced (UMO) factor, based on firms' external financing activities. The UMO factor is constructed by going long firms which repurchased debt or equity over the previous 24 months, and short firms which issued either debt or equity through an IPO or SEO over the same period. They find that UMO loadings help predict the cross-section of returns, including even firms that are not engaged in new issues or repurchases. In essence, the argument here is that managers who do not share in the market's biased expectations observe mispricing and exploit it in the interest

[3]See Loughran and Ritter (1995, 2000), Spiess and Affleck-Graves (1995), Brav, Geczy, and Gompers (2000), Bradshaw, Richardson, and Sloan (2006), for post-event underperformance of new issues. See Lakonishok and Vermaelen (1990), Ikenberry, Lakonishok, and Vermaelen (1995), and Bradshaw, Richardson, and Sloan (2006) for post-event outperformance of repurchases. Daniel and Titman (2006) and Pontiff and Woodgate (2008) develop comprehensive measures of aggregate issuance/repurchase activity.

[4]Eckbo, Masulis, and Norli (2000), Berk, Green, and Naik (1999) and Lyandres, Sun, and Zhang (2008) propose risk-based explanations for the new-issues anomaly.

of existing shareholders (who don't participate in either the firm's new issues or repurchases).

Motivated by the same insights, we create a modified financing factor (FIN) based on the 1-year net-share-issuance and 5-year composite-issuance measures of Pontiff and Woodgate (2008) and Daniel and Titman (2006), respectively. Our FIN factor is constructed by two-by-three sorts on size and financing characteristics (a combination of the 1- and 5-year measures), using methods that are routine in the literature. In untabulated results, we confirm that a financing factor based upon firms' financing characteristics derived from annual accounting reports exhibits stronger pricing power for the cross-section of stock returns than a factor based upon external financing events (e.g., the UMO factor).

FIN is designed to capture primarily longer-term overreaction and correction.It is unlikely to capture mispricing associated with shorter-term underreaction. Firms will likely not attempt to exploit mispricing with a horizon of less than about 1 year via share issuance and repurchases, because the time horizon associated with undertaking such activities is long enough to make high-frequency issuance/repurchase strategies infeasible.Our approach is therefore to build a second behavioral factor based upon earnings momentum to capture short-term underreaction to earnings information and, more generally, the correction of high-frequency mispricing.

A natural way to identify mispricing that corrects at a frequency of quarters rather than years is to make use of earnings momentum or post-earnings announcement drift, as documented by Ball and Brown (1968). Post-earnings announcement drift refers to the fact that firms reporting positive earnings surprises subsequently outperform those reporting negative earnings surprises. Bernard and Thomas (1989) find that drift is difficult to reconcile with explanations based on incomplete risk adjustment but more consistent with a delayed price response to information. A recent literature suggests that the drift is attributed to limited investor attention. For example, market reactions to earnings surprises are muted when the earnings announcement is released during low-attention periods such as non-trading hours (Francis, Pagach, and Stephan, 1992; Bagnoli, Clement, and Watts, 2005), Fridays (DellaVigna and Pollet, 2009), days with many same-day earnings announcements by other firms (Hirshleifer, Lim, and Teoh, 2009), and in down market or low trading volume periods (Hou, Peng, and Xiong, 2009). At these times, the immediate price and volume reactions to earnings surprises are weaker and the post-earnings announcement drift is stronger.

Recent theoretical models show how investor inattention causes underreaction to earnings news and the post-earnings announcement drift. In the models of DellaVigna and Pollet (2009) and Hirshleifer, Lim, and Teoh (2011), investors with limited attention and cognitive processing power condition on different subsets of earnings signals in valuing a stock. In equilibrium stock prices reflect a weighted average of the beliefs of less attentive and more attentive investors. In consequence, stock prices underreact to earnings surprises. This results in mispricing at the earnings announcement date, and abnormal returns when this mispricing is eventually corrected. This provides a possible explanation for post-earnings announcement drift.

We therefore hypothesize that PEAD captures high-frequency systematic mispricing caused by limited investor attention to earnings-related information, and use a PEAD factor to capture comovement associated with high-frequency mispricing. Earnings announcements are of course not the only source of fundamental news that investors might underreact to at a quarterly frequency. However, earnings announcements provide an especially good window into short term underreaction because they are highly relevant for fundamental value and arrive regularly for every firm each quarter.

We construct the PEAD factor by going long on firms with positive earnings surprises and short on firms with negative surprises. We are not the first to construct a PEAD factor; the PEAD factors constructed in previous studies have been used for different purposes.[5]

We therefore augment the CAPM with the two behavioral factors to form a three-factor risk-and-behavioral composite model, with behavioral factors designed to capture common mispricing induced by investors' psychological biases. This approach is consistent with theoretical models in which both risk and mispricing proxies predict returns (Daniel, Hirshleifer, and Subrahmanyam (2001); Barberis and Huang (2001)). Furthermore, we attempt to capture both long-horizon mispricing that takes a few years to correct and short-horizon mispricing that takes a few quarters to correct. (This has a broad parallel with the use of short-term and long-term factors in models of the term structure of interest rates.) We hypothesize that FIN captures primarily long-term overreaction and the correction of low-frequency mispricing, and that PEAD captures short-term underreaction and the correction of high-frequency mispricing.

[5]Chordia and Shivakumar (2006) and Novy-Marx (2015a) create PEAD factors to show that the systematic component of earnings momentum subsumes return momentum, and Novy-Marx (2015b) uses a PEAD factor to price the ROE factor of Hou, Xue, and Zhang (2015). Our paper differs from these in examining the ability of a PEAD factor to explain the general cross-section of stock returns, and the role of this factor in a parsimonious overall factor pricing model.

We empirically assess the incremental ability of behavioral factors to explain expected returns relative to the factors used in other models, including both traditional factors (such as the market, size, value, and return momentum factors) and other recently prominent factors (such as the investment and profitability factors). Barillas and Shanken (2016) suggest that when comparing models with traded factors, "...the models should be compared in terms of their ability to price all returns, both test assets and traded factors." To do this, we first examine how well other (traded) factors explain the performance of FIN and PEAD and *vice-versa*. We find that a factor model that includes both FIN and PEAD prices most of the traded factors proposed in the literature, including the five factors of Fama and French (2015), the four factors of Hou, Xue, and Zhang (2015), and the four factors of Stambaugh and Yuan (2016). In sharp contrast, reverse regressions show that these other (traded) factors do *not* fully explain the abnormal returns associated with FIN and PEAD.

We then explore the extent to which FIN and PEAD explain the returns of portfolios constructed by sorting on the characteristics associated with well-known return anomalies. We consider 34 anomalies, closely following the list of anomalies considered in Hou, Xue, and Zhang (2015). Given that FIN and PEAD are designed to capture mispricing over different horizons, we are particularly interested in how well FIN captures long-horizon anomalies and how well PEAD captures short-horizon anomalies. Therefore, we further categorize the 34 anomalies into two groups: 12 short-horizon anomalies including return momentum, earnings momentum, and short-term profitability, and 22 long-horizon anomalies including long-term profitability, value vs. growth, investment and financing, and intangibles. We compare the performance of our three-factor composite model with the profitability-based factor model of Novy-Marx (2013, NM), the five-factor model of Fama and French (2015, FF5), the q-factor model of Hou et al. (2015, HXZ), and the four-factor mispricing model of Stambaugh and Yuan (2016, SY4).

We find that across the 12 short-horizon anomalies, the composite model fully captures all anomalies at the 5% significance level (i.e., none have significant alphas). In contrast, 11 anomalies have significant FF5 alphas, 2 have significant NM alphas, 1 have significant HXZ alpha, and 4 have significant SY4 alphas. Moreover, the composite model gives the smallest average magnitude of alphas. The GRS F-test (Gibbons, Ross, and Shanken, 1989) does not reject the null hypothesis that all alphas are jointly zero under the composite model, but rejects the null at the 1% significance level under all other models.

Across the 22 long-horizon anomalies, the composite model outperforms the FF5 and HXZ models and performs equally well as the NM and SY4 models. The composite model gives 3 significant alphas at the 5% significance level, as compared to 7 significant FF5 alphas, 3 significant NM alphas, 5 significant HXZ alphas, and 3 significant SY4 alphas. The GRS F-test does not reject the null hypothesis of all alphas jointly zero under the SY4 model, and not reject the null at 5% significance level under the NM and the composite models. It does reject the null at 1% significance level under both the FF5 and HXZ models. The superior performance of the SY4 model derives primarily from its MGMT factor, which is constructed from the characteristics of *six* long-horizon anomalies related to investment and financing.

Overall, across all 34 anomalies, our composite model provides the best fit. Under this model, only 3 anomalies have 5% significant alphas. In comparison, there are 18 significant FF5 alphas, 5 significant NM alphas, 6 significant HXZ alphas, and 7 significant SY4 alphas. The composite model also gives the smallest GRS F-statistic. The composite model therefore outperforms both standard and recent enhanced factor models in explaining the robust set of anomalies studied in Hou, Xue, and Zhang (2015).

Along with its superior pricing power, the composite model is more parsimonious in that it includes factors built upon just three characteristics. This contrasts with other recent models which in some cases are built based upon larger numbers of characteristics (see footnote 1).

This evidence is consistent with the hypothesis that many existing anomalies, such as momentum, profitability, value, investment and financing, and intangibles, can be attributed to systematic mispricing. Moreover, we find that two behavioral factors (FIN and PEAD), each constructed on just one firm characteristic and using methods that are routine in the literature, have stronger explanatory power for existing return anomalies than the two mispricing factors of Stambaugh and Yuan (2016), which are constructed based upon a set of 11 firm characteristics.

To further evaluate the factor model, we perform cross-sectional tests. If FIN and PEAD are behavioral factors that capture common mispricing, then as discussed above, loadings on FIN and PEAD should be firm-level underpricing proxies, and a firm's loadings on these factors should forecast its future returns. However, the dynamic nature of the FIN and PEAD factors ensures that any given firm's loadings on these factors will exhibit large variation over time. We therefore estimate firms' loadings on behavioral factors using daily stock returns over short horizons, e.g., one month. Using Fama and MacBeth (1973) cross-sectional regressions, we find that FIN loadings significantly predict future stock returns, even after controlling for a broad set of firm characteristics underlying the list of 34 robust anomalies that we examine. On the other hand, the estimated PEAD loadings show no return predictive ability at all, probably because PEAD captures short-horizon mispricing that corrects very quickly and thereby PEAD loadings are rather noisy proxy of such high-frequency mispricing.

We also conduct several robustness tests to provide additional evidence regarding the performance of the FIN and PEAD factors. We focus on market frictions and arbitrage capital, both of which affect the ability of arbitrageurs to exploit mispricing. First, owing to short-sale constraints, we expect behavioral factors to be especially good at explaining returns of stocks in the short-leg of anomaly portfolios (overpriced stocks). Consistent with this hypothesis, we find that for short-horizon anomalies, loadings on PEAD are significantly larger (in absolute magnitude) on the short side than the long side, and for long-horizon anomalies, loadings on FIN are significantly larger on the short side as well. This is consistent with our proposition that PEAD captures primarily high-frequency mispricing embedded in short-horizon anomalies, and that FIN captures low-frequency mispricing in long-horizon anomalies.

Second, other market frictions also impede arbitrage, so high friction stocks should be more subject to mispricing. Sample estimates of the return premia associated with mispricing proxies for such stocks should be higher and more accurate owing to a higher signal-to-noise ratio. (For example, sample estimates of mispricing in a pool of stocks that were known to have zero mispricing would be pure noise.) If behavioral factors truly capture mispricing, we would expect the factor beta-return relation to be stronger for high friction stocks, such as stocks with lower liquidity or institutional ownership. Using both two-way portfolio sorts and cross-sectional regressions, we find that the FIN beta-return relation is indeed stronger among high friction stocks.

Third, on the premise that sophisticated investors help to mitigate or alleviate mispricing, we examine how changes in the supply of arbitrage capital affect contemporaneous and future FIN and PEAD factor returns. We focus on a specific group of sophisticated investors, hedge funds, which are commonly viewed as the most active and effective arbitrageurs in exploiting market mispricing.

We find moderate evidence that the supply of arbitrage capital, as measured by changes in aggregate assets under management and capital flows to hedge funds, positively predicts *contemporaneous* FIN and PEAD premia (as more mispricing being corrected) and negatively predicts *future* factor premia in the months and quarters ahead (as less mispricing remained to be corrected). Interestingly, we also find that the effect of a change in arbitrage capital on PEAD factor return is stronger over a monthly horizon, while the effect on FIN premia is stronger over a quarterly horizon. This is consistent with our proposition of PEAD capturing high-frequency mispricing and FIN capturing low-frequency mispricing.

A large literature has attempted to explain sets of anomaly returns with a small set of factors. This is the motivation behind the work of Fama and French (1996, 2016b), and more recently Stambaugh and Yuan (2016). Our paper builds on this earlier work in three key ways. First, as noted earlier, our factor model provides a better fit to a wide set of anomalies and factors. Second, we identify a strong dichotomy between short- and long-horizon anomalies, with short-horizon anomalies predominantly explained by our PEAD-based factor, and long-horizon anomalies predominantly explained by the financing factor. Third, our behavioral factors are constructed on the basis of two economic characteristics which are not obviously related to the set of anomalies we are seeking to explain.

A key criterion for choosing among factor models is parsimony. Less parsimonious models are more subject to an overfitting bias. For example, we would expect severe overfitting in a 20-factor model based on 20 economic characteristics that was used to explain the 20 anomalies associated with those same characteristics. Such a model could easily match even anomalies that have arisen by sheer chance in the sample rather than from genuine risk premia or mispricing. Importantly, the problem with such a procedure is not the number of factors, since, as discussed in footnote 1, a single ex post mean-variance efficient factor-portfolio will price all assets. So a relevant parsimony criterion for a factor model is the number of economically independent characteristics are used in constructing the factors. The problem with the 20-factor model described above is that it draws upon the same set of economic characteristics in forming factors as the anomalies to be explained. Thus, it is valuable to have a factor model which more stringently avoids potential parsimony concerns by strictly limiting the set of characteristics drawn upon. A key strength of our model is that it explains a wide range of anomalies using just two economic characteristics, and these two economic characteristics are distinct from those used to construct the anomaly portfolios themselves.

1 Comparison of Behavioral Factors with Other Factors

1.1 Factor definitions

FIN is the financing-based mispricing factor, constructed as follows. We use all NYSE, AMEX, and NASDAQ common stocks with CRSP share codes of 10 or 11, excluding financial firms. Each June, we assign these firms to one of the two size groups (small "S" and big "B") based on whether that firm's market equity at the end of June is below or above the NYSE median size breakpoint. Independently, firms are sorted into one of the three financing groups (low "L", middle "M", or high "H") based on the one-year net share issuance (NSI) measure of Pontiff and Woodgate (2008)) and the corresponding 5-year composite issuance (IR) measure of Daniel and Titman (2006), respectively.[6] The three financing groups are created based on an index of NSI and IR rankings.

Specifically, we first sort firms into three IR groups (low, middle, or high) using 20% and 80% breakpoints for NYSE firms. Special care is needed when sorting firms into NSI groups. We notice that about one quarter of our sample observations have negative NSI (repurchasing firms), and three quarters with positive NSI (issuing firms). If we use the NYSE 20% and 80% breakpoints to assign NSI groups, we may have all repurchasing firms into the bottom 20% group, without differentiating between firms with high and low repurchases. To address this concern, we separately sort repurchasing firms (with negative NSI) into two groups using NYSE median breakpoints, and sort issuing firms (with positive NSI) into three groups using NYSE 30% and 70% breakpoints. We assign firms in the bottom group of repurchasing firms to the low NSI group, firms in the top group of issuing firms to the high NSI group, and all other firms to the middle group.

We then assign firms into one of the three financing groups (low "L", middle "M", or high "H") based on an index of NSI and IR rankings. If a firm belongs to the high group by both NSI and IR rankings, or to the high group by NSI rankings while missing IR rankings (or vice versa), the firm is assigned to the high financing group ("H"). If a firm belongs to the low group by both NSI and

[6] Net share issuance and composite issuance both earn significant abnormal returns during our sample period of 1972 to 2014. Pontiff and Woodgate (2008) note that Daniel and Titman's 5-year composite issuance measure, while strong in the post-1968, is weak pre-1970 (also consistent with the discussion in Daniel and Titman (2016)).

IR rankings, or to the low group by one ranking while missing the other, it is assigned to the low financing group ("L"). In all other cases, firms are assigned to the middle financing group ("M").

Six portfolios (SL, SM, SH, BL, BM, and BH) are formed based on the intersections of size and financing groups, value-weighted portfolio returns are calculated for each month from July to the next June, and the portfolios are rebalanced at the end of the next June. The FIN factor return each month is calculated as average return of the low financing portfolios (SL and BL) minus the average return of the high financing portfolios (SH and BH), that is, $FIN = (r_{SL} + r_{BL})/2 - (r_{SH} + r_{BH})/2$.

PEAD is the post-earnings announcement drift factor, constructed in the fashion of Fama and French (1993). Following Chan, Jegadeesh, and Lakonishok (1996), earnings surprise is measured as the four-day cumulative abnormal returns ($t-2$, $t+1$) around the latest quarterly earnings announcement date (COMPUSTAT quarterly item RDQ):

$$CAR_i = \sum_{d=-2}^{d=1} R_{i,d} - R_{m,d}$$

where $R_{i,d}$ is stock $i's$ return on day d and $R_{m,d}$ is the market return on day d relative to the earnings-announcement-date. We require valid daily returns on at least two trading days during the four-day window. We also require the COMPUSTAT earnings date (RDQ) to be at least two trading days prior to the month end. [7]

The set of firms which are used in calculated the PEAD factor in month t are all NYSE, AMEX, and NASDAQ common stocks with CRSP share codes of 10 or 11, excluding financial firms. At the beginning of each month t, we first assign firms to one of two size groups (small "S" or big "B") based on whether that firm's market equity at the end of month $t-1$ is below or above the NYSE median size breakpoint. Each stock is independently sorted into one of three earnings surprise groups (low "L", middle "M", or high "H") based on its CAR at the end of month $t-1$, using 20% and 80% breakpoints for NYSE firms. Six portfolios (SL, SM, SH, BL, BM, and BH) are formed based on the intersections of the two groups, value-weighted portfolio returns are calculated for the current month, and the portfolios are rebalanced in the next month. The PEAD factor return each month is calculated as average return of the high earnings surprise portfolios (SH and BH) minus the average return of

[7] In unreported results, we find that a PEAD factor based on CAR has stronger explanatory power for return anomalies than a PEAD factor based on standardized unexpected earnings (SUE) of Chan, Jegadeesh, and Lakonishok (1996).

the low earnings surprise portfolios (SL and BL), that is, $PEAD = (r_{SH} + r_{BH})/2 - (r_{SL} + r_{BL})/2$.

1.2 Summary statistics

We now compare our two behavioral factors, FIN and PEAD, with standard factors and other recent factors. Table 1 reports the summary statistics for our zero-investment behavioral factors, and a set of well-known factors from the academic literature. These factors include the Mkt-Rf, SMB, HML, MOM factors proposed by Fama and French (1993) and Carhart (1997), and modified versions of these factors proposed by Novy-Marx (2013), Hou, Xue, and Zhang (2015), and Stambaugh and Yuan (2016). For example, Novy-Marx (2013) creates industry-adjusted HML(NM) and MOM(NM) factors by demeaning book-to-market and past returns by industry, to hedge the factor returns for industry exposure. Hou, Xue, and Zhang (2015) construct the SMB(HXZ) factor by a triple sort on size, investment-to-assets, and ROE. Stambaugh and Yuan (2016) form the SMB(SY4) factor using only stocks least likely to be mispriced, to reduce the effect of arbitrage asymmetry.

In addition we include: the investment factors CMA and IVA of Fama and French (2015) and Hou, Xue, and Zhang (2015), respectively; the profitability factors PMU, RMW, and ROE of Novy-Marx (2013), Fama and French (2015), and Hou, Xue, and Zhang (2015), respectively; and the two mispricing factors MGMT and PERF proposed by Stambaugh and Yuan (2016). In particular, MGMT is a composite factor constructed on six anomaly variables related to investment and financing, and PERF is a composite factor based on five anomaly variables including return momentum and profitability. Monthly factor returns are either downloaded from Kenneth French's website or provided by the relevant authors.[8]

Panel A of Table 1 shows that, over our sample period, FIN offers the highest average premium of 0.80% per month and a Sharpe ratio of 0.20. The t-statistic of FIN factor returns is 4.6, well above the higher hurdle of a t-statistic greater than 3.0 for new factors as proposed by Harvey, Liu, and Zhu (2016). PEAD offers an average premium of 0.65% per month and the highest Sharpe ratio of 0.35. Consistent with this, the t-statistic testing whether the mean PEAD factor returns is zero is 7.91, the highest among all factors.

Comparing FIN with recently prominent investment and profitability factors (e.g., CMA, IVA,

[8] We are grateful to all these authors for providing their factor return data.

PMU, RMW) and the composite mispricing factor MGMT based on six investment and financing anomalies, FIN offers a substantially higher factor premium and comparable Sharpe ratio and t-statistic. Comparing PEAD with factors based on short-horizon characteristics (e.g., MOM, ROE) and the composite mispricing factor PERF based on five anomalies including return momentum and profitability, PEAD offers comparable factor premium but substantially higher Sharpe ratio and t-statistic.

Panel B reports pairwise correlation coefficients between factor portfolios. We find that different versions of SMB, HML, and MOM are highly correlated, with correlation coefficients (ρ) greater than 0.90 in most cases. The two investment factors (CMA, IVA) are highly correlated with $\rho = 0.90$, and strongly correlated with the value factors (HML, HML(NM)) with ρ between 0.55 to 0.69. The three profitability factors (PMU, RMW, ROE) are strongly correlated with each other with ρ around 0.60. Moreover, ROE is also strongly correlated with the momentum factors (MOM, MOM(NM)) with ρ around 0.50.

Not surprisingly, the MGMT factor, constructed on six investment and financing anomalies, is highly correlated with value factors (HML, HML(NM)) and investment factors (CMA, IVA), with ρ ranging from 0.59 to 0.76. The PERF factor, constructed on five anomalies including return momentum and profitability, is highly correlated with momentum factors (MOM, MOM(NM)) and profitability factors (PMU, RMW, ROE), with ρ ranging from 0.48 to 0.72.[9]

Lastly, for our two behavioral factors, FIN is strongly correlated with the value factors (HML, HML(NM)) and investment factors (CMA, IVA), with ρ between 0.50 and 0.66. FIN is highly correlated with the composite MGMT factor with $\rho = 0.80$, suggesting that financing characteristics might be a dominant principle component in the composition of the MGMT factor. Meanwhile, FIN is moderately correlated with profitability factors (PMU, RMW, ROE) and the composite PERF factor, with ρ around 0.35. Overall, the evidence suggests that FIN may contain important information related to value vs. growth, investment, and profitability. On the other hand, PEAD is strongly correlated with momentum factors (MOM, MOM(NM)) and the composite PERF factor, with ρ ranging from 0.38 to 0.48, and moderately correlated with the earnings profitability factor

[9]The six anomaly variables underlying the MGMT factor are: net share issuance, composite issuance, operating accruals, net operating assets, asset growth, and investment-to-assets. The five anomaly variables underlying the PERF factor are: distress, O-Score, momentum, gross profitability, and return on assets.

ROE, with $\rho = 0.22$. This is consistent with the finding in the literature that earnings momentum, return momentum, and earnings profitability are fundamentally correlated, driven by market underreaction to latest earnings news. Finally, the correlation between FIN and PEAD is -0.05, suggesting that the two behavioral factors capture different sources of mispricing.

Panel C describes the portfolio weights, returns, and the maximum *ex post* Sharpe ratios that can be achieved by combining various factors to form the tangency portfolio. Rows (1) and (2) show that combining the Fama-French three factors achieves a maximum monthly Sharpe ratio of 0.22, and adding the MOM factor increases the Sharpe ratio to 0.31. Rows (3)−(6) show that combining factors of the Fama and French (2015) model, the Novy-Marx (2013) model, the Hou, Xue, and Zhang (2015) model, and the Stambaugh and Yuan (2016) model achieves a maximum Sharpe ratio of 0.36, 0.57, 0.43, and 0.50, respectively. In rows (7) and (8), combining two behavioral factors, FIN and PEAD, achieves a Sharpe ratio of 0.41, while adding the MKT factor increases the Sharpe ratio to 0.52. So far, the three-factor risk-and-behavioral composite model earns a Sharpe ratio higher than standard factor models and all recently prominent models, except for the Novy-Marx (2013) model.

Rows (9)−(12) show that with the three-factor risk-and-behavioral composite model in place, other recent prominent factors only marginally increase the Sharpe ratio. For example, adding PMU of the Novy-Marx (2013) model, or CMA and RMW of the Fama and French (2015) model, each increases the Sharpe ratio from 0.52 to 0.54. Adding IVA and ROE of the Hou, Xue, and Zhang (2015) model increases the Sharpe ratio from 0.52 to 0.55, and adding MGMT and PERF of the Stambaugh and Yuan (2016) model increases it to 0.56.

Rows (13) and (14) show that combining all factors excluding FIN and PEAD achieves a maximum Sharpe ratio of 0.54. Adding FIN and PEAD results in a very substantial further increase of the Sharpe ratio to 0.65. Moreover, row (14) shows that out of the 13 factors, the tangency portfolio places 86% of total weights on 4 factors: PMU (23%), IVA (17%), MGMT (20%), and PEAD (26%). Noticeably, the tangency portfolio places zero weight on FIN and 20% weight on MGMT. The MGMT factor subsumes our FIN factor in the tangency portfolio, probably because MGMT is a composite factor based on six anomalies including two financing characteristics, net share issuance and composite issuance, which our FIN factor is built upon. Overall, the evidence suggests that FIN and PEAD carry important incremental information relative to alternative factors for improving Sharpe ratios.

1.3 Comparing behavioral factors with other factors

As discussed in the introduction, Barillas and Shanken (2016) point out that in comparing traded factor models it is important to compared their abilities to price traded factors as well as assets. We therefore assess the power of behavioral factors pricing other factors, including traditional factors and recently prominent factors. Specifically, we examine how well other factors explain the performance of FIN and PEAD and how well FIN and PEAD explain other factors. We run time-series regressions of the monthly returns of FIN and PEAD on returns of other factors, or vice versa, and examine the regression intercepts or alphas. If a factor is subsumed by a set of other factors, we would expect the regression alpha to be not significantly different from zero.

Table 2 reports the results of regressions of our behavioral factors on other sets of factors proposed in the literature. The Fama-French three-factor model, the Carhart model, and recently prominent factor models, such as the five-factor model of Fama and French (2015) and the q-factor model of Hou, Xue, and Zhang (2015) do not explain FIN premiums. However, the profitability-based model of Novy-Marx (2013) and the four-factor mispricing model of Stambaugh and Yuan (2016) are able to fully capture FIN premiums. The former model derives its explanatory power from its HML and PMU factors, and the latter from its MGMT factor. Given the high correlation between MGMT and FIN ($\rho = 0.80$, in Panel B of Table 1), it is not surprising that the MGMT factor subsumes FIN. On the other hand, none of those models can fully explain PEAD premiums. Under a 'kitchen sink' model including all those factors, PEAD still earns a significant alpha of 0.58% per month ($t = 6.76$).

Overall, we confirm that PEAD offers abnormally high returns relative to all other factors, including recently popular investment and profitability factors and the mispricing factors of Stambaugh and Yuan (2016). FIN offers abnormal returns relative to many other factors, except for the profitability factor PMU of Novy-Marx (2013) and the composite MGMT factor of Stambaugh and Yuan (2016).

Table 3 reports the results of regressions of other factors on our two behavioral factors.[10] With

[10]Modified versions of SMB, HML, and MOM factors are not examined here, as Table 1 shows that those modified versions are highly correlated with each other.

just FIN and PEAD, our two-factor behavioral model fully explains 7 out of the 10 factors we examine, such as the value factor HML, the momentum factor MOM, the investment and profitability factors CMA and RMW of Fama and French (2015), the profitability factor ROE of Hou, Xue, and Zhang (2015), and the MGMT and PERF factors of Stambaugh and Yuan (2016). The exceptions are the size factor SMB, the profitability factor PMU of Novy-Marx (2013), and the investment factor IVA of Hou, Xue, and Zhang (2015). Adding the market factor, our three-factor risk-and-behavioral composite model does not explain CMA and MGMT factors either, which load negatively on the market factor and therefore earn significant alphas under our composite model.

Collectively, we find that FIN and PEAD subsume most of the traditional factors and recently prominent factors, but not vice versa. The evidence suggests that FIN and PEAD contain incremental information about average returns relative to existing factors, and thereby motivates us to further explore their pricing power on well-known return anomalies.

2 Explaining Anomaly Returns with Behavioral Factors

2.1 Anomaly magnitudes and correlations

We next examine whether our behavioral factor model explains the various return anomalies documented in the academic literature. We focus on 34 robust anomalies based upon the list of anomalies considered in Hou, Xue, and Zhang (2015) that earn significant abnormal returns over their sample period of 1972 to 2012. We exclude the systematic volatility (Svol) of Ang et al. (2006) and the revisions in analysts' earnings forecasts (6-month holding period, RE-6) of Chan, Jegadeesh, and Lakonishok (1996) from the set of anomalies considered by Hou, Xue, and Zhang (2015), as these two portfolios do not earn statistically significant excess returns over our sample period. In addition, we include the cash-based operating profitability (CbOP) of Ball et al. (2016), which is not considered in Hou, Xue, and Zhang (2015), but is related to the profitability factor RMW of the Fama and French (2015) model. RMW is originally built on operating profitability. Later, Fama and French (2016a) find that a RMW factor based on cash profitability dominates one based on operating profitability. We therefore add cash profitability to our list of anomalies. This gives us a total of 34 anomalies.

Because FIN is constructed on a firm's financing activities and PEAD on quarterly earnings surprises, we further posit that FIN captures long-term overreaction to firms' growth prospects and the correction of such low-frequency mispricing, and that PEAD captures short-term underreaction to recent earnings news and the correction to such high-frequency mispricing. Given that FIN and PEAD capture mispricing over different horizons, we are particularly interested in how well FIN captures long-horizon anomalies and how well PEAD captures short-horizon anomalies.

We define as *long-horizon* those anomalies based upon annual accounting reports which continue to earn statistically significant positive abnormal returns for 1 to 3 years after portfolio formation. The trading strategies for each of these long-horizon anomaly portfolios are rebalanced annually. In contrast, *short-horizon* anomalies are those based upon quarterly accounting reports or high-frequency price information. Such anomalies typically have a higher rate of decay of return predictability as the forecast horizon is extended. The premia earned by short-horizon anomaly portfolios generally become statistically insignificant after 1 year, and the trading strategies based on these anomalies are rebalanced monthly.

Based on these criteria, we group the 34 anomalies into 12 short-horizon anomalies, including return momentum, earnings momentum, and short-term profitability, and 22 long-horizon anomalies including long-term profitability, value vs. growth, investment and financing, and intangibles. Table 4 describes the list of anomalies under each group, as well as the mean abnormal returns and Sharpe ratios of those long/short anomaly portfolios. Definitions of anomaly characteristics are provided in Appendix A.

To further validate our classification of long- vs. short-horizon anomalies, Table 5 reports the decay rate of return predictability of each group of anomalies. Short-horizon anomaly portfolios are formed and rebalanced each month, and long-horizon anomaly portfolios are annually rebalanced. Using an event time approach, we examine the buy-and-hold returns of the short-horizon anomaly portfolios in each of the 12 months after portfolio formation. Similarly, for long-horizon anomaly portfolios, we examine the buy-and-hold returns in each of the 12 quarters post formation. Panel A confirms that the premia earned by short-horizon anomaly portfolios become statistically insignificant after 6 to 9 months. On the other hand, Panel B shows that most long-horizon anomaly portfolios continue to earn statistically significant abnormal returns for 1 to 3 years after portfolio formation.[11]

An immediate question is how correlated these anomalies are with each other—particularly those within the same category. To answer this question, we calculate the pairwise correlations between the returns of the long/short (L/S) hedged anomaly portfolios. The signs of L/S portfolios returns are converted, when necessary, to ensure that the portfolio returns reflect the actual (positive) arbitrage profits.

Table 6 presents in pairwise time series correlations of the anomaly portfolios, grouped by the anomaly horizon. Panel A shows that, among short-horizon anomalies, the L/S portfolio returns of return momentum, earnings momentum, and short-term earnings profitability are strongly positively correlated, consistent with the literature that the three effects may be fundamentally correlated (Chordia and Shivakumar, 2006; Novy-Marx, 2015a,b). Panel B presents the long-horizon anomalies return correlation matrix. Noticeably, the HML portfolio returns are positively correlated with investment and financing, but negatively correlated with long-term profitability. This is consistent with existing evidence that growth firms generally issue more equity and invest more heavily.

2.2 Summary of comparative model performance

To examine how well behavioral factors account for various return anomalies, we run factor regressions of the L/S portfolio returns on FIN alone, PEAD alone, a two-factor model with FIN and PEAD (BF2), and a three-factor risk-and-behavioral composite model with MKT, FIN, and PEAD (BF3). If a model is efficient, the regression alphas of the L/S portfolios should be statistically indistinguishable from zero. We compare the performance of our behavioral-motivated models with standard factor models, such as the CAPM, the Fama-French three-factor model (FF3), and the Carhart four-factor model (Carhart), and recent prominent models, such as the profitability-based factor model of Novy-Marx (2013, NM), the five-factor model of Fama and French (2015, FF5), the q-factor model of Hou et al. (2015, HXZ), and the four-factor mispricing model of Stambaugh and

[11] There are a few exceptions. For example, GP/A and CbOP do not earn significant abnormal returns using this event window approach. IvG, IvC, OA, and OC/A earn significant abnormal returns for less than 1 year. Still, we classify these anomalies as long-horizon, as they are based upon annual accounting reports and it makes more sense to form annually rebalanced trading strategies based on them.

Yuan (2016, SY4).[12]

Table 7 summarizes the comparative performance of our behavioral-motivated factor models in explaining the set of 34 anomalies. We separately compare model performance on the 12 short-horizon anomalies (Panel A), the 22 long-horizon anomalies (Panel B), and all 34 anomalies (Panel C). The column labeled "H-L Ret" reports the monthly average excess return of each L/S anomaly portfolio. As expected, most anomalies earn large and significant excess returns.[13] The rest of the columns report the regression alphas of each L/S portfolio returns under different factor models. At the bottom of each panel, we summarize model performance by three comparative statistics: the number of significant alphas at 5% significance level, the average (absolute) alphas, and the GRS F-statistics and p-values which test the null hypothesis that all alphas are jointly zero (Gibbons, Ross, and Shanken (1989)).

2.2.1 Fitting short-horizon anomalies

Panel A of Table 7 compares different models on explaining the list of 12 short-horizon anomalies. We first look at the number of significant alphas at 5% significance level. Among standard factor models, the CAPM and FF3 models do not capture most of these anomalies and the Carhart model with a momentum factor explains about half of them. Among prominent models, the FF5 model does not outperform the FF3 model, understandably, as these models are designed to price only the longer horizon anomalies and not shorter-horizon momentum-like anomalies. The NM, HXZ, and SY4 models each miss 2, 1, and 4 anomalies, respectively, owing to the explanatory power of the MOM factor, the ROE factor, and the PERF factor, respectively. Among our behaviorally-motivated models, we see that FIN alone captures only a few of these anomalies and PEAD alone captures *all* of them. Combining the CAPM with FIN and PEAD, our BF3 model fully captures *all* 12 anomalies. Overall, the evidence suggests that the PEAD factor achieves great success in capturing abnormal returns associated with return momentum, earnings momentum, and short-term profitability.

Other comparative statistics such as average (absolute) alphas and the GRS F-statistics confirm

[12] In unreported results, we also check the performance of the liquidity factor model of Pastor and Stambaugh (2003), which adds a traded liquidity factor to the Carhart model. We find that the liquidity factor does not help for explaining most anomalies.

[13] The only anomaly not earning significant excess return is the gross profits-to-assets ratio (GP/A) of Novy-Marx (2013). Novy-Marx (2013) reports significant high-minus-low GP/A excess returns over the sample period of 1963 to 2010, while our sample period is 1972 to 2014. When restricting to the same period as Novy-Marx (2013), we do find significant excess returns associated with GP/A. Still, we include GP/A in our analysis because it serves as the fundamental characteristic of the profitability factor (PMU) of the Novy-Marx (2013) model.

the superior performance of the PEAD factor and our BF3 model. The BF3 model gives the smallest average alpha ($|\alpha| = 0.09\%$) among all models and the GRS F-test cannot reject the null hypothesis that all alphas are jointly zero ($GRS\ F = 1.15$ and $p = 0.32$). In contrast, all other models give significantly higher average alphas and the GRS F-tests reject the null hypotheses at 1% significance level.

It should be noted that although the PERF factor of the SY4 model is constructed on five anomaly variables related to return momentum and profitability,[14] our PEAD factor, which is constructed on a *single* characteristic, earnings surprises, outperforms the composite PERF factor in capturing the 12 short-horizon anomalies.

2.2.2 Fitting long-horizon anomalies

Panel B of Table 7 compares different models on explaining the list of 22 long-horizon anomalies. We first look at the number of significant alphas at 5% significance level. Among standard factor models, the CAPM does not capture most of these anomalies, the FF3 model gives 12 significant alphas, and the Carhart model gives 8 significant alphas. Among recently prominent models, the FF5, NM, HXZ, and SY4 models give 7, 3, 5, and 3 significant alphas, respectively. Among our behavioral-motivated models, a single FIN factor gives 6 significant alphas, performing as well as the FF5 and HXZ models. A single PEAD factor does not capture most of these long-horizon anomalies, which is not surprising as PEAD is designed to capture short-term mispricing. Lastly, Our BF3 model (with MKT, FIN, and PEAD) gives 3 significant alphas, outperforming the FF5 and HXZ models and performing equally well as the NW and SY4 models.

Other tests confirm the superior performance of the NM and SY4 models and our BF3 model in explaining long-horizon anomalies. The SY4 model gives the smallest average alpha of 0.12% and the GRS F-test cannot reject the null hypothesis that all alphas are jointly zero ($F = 0.74$ and $p = 0.80$). The average alpha is 0.21% under the NM model, and 0.28% under our BF3 model. The GRS F-tests for both NM and BF3 models cannot reject the null hypothesis of all alphas jointly zero under 5% significance level. All other models, including the FF5 and HXZ models, earn high average alphas and the GRS F-tests reject the null hypotheses at 1% significance level.

[14]The five anomaly variables underlying the PERF factor are: distress, O-score, momentum, gross profitability, and return on assets.

While the FF5 and HXZ models each include an investment factor, both models fail to explain the average returns of several investment-related anomaly portfolios: net operating assets (NOA), investment-to-asset ratio (IVA), inventory changes (IvC), operating accruals (OA), etc. Similarly, the FF5 and HXZ models, each with a profitability factor, do not capture the cash-based operating profitability (CbOP) effect, while our BF3 model does, despite the fact that neither FIN nor PEAD is directly constructed on investment or profitability characteristics.

The superior performance of the SY4 model is derived primarily from its MGMT factor, which is constructed on six long-horizon anomalies related to investment and financing.[15] Therefore, it is not surprising that the SY4 model captures these long-horizon anomalies particularly well. On the other hand, FIN and PEAD, constructed on just two characteristics, perform as well as the MGMT factor in capturing return comovement associated with 22 firm characteristics.

2.2.3 Fitting all anomalies

Panel C of Table 7 summarizes model performance on the whole list of 34 anomalies. Our BF3 model gives just 3 significant alphas at 5% significance level, while the FF5, NM, HXZ, and SY4 models give 18, 5, 6, and 7 significant alphas, respectively. In addition, our BF3 model gives an average alpha of 0.23%, comparing with 0.36% under the FF5 model, 0.26% under the NM model, 0.31% under the HXZ model, and 0.18% under the SY4 model. Unlike in Panel A and B, the GRS F-tests reject the null hypotheses of all alphas jointly zero under all models, but our BF3 model achieves the smallest GRS F-statistic of $F = 1.61$, comparing with $F = 2.60$ under FF5, $F = 2.65$ under NM, $F = 2.42$ under HXZ, and $F = 1.71$ under SY4.

Overall, a three-factor risk-and-behavioral composite model (BF3) with a market factor and two behavioral factors outperforms both standard factor models and recently prominent models in explaining a list of 34 robust anomalies. Our findings suggest that many of the existing anomalies, such as return and earnings momentum, profitability, value vs. growth, investment and financing, and intangibles, can be attributed to systematic mispricing. Moreover, two behavioral factors FIN and PEAD, constructed on just *two* firm characteristics (along with from size, which since Fama and French (1993) has routinely been used as a control in factor construction), show stronger pricing

[15] The six anomaly variables underlying the MGMT factor are: net share issuance (NSI), composite issuance (IR), accruals (OA), net operating assets (NOA), asset growth (AG), and investment-to-assets (IVA).

power than the two mispricing factors of Stambaugh and Yuan (2016), constructed on a total of 11 firm characteristics.

Next, we present detailed factor regression results for each anomaly. For conciseness, we show statistics only for the L/S anomaly portfolios. Definitions of anomaly variables and portfolio constructions are described in Appendix A. Table 8 reports alphas and factor loadings from time-series regressions of each L/S anomaly portfolio returns on recent prominent factor models. We examine factor loadings to gain insights on which factors contribute to explaining which anomalies.

2.2.4 Earnings and return momentum

We examine five earnings momentum characteristics (SUE-1, SUE-6, Abr-1, Abr-6, RE-1) and three return momentum characteristics (R6-6, R11-1, I-Mom). Panel A of Table 8 shows that, perhaps due to lack of a momentum factor, the FF5 model does not capture any of these anomalies. Panel B and C show that the momentum factor (UMD) of the NM model and the ROE factor of the HXZ model help fully explains all anomalies, except for the post-earnings announcement drift (Abr-1). Similarly, Panel D shows that the PERF factor, which is a composite factor formed on five anomaly variables including return momentum, fully explains many of these anomalies but the post-earnings announcement drift (Abr-1, Abr-6). Lastly, Panel E shows that the PEAD factor contributes to fully capturing *all* anomalies.

Overall, the PEAD factor, constructed on earnings surprises, exhibits stronger pricing power for return and earnings momentum than the MOM factor based on past returns, the ROE factor based on earnings profitability, and the composite PERF factor based on momentum, distress, and profitability.

2.2.5 Profitability

We include six profitability anomalies: four are short-term profitability characteristics computed from quarterly COMPUSTAT files or based on earnings realizations (ROAQ, ROEQ, NEI, FP) and two are long-term profitability characteristics from annual COMPUSTAT files (GP/A, CbOP). Short-term profitability portfolios are monthly rebalanced and long-term profitability portfolios are annually rebalanced.

Panel A of Table 8 shows that the profitability factor RMW of the FF5 model helps explain a bit, but leaves most of these anomalies earning large and significant alphas. Panel B shows that the profitability factor PMU of the NM model fully explains all but the failure probability effect (FP). Panel C shows that the short-term profitability factor ROE of the HXZ model fully explains all but the cash-based operating profitability effect (CbOP). Panel D shows that the PERF factor of the SY4 model does not explain the quarterly ROE effect (ROEQ), earnings surprises measured by the number of consecutive quarters with earnings increases (NEI), and the cash-based operating profitability effect (CbOP). Lastly, Panel E shows that the PEAD factor based on earnings surprises contributes to fully capturing *all* these profitability anomalies.

Overall, the PEAD factor, constructed on earnings surprises, performs better in capturing the profitability effects than the profitability factors of the FF5, NM, and HXZ models and the PERF factor of the SY4 model based on return momentum, distress, and profitability.

2.2.6 Value vs. growth

We include five value vs. growth anomalies: B/M, E/P, CF/P, NO/P, and Dur. Panel A and B of Table 8 show that the FF5 and NM models fully explain *all* these anomalies, owing to the inclusion of a value factor HML. In Panel C, without a value factor, the investment factor IVA of the HXZ model explains all these anomalies but the net payout yield effect (NO/P). In Panel D, the MGMT factor of the SY4 model, constructed on six anomaly variables related to investment and financing, contribute to fully capturing *all* these anomalies. Lastly, in Panel E, the FIN factor, constructed on external financing activities, successfully captures *all* anomalies as well.

2.2.7 Investment and financing

We include nine investment anomalies (AG, NOA, IVA, IG, IvG, IvC, OA, POA, PTA) and two financing anomalies (NSI, IR). Panel A of Table 8 shows that the investment factor CMA of the FF5 model fails to explain five anomalies (NOA, IVA, IvC, OA, NSI). Panel B shows that the NM model derives most of its explanatory power from the value factor HML and fully explains all but two anomalies (IvC and OA). In Panel C, the investment factor IVA of the HXZ model fully explains all but two anomalies (OA and NSI). In Panel D, the MGMT factor of the SY4 model fully explains all but one anomaly (OA). Lastly, Panel E shows that our FIN factor fully captures all but one anomaly (IvC).

Overall, the value factor (HML) and the investment factors (CMA and IVA) help explain many investment and financing anomalies, but fail to capture all of them. The profitability factors (RMW, PMU, and ROE) help explain a bit financing anomalies, but go in the wrong direction for many investment anomalies. Not surprisingly, the MGMT factor, constructed on six investment and financing characteristics, delivers the best performance. Interestingly, our FIN factor, constructed on a *single* firm characteristic on external financing, delivers equally good performance as the composite MGMT factor.

2.2.8 Intangibles

We include four intangibles anomalies: OC/A, AD/M, RD/M, and OL. Panel A of Table 8 shows that the FF5 model fully captures all but one anomaly (OC/A), and derives its superior explanatory power from the MKT and SMB factors. In Panel B, lack of a size factor, the MKT and HML factors of the NM model explain all but one anomaly (OC/A), for which the profitability factor PMU goes in the wrong direction. Similarly, Panel C shows that the MKT and ME factors of the HXZ model explain all but one anomaly (RD/M), for which the profitability factor ROE explains in the wrong direction. Panel D shows that with a modified size factor, the SY4 model captures *all* but one anomaly (OC/A). Lastly, Panel E shows that without a size factor, our FIN factor fails to explain two anomalies (OC/A and RD/M).

Overall, our three-factor risk-and-behavioral composite model (BF3) exhibits weak performance on explaining the intangibles-related anomalies.

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3 Return Predictive Ability of Behavioral Factor Loadings

3.1 Estimation methods and results

If FIN and PEAD are behavioral factors that capture return comovement associated with common mispricing, then according to recent behavioral models, loadings on FIN and PEAD will be underpricing proxies. As such, these loadings should positively predict the cross-section of future stock returns. We now test this hypothesis.

As mentioned in the introduction, a challenge to such tests is that we expect proxies for mispricing to shift over time, since firm-level mispricing should tend to correct over time. We therefore expect substantial instability in firm-level behavioral factor loadings. This implies substantial error in the estimation of such loadings unless an appropriate conditional estimation technique is used to address the instability. This problem is especially severe for short-horizon mispricing, which tends to correct more quickly.

A common presumption for risk factors (such as MKT) in many monthly return tests is that loadings are persistent over periods of 3 to 5 years. As such, when estimating risk factor loadings, the standard method is to run rolling window regressions over the previous 60 months. However, for many behavioral factors, this presumption is unlikely to apply. Though a firm characteristic (upon which the behavioral factor is constructed) can be indefinitely mispriced by the market, no particular firm is likely to stay over- or underpriced forever, and therefore firm loadings on behavioral factors should not be stable over long horizons.

We therefore estimate firms' loadings on behavioral factors using daily stock returns over short horizons, e.g., one month. We estimate firm loadings on FIN and PEAD using our three-factor risk-and-behavioral composite model (BF3), which includes a daily market factor, a daily FIN factor, and a daily PEAD factor.[16] The daily FIN factor is constructed in similar way as the monthly factor. The factor portfolios are rebalanced every June, and we calculate daily FIN factor returns from July to the next June. Similarly, the daily PEAD factor is rebalanced every month, and we calculate daily factor portfolio returns during the month. We then run monthly rolling regressions of daily stock returns in the previous month $t-1$ on the daily market, daily FIN, and daily PEAD factor returns in month

[16]We are grateful to Ken French for providing the daily market factor data.

$t-1$ (a minimum of 15 valid daily returns required). The regression coefficients on FIN and PEAD are the estimated β_{FIN} and β_{PEAD} at the end of month $t-1$, and are used to forecast stock returns in month t.

Next, we run Fama and MacBeth (1973) cross-sectional regressions of monthly stock returns on firms' β_{FIN} and β_{PEAD}, with standard control variables and a broad set of firm characteristics underlying the list of 34 robust anomalies that we examine. Standard controls include log(ME), log(B/M), and the previous one-month, one-year, and three-year returns to control for short-run contrarian, momentum, and long-term reversal, respectively. All regressors are winsorized at top and bottom 1% and standardized to have zero mean and unit standard deviation, to make the coefficients comparable.

Table 9 reports the regression results. Models (1) and (2) show that β_{FIN} positively and significantly predicts the next month stock returns, with or without standard controls. In models (3)−(9), we add one by one earnings momentum and short-term profitability characteristics, and in model (10), we run a horse race between β_{FIN} and all these characteristics, we find that the coefficients on β_{FIN} remain positive and statistically significant in all settings. This suggesting that the return predictive ability of β_{FIN} is incremental to these short-horizon anomaly characteristics.

In models (11)−(13), we include two financing characteristics which our FIN factor is built upon. We find that the coefficient on β_{FIN} remains statistically significant when controlling for net share issuance (NSI), while marginally significant when controlling for composite issuance (IR). When including both NSI and IR, β_{FIN} becomes significant again. In models (14)−(22), we add one by one a number of investment characteristics, and in model (23), we run a horse race between β_{FIN} and all these characteristics, we find that the coefficient on β_{FIN} remain highly significant in all regressions. In model (24), when controlling for all financing and investment characteristics, the coefficient on β_{FIN} becomes weakly significant, primarily driven by the strong predictive power of composite issuance (IR). The evidence suggests that the return predictive ability of β_{FIN} is incremental to both investment and financing characteristics.

In models (25)−(38), we control for characteristics related to profitability, value vs. growth, and intangibles. Consistent with earlier evidence, the return predictive ability of β_{FIN} stays robust and incremental to profitability and value vs. growth characteristics. When controlling for intangibles, the coefficients on β_{FIN} become weaker or statistically insignificant. This is consistent with evidence in Table 7 and Table 8 that our behavioral factors exhibit weak performance on explaining the intangibles-related anomalies.

Overall, our findings suggest that if estimated precisely, firm loadings on FIN positively and significantly predict future stock returns. The predictive ability remains robust after controlling for a broad set of firm characteristics that are well-known return predictors in the literature. The evidence supports our hypothesis that FIN capture return comovement due to common mispricing.

While we find very strong return predictive ability of β_{FIN}, the coefficients on β_{PEAD} are statistically insignificant in all models. A possible explanation is that PEAD captures short-horizon mispricing, which tends to correct very quickly. PEAD is built on cumulative abnormal returns during the four-day window around earnings announcement (Abr). Table 5 shows that the return predictive ability of Abr portfolios becomes much weaker or insignificant just one month after portfolio formation. This suggests that firm loadings on PEAD, β_{PEAD}, might be a rather noisy proxy of such high-frequency mispricing. This may explain the inability of β_{PEAD} to predict the next month stock returns.

3.2 Discussion

Although these cross-sectional tests are generally consistent with the earlier tests, we place less weight on the cross-sectional tests for two reasons.

First is the well-known errors-in-variables problem. As discussed above, this is likely to be especially severe for the loadings on short-horizon behavioral factors.

Second, as discussed by Daniel and Titman (2006), each cross-sectional coefficient in a Fama and MacBeth (1973) regression represents the return on a portfolio. In a setting where the characteristics (the independent variables in the cross-sectional regression) are fairly stable, these coefficient portfolios regressions implicitly place relatively constant weight on high- and low-characteristic securities from month-to-month, much like an equal-weighted portfolio. Actually achieving such returns, however, is likely to be difficult. To maintain the approximate equal-weighting, it is necessary to rebalance the portfolio each month, buying firms that fell in value in selling firms that rose. This means that bid-ask bounce, illiquidity, and transaction costs might make the actual returns from such a strategy unachievable, especially for low market capitalization portfolios, and results in upwardly-biased estimated of the returns of illiquid firms.

This can help explain a difference between the Fama-MacBeth tests and our earlier tests. The ability of factor models to explain anomalies was consistently better in the earlier tests than in the Fama-MacBeth tests. This include our own model. A possible explanation is that factor models do better in explaining implementable anomalies than non-implementable ones.

In particular, in the earlier tests the PEAD factor captured short-horizon anomalies extremely well, whereas in the Fama-MacBeth tests it does so more imperfectly (though our model still competes well against alternative factor models). But exploiting short-horizon anomalies requires greater rebalancing, making them more costly to implement. So the model is doing less well in the Fama-MacBeth tests exactly in the set of anomalies that are harder to implement.

This is what we would expect on theoretical grounds if factor risk is a deterrent to arbitrage. In the frictionless model of mispricing and arbitrage of (Daniel, Hirshleifer, and Subrahmanyam, 2001), mispricing of idiosyncratic components of security payoffs is almost completely arbitraged away, because rational arbitrageurs can profit by taking small bets in many idiosyncratic components while bearing little overall risk. In contrast, the only way to arbitrage factor mispricing is to bear substantial non-diversifiable risk, so factor mispricing persists.

In our earlier tests, which focus on large liquid stocks, factor loadings (a measure of systematic mispricing) almost completely explain characteristic-based anomalies, meaning that almost all the mispricing seems to be derived from factor mispricing. In contrast, in the Fama-MacBeth tests, which focus heavily on small illiquid stocks, characteristics more often remain incrementally significant in predicting returns. This suggests that in the small and illiquid stocks that dominate in Fama-MacBeth regressions, idiosyncratic mispricing remains important. This is reasonable, since the arbitrage arguments for the elimination of idiosyncratic mispricing are weakened when trading frictions are severe.

This explains why it is exactly the short-horizon anomalies which the factor models find harder to explain in the Fama-MacBeth tests. It is these anomalies whose Fama-MacBeth coefficients are driven most strongly by monthly rebalancing of illiquid stocks.

However, there is an alternative explanation based simply on measurement error. This is that the small, illiquid stocks that dominate Fama-MacBeth regressions (again, especially for short-horizon anomalies) are traded by actual investors less frequently. So owing to asynchronous trading, their factor loadings are estimated poorly. This would reduce the ability of the factor loadings to subsume the effect of the characteristic in predicting returns.

4 Robustness Tests

We next conduct a set of robustness tests to further evaluate FIN and PEAD as behavioral factors. We focus on market frictions and arbitrage capital, two important factors that affect arbitrageurs' ability to exploit mispricing. Owing to limits to arbitrage and short-sale constraints, we expect that behavioral factors are especially good at explaining returns of stocks with high arbitrage frictions, such as stocks in the short-leg portfolios and stocks with greater market frictions. Moreover, on the premise that sophisticated investors such as hedge funds mitigate or eliminate mispricing, we expect that the performance of behavioral factors comoves with the supply of arbitrage capital.

4.1 The loadings on behavioral factors of long-leg and short-leg portfolios

To exploit anomaly profits, the common practice is to form a zero-investment portfolio by going long on underpriced stocks and short on overpriced stocks. Due to short-sale constraints, overpriced stocks in the short-leg portfolios are more difficult to correct and therefore subject to a greater degree of mispricing. If FIN and PEAD capture mispricing, they should explain the returns of the short-leg portfolios particularly well. Generally, we expect the long-leg portfolios (underpriced) to load positively on FIN and PEAD and the short-leg portfolios (overpriced) to load negatively. If FIN and PEAD explain the short legs particularly well, we would expect that the negative loadings of the short legs are larger in absolute magnitude than the positive loadings of the long legs. Moreover, since PEAD primarily captures high-frequency mispricing and FIN captures low-frequency mispricing, we expect that the result for PEAD factor loadings is more pronounced among short-horizon anomalies and the result for FIN factor loadings more pronounced among long-horizon anomalies.

We run time-series regressions of the long-leg and short-leg portfolio returns on the three-factor risk-and-behavioral composite model. We count how many short-horizon (long-horizon) anomalies have larger (in absolute magnitude) negative PEAD (FIN) factor loadings in the short legs than the positive loadings in the long legs, and we highlight this case in boldface. Table 10 reports the results. Panel A shows that for the 12 short-horizon anomalies, 11 anomalies have larger negative and statistically significant β_{PEAD} in the short legs. In contrast, only 1 anomaly has larger positive and statistically significant β_{PEAD} in the long legs. The average β_{PEAD} is -0.51 for the short legs and 0.31 for the long legs. The evidence is consistent with our hypothesis that PEAD primarily captures high-frequency mispricing embedded in short-horizon anomalies and explains the returns of the short-leg portfolios particularly well.

Similarly, Panel B shows that for the 22 long-horizon anomalies, 15 anomalies have larger negative and statistically significant β_{FIN} in the short legs. In contrast, just 3 anomalies has larger positive and statistically significant β_{FIN} in the long legs. The average β_{FIN} is -0.27 for the short legs and 0.03 for the long legs. Again, the evidence confirms that FIN primarily captures low-frequency mispricing embedded in long-horizon anomalies and explains the returns of the short-leg portfolios particularly well. Overall, the findings support that FIN and PEAD are behavioral factors that capture common mispricing.

4.2 Market frictions and the sensitivity of beta-return relation

If FIN and PEAD are behavioral factors, then firm loadings or betas on FIN and PEAD are proxies for the degree of mispricing, and we expect a positive relation between FIN or PEAD betas and future stock returns. In Section 3, we confirm the strong return predictive ability of FIN betas. On the other hand, PEAD betas show no return predictability at all, probably because PEAD captures short-horizon mispricing which tends to correct within a few months, so PEAD betas are rather noisy proxy of such high-frequency mispricing. In this section, we further propose that market frictions impede arbitrage in mispricing and affect the *sensitivity* of the FIN beta-return relation, given that FIN betas capture mispricing.

Owing to limits to arbitrage and short-sale constraints, we expect that high friction stocks have greater mispricing, but not necessarily the *sensitivity* of expected returns to any given amount of mispricing. However, mispricing, as proxied by factor betas on FIN, is measured with noise. In case of low frictions and low mispricing (hence low factor expected return), most of the variation in the mispricing proxies (factor betas) would be noise and we would observe low sensitivity of expected returns to factor betas. On the other hand, in case of high friction and high mispricing, we expect less noise in the mispricing proxies and high sensitivity of expected returns to factor betas. Therefore, we hypothesize that the FIN beta-return relation should be stronger for high friction stocks.

We first test our hypothesis by two-way portfolio sorts on friction proxies and factor betas. Specifically, at the beginning of each month, we rank firms into 25 portfolios by independent sorts on their FIN betas (from Section 3) and market friction proxies. Portfolios are held for the current month and rebalanced at the beginning of the next month. Value-weighted average returns of each portfolio are calculated, with Newey and West (1987) corrected standard errors. Following the literature, we use three friction proxies: the illiquidity measure (ILLIQ) of Amihud (2002), the institutional ownership defined as shares held by institutions divided by shares outstanding (IO), and the residual institutional ownership (RIO) of Nagel (2005) controlling for size. Firms with larger ILLIQ, or smaller IO and RIO, have greater market frictions. Consistent with our hypothesis, Panel A of Table 11 shows that, using ILLIQ and IO as friction proxies, the FIN beta-return relation is positive and statistically significant *only* for high friction stocks. The results using RIO are consistent with our hypothesis but statistically insignificant.

Next, we run Fama and MacBeth (1973) cross-sectional regressions of monthly stock returns on firms' β_{FIN}, the quintile ranks of their market friction proxies, and the interactions between β_{FIN} and friction ranks, controlling for standard return predictors. All regressors are winsorized at top and bottom 1% and standardized to have zero mean and unit standard deviation, to make the coefficients comparable. Panel B of Table 11 shows the results. We are particularly interested in the interaction terms. The coefficients on the interaction between β_{FIN} and ILLIQ ranks are statistically insignificant. On the other hand, the coefficients on the interactions between β_{FIN} and IO or RIO ranks are both negative and statistically significant, suggesting that high friction stocks (with low IO or RIO ranks) have stronger beta-return sensitivity.

Overall, the evidence from portfolio sorts and cross-sectional regressions is largely consistent with our hypothesis that high friction stocks have stronger sensitivity of expected returns to FIN betas, given that FIN betas capture mispricing.

4.3 Arbitrage capital and behavioral factor premiums

Lastly, on the premise that sophisticated investors help to mitigate or alleviate mispricing, we examine whether FIN and PEAD factor premia comove with the supply of arbitrage capital. We focus on a specific group of sophisticated investors, hedge funds, which are generally viewed as the most active and effective arbitrageurs in exploiting market mispricing.

The hedge fund data are from Thomson Reuters Lipper Hedge Fund Database (TASS), one of the leading sources of hedge fund information. The main data include monthly hedge fund performance and assets under management. TASS classifies hedge funds into 11 self-reported style categories, and for our purposes we keep only funds in the style of long/short equity hedge that most likely trade against market mispricing.[17] We measure arbitrage capital by two variables: changes in aggregate hedge funds assets under management (ΔAUM) and aggregate capital flows to the hedge fund sector ($FLOW$).

If FIN and PEAD are behavioral factors, their factor premia reflect the amount of corrections to previous mispricing. On the premise that arbitrageurs trade against mispricing, we would expect that the supply of arbitrage capital positively predicts *contemporaneous* FIN and PEAD factor premia (as more mispricing being corrected) and negatively predicts *future* factor premia (as less mispricing remained to be corrected). We run time-series regressions of FIN or PEAD factor premia on the supply of arbitrage capital, as proxied by ΔAUM and $FLOW$, in both contemporaneous and lagged periods. We examine the relation over both monthly and quarterly horizons and report the results in Table 12.

Panel A shows monthly regression results. Consistent with our hypothesis, we find that FIN and PEAD factor premia are positively associated with *contemporaneous* hedge funds capital flows ($FLOW$) and negatively associated with *lagged* $FLOW$. PEAD factor premia are also positively associated with *contemporaneous* changes in hedge funds assets (ΔAUM). Noticeably, the results over

[17] The 11 investment styles are: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, long/short equity hedge, managed futures, multi-strategies, and fund of funds. The long/short equity hedge and fund of funds category each accounts for about one third of the total sample funds.

monthly horizon are stronger for PEAD than FIN, probably because PEAD captures high-frequency mispricing that corrects over a few months while FIN captures low-frequency mispricing that corrects over years. Panel B shows results over quarterly horizon. Interestingly, the association between ΔAUM and FIN premia becomes stronger, while the effect for PEAD disappears. Again, this is consistent with our proposition of FIN capturing low-frequency mispricing that corrects over longer horizon.

Overall, we find moderate evidence of comovement between the performance of FIN and PEAD factors and the supply of arbitrage capital, in line with FIN and PEAD as behavioral factors capturing mispricing.

5 Conclusion

In this study, we supplement the market factor of the CAPM with behavioral factors which capture the common mispricing caused by psychological biases. We concentrate on two psychological biases that are likely to affect asset prices: overconfidence and limited attention. Hirshleifer and Jiang (2010) propose a financing-based misvaluation factor, constructed based on firms' financing events (such as IPOs, SEOs, equity repurchases, debt issues and repurchases), motivated by the theory of investor overconfidence. In line with the same theory and motivation, we create a modified financing factor (FIN) based upon two prominent financing-related firm characteristics, net share issuance and composite issuance. We also consider a post-earnings announcement drift factor (PEAD) constructed based upon earning surprises, motivated by the theory of limited investor attention. We further hypothesize that FIN captures the returns associated with long-term (>1 year) mispricing, and PEAD captures the returns associated with shorter-term (<1 year) mispricing.

Our new factor model is designed to capture these complementary aspects of mispricing. We test the ability of our three-factor risk-and-behavioral composite model to explain well-known return anomalies. This composite approach is suggested by theoretical models in which both risk and misvaluation proxies predict returns. We find that the FIN factor is dominant in explaining long-horizon return anomalies, and the PEAD factor is dominant in explaining short-horizon return anomalies.

We compare the model performance with standard factor models and recently prominent models, such as the profitability-based model of Novy-Marx (2013), the five-factor model of Fama and French (2015), the q-factor model of Hou, Xue, and Zhang (2015), and the four-factor mispricing model of Stambaugh and Yuan (2016). Our composite model outperforms all other models in explaining 34 robust anomalies, based on the list of anomalies considered in Hou, Xue, and Zhang (2015). The composite model is also parsimonious; along with the market, two behavioral factors built upon only two economic characteristics capture a wide range of anomalies.

If FIN and PEAD are indeed priced behavioral factors that capture common mispricing, then behavioral models imply that firm loadings on FIN and PEAD are underpricing proxies, and therefore should positively predict the cross-section of stock returns. Using Fama-MacBeth cross-sectional regressions, we confirm that FIN loadings (estimated using daily stock returns over the previous month) positively and significantly predict future returns, even after controlling for a broad set of firm characteristics underlying the list of 34 robust anomalies that we examine. However, PEAD loadings exhibit no return predictive ability, probably because PEAD captures short-horizon mispricing that corrects very quickly and thereby PEAD loadings are rather noisy proxy of such high-frequency mispricing.

At last, we conduct several robustness tests and provide additional evidence in support of FIN and PEAD as behavioral factors. In light of limits to arbitrage and short-sale constraints, we find that FIN and PEAD are particularly good at explaining returns of stocks with high arbitrage frictions, such as overpriced stocks and stocks with greater market frictions. Moreover, motivated by the idea that arbitrageurs exploit market mispricing, we find that FIN and PEAD factor premiums comove with the supply of arbitrage capital.

The broader message of this study is that it is useful to give behavioral-motivated as well as traditional return factors a prominent role in understanding return comovement and predictability at short- versus long-horizons.

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Table 1: Summary Statistics of Factor Portfolios

Panel A reports the mean and standard deviations of monthly factor returns for a set of traded-factor returns. In addition we report the t-statistic testing whether this the mean return is different from zero, the corresponding monthly Sharpe Ratio, and the sample period for each return factor. Panel B reports Pearson correlations between factor portfolio returns, and Panel C reports summary statistics for the *ex-post* tangency portfolios of various factor-portfolio combinations. These factors include the Mkt-Rf, SMB, HML, MOM factors proposed by Fama and French (1993) and Carhart (1997), and modified versions of these factors proposed by Novy-Marx (2013, NM), Hou, Xue, and Zhang (2015, HXZ), and Stambaugh and Yuan (2016, SY4). In addition we include: the investment factors CMA and IVA of Fama and French (2015) and Hou, Xue, and Zhang (2015), the profitability factors PMU, RMW, and ROE of Novy-Marx (2013), Fama and French (2015), and Hou, Xue, and Zhang (2015), and the two mispricing factors MGMT and PERF of Stambaugh and Yuan (2016). Monthly factor returns are either from Kenneth French's web page or provided by corresponding authors. FIN and PEAD are our behavioral factors. FIN is the financing-based misvaluation factor constructed based upon two financing characteristics, net share issuance and composite issuance. PEAD is the post-earnings announcement drift factor, constructed based upon earnings surprises (measured as the four-day cumulative abnormal returns around quarterly earnings announcements). The sample period for each factor is indicated in the table.

Panel A: Factor premiums

	Mean	Std	t-value	SR	N. obs	Sample period
MKT	0.53	4.59	2.62	0.12	510	1972:07 – 2014:12
SMB	0.17	3.13	1.19	0.05	510	1972:07 – 2014:12
SMB(HXZ)	0.29	3.14	2.06	0.09	510	1972:07 – 2014:12
SMB(SY)	0.41	2.81	3.28	0.15	498	1972:07 – 2013:12
HML	0.41	2.94	3.14	0.14	510	1972:07 – 2014:12
HML(NM)	0.44	1.49	6.43	0.29	486	1972:07 – 2012:12
MOM	0.68	4.44	3.45	0.15	510	1972:07 – 2014:12
MOM(NM)	0.61	2.90	4.6	0.21	486	1972:07 – 2012:12
CMA	0.37	1.95	4.27	0.19	510	1972:07 – 2014:12
IVA	0.43	1.86	5.23	0.23	510	1972:07 – 2014:12
PMU	0.27	1.18	5.06	0.23	486	1972:07 – 2012:12
RMW	0.34	2.24	3.44	0.15	510	1972:07 – 2014:12
ROE	0.56	2.59	4.88	0.22	510	1972:07 – 2014:12
MGMT	0.67	2.87	5.24	0.23	498	1972:07 – 2013:12
PERF	0.65	3.90	3.73	0.17	498	1972:07 – 2013:12
FIN	0.80	3.92	4.6	0.20	510	1972:07 – 2014:12
PEAD	0.65	1.85	7.91	0.35	510	1972:07 – 2014:12

Panel B: Correlation matrix

	MKT	SMB	SMB (HXZ)	SMB (SY4)	HML	HML (NM)	MOM	MOM (NM)	CMA	IVA	PMU	RMW	ROE	MGMT	PERF	FIN
SMB	0.26															
SMB(HXZ)	0.25	**0.95**														
SMB(SY4)	0.21	**0.92**	**0.93**													
HML	-0.28	-0.22	-0.05	-0.05												
HML(NM)	-0.19	-0.04	0.09	0.10	**0.81**											
MOM	-0.14	0.01	0.01	0.03	-0.17	-0.12										
MOM(NM)	-0.19	-0.06	-0.07	-0.04	-0.20	-0.18	**0.95**									
CMA	-0.39	-0.12	-0.02	0.01	**0.69**	**0.61**	0.02	-0.01								
IVA	-0.37	-0.23	-0.12	-0.09	**0.68**	**0.55**	0.04	0.02	**0.90**							
PMU	-0.29	-0.27	-0.25	-0.17	-0.10	-0.22	0.25	0.28	-0.03	0.03						
RMW	-0.21	-0.22	-0.16	-0.13	0.01	-0.01	0.21	0.24	-0.03	0.00	**0.57**					
ROE	-0.19	-0.38	-0.31	-0.28	-0.10	-0.21	**0.49**	**0.52**	-0.08	0.06	**0.59**	**0.58**				
MGMT	-0.54	-0.39	-0.29	-0.25	**0.72**	**0.59**	0.06	0.06	**0.76**	**0.76**	0.16	0.16	0.09			
PERF	-0.26	-0.09	-0.12	-0.05	-0.30	-0.24	**0.72**	**0.70**	-0.06	-0.06	**0.59**	**0.48**	**0.63**	0.01		
FIN	-0.50	-0.49	-0.38	-0.30	**0.65**	**0.50**	0.09	0.09	**0.58**	**0.66**	0.35	0.35	0.33	**0.80**	0.15	
PEAD	-0.10	0.03	0.00	0.01	-0.16	-0.13	**0.46**	**0.48**	0.00	-0.04	0.09	0.07	0.22	0.00	**0.38**	-0.05

Panel C: Ex post tangency portfolios

	Portfolio Weights													Tangency Portfolios		
	MKT	SMB	HML	MOM	RMW	CMA	PMU	IVA	ROE	MGMT	PERF	FIN	PEAD	Mean	Std	SR
(1) FF3	0.29	0.15	0.56											0.41	1.86	0.22
(2) Carhart	0.23	0.09	0.43	0.26										0.49	1.58	0.31
(3) FF5	0.17	0.06	-0.01		0.31	0.47								0.38	1.06	0.36
(4) NM	0.10		0.40	0.11			0.39							0.40	0.70	**0.57**
(5) HXZ	0.14	0.13						0.44	0.29					0.46	1.08	0.43
(6) SY4	0.22	0.17								0.43	0.18			0.59	1.20	0.50
(7) BF2												0.22	0.78	0.68	1.64	0.41
(8) BF3	0.19											0.26	0.55	0.66	1.29	**0.52**
(9) BF3 + PMU	0.16						0.29					0.17	0.39	0.55	1.01	0.54
(10) BF3 + RMW + CMA	0.16				0.10	0.19						0.13	0.41	0.56	1.05	0.54
(11) BF3 + IVA + ROE	0.16							0.25	0.09			0.11	0.40	0.58	1.06	0.55
(12) BF3 + MGMT + PERF	0.20									0.27	0.07	0.06	0.39	0.64	1.15	0.56
(13) All factors ex. BF2	0.15	0.15	-0.01	-0.02	-0.04	-0.09	0.25	0.14	0.13	0.28	0.05			0.47	0.86	0.54
(14) All factors	0.12	0.11	0.01	-0.05	-0.02	-0.13	**0.23**	**0.17**	0.08	**0.20**	0.02	0.00	**0.26**	0.49	0.76	**0.65**

Table 2: Factor Regressions of Behavioral Factors on Other Factors

This table reports time-series regressions of behavioral factors on standard factor models and other recent models: (1) the Fama-French three-factor model (FF3), (2) the Carhart four-factor model (Carhart), (3) the profitability-based model of Novy-Marx (2013, NM), (4) the five-factor model of Fama and French (2015, FF5), (5) the q-factor model of Hou, Xue, and Zhang (2015, HXZ), (6) the four-factor mispricing model of Stambaugh and Yuan (2016, SY4), and (7) the "kitchen sink" model with all factors. The sample period is from 1972:07 to 2014:12, depending on data availability. Newey-West corrected t-statistics (with 6 lags) are shown in parentheses.

	Mean		α	MKT	SMB	HML	MOM	PMU	RMW	CMA	IVA	ROE	MGMT	PERF	Adj. R^2
FIN	0.80***	(1) FF3	0.71***	-0.24***	-0.38***	0.67***									60.4%
	(4.60)		(5.61)	(-5.55)	(-5.55)	(9.22)									
		(2) Carhart	0.59***	-0.21***	-0.38***	0.72***	0.13***								63.2%
			(4.64)	(-5.74)	(-4.92)	(10.54)	(2.93)								
		(3) NM	-0.02	-0.26***		1.41***	0.04	1.23***							56.4%
			(-0.13)	(-8.29)		(13.29)	(0.27)	(4.10)							
		(4) FF5	0.34***	-0.13***	-0.19***	0.45***			0.68***	0.56***					73.9%
			(3.59)	(-4.88)	(-3.58)	(9.26)			(9.20)	(7.43)					
		(5) HXZ	0.31**	-0.19***	-0.25***						1.14***	0.29***			58.5%
			(2.42)	(-4.32)	(-2.68)						(10.49)	(3.01)			
		(6) SY4	0.12	-0.05	-0.14								1.02***	0.13**	68.1%
			(1.14)	(-1.22)	(-1.25)								(16.69)	(2.54)	
		(7) All factors	-0.03	-0.06*	-0.14***	0.41***	-0.04	0.35**	0.14	-0.42**	0.54***	0.13	0.58***	0.09	79.1%
			(-0.24)	(-1.77)	(-2.70)	(5.51)	(-0.69)	(2.07)	(0.83)	(-2.22)	(3.07)	(1.49)	(10.12)	(1.51)	
PEAD	0.65***	(1) FF3	0.73***	-0.06***	0.02	-0.12***									3.2%
	(7.91)		(8.47)	(-2.70)	(0.34)	(-2.75)									
		(2) Carhart	0.56***	-0.03	0.01	-0.06	0.18***								19.2%
			(7.34)	(-1.27)	(0.40)	(-1.47)	(6.31)								
		(3) NM	0.54***	-0.02		-0.09	0.31***	-0.11							20.3%
			(6.27)	(-0.66)		(-1.27)	(6.74)	(-1.04)							
		(4) FF5	0.70***	-0.05**	-0.05	-0.14***			-0.05	0.10					3.8%
			(7.90)	(-2.05)	(-1.31)	(-2.95)			(-0.94)	(1.18)					
		(5) HXZ	0.60***	-0.04*	0.05						-0.09	0.16***			7.0%
			(5.78)	(-1.71)	(0.89)						(-1.11)	(2.91)			
		(6) SY4	0.53***	-0.00	0.02								-0.00	0.18***	13.6%
			(5.61)	(-0.14)	(0.42)								(-0.03)	(5.23)	
		(7) All factors	0.58***	-0.02	-0.01	-0.06	0.15***	-0.15	-0.03	0.25*	-0.27**	0.04	0.03	0.06	23.9%
			(6.76)	(-0.76)	(-0.15)	(-1.24)	(3.38)	(-1.10)	(-0.24)	(1.72)	(-2.11)	(0.41)	(0.41)	(1.17)	

Table 3: Factor Regressions of Other Factors on Behavioral Factors

This table reports time-series regressions of other factors on behavioral factors. SMB, HML, and MOM are the standard size, value, and momentum factors. PMU is the profitability factor of Novy-Marx (2013). RMW and CMA are the investment and profitability factors of Fama and French (2015). IVA and ROE are the investment and profitability factors of Hou, Xue, and Zhang (2015). MGMT and PERF are the two composite mispricing factors of Stambaugh and Yuan (2016). The sample period is from 1972:07 to 2014:12, depending on data availability. Newey-West corrected t-statistics (with 6 lags) are shown in parentheses.

	Mean	α	FIN	PEAD	Adj. R^2	α	MKT	FIN	PEAD	Adj. R^2
SMB	0.17	0.47***	-0.39***	0.01	23.6%	0.45***	0.02	-0.38***	0.02	23.5%
	(1.19)	(3.65)	(-4.56)	(0.10)		(3.09)	(0.25)	(-3.44)	(0.14)	
HML	0.41***	0.15	0.49***	-0.20***	43.9%	0.12	0.03	0.50***	-0.19***	43.9%
	(3.14)	(1.24)	(13.76)	(-3.36)		(0.89)	(0.53)	(11.94)	(-3.43)	
MOM	0.68***	-0.15	0.13	1.12***	22.2%	-0.09	-0.05	0.10	1.11***	22.2%
	(3.45)	(-0.53)	(0.97)	(5.30)		(-0.34)	(-0.66)	(0.68)	(5.62)	
PMU	0.27***	0.14**	0.10***	0.07	12.8%	0.18***	-0.04	0.08***	0.06	14.0%
	(5.06)	(2.28)	(4.04)	(1.43)		(2.96)	(-1.63)	(2.68)	(1.28)	
RMW	0.34***	0.11	0.20***	0.11	12.6%	0.13	-0.02	0.19***	0.10	12.5%
	(3.44)	(1.29)	(2.97)	(0.90)		(1.50)	(-0.63)	(2.65)	(0.89)	
CMA	0.37***	0.12	0.29***	0.03	33.9%	0.18**	-0.06*	0.26***	0.01	35.1%
	(4.27)	(1.36)	(6.47)	(0.53)		(2.02)	(-1.89)	(5.17)	(0.25)	
IVA	0.43***	0.19***	0.31***	-0.01	43.2%	0.22***	-0.02	0.30***	-0.02	43.3%
	(5.23)	(2.65)	(10.25)	(-0.31)		(2.90)	(-0.99)	(9.40)	(-0.51)	
ROE	0.56***	0.17	0.22***	0.33***	16.0%	0.16	0.00	0.23***	0.33***	15.8%
	(4.88)	(1.14)	(3.40)	(2.70)		(1.24)	(0.11)	(3.23)	(2.86)	
MGMT	0.67***	0.16*	0.59***	0.06	64.2%	0.29***	-0.11***	0.52***	0.02	66.2%
	(5.24)	(1.82)	(12.25)	(0.96)		(3.05)	(-3.25)	(9.72)	(0.48)	
PERF	0.65***	-0.02	0.17	0.82***	17.1%	0.17	-0.16**	0.07	0.77***	19.4%
	(3.73)	(-0.09)	(1.54)	(6.21)		(0.87)	(-2.29)	(0.63)	(6.61)	

Table 4: List of Anomalies

This table reports the list of anomalies considered in the paper, closely matching the set of robust anomalies (with significant abnormal returns) considered in Hou, Xue, and Zhang (2015). We classify the total 34 anomalies into two groups: 12 short-horizon anomalies and 22 long-horizon anomalies. Short-horizon anomalies include earning momentum, return momentum, and short-term profitability. Long-horizon anomalies include long-horizon profitability, value vs. growth, investment and financing, and intangibles. The last two columns report the monthly mean abnormal returns (in percent) and Sharpe ratios of the long/short anomaly portfolios. The sample period runs from 1972:07 to 2014:12, depending on data availability.

Panel A: Short-horizon anomalies (12)

Category	Symbol	List of anomalies	Mean	Sharpe ratio
Earnings momentum	SUE-1	Standardized unexpected earnings (1-month holding period), Foster, Olsen, and Shevlin (1984)	0.40	0.13
	SUE-6	Standardized unexpected earnings (6-month holding period), Foster, Olsen, and Shevlin (1984)	0.19	0.07
	Abr-1	Cumulative abnormal returns around earnings announcements (1-month holding period), Chan et al. (1996)	0.79	0.25
	Abr-6	Cumulative abnormal returns around earnings announcements (6-month holding period), Chan et al. (1996)	0.28	0.14
	RE-1	Revisions in analysts' earnings forecasts (1-month holding period), Chan, Jegadeesh, and Lakonishok (1996)	0.60	0.13
Return momentum	R6-6	Return momentum (6-month prior returns, 6-month holding period), Jegadeesh and Titman (1993)	0.72	0.13
	R11-1	Return momentum (11-month prior returns, 1-month holding period), Fama and French (1996)	1.18	0.18
	I-Mom	Industry momentum (6-month prior returns, 6-month holding period), Moskowitz and Grinblatt (1999)	0.62	0.12
Profitability	ROEQ	Quarterly ROE (1-month holding period), Haugen and Baker (1996)	0.75	0.15
	ROAQ	Quarterly ROA (1-month holding period), Balakrishnan, Bartov, and Faurel (2010)	0.53	0.11
	NEI	Number of consecutive quarters with earnings increases (1-month holding period), Barth et al. (1999)	0.34	0.12
	FP	Failure probability (quarterly updated, 6-month holding period), Campbell, Hilscher, and Szilagyi (2008)	−0.58	0.09

Panel B: Long-horizon anomalies (22)

Category	Symbol	List of anomalies	Mean	Sharpe ratio
Profitability	GP/A	Gross profits-to-assets ratio, Novy-Marx (2013)	0.22	0.06
	CbOP	Cash-based operating profitability, Ball et al. (2016)	0.42	0.10
Value vs. growth	B/M	Book-to-market equity, Rosenberg, Reid, and Lanstein (1985)	0.62	0.14
	E/P	Earnings-to-price, Basu (1983)	0.47	0.10
	CF/P	Cash flow-to-price, Lakonishok, Shleifer, and Vishny (1994)	0.45	0.10
	NO/P	Net payout yield, Boudoukh et al. (2007)	0.65	0.17
	Dur	Equity duration, Dechow, Sloan, and Soliman (2004)	−0.64	0.15
Investment and financing	AG	Asset growth, Cooper, Gulen, and Schill (2008)	−0.43	0.12
	NOA	Net operating assets, Hirshleifer et al. (2004)	−0.38	0.12
	IVA	Investment-to-assets, Lyandres, Sun, and Zhang (2008)	−0.50	0.17
	IG	Investment growth, Xing (2008)	−0.38	0.13
	IvG	Inventory growth, Belo and Lin (2012)	−0.33	0.10
	IvC	Inventory changes, Thomas and Zhang (2002)	−0.45	0.14
	OA	Operating accruals, Sloan (1996) and Hribar and Collins (2002)	−0.24	0.08
	POA	Percent operating accruals, Hafzalla, Lundholm, and Van Winkle (2011)	−0.39	0.13
	PTA	Percent total accruals, Hafzalla, Lundholm, and Van Winkle (2011)	−0.40	0.12
	NSI	Net share issuance, Pontiff and Woodgate (2008)	−0.69	0.22
	IR	Composite issuance, Daniel and Titman (2006)	−0.56	0.14
Intangibles	OC/A	Organizational capital-to-assets, Eisfeldt and Papanikolaou (2013)	0.40	0.11
	AD/M	Advertisement expense-to-market, Chan, Lakonishok, and Sougiannis (2001)	0.67	0.13
	RD/M	R&D-to-market, Chan, Lakonishok, and Sougiannis (2001)	0.71	0.12
	OL	Operating leverage, Novy-Marx (2011)	0.37	0.09

Table 5: Decay Rate of Anomaly Portfolio Returns

This table reports the decay rate of various anomaly portfolio returns. Short-horizon anomaly portfolios are formed and rebalanced each month. Using an event time approach, we calculate the value-weighted buy-and-hold portfolio returns in each of the 12 months, and in each of the 4 quarters, after portfolio formation (weighted by firm size in the ranking month). Long-horizon anomaly portfolios are formed and rebalanced each June. We calculate value-weighted buy-and-hold portfolio returns in each of the 12 quarters, and in each of the 3 years, after portfolio formation (weighted by firm size in the ranking month). Panel A reports the average long/short portfolio returns of short-horizon anomalies over each return window, and Panel B for long-horizon anomalies, with Newey-West corrected t-statistics (6 lags for monthly or quarterly window, 12 lags for annual window). When a long/short portfolio earns significant returns in predicted direction over a return window, we highlight this case in boldface. The sample period runs from 1972:07 to 2014:12, depending on data availability.

Panel A: Short-horizon anomalies

	SUE	Abr	RE	R6	R11	I-Mom	ROEQ	ROAQ	NEI	FP
	Long/short portfolio returns in each of the 12 months post formation									
Month $t+1$	**0.40*****	**0.78*****	**0.60*****	0.50	**1.18*****	**0.57****	**0.75*****	**0.53****	**0.34*****	-0.63*
	(3.59)	**(6.02)**	**(2.80)**	(1.65)	**(4.06)**	**(2.23)**	**(3.11)**	**(2.35)**	**(3.01)**	(-1.89)
Month $t+2$	0.20	0.15	**0.44****	0.51*	**0.98*****	0.47*	0.46*	0.39*	0.23*	-0.61*
	(1.47)	(1.08)	**(2.08)**	(1.80)	**(3.27)**	(1.88)	(1.86)	(1.65)	(1.95)	(-1.94)
Month $t+3$	0.06	0.01	0.26	**0.68****	**0.78*****	0.41	0.38*	0.31	0.15	-0.43
	(0.48)	(0.10)	(1.28)	**(2.32)**	**(2.69)**	(1.63)	(1.66)	(1.36)	(1.27)	(-1.30)
Month $t+4$	0.16	0.11	0.15	**0.70****	**0.84*****	**0.57****	0.35	0.32	0.18	-0.52
	(1.29)	(0.92)	(0.78)	**(2.16)**	**(2.89)**	**(2.34)**	(1.42)	(1.39)	(1.48)	(-1.62)
Month $t+5$	0.13	**0.33****	-0.09	**0.92*****	0.56*	**0.55****	0.34	0.29	0.17	-0.48
	(1.02)	**(2.16)**	(-0.48)	**(3.11)**	(1.91)	**(2.21)**	(1.42)	(1.28)	(1.40)	(-1.57)
Month $t+6$	0.19	0.26*	0.06	**1.15*****	0.35	**0.92*****	0.29	0.23	0.14	-0.49
	(1.38)	(1.84)	(0.30)	**(4.10)**	(1.30)	**(3.58)**	(1.16)	(1.03)	(1.15)	(-1.58)
Month $t+7$	0.18	0.23*	0.06	**0.88*****	0.38	**1.00*****	0.13	0.14	0.08	-0.41
	(1.31)	(1.83)	(0.33)	**(3.00)**	(1.38)	**(3.57)**	(0.50)	(0.62)	(0.64)	(-1.36)
Month $t+8$	0.17	0.12	0.11	**0.70*****	0.14	**0.78****	0.05	0.05	0.06	-0.28
	(1.12)	(0.78)	(0.51)	**(2.78)**	(0.50)	**(2.44)**	(0.20)	(0.22)	(0.49)	(-0.90)
Month $t+9$	-0.04	0.11	0.15	0.34	-0.02	**0.69****	-0.04	0.00	0.02	-0.18
	(-0.29)	(0.78)	(0.74)	(1.41)	(-0.06)	**(2.52)**	(-0.14)	(0.01)	(0.13)	(-0.58)
Month $t+10$	-0.13	0.08	0.08	0.14	-0.06	0.30	0.14	0.20	0.00	-0.12
	(-0.96)	(0.57)	(0.39)	(0.63)	(-0.20)	(1.30)	(0.57)	(0.93)	(0.01)	(-0.39)
Month $t+11$	-0.17	0.17	0.14	-0.31	-0.19	0.20	0.16	0.22	-0.03	0.01
	(-1.36)	(1.41)	(0.69)	(-1.25)	(-0.71)	(0.79)	(0.62)	(1.01)	(-0.23)	(0.03)
Month $t+12$	-0.14	0.05	0.21	-0.60**	-0.50*	-0.01	-0.04	0.09	-0.02	0.29
	(-1.14)	(0.42)	(0.93)	(-2.23)	(-1.82)	(-0.03)	(-0.14)	(0.43)	(-0.14)	(0.89)
	Long/short portfolio returns in each of the 4 quarters post formation									
Quarter $t+1$	**0.75****	**1.09*****	**1.33****	**1.92****	**3.09*****	**1.61****	**1.54****	1.20*	**0.72****	-1.58*
	(2.34)	**(3.30)**	**(2.42)**	**(2.34)**	**(3.85)**	**(2.35)**	**(2.29)**	(1.85)	**(2.28)**	(-1.73)
Quarter $t+2$	0.42	**0.81****	0.06	**2.88*****	**1.79****	**2.10*****	0.90	0.81	0.45	-1.45*
	(1.24)	**(2.24)**	(0.13)	**(3.46)**	**(2.29)**	**(3.14)**	(1.33)	(1.28)	(1.35)	(-1.67)
Quarter $t+3$	0.32	0.47	0.23	**1.94*****	0.55	**2.51*****	0.10	0.18	0.10	-0.91
	(0.80)	(1.31)	(0.43)	**(2.75)**	(0.73)	**(3.09)**	(0.15)	(0.29)	(0.30)	(-1.04)
Quarter $t+4$	-0.44	0.30	0.39	-0.78	-0.80	0.45	0.31	0.51	-0.09	0.18
	(-1.32)	(0.96)	(0.80)	(-1.19)	(-1.07)	(0.67)	(0.46)	(0.85)	(-0.27)	(0.21)

Panel B: Long-horizon anomalies

	GP/A	CbOP	B/M	E/P	CF/P	NO/P	Dur	AG	NOA	IVA	IG
Long/short portfolio returns in each of the 12 quarters post formation											
Quarter $t+1$	0.58	0.97*	1.98***	1.51**	1.37**	1.84***	-1.95***	-1.25**	-1.11***	-1.42***	-1.21***
	(1.40)	(1.68)	(3.17)	(2.38)	(2.27)	(3.31)	(-3.46)	(-2.57)	(-2.59)	(-3.37)	(-3.18)
Quarter $t+2$	0.47	0.73	2.34***	1.55***	1.34**	1.76***	-2.11***	-1.61***	-1.00**	-1.62***	-1.47***
	(1.15)	(1.20)	(3.92)	(2.74)	(2.37)	(3.38)	(-3.86)	(-3.42)	(-2.32)	(-3.89)	(-3.91)
Quarter $t+3$	0.40	0.64	2.36***	1.92***	1.51***	1.63***	-2.07***	-1.40***	-0.82**	-1.47***	-1.50***
	(0.92)	(1.03)	(4.22)	(3.56)	(2.64)	(3.35)	(-3.79)	(-3.14)	(-2.01)	(-3.59)	(-3.93)
Quarter $t+4$	0.27	0.45	2.09***	1.81***	1.54***	1.24***	-2.00***	-1.08**	-0.86**	-1.26***	-1.33***
	(0.61)	(0.73)	(3.85)	(3.46)	(2.71)	(2.91)	(-3.50)	(-2.35)	(-2.14)	(-3.21)	(-3.58)
Quarter $t+5$	0.18	0.52	1.95***	1.65***	1.35**	1.43***	-1.83***	-1.11**	-1.08***	-1.28***	-1.00***
	(0.41)	(0.90)	(3.43)	(3.21)	(2.39)	(3.58)	(-3.14)	(-2.51)	(-2.78)	(-3.22)	(-2.85)
Quarter $t+6$	-0.02	0.39	1.63***	1.66***	1.36**	1.41***	-1.74***	-0.79**	-0.92**	-0.95**	-0.87**
	(-0.05)	(0.70)	(2.84)	(3.01)	(2.40)	(3.28)	(-3.09)	(-2.04)	(-2.23)	(-2.49)	(-2.41)
Quarter $t+7$	0.05	0.11	1.27**	1.18**	1.10**	1.07**	-1.41***	-0.48	-0.82*	-0.65	-0.65*
	(0.10)	(0.19)	(2.24)	(2.22)	(1.99)	(2.32)	(-2.60)	(-1.24)	(-1.88)	(-1.51)	(-1.72)
Quarter $t+8$	0.10	0.15	1.11*	0.89*	0.81	0.75	-1.45**	-0.48	-0.64	-0.67	-0.18
	(0.22)	(0.25)	(1.96)	(1.70)	(1.42)	(1.53)	(-2.38)	(-1.22)	(-1.39)	(-1.49)	(-0.43)
Quarter $t+9$	0.01	-0.11	0.94*	1.00**	0.70	0.54	-1.18**	-0.30	-0.38	-0.60	-0.01
	(0.03)	(-0.19)	(1.79)	(1.99)	(1.23)	(1.15)	(-2.00)	(-0.74)	(-0.79)	(-1.27)	(-0.01)
Quarter $t+10$	-0.06	-0.22	0.99*	0.81	0.71	0.42	-0.97*	-0.25	-0.42	-0.82*	0.04
	(-0.13)	(-0.36)	(1.94)	(1.64)	(1.28)	(0.91)	(-1.72)	(-0.59)	(-0.98)	(-1.72)	(0.08)
Quarter $t+11$	-0.02	-0.20	1.11**	0.79	0.64	0.27	-0.99*	-0.16	-0.30	-0.78	0.05
	(-0.04)	(-0.35)	(2.25)	(1.59)	(1.15)	(0.58)	(-1.83)	(-0.35)	(-0.75)	(-1.60)	(0.11)
Quarter $t+12$	-0.15	-0.30	1.30***	0.68	0.65	0.32	-0.90*	-0.01	-0.33	-0.87*	-0.32
	(-0.36)	(-0.57)	(2.70)	(1.30)	(1.18)	(0.69)	(-1.72)	(-0.03)	(-0.85)	(-1.96)	(-0.72)
Long/short portfolio returns in each of the 3 years post formation											
Year $t+1$	1.56	2.83	8.60***	6.32***	5.21**	6.58***	-8.09***	-4.39***	-3.67**	-5.33***	-5.30***
	(0.96)	(1.29)	(3.58)	(2.93)	(2.18)	(3.46)	(-3.55)	(-2.62)	(-2.06)	(-3.23)	(-4.39)
Year $t+2$	-0.13	0.91	6.15**	5.74***	4.57**	5.36***	-6.25***	-2.35	-3.31**	-2.89*	-2.25
	(-0.07)	(0.40)	(2.55)	(2.94)	(2.07)	(3.50)	(-2.66)	(-1.53)	(-2.19)	(-1.77)	(-1.48)
Year $t+3$	-0.51	-1.09	4.85**	3.49*	2.94	1.59	-4.45**	0.10	-0.93	-2.49	-0.03
	(-0.31)	(-0.47)	(2.45)	(1.85)	(1.35)	(0.94)	(-2.07)	(0.06)	(-0.58)	(-1.32)	(-0.02)

Panel B: Long-horizon anomalies (*continued*)

	IvG	IvC	OA	POA	PTA	NSI	IR	OC/A	AD/M	RD/M	OL
Long/short portfolio returns in each of the 12 quarters post formation											
Quarter $t+1$	**-0.89****	**-1.26*****	-0.62*	**-1.07*****	**-1.15*****	**-1.94*****	**-1.57*****	**1.01****	**2.11*****	**2.24*****	**1.12****
	(-2.35)	**(-3.44)**	(-1.75)	**(-2.63)**	**(-2.90)**	**(-4.24)**	**(-2.99)**	**(2.28)**	**(2.96)**	**(2.92)**	**(2.09)**
Quarter $t+2$	-0.72*	**-1.06*****	-0.66*	**-1.17*****	**-1.17*****	**-1.91*****	**-1.70*****	0.66	**2.16*****	**2.40*****	**1.22****
	(-1.92)	**(-2.77)**	(-1.78)	**(-3.18)**	**(-3.01)**	**(-4.23)**	**(-3.31)**	(1.27)	**(2.99)**	**(3.23)**	**(2.26)**
Quarter $t+3$	**-0.68****	**-0.87****	**-0.86****	**-1.24*****	**-1.28*****	**-1.75*****	**-1.70*****	0.44	**2.18*****	**2.06*****	**1.33****
	(-1.97)	**(-2.26)**	**(-2.36)**	**(-3.69)**	**(-3.51)**	**(-4.12)**	**(-3.38)**	(0.78)	**(3.01)**	**(3.15)**	**(2.48)**
Quarter $t+4$	-0.45	-0.57	-0.72*	**-0.90*****	**-0.97****	**-1.83*****	**-1.67*****	0.43	**1.80*****	**1.72*****	**1.33****
	(-1.27)	(-1.46)	(-1.84)	**(-2.68)**	**(-2.36)**	**(-4.73)**	**(-3.38)**	(0.78)	**(2.64)**	**(2.62)**	**(2.55)**
Quarter $t+5$	-0.40	-0.44	-0.65	**-0.94*****	**-1.36*****	**-1.90*****	**-1.65*****	0.44	**1.52****	**1.50****	**1.23****
	(-1.20)	(-1.13)	(-1.60)	**(-2.68)**	**(-3.29)**	**(-5.21)**	**(-3.34)**	(0.81)	**(2.29)**	**(2.32)**	**(2.42)**
Quarter $t+6$	0.05	-0.12	-0.23	-0.62*	**-1.09****	**-1.57*****	**-1.40*****	0.52	**1.59****	**1.37****	**1.03****
	(0.14)	(-0.28)	(-0.58)	(-1.70)	**(-2.54)**	**(-4.13)**	**(-2.73)**	(1.02)	**(2.36)**	**(2.01)**	**(1.99)**
Quarter $t+7$	0.14	0.04	0.21	-0.27	**-0.91****	**-1.51*****	**-1.14****	0.70	**1.51****	1.24*	0.95*
	(0.36)	(0.09)	(0.54)	(-0.72)	**(-2.11)**	**(-3.66)**	**(-2.20)**	(1.36)	**(2.25)**	(1.77)	(1.81)
Quarter $t+8$	0.07	-0.14	0.20	-0.37	**-0.81****	**-1.31*****	**-1.04****	0.58	1.23*	0.80	0.83
	(0.17)	(-0.35)	(0.53)	(-0.99)	**(-2.02)**	**(-2.90)**	**(-1.98)**	(1.10)	(1.86)	(1.11)	(1.56)
Quarter $t+9$	0.04	0.04	0.33	-0.11	-0.57	**-1.22****	-0.91*	0.52	1.19*	0.68	0.76
	(0.10)	(0.11)	(0.89)	(-0.29)	(-1.47)	**(-2.52)**	(-1.72)	(0.94)	(1.81)	(0.88)	(1.41)
Quarter $t+10$	0.05	0.02	0.29	-0.02	**-0.75****	**-1.45*****	-0.68	0.65	1.06	0.87	0.78
	(0.13)	(0.06)	(0.80)	(-0.04)	**(-2.10)**	**(-2.87)**	(-1.28)	(1.24)	(1.62)	(1.18)	(1.39)
Quarter $t+11$	0.07	0.08	0.29	0.07	-0.68*	**-1.35*****	-0.62	0.87*	0.68	0.84	0.78
	(0.15)	(0.25)	(0.76)	(0.18)	(-1.81)	**(-2.85)**	(-1.19)	(1.67)	(1.00)	(1.20)	(1.38)
Quarter $t+12$	0.08	0.14	0.01	0.09	**-0.88****	**-1.17*****	-0.76	0.90*	0.85	1.00	0.80
	(0.20)	(0.41)	(0.04)	(0.22)	**(-2.42)**	**(-2.65)**	(-1.48)	(1.82)	(1.22)	(1.45)	(1.42)
Long/short portfolio returns in each of the 3 years post formation											
Year $t+1$	**-2.49****	**-3.38*****	**-2.76****	**-3.69*****	**-4.26*****	**-7.30*****	**-6.71*****	3.06	**8.08*****	**8.15*****	**4.65****
	(-2.13)	**(-2.59)**	**(-2.54)**	**(-3.00)**	**(-3.22)**	**(-4.92)**	**(-3.82)**	(1.58)	**(2.87)**	**(3.13)**	**(2.28)**
Year $t+2$	0.27	-0.14	-0.38	-2.15*	**-4.26*****	**-6.61*****	**-5.38*****	2.70	**6.38****	**5.71****	**3.69****
	(0.21)	(-0.09)	(-0.27)	(-1.88)	**(-3.18)**	**(-4.93)**	**(-3.02)**	(1.38)	**(2.20)**	**(2.25)**	**(2.01)**
Year $t+3$	0.62	0.45	1.03	0.18	**-2.96****	**-5.00*****	-3.07*	3.12	4.28	4.04	2.84
	(0.39)	(0.33)	(0.83)	(0.14)	**(-2.06)**	**(-3.31)**	(-1.86)	(1.61)	(1.55)	(1.41)	(1.42)

Table 6: Correlations Between Anomaly Portfolios

This table reports pairwise correlation coefficients between returns of the long/short hedged anomaly portfolios. The signs of L/S portfolios are converted, when necessary, to ensure that the L/S portfolio returns reflect the actual (positive) arbitrage profits. Panel A reports correlations among 12 short-horizon anomalies, and Panel B reports correlations among 22 long-horizon anomalies. Correlation coefficients greater than 0.30 are highlighted in bold. The sample period runs from 1972:07 to 2014:12, depending on data availability.

Panel A: Short-horizon anomalies

	SUE-1	SUE-6	Abr-1	Abr-6	RE-1	R6-6	R11-1	I-Mom	ROEQ	ROAQ	NEI
Earnings momentum											
SUE-6	**0.73**										
Abr-1	0.31	0.24									
Abr-6	0.28	0.20	**0.60**								
RE-1	**0.34**	**0.32**	0.29	0.30							
Return momentum											
R6-6	**0.34**	**0.36**	**0.34**	**0.53**	**0.48**						
R11-1	**0.37**	**0.41**	**0.38**	**0.50**	**0.50**	**0.91**					
I-Mom	**0.34**	**0.35**	**0.33**	**0.44**	**0.36**	**0.78**	**0.77**				
Profitability											
ROEQ	**0.36**	**0.33**	0.16	0.11	**0.35**	0.20	0.25	0.19			
ROAQ	**0.36**	**0.35**	0.16	0.14	**0.32**	0.26	0.29	0.23	**0.91**		
NEI	**0.46**	**0.50**	0.20	0.29	0.27	**0.38**	**0.41**	**0.32**	**0.57**	**0.60**	
FP	**0.38**	**0.41**	0.20	0.20	**0.34**	**0.37**	**0.39**	**0.36**	**0.77**	**0.81**	**0.49**

Panel B: Long-horizon anomalies

	GP/A	CashOP	B/M	E/P	CF/P	NO/P	Dur	AG	NOA	IVA	IG	NSI	IR	IvG	IvC	OA	POA	PTA	OC/A	Ad/M	RD/M
Profitability																					
CashOP	**0.43**																				
Value vs. growth																					
B/M	-0.45	-0.44																			
E/P	-0.28	-0.11	**0.68**																		
CF/P	-0.35	-0.15	**0.71**	**0.90**																	
NO/P	0.07	**0.34**	**0.32**	**0.49**	**0.43**																
Dur	-0.41	-0.30	**0.87**	**0.70**	**0.75**	**0.34**															
Investment and financing																					
AG	-0.14	-0.11	**0.52**	**0.43**	**0.43**	**0.48**	**0.49**														
NOA	**0.32**	**0.30**	-0.24	-0.20	-0.23	0.14	-0.27	0.11													
IVA	-0.14	-0.01	**0.33**	0.21	0.19	**0.32**	**0.31**	**0.57**	0.26												
IG	-0.06	-0.06	**0.32**	0.27	0.23	**0.39**	0.26	**0.52**	0.18	**0.43**											
NSI	0.24	**0.40**	0.20	**0.36**	**0.32**	**0.68**	0.20	**0.39**	**0.31**	**0.38**	**0.33**										
IR	-0.04	**0.39**	**0.34**	**0.49**	**0.49**	**0.72**	**0.40**	**0.44**	0.09	**0.37**	**0.36**	**0.64**									
IvG	-0.14	0.00	**0.33**	0.24	0.28	**0.36**	**0.29**	**0.51**	0.20	**0.49**	**0.48**	**0.30**	**0.39**								
IvC	-0.22	-0.09	**0.34**	0.22	0.28	0.23	**0.32**	**0.45**	0.14	**0.50**	**0.37**	0.19	0.33	**0.58**							
OA	-0.11	0.11	-0.06	-0.16	-0.02	0.00	-0.10	-0.05	0.22	0.05	-0.02	-0.10	0.10	0.19	0.30						
POA	-0.12	0.09	**0.33**	0.24	**0.35**	**0.40**	**0.33**	**0.45**	0.06	**0.30**	0.30	0.29	**0.45**	**0.46**	**0.40**	**0.36**					
PTA	0.06	0.14	0.28	0.30	0.29	**0.60**	0.28	**0.50**	0.10	**0.37**	**0.37**	**0.46**	**0.47**	**0.41**	**0.36**	0.05	**0.45**				
Intangibles																					
OC/A	-0.08	-0.38	0.04	-0.13	-0.06	-0.41	-0.01	-0.06	0.02	-0.01	-0.03	-0.24	-0.29	-0.10	0.05	0.12	-0.11	-0.26			
Ad/M	-0.03	-0.31	**0.49**	**0.46**	**0.43**	0.27	**0.45**	**0.36**	-0.16	0.18	0.25	0.15	0.20	0.11	0.11	-0.14	0.19	0.24	-0.01		
RD/M	-0.06	-0.40	**0.31**	0.09	0.08	-0.07	0.20	0.12	0.17	0.21	0.08	-0.06	-0.18	-0.02	0.10	0.00	-0.06	-0.05	0.24	**0.32**	
OL	**0.31**	0.18	0.04	0.18	0.06	0.26	0.07	0.11	0.17	0.15	0.19	**0.32**	0.16	0.00	-0.13	-0.33	-0.05	0.15	-0.17	0.25	0.16

Table 7: Comparative Model Performance

This table reports comparative performance of different factor models in explaining anomalies. We compare three sets of factor models. The first set includes standard factor models: the CAPM, Fama-French three-factor model (FF3), and Carhart four-factor model (Carhart). The second set includes four recent models: the five-factor model of Fama and French (2015, FF5), the profitability-based model of Novy-Marx (2013, NM), the q-factor model of Hou, Xue, and Zhang (2015, HXZ), and the four-factor mispricing model of Stambaugh and Yuan (2016, SY4). The last set includes our behavioral-motivated models: a single factor FIN, a single factor PEAD, a two-factor model with FIN and PEAD (BF2), and a three-factor risk-and-behavioral composite model with MKT, FIN, and PEAD (BF3). The table reports the regression alphas from time-series regressions of long/short anomaly portfolio returns on each factor model, with Newey-West corrected t-statistics (6 lags). Panel A compares model performance for short-horizon anomalies, Panel B for long-horizon anomalies, and Panel C for all anomalies. As comparative statistics, we summarize the number of significant alphas at 5% level, the average (absolute) alphas, and the GRS F-statistics and associated p-values, following Gibbons, Ross, and Shanken (1989). The sample period runs from 1972:07 to 2014:12, depending on data availability.

Panel A: Short-horizon anomalies

	List of Anomalies		H-L Ret	CAPM	FF3	Carhart	FF5	NM	HXZ	SY4	FIN	PEAD	BF2	BF3
Earnings momentum (5)	Standardized Unexpected Earnings	SUE-1	0.40***	0.46***	0.51***	0.30**	0.42***	0.25*	0.13	0.18	0.33***	0.07	-0.01	0.08
		SUE-6	0.19*	0.23**	0.33***	0.12	0.19*	0.07	-0.02	0.03	0.18	-0.07	-0.10	-0.01
	CAR around earnings announcements	Abr-1	0.79***	0.82***	0.91***	0.69***	0.87***	0.69***	0.73***	0.67***	0.83***	-0.08	-0.07	-0.04
		Abr-6	0.28***	0.29***	0.37***	0.18**	0.40***	0.18*	0.23*	0.22**	0.32***	-0.12*	-0.09	-0.06
	Revisions in analysts' earnings forecasts	RE-1	0.60***	0.63***	0.75***	0.31	0.55**	0.23	0.14	0.28	0.61***	0.15	0.14	0.18
Return momentum (3)	Past returns	R6-6	0.72***	0.74***	0.95***	-0.05	0.82***	-0.30*	0.21	0.02	0.77**	-0.12	-0.09	-0.08
		R11-1	1.18***	1.22***	1.43***	0.18	1.15***	-0.21	0.39	0.09	1.20***	0.11	0.10	0.10
	Industry momentum	I-Mom	0.62***	0.66***	0.76***	-0.07	0.58**	-0.42*	0.14	-0.10	0.57**	-0.17	-0.25	-0.26
Profitability (4)	Quarterly ROE	ROEQ	0.75***	0.92***	1.12***	0.82***	0.58***	0.10	0.10	0.48***	0.30	0.51*	0.02	0.12
	Quarterly ROA	ROAQ	0.53**	0.71***	0.94***	0.62***	0.42***	-0.15	0.04	0.25	0.10	0.26	-0.21	-0.07
	N. consecutive qtrs with earnings increases	NEI	0.34***	0.35***	0.57***	0.37***	0.42***	0.18	0.13	0.28**	0.33***	0.07	0.05	0.04
	Failure probability	FP	-0.58*	-1.01***	-1.24***	-0.62***	-0.39**	0.73***	-0.04	0.04	0.07	-0.14	0.64**	0.20
Short-horizon anomalies (12)	N. significant α at 5%		10	12	12	7	11	2	1	4	8	0	0	0
	Average $\lvert\alpha\rvert$		0.58	0.67	0.82	0.41	0.57	0.37	0.26	0.35	0.56	0.17	0.18	0.09
	GRS F-statistic		4.08***	4.73***	5.88***	4.25***	3.44***	4.37***	2.37***	2.70***	4.87***	2.00**	2.38***	1.15
	p-value		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.32)

Panel B: Long-horizon anomalies

	List of Anomalies		H-L Ret	CAPM	FF3	Carhart	FF5	NM	HXZ	SY4	FIN	PEAD	BF2	BF3
Profitability (2)	Gross profits-to-assets	GP/A	0.22	0.18	0.37**	0.33**	0.01	-0.14	0.03	-0.02	0.20	0.19	0.18	0.06
	Cash-based operating profitability	CashOP	0.42**	0.60***	0.89***	0.71***	0.61***	0.04	0.53***	0.41***	0.14	0.17	-0.14	0.14
Value vs. growth (5)	Book-to-market	B/M	0.62***	0.69***	0.05	0.06	0.10	0.07	0.26	-0.00	0.30	0.75***	0.41*	0.36
	Earnings-to-price	E/P	0.47**	0.61***	0.01	-0.04	-0.01	-0.27	0.05	-0.02	-0.01	0.74***	0.22	0.22
	Cash flow-to-price	CF/P	0.45**	0.58***	0.01	-0.06	0.02	-0.20	0.12	0.06	0.01	0.66***	0.18	0.21
	Net payout-to-price	NO/P	0.65***	0.85***	0.56***	0.52***	0.24*	-0.03	0.39***	0.09	0.02	0.73***	0.05	0.11
	Equity duration	DUR	-0.64***	-0.75***	-0.16	-0.08	-0.15	0.01	-0.28	-0.03	-0.28	-0.75***	-0.36*	-0.38*
Investment and financing (11)	Asset growth	AG	-0.43**	-0.52***	-0.17	-0.10	0.08	0.07	0.10	0.25	-0.10	-0.48***	-0.13	-0.13
	Net operating assets	NOA	-0.38**	-0.37**	-0.49***	-0.37***	-0.38**	-0.15	-0.36*	-0.03	-0.43**	-0.21	-0.26*	-0.27*
	Investment-to-assets	IVA	-0.50***	-0.58***	-0.40***	-0.34**	-0.31**	-0.30	-0.25*	-0.09	-0.29**	-0.46***	-0.23	-0.27*
	Investment growth	IG	-0.38***	-0.44***	-0.24*	-0.18	-0.08	-0.10	0.02	0.05	-0.18	-0.44***	-0.22*	-0.22
	Inventory growth	IvG	-0.33**	-0.40***	-0.22	-0.11	-0.08	-0.11	0.04	0.02	-0.07	-0.36**	-0.09	-0.09
	Inventory changes	IvC	-0.45***	-0.51***	-0.36***	-0.28**	-0.32**	-0.47**	-0.26*	-0.19	-0.32**	-0.45***	-0.32**	-0.42**
	Operating accruals	OA	-0.24*	-0.26**	-0.29**	-0.27*	-0.48***	-0.51***	-0.52***	-0.37**	-0.25*	-0.21	-0.22	-0.29*
	Percent operating accruals	POA	-0.39***	-0.48***	-0.28**	-0.20	-0.09	-0.13	-0.08	-0.07	-0.11	-0.42***	-0.11	-0.12
	Percent total accruals	PTA	-0.40***	-0.50***	-0.30**	-0.27*	-0.06	-0.06	-0.10	-0.00	-0.01	-0.48***	-0.06	-0.05
	Net share issuance	NSI	-0.69***	-0.80***	-0.67***	-0.58***	-0.28**	-0.10	-0.32**	-0.12	-0.22**	-0.69***	-0.19	-0.11
	Composite issuance	IR	-0.56***	-0.80***	-0.51***	-0.41***	-0.20*	-0.02	-0.20	-0.07	0.10	-0.60***	0.12	-0.04
Intangibles (4)	Organizational capital-to-assets	OC/A	0.40**	0.28*	0.28**	0.15	0.30**	0.53***	0.20	0.28**	0.73***	0.20	0.56***	0.47***
	Advertisement expense-to-market	Ad/M	0.67***	0.69***	0.10	0.17	-0.05	0.07	0.05	0.03	0.35	1.04***	0.71***	0.52*
	R&D-to-market	RD/M	0.71***	0.53**	0.30	0.37*	0.43*	0.53	0.80***	0.10	1.05***	0.67**	1.05***	0.83***
	Operating leverage	OL	0.37*	0.41**	0.33*	0.29	-0.00	-0.22	-0.11	-0.06	0.17	0.34*	0.12	0.08
Long-horizon anomalies (22)	N. significant α at 5%		20	20	12	8	7	3	5	3	6	16	4	3
	Average $\lvert\alpha\rvert$		0.48	0.55	0.38	0.29	0.23	0.21	0.32	0.12	0.29	0.55	0.32	0.28
	GRS F-statistic		3.06***	3.91***	3.13***	2.22***	1.97***	1.55*	2.08***	0.74	2.59***	2.29***	1.94***	1.47*
	p-value		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.05)	(0.00)	(0.80)	(0.00)	(0.00)	(0.01)	(0.08)

Panel C: All anomalies

		H-L Ret	CAPM	FF3	Carhart	FF5	NM	HXZ	SY4	FIN	PEAD	BF2	BF3
All anomalies (34)	N. significant α at 5%	30	32	24	15	18	5	6	7	14	16	4	3
	Average $\lvert\alpha\rvert$	0.52	0.60	0.57	0.33	0.36	0.26	0.31	0.18	0.40	0.45	0.27	0.23
	GRS F-statistic	3.54***	3.95***	3.70***	3.10***	2.60***	2.65***	2.42***	1.71***	3.31***	2.41***	2.12***	1.61**
	p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)

Table 8: Factor Regressions of Long/Short Anomaly Portfolios

This table reports alphas and factor betas from time-series regressions of long/short anomaly portfolio returns on recent prominent factor models. Panel A, B, C, D report regression alphas and factor betas under the five-factor model of Fama and French (2015), the profitability-based factor model of Novy-Marx (2013), the q-factor model of Hou, Xue, and Zhang (2015), and the four-factor mispricing model of Stambaugh and Yuan (2016), respectively. Panel E reports the alphas and betas under our three-factor risk-and-behavioral composite model (BF3). Newey-West corrected t-statistics (with 6 lags) are shown in parentheses. The sample period runs from 1972:07 to 2014:12, depending on data availability.

	Earnings momentum					Return momentum			Profitability						Value vs. growth		
	SUE-1	SUE-6	Abr-1	Abr-6	RE-1	R6-6	R11-1	I-Mom	ROEQ	ROAQ	NEI	FP	GP/A	CbOP	B/M	E/P	CF/P
Panel A: The five-factor model of Fama and French (2015, FF5)																	
α	0.42***	0.19*	0.87***	0.40***	0.55**	0.82***	1.15***	0.58**	0.58***	0.41***	0.42***	-0.39**	0.01	0.61***	0.10	-0.01	0.02
β_{MKT}	-0.10**	-0.07*	-0.08**	-0.06**	-0.03	-0.09	-0.10	-0.09	-0.12***	-0.16***	-0.03	0.40***	0.09*	-0.25***	0.01	-0.07	-0.07
β_{SMB}	-0.03	-0.06	-0.08	-0.01	-0.09	-0.03	0.07	0.06	-0.48***	-0.47***	-0.17***	0.71***	0.06	-0.61***	0.46***	0.33***	0.27***
β_{HML}	-0.18	-0.25***	-0.15	-0.14**	-0.28	-0.47**	-0.60**	-0.23	-0.27**	-0.26***	-0.33***	0.35**	-0.47***	-0.34***	1.04***	1.29***	1.23***
β_{RMW}	0.14	0.18**	-0.06	-0.07	0.26*	0.03	0.27	0.17	1.37***	1.32***	0.46***	-1.47***	0.90***	0.73***	-0.32***	0.27***	0.12
β_{CMA}	0.20	0.20	0.06	-0.05	0.22	0.25	0.51	0.19	0.15	0.05	-0.08	-0.49*	0.21	-0.08	0.23*	-0.36**	-0.30**
Panel B: The profitability-based model of Novy-Marx (2013, NM)																	
α	0.25*	0.07	0.69***	0.18*	0.23	-0.30*	-0.21	-0.42*	0.10	-0.15	0.18	0.73***	-0.14	0.04	0.07	-0.27	-0.20
β_{MKT}	-0.07*	-0.04	-0.04	-0.00	0.01	0.15***	0.18***	0.08**	-0.13***	-0.14***	0.04	0.39***	0.15***	-0.22***	-0.07	-0.14***	-0.15***
β_{HML}	-0.13	-0.15	-0.19*	-0.19**	-0.19	0.13	0.29*	0.51***	-0.08	-0.01	-0.40***	-0.72***	-0.17	-0.15	1.76***	1.89***	1.75***
β_{UMD}	0.32***	0.34***	0.40***	0.33***	0.77***	1.70***	2.10***	1.36***	0.36*	0.43***	0.30***	-0.84***	-0.02	0.32***	-0.10	-0.07	0.01
β_{PMU}	0.18	0.05	-0.17	-0.09	0.02	-0.35**	-0.27	-0.35	2.09***	2.00***	0.63***	-2.36***	1.39***	1.35***	-0.45**	0.20	-0.11
Panel C: The q-factor model of Hou, Xue, and Zhang (2015, HXZ)																	
α	0.13	-0.02	0.73***	0.23*	0.14	0.21	0.39	0.14	0.10	0.04	0.13	-0.04	0.03	0.53***	0.26	0.05	0.12
β_{MKT}	-0.08*	-0.06	-0.07*	-0.04	0.01	-0.02	-0.03	-0.06	-0.10***	-0.16***	0.02	0.42***	0.07	-0.26***	-0.07	-0.15**	-0.14**
β_{ME}	0.10*	0.10	0.07	0.07	0.10	0.34*	0.50**	0.37*	-0.37***	-0.35***	-0.08*	0.52***	0.01	-0.51***	0.41***	0.27*	0.18
β_{IVA}	0.01	-0.10	-0.16*	-0.16**	-0.09	-0.16	-0.02	0.01	0.04	-0.13	-0.30***	-0.16	-0.30***	-0.46***	1.26***	1.01***	0.99***
β_{ROE}	0.49***	0.46***	0.26***	0.20***	0.76***	0.88***	1.20***	0.73***	1.42***	1.30***	0.64***	-1.50***	0.50***	0.66***	-0.48***	-0.01	-0.14
Panel D: The four-factor mispricing model of Stambaugh and Yuan (2016, SY4)																	
α	0.18	0.03	0.67***	0.22**	0.28	0.02	0.09	-0.10	0.48***	0.25	0.28**	0.04	-0.02	0.41***	-0.00	-0.02	0.06
β_{MKT}	-0.03	-0.03	-0.03	-0.02	0.06	0.14**	0.21***	0.09	-0.02	-0.05	0.04	0.19**	0.13**	-0.15***	-0.01	-0.08	-0.09
β_{SMB}	0.02	0.01	0.02	0.01	-0.11	0.18	0.31*	0.24	-0.69***	-0.61***	-0.24***	0.75***	-0.03	-0.66***	0.66***	0.36**	0.30**
β_{MGMT}	0.07	-0.01	-0.05	-0.09	-0.10	0.03	0.21	0.12	0.18	0.15	-0.14**	-0.64***	-0.03	0.03	0.81***	0.77***	0.67***
β_{PERF}	0.28***	0.26***	0.24***	0.17***	0.58***	0.85***	1.13***	0.73***	0.70***	0.72***	0.37***	-0.97***	0.33***	0.49***	-0.30***	-0.17*	-0.18*
Panel E: The three-factor behavioral factor model (BF3)																	
α	0.08	-0.01	-0.04	-0.06	0.18	-0.08	0.10	-0.26	0.12	-0.07	0.04	0.20	0.06	0.14	0.36	0.22	0.21
β_{MKT}	-0.08	-0.07	-0.02	-0.02	-0.03	-0.00	0.00	0.01	-0.08	-0.12*	0.01	0.37***	0.10**	-0.24***	0.04	-0.01	-0.02
β_{FIN}	0.05	-0.02	-0.02	-0.06*	-0.00	-0.04	0.02	0.10	0.52***	0.47***	0.02	-0.73***	0.08	0.22***	0.42***	0.60***	0.53***
β_{PEAD}	0.49***	0.39***	1.34***	0.61***	0.72***	1.29***	1.65***	1.23***	0.40*	0.44***	0.43***	-0.79***	0.07	0.35***	-0.15	-0.35***	-0.27**

(*Continued*)

	Value vs. growth		Investment and financing											Intangibles			
	NO/P	Dur	AG	NOA	IVA	IG	IvG	IvC	OA	POA	PTA	NSI	IR	OC/A	AD/M	RD/M	OL
	Panel A: The five-factor model of Fama and French (2015, FF5)																
α	0.24*	-0.15	0.08	-0.38**	-0.31**	-0.08	-0.08	-0.32**	-0.48***	-0.09	-0.06	-0.28**	-0.20*	0.30**	-0.05	0.43*	-0.00
β_{MKT}	-0.10***	0.03	-0.03	-0.02	0.04	-0.00	-0.02	0.04	0.06	-0.03	0.00	0.00	0.18***	0.09**	0.11**	0.21***	-0.01
β_{SMB}	-0.24***	-0.34***	-0.06	0.14*	-0.01	-0.14***	0.15**	0.04	0.26***	0.20***	0.17**	0.10*	0.25***	0.52***	0.67***	0.68***	0.30***
β_{HML}	0.45***	-1.06***	-0.17***	0.41***	0.07	-0.03	-0.03	0.02	-0.04	-0.19***	-0.16	-0.04	-0.38***	-0.28***	0.85***	0.07	0.05
β_{RMW}	0.53***	0.17**	0.06	-0.02	0.25***	-0.06	0.12	0.32***	0.42***	-0.06	-0.22**	-0.69***	-0.42***	-0.25***	0.29**	-0.55***	0.88***
β_{CMA}	0.50***	-0.14	-1.16***	-0.42**	-0.85***	-0.71***	-0.82***	-0.70***	0.12	-0.64***	-0.69***	-0.60***	-0.64***	0.27*	0.25	0.33	0.12
	Panel B: The profitability-based model of Novy-Marx (2013, NM)																
α	-0.03	0.01	0.07	-0.15	-0.30	-0.10	-0.11	-0.47**	-0.51***	-0.13	-0.06	-0.10	-0.02	0.53***	0.07	0.53	-0.22
β_{MKT}	-0.23***	0.12**	0.11***	-0.05	0.11***	0.05*	0.09**	0.14***	0.09**	0.10***	0.13***	0.07*	0.33***	0.18***	0.05	0.29***	0.04
β_{HML}	1.30***	-1.79***	-1.21***	0.00	-0.58***	-0.67***	-0.66***	-0.35***	0.09	-0.70***	-0.77***	-0.77***	-1.17***	-0.23*	1.76***	0.63***	0.42**
β_{UMD}	-0.06	-0.03	-0.07	-0.21	-0.10	-0.01	-0.11	-0.09	-0.07	-0.05	0.09	-0.03	-0.05	0.31**	-0.27**	-0.05	-0.11
β_{PMU}	1.02***	0.34**	0.11	-0.21	0.15	-0.14	0.08	0.62***	0.70***	-0.12	-0.54**	-1.09***	-0.67***	-0.99***	0.19	-0.89	1.60***
	Panel C: The q-factor model of Hou, Xue, and Zhang (2015, HXZ)																
α	0.39***	-0.28	0.10	-0.36*	-0.25*	0.02	0.04	-0.26*	-0.52***	-0.08	-0.10	-0.32**	-0.20	0.20	0.05	0.80***	-0.11
β_{MKT}	-0.17***	0.12***	0.01	-0.02	0.05	0.00	-0.02	0.04	0.03	0.01	0.04	0.05	0.23***	0.11**	0.04	0.14**	-0.04
β_{ME}	-0.32***	-0.34***	-0.11*	0.05	-0.06	-0.15***	0.11**	-0.03	0.28***	0.15***	0.20***	0.16**	0.26***	0.62***	0.55***	0.71***	0.28***
β_{IVA}	0.98***	-1.16***	-1.36***	0.01	-0.80***	-0.81***	-0.95***	-0.70***	0.01	-0.87***	-0.91***	-0.65***	-1.09***	-0.07	1.24***	0.07	0.21
β_{ROE}	0.03	0.31***	0.16**	-0.04	0.14	-0.04	0.04	0.18*	0.31***	0.02	0.04	-0.28***	-0.15*	-0.02	-0.23	-0.72***	0.58***
	Panel D: The four-factor mispricing model of Stambaugh and Yuan (2016, SY4)																
α	0.09	-0.03	0.25	-0.03	-0.09	0.05	0.02	-0.19	-0.37**	-0.07	-0.00	-0.12	-0.07	0.28**	0.03	0.10	-0.06
β_{MKT}	-0.03	0.05	-0.06	-0.13***	-0.00	-0.03	-0.05	0.03	0.02	-0.03	-0.03	-0.07**	0.12***	0.07	0.07	0.25***	0.02
β_{SMB}	-0.18**	-0.53***	-0.27***	0.03	-0.21***	-0.21***	0.03	-0.12*	0.20***	0.08	0.08	0.10	0.20**	0.62***	0.71***	0.92***	0.21*
β_{MGMT}	0.93***	-0.80***	-0.88***	-0.19**	-0.57***	-0.50***	-0.55***	-0.41***	-0.03	-0.54***	-0.67***	-0.67***	-0.88***	-0.23***	0.82***	0.25**	0.25**
β_{PERF}	0.06	0.20***	0.10**	-0.23***	0.08	0.01	0.01	0.10*	0.06	0.01	0.02	-0.21***	-0.06	0.01	-0.32***	-0.16	0.23***
	Panel E: The three-factor behavioral factor model (BF3)																
α	0.11	-0.38*	-0.13	-0.27*	-0.27*	-0.22	-0.09	-0.42**	-0.29*	-0.12	-0.05	-0.11	-0.04	0.47***	0.52*	0.83***	0.08
β_{MKT}	-0.05*	0.02	0.01	0.01	0.03	-0.00	0.00	0.08*	0.06	0.01	-0.00	-0.06*	0.13***	0.08	0.16*	0.18*	0.04
β_{FIN}	0.76***	-0.44***	-0.40***	0.07	-0.25***	-0.26***	-0.32***	-0.10	0.05	-0.35***	-0.49***	-0.62***	-0.75***	-0.37***	0.51***	-0.33*	0.27***
β_{PEAD}	-0.05	0.12	0.04	-0.26*	-0.08	0.06	0.02	0.02	-0.02	0.00	0.08	-0.07	0.02	0.28*	-0.49**	0.06	0.08

Table 9: Firm-Level Fama-MacBeth Regressions on Behavioral Factor Loadings

This table reports firm-level Fama-MacBeth regressions of monthly stock returns on factor loadings of FIN and PEAD, while controlling for standard return predictors and firm characteristics. β_{FIN} and β_{PEAD} are estimated by monthly rolling regressions of daily stock returns in the previous month on the three-factor behavioral factor model (BF3), which includes a daily market factor, a daily FIN factor, and a daily PEAD factor, with a minimum of 15 daily returns required. Standard return predictors include log(ME) at the end of the previous month, log(B/M) as of the previous fiscal year end, past 1-month return, past 1-year return from month $t-12$ to $t-2$, and past 3-year return from month $t-36$ to $t-13$. All past returns are on monthly basis. Firm characteristics include all short-horizon and long-horizon anomaly characteristics described in Table 4. Intercepts are included in all regressions but not reported here. All regressors are winsorized at top and bottom 1% and standardized to have zero mean and unit standard deviation. Newey-West corrected t-statistics are reported in parentheses (with 6 lags). The sample period runs from 1972:08 to 2014:12 (507 months), depending on data availability.

	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(5)	(9)	(10)
β_{FIN}	0.148**	0.137**	0.146**	0.148***	0.263***	0.144**	0.141**	0.151***	0.114**	0.185***
	(2.04)	(2.38)	(2.54)	(2.67)	(3.88)	(2.55)	(2.52)	(2.66)	(2.22)	(3.39)
β_{PEAD}	-0.019	0.015	0.016	0.009	-0.003	0.016	0.014	0.014	0.012	-0.010
	(-0.33)	(0.34)	(0.36)	(0.21)	(-0.05)	(0.36)	(0.33)	(0.32)	(0.25)	(-0.18)
Earnings momentum characteristics										
Abr			0.513***							0.355***
			(18.37)							(12.13)
SUE				0.452***						0.120***
				(15.49)						(5.32)
RE					0.203***					0.139***
					(5.03)					(3.79)
Short-term profitability characteristics										
ROEQ						0.612***				0.258**
						(8.03)				(2.39)
ROAQ							0.710***			0.110
							(6.97)			(1.01)
NEI								0.365***		0.110***
								(10.38)		(3.76)
FP									-0.362***	-0.163
									(-3.65)	(-1.61)
$log(ME)$		-0.260**	-0.230**	-0.265**	-0.227*	-0.309***	-0.322***	-0.299***	-0.232***	-0.327***
		(-2.44)	(-2.20)	(-2.54)	(-1.95)	(-3.13)	(-3.39)	(-2.88)	(-3.14)	(-3.62)
$log(B/M)$		0.203**	0.177**	0.198**	0.083	0.191**	0.222***	0.245***	0.208***	0.133*
		(2.50)	(2.19)	(2.49)	(1.06)	(2.45)	(2.87)	(3.06)	(2.80)	(1.74)
$r(t-1)$		-0.969***	-1.055***	-0.999***	-0.646***	-0.983***	-0.998***	-0.975***	-0.830***	-0.737***
		(-11.41)	(-12.14)	(-11.09)	(-8.57)	(-11.20)	(-11.32)	(-10.98)	(-9.55)	(-9.97)
$r(t-12,t-2)$		0.168*	0.188*	0.096	0.361***	0.175*	0.159	0.127	0.250***	0.098
		(1.75)	(1.80)	(0.93)	(2.92)	(1.75)	(1.60)	(1.21)	(2.63)	(0.86)
$r(t-36,t-13)$		-0.271***	-0.246***	-0.237***	-0.176**	-0.308***	-0.307***	-0.297***	-0.224***	-0.208***
		(-3.64)	(-3.19)	(-2.97)	(-2.33)	(-4.23)	(-4.40)	(-3.86)	(-3.74)	(-3.39)
$Adj.R^2$	0.4%	3.8%	4.5%	4.6%	5.1%	4.7%	4.8%	4.5%	4.9%	6.5%
N.obs	1,558,118	1,558,118	1,350,525	1,345,932	916,329	1,377,779	1,374,597	1,377,479	1,321,624	848,309

(*Continued*)

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
β_{FIN}	0.137**	0.100*	0.111**	0.125**	0.135**	0.127**	0.137**	0.132**	0.135**	0.131**	0.132**	0.131**	0.127**	0.103*
	(2.39)	(1.89)	(1.99)	(2.23)	(2.37)	(2.29)	(2.36)	(2.22)	(2.36)	(2.31)	(2.31)	(2.28)	(2.21)	(1.78)
β_{PEAD}	0.023	-0.016	-0.012	0.015	0.013	0.011	0.017	-0.003	0.014	0.017	0.017	0.016	0.001	-0.012
	(0.50)	(-0.38)	(-0.27)	(0.34)	(0.29)	(0.25)	(0.39)	(-0.06)	(0.30)	(0.38)	(0.38)	(0.36)	(0.02)	(-0.26)
Financing characteristics														
NS	-0.237***		-0.101***											-0.041
	(-6.48)		(-3.20)											(-1.07)
IR		-0.194***	-0.149***											-0.146***
		(-3.88)	(-3.13)											(-2.77)
Investment characteristics														
AG				-0.273***									-0.070	-0.035
				(-8.43)									(-1.44)	(-0.62)
NOA					-0.290***								-0.213***	-0.112*
					(-6.96)								(-3.62)	(-1.96)
IVA						-0.211***							0.007	-0.003
						(-6.47)							(0.16)	(-0.06)
IG							-0.135***						-0.071***	-0.083***
							(-6.30)						(-3.09)	(-2.90)
IvG								-0.160***					-0.033	-0.031
								(-6.57)					(-1.08)	(-0.92)
IvC									-0.140***				0.005	0.021
									(-4.88)				(0.15)	(0.55)
OA										-0.124***			-0.072**	-0.126***
										(-3.53)			(-2.19)	(-3.49)
POA											-0.046**		-0.002	0.006
											(-2.45)		(-0.09)	(0.29)
PTA												-0.064***	0.005	0.013
												(-3.31)	(0.26)	(0.53)
$log(ME)$	-0.256**	-0.291***	-0.270***	-0.247**	-0.226**	-0.249**	-0.271**	-0.233**	-0.264**	-0.262**	-0.262**	-0.260**	-0.213**	-0.243***
	(-2.46)	(-3.13)	(-2.93)	(-2.32)	(-2.17)	(-2.35)	(-2.55)	(-2.25)	(-2.48)	(-2.49)	(-2.47)	(-2.44)	(-2.13)	(-2.82)
$log(B/M)$	0.203**	0.111	0.130*	0.176**	0.249***	0.181**	0.194**	0.202**	0.193**	0.201**	0.199**	0.203**	0.228***	0.180***
	(2.57)	(1.63)	(1.86)	(2.20)	(3.26)	(2.23)	(2.39)	(2.58)	(2.37)	(2.51)	(2.47)	(2.50)	(3.24)	(2.91)
$r(t-1)$	-0.947***	-0.999***	-0.980***	-0.978***	-0.985***	-0.981***	-0.967***	-0.967***	-0.978***	-0.974***	-0.968***	-0.969***	-0.978***	-0.986***
	(-11.32)	(-12.23)	(-12.24)	(-11.49)	(-11.62)	(-11.49)	(-11.22)	(-11.17)	(-11.42)	(-11.36)	(-11.34)	(-11.32)	(-11.23)	(-12.04)
$r(t-12,t-2)$	0.195**	0.162	0.196*	0.152	0.136	0.148	0.172*	0.174*	0.154	0.157	0.166*	0.166*	0.145	0.177*
	(1.97)	(1.60)	(1.89)	(1.59)	(1.44)	(1.56)	(1.79)	(1.74)	(1.62)	(1.63)	(1.73)	(1.72)	(1.48)	(1.66)
$r(t-36,t-13)$	-0.226***	-0.247***	-0.215***	-0.202***	-0.222***	-0.236***	-0.246***	-0.234***	-0.245***	-0.250***	-0.267***	-0.262***	-0.171**	-0.125*
	(-3.04)	(-3.21)	(-2.82)	(-2.73)	(-3.11)	(-3.19)	(-3.31)	(-3.08)	(-3.32)	(-3.45)	(-3.59)	(-3.52)	(-2.31)	(-1.71)
$Adj.R^2$	4.2%	4.6%	4.9%	3.9%	3.9%	3.9%	3.9%	4.0%	3.9%	3.9%	3.8%	3.8%	4.4%	5.6%
N.obs	1,360,804	1,176,542	1,047,649	1,558,110	1,555,185	1,534,322	1,525,874	1,341,026	1,540,736	1,535,046	1,534,231	1,533,912	1,308,130	901,523

(*Continued*)

	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)
β_{FIN}	0.129**	0.127**	0.122**	0.148**	0.161***	0.132**	0.138**	0.150**	0.127**	0.132*	0.129**	0.125**	0.128	0.134
	(2.27)	(2.21)	(2.15)	(2.45)	(2.67)	(2.20)	(2.44)	(2.52)	(2.17)	(1.93)	(2.14)	(2.16)	(1.65)	(1.57)
β_{PEAD}	0.015	0.016	0.014	-0.022	-0.001	0.053	0.006	-0.016	0.010	0.008	0.029	0.012	-0.014	-0.018
	(0.34)	(0.34)	(0.32)	(-0.45)	(-0.02)	(1.12)	(0.15)	(-0.31)	(0.21)	(0.15)	(0.63)	(0.27)	(-0.25)	(-0.27)
Long-term profitability characteristics														
GP/A	0.142***		0.110**											0.254***
	(2.97)		(2.16)											(2.88)
$CbOP$		0.274***	0.219***											-0.008
		(5.95)	(4.72)											(-0.09)
Value vs. growth characteristics														
E/P				0.047				-0.107						-0.140
				(1.24)				(-1.60)						(-0.94)
CF/P					0.059			0.164**						0.056
					(1.60)			(2.54)						(0.35)
NO/P						0.118***		0.104***						0.027
						(3.23)		(2.79)						(0.38)
Dur							-0.108*	-0.066						-0.106
							(-1.70)	(-1.13)						(-0.76)
Intangibles characteristics														
OC/A									0.053				0.033	0.035
									(1.56)				(0.58)	(0.59)
AD/M										-0.034			-0.003	-0.115
										(-0.69)			(-0.03)	(-0.97)
RD/M											0.242***		0.245**	0.162
											(3.23)		(2.32)	(1.26)
OL												0.069	-0.000	-0.174*
												(1.52)	(-0.00)	(-1.71)
$log(ME)$	-0.252**	-0.320***	-0.294***	-0.192**	-0.216**	-0.227**	-0.266**	-0.185**	-0.234**	-0.250**	-0.239**	-0.232**	-0.239**	-0.156
	(-2.34)	(-3.33)	(-3.04)	(-2.25)	(-2.53)	(-2.27)	(-2.52)	(-2.20)	(-2.37)	(-2.43)	(-2.17)	(-2.20)	(-2.00)	(-1.51)
$log(B/M)$	0.217***	0.221***	0.235***	0.136**	0.131**	0.188**	0.136**	0.063	0.221***	0.136*	0.209**	0.217***	0.124	0.260**
	(2.60)	(2.83)	(2.97)	(2.04)	(1.99)	(2.48)	(2.22)	(1.01)	(2.90)	(1.81)	(2.15)	(2.82)	(1.21)	(2.52)
$r(t-1)$	-0.983***	-0.985***	-0.998***	-0.860***	-0.851***	-0.937***	-0.973***	-0.880***	-0.980***	-0.937***	-1.102***	-0.981***	-1.109***	-1.002***
	(-11.61)	(-11.39)	(-11.51)	(-10.27)	(-10.11)	(-11.14)	(-11.31)	(-10.70)	(-11.37)	(-10.92)	(-12.80)	(-11.20)	(-12.26)	(-10.17)
$r(t-12,t-2)$	0.148	0.172*	0.147	0.348***	0.324***	0.211**	0.174*	0.348***	0.172*	0.096	0.026	0.166*	-0.087	0.106
	(1.57)	(1.77)	(1.54)	(3.22)	(3.05)	(2.16)	(1.80)	(3.19)	(1.74)	(0.98)	(0.29)	(1.70)	(-0.90)	(0.93)
$r(t-36,t-13)$	-0.279***	-0.298***	-0.299***	-0.205***	-0.210***	-0.222***	-0.268***	-0.169***	-0.265***	-0.295***	-0.283***	-0.275***	-0.286***	-0.110
	(-3.85)	(-4.29)	(-4.41)	(-3.28)	(-3.36)	(-2.94)	(-3.76)	(-2.72)	(-3.65)	(-4.13)	(-4.34)	(-3.90)	(-3.70)	(-1.40)
$Adj.R^2$	4.1%	3.9%	4.0%	4.3%	4.3%	4.2%	4.0%	4.9%	3.8%	3.8%	4.4%	3.8%	5.4%	7.6%
$N.obs$	1,556,679	1,420,191	1,420,191	1,167,972	1,221,193	1,280,041	1,531,579	991,025	1,353,450	568,073	719,589	1,375,409	271,606	175,928

Table 10: Behavioral Factor Loadings of the Long-Leg and Short-Leg Portfolios

This table reports time-series regressions of the long-leg and short-leg portfolio returns on the three-factor behavioral model (MKT, FIN, and PEAD). Panel A shows PEAD factor betas of the short-leg and long-leg portfolios for each of the 12 short-horizon anomalies. Panel B shows FIN factor betas for long-horizon anomalies. At the bottom of each panel, we summarize the average FIN or PEAD betas in the short legs and long legs, and count how many anomalies have larger (absolute) and significant FIN or PEAD betas in the short legs than in the long legs (highlighted in boldface), and vice versa. The sample period runs from 1972:07 to 2014:12, depending on data availability.

Panel A: β_{PEAD} of short-horizon anomaly portfolios

Anomalies	Long legs	Short legs	Anomalies	Long legs	Short legs
SUE-1	0.18	**-0.31**	R11-1	0.68	**-0.98**
	(3.73)	**(-3.40)**		(6.15)	**(-6.05)**
SUE-6	0.15	**-0.24**	I-Mom	0.50	**-0.73**
	(3.24)	**(-3.09)**		(4.74)	**(-6.31)**
Abr-1	0.59	**-0.74**	ROEQ	0.14	**-0.25**
	(8.57)	**(-8.78)**		(1.63)	**(-1.95)**
Abr-6	0.17	**-0.44**	ROAQ	**0.26**	-0.19
	(2.87)	**(-6.79)**		**(4.72)**	(-1.69)
RE-1	0.15	**-0.57**	NEI	0.18	**-0.25**
	(1.40)	**(-4.01)**		(3.10)	**(-4.38)**
R6-6	0.45	**-0.84**	FP	0.25	**-0.54**
	(4.39)	**(-5.02)**		(4.70)	**(-3.16)**

Average β_{PEAD} in the long legs: 0.31
Average β_{PEAD} in the short legs: -0.51

N. larger positive and significant β_{PEAD} in the long legs: 1 out of 12
N. larger negative and significant β_{PEAD} in the short legs: 11 out of 12

Panel B: β_{FIN} of long-horizon anomaly portfolios

Anomalies	Long legs	Short legs	Anomalies	Long legs	Short legs
GP/A	0.01	**-0.07**	IvG	-0.07	**-0.38**
	(0.16)	**(-2.14)**		(-1.30)	**(-7.35)**
CbOP	-0.19	**-0.41**	IvC	-0.13	**-0.23**
	(-6.66)	**(-8.74)**		(-2.56)	**(-4.98)**
B/M	**0.25**	-0.17	OA	-0.38	-0.34
	(3.94)	(-4.70)		(-6.93)	(-8.89)
E/P	0.23	**-0.37**	POA	0.00	**-0.35**
	(4.06)	**(-7.12)**		(0.06)	**(-7.58)**
CF/P	0.24	**-0.29**	PTA	0.03	**-0.46**
	(4.10)	**(-6.71)**		(0.71)	**(-11.01)**
NO/P	0.36	**-0.40**	NS	0.29	**-0.33**
	(5.49)	**(-7.36)**		(6.17)	**(-8.64)**
Dur	**0.23**	-0.21	IR	**0.38**	-0.37
	(3.39)	(-5.85)		**(13.09)**	(-11.21)
AG	0.04	**-0.36**	OC/A	-0.33	0.03
	(0.83)	**(-7.82)**		(-7.54)	(0.51)
NOA	-0.24	-0.18	AD/M	0.25	**-0.26**
	(-7.70)	(-2.52)		(3.15)	**(-5.18)**
IVA	0.06	**-0.19**	RD/M	-0.31	0.02
	(1.56)	**(-3.62)**		(-2.08)	(0.37)
IG	-0.22	**-0.48**	OL	0.07	**-0.20**
	(-5.04)	**(-14.22)**		(1.25)	**(-3.12)**

Average β_{FIN} in the long legs: 0.03
Average β_{FIN} in the short legs: -0.27

N. larger positive and significant β_{FIN} in the long legs: 3 out of 22
N. larger negative and significant β_{FIN} in the short legs: 15 out of 22

Table 11: Market Frictions and Sensitivity of Beta-Return Relation

Panel A reports returns of double-sorted portfolios by market frictions and FIN factor loadings (β_{FIN}). At the beginning of each month, firms are ranked into 25 portfolios by independent sorts on β_{FIN} and market friction proxies (estimated in the previous month). Value-weighted portfolio returns are calculated for the current month and portfolios are rebalanced at the beginning of the next month. Panel B reports results of Fama-MacBeth cross-sectional regression of monthly stock returns on β_{FIN}, the quintile ranks of market friction proxies, and the interactions between β_{FIN} and friction ranks, with standard control variables. Newey-West corrected t-statistics are shown in the parentheses (with 3 lags). We use three friction proxies: the illiquidity measure (ILLIQ) of Amihud (2002), the institutional ownership defined as shares held by institutions divided by shares outstanding (IO), and the residual institutional ownership (RIO) of Nagel (2005) controlling for size. All regressors are winsorized at top and bottom 1% and standardized to have zero mean and unit standard deviation, to make the coefficients comparable.The sample period runs from 1972:08 to 2014:12 (507 months) using ILLIQ, and from 1980:02 to 2014:12 (417 months) using IO and RIO.

Panel A: Double-sorted portfolios

	Low β	2	3	4	High β	H − L
Low ILLIQ (Low frictions)	0.73	0.86	0.81	1.05	1.05	0.32*
	(2.71)	(4.18)	(4.36)	(5.81)	(5.44)	(1.73)
2	0.94	1.00	1.19	1.09	1.14	0.20
	(3.11)	(4.23)	(5.33)	(5.07)	(4.62)	(1.35)
3	1.08	1.27	1.24	1.25	1.18	0.10
	(3.58)	(4.91)	(5.27)	(5.41)	(4.59)	(0.71)
4	1.08	1.18	1.23	1.13	1.18	0.10
	(3.43)	(4.33)	(4.70)	(4.32)	(4.05)	(0.67)
High ILLIQ (High frictions)	0.80	1.24	1.16	1.17	1.23	0.44***
	(2.47)	(4.19)	(4.35)	(4.16)	(4.18)	(2.84)

	Low β	2	3	4	High β	H − L
Low IO (High frictions)	0.18	1.01	1.10	0.82	1.18	1.00**
	(0.43)	(2.59)	(3.88)	(2.53)	(3.37)	(2.39)
2	0.34	0.94	1.17	0.96	0.95	0.61*
	(0.84)	(3.12)	(5.45)	(4.40)	(3.66)	(1.73)
3	1.02	0.84	0.87	1.15	1.48	0.46*
	(2.91)	(3.16)	(3.51)	(5.44)	(5.71)	(1.77)
4	0.88	1.15	1.14	1.17	1.27	0.39
	(2.62)	(4.11)	(4.62)	(5.09)	(5.33)	(1.59)
High IO (Low frictions)	1.28	1.21	1.13	1.27	1.24	-0.04
	(3.79)	(4.61)	(4.46)	(5.01)	(4.33)	(-0.20)

	Low β	2	3	4	High β	H − L
Low RIO (High frictions)	0.64	1.03	0.95	1.20	1.09	0.45
	(1.69)	(3.66)	(4.23)	(5.72)	(4.69)	(1.32)
2	0.91	1.02	1.06	1.12	1.31	0.40*
	(2.73)	(3.84)	(4.58)	(5.08)	(5.29)	(1.69)
3	1.14	1.14	1.09	1.22	1.05	-0.09
	(3.52)	(4.39)	(4.40)	(5.38)	(4.37)	(-0.39)
4	1.19	1.09	1.17	1.21	1.31	0.11
	(3.14)	(3.98)	(4.54)	(4.77)	(4.40)	(0.45)
High RIO (Low frictions)	1.02	1.02	1.11	1.03	1.27	0.24
	(2.82)	(3.46)	(3.68)	(3.34)	(3.75)	(1.11)

Panel B: Fama-MacBeth cross-sectional regressions

	(1)	(2)	(3)	(4)	(5)	(6)
β_{FIN}	0.200	0.170	0.388***	0.381***	0.407***	0.383***
	(1.28)	(1.28)	(2.82)	(2.98)	(2.86)	(3.03)
$ILLIQ\_rank$	0.074**	-0.080*				
	(1.97)	(-1.87)				
$\beta_{FIN} * ILLIQ\_rank$	-0.026	-0.024				
	(-0.80)	(-0.83)				
IO_rank			0.025	0.152***		
			(0.64)	(4.19)		
$\beta_{FIN} * IO\_rank$			-0.093**	-0.091**		
			(-2.34)	(-2.46)		
RIO_rank					-0.204***	-0.254***
					(-5.72)	(-9.15)
$\beta_{FIN} * RIO\_rank$					-0.089***	-0.079**
					(-2.66)	(-2.50)
$log(ME)$		-0.248**		-0.249**		-0.176*
		(-2.17)		(-2.33)		(-1.83)
$log(B/M)$		0.172***		0.138**		0.171***
		(2.84)		(2.22)		(2.79)
$r(t-1)$		-0.505***		-0.611***		-0.639***
		(-6.77)		(-7.34)		(-7.72)
$r(t-12,t-2)$		0.401***		0.318***		0.288**
		(3.90)		(2.64)		(2.38)
$r(t-36,t-13)$		-0.041		-0.115		-0.118
		(-0.60)		(-1.31)		(-1.35)
$Adj.R^2$	1.9%	5.6%	1.4%	5.0%	1.1%	5.0%
$N.obs$	634,529	634,529	477,847	477,847	477,847	477,847

Table 12: Arbitrage Capital and Behavioral Factor Premia

This table reports time-series regressions of FIN and PEAD factor premia on the supply of arbitrage capital in both contemporaneous and lagged periods. Arbitrage capital is estimated by changes in aggregate assets under management of hedge funds (ΔAUM) and aggregate capital flows to the hedge fund sector ($FLOW$). We control for contemporaneous and lagged stock market performance and lagged factor premia. We run regressions over both monthly and quarterly horizons. Newey-West adjusted t-statistics are shown in parentheses (with 3 lags). The sample period is from 1994:01 to 2014:12 (252 months and 84 quarters).

Panel A: Monthly regressions

	FIN (t)		PEAD (t)	
$\Delta AUM(t)$	-0.10		1.01**	
	(-0.14)		(2.28)	
$\Delta AUM(t-1)$	-0.05		-0.24	
	(-0.04)		(-0.70)	
$\Delta AUM(t-2)$	-0.51		0.28	
	(-0.34)		(0.55)	
$\Delta AUM(t-3)$	0.89		0.58*	
	(1.48)		(1.82)	
$FLOW(t)$		1.68		4.62*
		(0.45)		(1.83)
$FLOW(t-1)$		6.57		3.82**
		(1.44)		(2.00)
$FLOW(t-2)$		6.65*		-5.26**
		(1.87)		(-2.05)
$FLOW(t-3)$		-11.21**		2.57
		(-2.53)		(0.95)
MKT	-0.59***	-0.62***	-0.10**	-0.07
	(-5.47)	(-6.76)	(-2.22)	(-1.56)
$MKT(t-1)$	0.10	0.06	-0.02	-0.04
	(1.58)	(1.09)	(-0.46)	(-0.91)
$Factor(t-1)$	0.08	0.07	0.04	0.02
	(0.87)	(0.71)	(0.49)	(0.23)
$Adj.R^2$	29.0%	30.6%	8.6%	5.4%
N.obs	248	248	248	248

Panel B: Quarterly regressions

	FIN (t)		PEAD (t)	
$\Delta AUM(t)$	0.51		-0.11	
	(0.73)		(-0.34)	
$\Delta AUM(t-1)$	0.78		0.30	
	(1.06)		(0.61)	
$\Delta AUM(t-2)$	-1.18**		0.49	
	(-2.11)		(1.12)	
$\Delta AUM(t-3)$	0.26		0.16	
	(0.86)		(0.69)	
$FLOW(t)$		0.86		3.94
		(0.22)		(1.58)
$FLOW(t-1)$		2.14		-3.45
		(0.29)		(-0.86)
$FLOW(t-2)$		0.43		9.08
		(0.06)		(1.24)
$FLOW(t-3)$		0.15		-1.57
		(0.03)		(-0.41)
MKT	-0.74***	-0.66***	0.02	-0.02
	(-4.40)	(-5.14)	(0.31)	(-0.26)
$MKT(t-1)$	0.05	0.17	0.04	0.04
	(0.34)	(1.47)	(0.63)	(1.00)
$Factor(t-1)$	0.20*	0.17	-0.16	-0.09
	(1.68)	(1.32)	(-1.16)	(-0.65)
$Adj.R^2$	44.1%	38.9%	7.0%	4.0%
N.obs	80	81	80	81

Appendix

A Definition of Anomaly Variables

A.1 Short-horizon anomalies

Standardized unexpected earnings (SUE-1, SUE-6):

Following Foster, Olsen, and Shevlin (1984), SUE is calculated as the change in quarterly earnings per share (Compustat quarterly item EPSPXQ) from its value four quarters ago divided by the standard deviation of this change over the prior eight quarters (six quarters minimum). To align quarterly SUE with monthly CRSP stock returns, SUE is used in the months immediately following the quarterly earnings announcement date (Compustat quarterly item RDQ) but within 6 months from the fiscal quarter end, to exclude stale earnings. To exclude recording errors, we also require the earnings announcement date to be after the corresponding fiscal quarter end.

At the beginning of each month t, we rank all NYSE, Amex, and NASDAQ stocks into deciles based on their lagged SUE in month $t-1$. Monthly portfolio returns are calculated separately for the current month t (SUE-1) and for the subsequent six months from t to $t+5$ (SUE-6). The portfolios are rebalanced at the beginning of month $t+1$. For SUE-6 portfolios, we calculated the monthly portfolio returns following Hou, Xue, and Zhang (2015). Because of the six-month holding period, in each month, a given SUE-6 decile has six sub-deciles that are initiated in the prior six-month period. We then take the simple average of the six sub-deciles returns as the monthly return of each SUE-6 decile.

Cumulative abnormal return around earnings announcements (Abr-1, Abr-6):

Following Chan, Jegadeesh, and Lakonishok (1996), Abr is calculated as the four-day cumulative abnormal returns ($t-2$, $t+1$) around the latest quarterly earnings announcement date (Compustat quarterly item RDQ):

$$CAR_i = \sum_{d=-2}^{d=1} R_{id} - R_{md}$$

where R_{id} is stock $i's$ return on day d and R_{md} is the market return on day d. To align quarterly Abr with monthly CRSP stock returns, Abr is used in the months immediately following the quarterly earnings announcement date (Compustat quarterly item RDQ) but within 6 months from the fiscal quarter end, to exclude stale earnings. To exclude recording errors, we also require the earnings announcement date to be after the corresponding fiscal quarter end.

At the beginning of each month t, we rank all NYSE, Amex, and NASDAQ stocks into deciles based on their lagged Abr in month $t-1$. Monthly portfolio returns are calculated separately for the current month t (Abr-1) and for the subsequent six months from t to $t+5$ (Abr-6). The portfolios are rebalanced at the beginning of month $t+1$. For Abr-6 portfolios, we calculated the monthly portfolio returns following Hou, Xue, and Zhang (2015). Because of the six-month holding period, in each month, a given Abr-6 decile has six sub-deciles that are initiated in the prior six-month period. We then take the simple average of the six sub-deciles returns as the monthly return of each Abr-6 decile.

Revisions in analysts' earnings forecasts (RE-1):

Analysts' earnings forecast data are from the Institutional Brokers' Estimate System (IBES). Following Chan, Jegadeesh, and Lakonishok (1996), RE is calculated as the six-month moving average of past changes in analysts' forecasts:

$$RE_{it} = \sum_{j=1}^{6} \frac{f_{it-j} - f_{it-j-1}}{p_{it-j-1}}$$

where f_{it-j} is the consensus mean forecast (IBES unadjusted file, item MEANEST) issued in month $t-j$ for firm i's current fiscal year earnings (IBES unadjusted file, item FPI (fiscal period indicator) =1), and p_{it-j-1} is the prior month's share price (IBES unadjusted file, item PRICE). A minimum of four monthly forecast changes is required.

At the beginning of month t, we rank all NYSE, Amex, and NASDAQ stocks into deciles based on their lagged RE in month $t-1$. Monthly portfolio returns are calculated for the current month t (RE-1) and the portfolios are rebalanced at the beginning of month $t+1$.

Price momentum (R6-6, R11-1):

Following Jegadeesh and Titman (1993), R6 is calculated as a stock's prior 6-month average returns from month $t-7$ to $t-2$. At the beginning of each month t, we rank all stocks into deciles based on R6 and calculate monthly decile returns from month t to $t+5$ (R6-6), skipping month $t-1$. The deciles are rebalanced at the beginning of month $t+1$. Because of the six-month holding period, in each month, a given R6-6 decile has six sub-deciles that are initiated in the prior six-month period. Following Hou, Xue, and Zhang (2015), we take the simple average of the six sub-deciles returns as the monthly return of each R6-6 decile.

The R11-1 deciles are constructed similarly. Following Fama and French (1996), R11 is calculated as a stock's prior 11-month average returns from month $t-12$ to $t-2$. At the beginning of each month t, we rank all stocks into deciles based on R11 and calculate monthly decile returns for month t (R11-1), skipping month $t-1$. The deciles are rebalanced at the beginning of month $t+1$.

Industry momentum (I-MOM):

We start with the Fama-French 49-industry classification. We exclude financial firms, which leaves 45 industries. For each industry, we calculate its prior six-month return from month $t-6$ to $t-1$, by taking a weighted-average of all stocks returns within the industry. Following Moskowitz and Grinblatt (1999), we do not skip month $t-1$ when measuring industry momentum.

At the beginning of each month t, we rank the 45 industries into 9 I-MOM portfolios (each with 5 industries) based on their prior six-month returns from month $t-6$ to $t-1$. Monthly portfolio returns are calculated for the subsequent six months from t to $t+5$, by taking the simple average of the 5 industry returns within each portfolio, and the portfolios are rebalanced at the beginning of month $t+1$. Because of the six-month holding period, in each month, a given I-MOM portfolio has six sub-portfolios that are initiated in the prior six-month period. Following Hou, Xue, and Zhang (2015), we take the simple average of the six sub-portfolios returns as the monthly return of each I-MOM portfolio.

Quarterly ROE and ROA (ROEQ, ROAQ):

ROEQ and ROAQ are calculated using Compustat quarterly files. ROEQ is income before extraordinary items (IBQ) divided by one-quarter lagged book equity. ROAQ is income before extraordinary items (IBQ) divided by one-quarter lagged total assets (ATQ). Book equity is shareholders' equity, plus deferred taxes and investment tax credit (TXDITCQ), minus book value of preferred stocks. Shareholders' equity is shareholders' equity (SEQQ), or common equity (CEQQ) plus the carrying value of preferred stocks(PSTKQ), or total assets (ATQ) minus total liabilities (LTQ), depending on data availability. Book value of preferred stocks equal the redemption value (PSTKRQ) if available, or the carrying value of preferred stocks(PSTKQ).

To align quarterly ROEQ and ROAQ with monthly CRSP stock returns, ROEQ and ROAQ are used in the months immediately following the quarterly earnings announcement date (RDQ) but within 6 months from the fiscal quarter end, to exclude stale earnings. To exclude recording errors, we also require the earnings announcement date to be after the corresponding fiscal quarter end.

At the beginning of each month t, we rank all stocks into deciles based on their lagged ROEQ or ROAQ in month $t-1$. We calculate value-weighted decile returns for month t and rebalance the deciles at the beginning of month $t+1$.

Number of consecutive quarters with earnings increases (NEI):

Following Barth, Elliott, and Finn (1999) and Green, Hand, and Zhang (2013), we measure NEI as the number of consecutive quarters (up to eight quarters) with an increase in earnings (Compustat quarterly item IBQ) over the same quarter in the prior year. NEI takes values from 0 to 8 quarters. To align quarterly NEI with monthly CRSP stock returns, NEI is used in the months immediately following the quarterly earnings announcement date (RDQ) but within 6 months from the fiscal quarter end, to exclude stale earnings. To exclude recording errors, we also require the earnings announcement date to be after the corresponding fiscal quarter end.

At the beginning of each month t, we rank all stocks into nine portfolios, with lagged NEI in month $t-1$ equal to 0, 1, 2, ..., and 8, respectively. We calculate value-weighted portfolio returns for month t and rebalance the portfolios at the beginning of month $t+1$.

Failure probability (FP):

We calculate failure probability (FP) following Campbell, Hilscher, and Szilagyi (2008),

$$\begin{aligned} FP_t = &- 9.164 - 20.264\, NIMTAAVG_t + 1.416\, TLMTA_t - 7.129\, EXRETAVG_t \\ &+ 1.411\, SIGMA_t - 0.045\, RSIZE_t - 2.132\, CASHMTA_t + 0.075\, MB_t - 0.058\, PRICE_t \end{aligned}$$

Detailed variable definitions in the above equation follows closely from Hou, Xue, and Zhang (2015).

Quarterly FP is aligned with monthly CRSP stock returns with at least four months gap after the fiscal quarter end, but within six months after the quarterly earnings announcement date (RDQ). We impose the four-month gap between the fiscal quarter end and portfolio formation to ensure that all quarterly data items in the definition of FP are available to public.

At the beginning of each month t, we rank stocks into deciles based on their lagged FP in month $t-1$. We calculate value-weighted decile returns for the subsequent six months from month t to $t+5$ and rebalance the deciles at the beginning of month $t+1$. Because of the six-month holding period, in each month, a given FP decile has six sub-deciles that are initiated in the prior six-month period. Following Hou, Xue, and Zhang (2015), we take the simple average of the six sub-decile returns as the monthly return of each FP decile.

A.2 Long-horizon anomalies

Gross profit-to-asset ratio (GP/A):

Following Novy-Marx (2013), we define GP/A as total revenue (Compustat item REVT) minus cost of goods sold (COGS) for the fiscal year ending in year $t-1$, adjusted by current (not lagged) total asset (AT) of fiscal year ending in year $t-1$. At the end of June of each year t, we sort stocks into deciles based on GP/A for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Cash-based operating profitability (CbOP):

Cash-based operating profitability (CbOP) is defined following Ball et al. (2016). Operating profitability is measured as revenue (REVT) minus cost of goods sold (COGS) minus reported sales, general, and administrative expenses (XSGA – XRD (zero if missing)). Prior to 1988, we use the balance sheet statement and measure CbOP as operating profitability minus the change in accounts receivable (RECT) minus the change in inventory (INVT) minus the change in prepaid expenses (XPP) plus the change in deferred revenues (DRC + DRLT) plus the change in accounts payable (AP) plus the change in accrued expenses (XACC), deflated by current total assets. Starting from 1988, we use the cash flow statement and measure CbOP as operating profitability plus decrease in accounts receivable (– RECCH) plus decrease in inventory (– INVCH) plus increase in accounts payable and accrued liabilities (APALCH), deflated by current total assets.

At the end of June of each year t, we sort stocks into deciles based on CbOP for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Book-to-market equity (B/M):

B/M is defined as the book equity for the fiscal year ending in year $t-1$ divided by the market equity at the end of December of $t-1$. Following Davis, Fama, and French (2000), book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (TXDITC) if available, minus the book value of preferred stocks. Shareholders' equity is Compustat item SEQ if available, or the book value of common equity (CEQ) plus the carrying value of preferred stocks(PSTK), or total assets (AT) minus total liabilities (LT), depending on data availability. Book value of preferred stocks is the redemption value (PSTKRV), or the liquidating value (PSTKL), or the carrying value of preferred stocks(PSTK), depending on availability.

At the end of June of each year t, we sort stocks into deciles based on B/M for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Earnings-to-price (E/P):

Following Basu (1983), we measure earnings-to-price (E/P) ratio as income before extraordinary items (IB) for the fiscal year ending in year $t-1$ divided by market equity at the end of December of $t-1$. We keep only firms with positive earnings. At the end of June of each year t, we sort stocks into deciles based on E/P for all fiscal years ending in year

$t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Cash flow-to-price (CF/P):

We measure cash flow (CF) as income before extraordinary items (IB), plus depreciation and amortization (DP), plus deferred taxes (TXDI, if available). CF/P is calculated as CF for the fiscal year ending in year $t-1$ divided by market equity at the end of December of $t-1$. We keep only firms with positive cash flows. At the end of June of each year t, we sort stocks into deciles based on CF/P for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Net payout yield (NO/P):

Following Boudoukh et al. (2007), total payout (O) is dividend on common stock (DVC) plus repurchase, where repurchase is the purchase of common and preferred stock (PRSTKC) plus any reduction (negative change over the prior year) in the value of the net number of preferred stocks outstanding (PSTKRV). Net payout (NO) is total payout minus equity issuance, which is the sale of common and preferred stock (SSTK) minus any increase (positive change over the prior year) in the value of the net number of preferred stocks outstanding (PSTKRV). Net payout yield (NO/P) is calculated as NO for the fiscal year ending in year $t-1$ divided by the market equity at the end of December of year $t-1$.

At the end of June of each year t, we sort stocks into deciles based on NO/P for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Equity duration (Dur):

Following Dechow, Sloan, and Soliman (2004), equity duration is calculated as:

$$Dur = \frac{\sum_{t=1}^{T} t \times CD_t/(1+r)^t}{ME} + \left(T + \frac{1+r}{r}\right) \frac{ME - \sum_{t=1}^{T} CD_t/(1+r)^t}{ME}$$

where CD_t is the net cash distribution of year t, ME is the market equity calculated as price per share times shares outstanding of year t ($PRCC\_F \times CSHO$), T is the length of forecasting period, and r is the cost of equity. The construction of CD_t follows closely from Hou, Xue, and Zhang (2015). Also, to be consistent with Hou, Xue, and Zhang (2015), we use a forecasting period of $T = 10$ and a cost of equity of $r = 0.12$.

At the end of June of each year t, we sort stocks into deciles based on Dur for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Asset Growth (AG):

Following Cooper, Gulen, and Schill (2008), asset growth is defined as the percentage change in total asset (Compustat item AT) scaled by beginning total asset. At the end of June of each year t, we sort stocks into deciles based on AG for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Net operating assets (NOA):

Following Hirshleifer et al. (2004), we define net operating assets as *NOA* = (*Operating Assets* – *Operating Liabilities*)/*Lagged Total Assets*, where *Operating Assets* = *Total Assets*(AT) – *Cash and Short-term Investment* (CHE), and *Operating Liabilities* = *Total Assets* (AT) – *Short-term Debt* (DLC) – *Long-term Debt* (DLTT) – *Minority Interest* (MIB) – *Preferred Stock* (PSTK) – *Common Equity* (CEQ).

At the end of June of each year t, we sort stocks into deciles based on NOA for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Investment-to-asset ratio (IVA):

Following Lyandres, Sun, and Zhang (2008), we measure IVA as the annual change in gross property, plant, and equipment (PPEGT) plus the annual change in inventories (INVT) divided by lagged total assets (AT). At the end of June of each year t, we sort stocks into deciles based on IVA for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Investment growth (IG):

Following Xing (2008), we measure IG as the percentage change in capital expenditure (CAPX). At the end of June of each year t, we sort stocks into deciles based on IG for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Net stock issues (NSI):

Following Pontiff and Woodgate (2008), we measure NSI of fiscal year $t-1$ as the natural log of the ratio of split-adjusted shares outstanding of fiscal year $t-1$ to split-adjusted shares outstanding of fiscal year $t-2$. The split-adjusted shares outstanding is the common share outstanding (CSHO) times the adjustment factor (AJEX).

At the end of June of each year t, we sort stocks into deciles based on NSI for all fiscal years ending in year $t-1$. We notice that about one quarter of our sample observations have negative NSI (repurchasing firms), and three quarters with positive NSI (issuing firms). We separately sort repurchasing firms (with negative NSI) into two groups and issuing firms (with positive NSI) into eight groups using NYSE breakpoints. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Composite issuance (IR):

Following Daniel and Titman (2006), we measure IR as the growth rate in market equity that is not attributable to the stock returns, $IR_t = log(ME_t/ME_{t-5}) - r(t-5,t)$. Specifically, for IR in June of year t, ME_t is the market equity at the end of June in year t, ME_{t-5} is the market equity at the end of June in year $t-5$, and $r(t-5,t)$ is the cumulative log return on the stock from end of June in year $t-5$ to end of June in year t.

At the end of June of each year t, we sort stocks into deciles based on IR measured in June of year t. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Inventory growth (IvG):

Following Belo and Lin (2012), we measure IvG of fiscal year $t-1$ as the ratio of inventory (INVT) of fiscal year ending in year $t-1$ over inventory of the fiscal year ending in $t-2$. At the end of June of each year t, we sort stocks into deciles based on IvG for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Inventory changes (IvC):

Following Thomas and Zhang (2002), we measure IvC of fiscal year $t-1$ as the change in inventory (INVT) from the fiscal year of $t-2$ to the fiscal year of $t-1$, scaled by average total assets (AT) of fiscal years $t-2$ and $t-1$. At the end of June of each year t, we sort stocks into deciles based on IvC for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Operating accruals (OA):

We define operating accruals in a way consistent with Hou, Xue, and Zhang (2015). Prior to 1988, we use the balance sheet approach of Sloan (1996) and measure operating accruals as *OA* = [(∆*Current Assets* – ∆*Cash*) – (∆*Current Liabilities* – ∆*Short-term Debt* – ∆*Taxes Payable*) – *Depreciation and Amortization Expense*]/*Lagged Total Assets*, where *Current Assets* is Compustat annual item ACT, *Cash* is CHE, *Current Liabilities* is LCT, *Short-term Debt* is DLC (zero if missing), *Taxes Payable* is TXP (zero if missing), *Depreciation and Amortization Expense* is DP (zero if missing), and *Total Assets* is AT.

Starting from 1988, we use the cash flow approach following Hribar and Collins (2002) and measure operating accruals as *OA* = [*Net Income* – *Net Cash Flow from Operations*]/*Lagged Total Assets*, where *Net Income* is NI and *Net Cash Flow from Operations* is OANCF. Data from the statement of cash flows are only available since 1988.

At the end of June of each year t, we sort stocks into deciles based on OA for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Percent operating accruals (POA):

Following Hafzalla, Lundholm, and Van Winkle (2011), we measure POA as operating accruals (OA) scaled by the absolute value of net income (Compustat item NI) for the fiscal year ending in year $t-1$. At the end of June of each year

t, we sort stocks into deciles based on POA for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Percent total accruals (PTA):

We first define total accruals (TA) in a way consistent with Hou, Xue, and Zhang (2015). Prior to 1988, we use the balance-sheet approach of Richardson et al. (2005) and measure TA as ΔWC + ΔNCO + ΔFIN. ΔWC is the change in net non-cash working capital (WC). WC is current operating asset (COA) minus current operating liabilities (COL), with COA = current assets (ACT) minus cash and short-term investments (CHE) and COL = current liabilities (LCT) minus debt in current liabilities (DLC, zero if missing). ΔNCO is the change in net non-current operating assets (NCO). NCO is non-current operating assets (NCOA) minus non-current operating liabilities (NCOL), with NCOA = total assets (AT) minus current assets (ACT) minus investments and advances (IVAO, zero if missing), and NCOL = total liabilities (LT) minus current liabilities (LCT) minus long-term debt (DLTT, zero if missing). ΔFIN is the change in net financial assets (FIN). FIN is financial assets (FINA) minus financial liabilities (FINL), with FINA = short-term investments (IVST, zero if missing) plus long-term investments (IVAO, zero if missing), and FINL= long-term debt (DLTT, zero if missing) plus debt in current liabilities (DLC, zero if missing) plus preferred stock (PSTK, zero if missing).

Starting from 1988, we use the cash flow approach following Hribar and Collins (2002) and measure TA as net income (NI) minus total operating, investing, and financing cash flows (OANCF, IVNCF, and FINCF) plus sales of stocks (SSTK, zero if missing) minus stock repurchases and dividends (PRSTKC and DV, zero if missing). Data from the statement of cash flows are only available since 1988.

Following Hafzalla, Lundholm, and Van Winkle (2011), we measure PTA as total accruals (TA) scaled by the absolute value of net income (NI) for the fiscal year ending in year $t-1$. At the end of June of each year t, we sort stocks into deciles based on PTA for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Organizational capital-to-assets (OC/A):

Following Eisfeldt and Papanikolaou (2013), OC/A is measured using the perpetual inventory method:

$$OC_{it} = (1-\delta)OC_{it-1} + SG\&A_{it}/CPI_t$$

where SG&A is Selling, General, and Administrative expenses (Compustat item XSGA), CPI is the consumer price index during year t, and δ is the annual depreciation rate of OC. For detailed definition of each variable, we follow closely Hou, Xue, and Zhang (2015).

At the end of June of each year t, we sort stocks into deciles based on OC/A for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Advertisement expense-to-market (AD/M):

Following Chan, Lakonishok, and Sougiannis (2001), we measure AD/M as advertising expenses (Compustat item XAD) for the fiscal year ending in year $t-1$ divided by the market equity at the end of December of year $t-1$. We keep only firms with positive advertising expenses. At the end of June of each year t, we sort stocks into deciles based on AD/M for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

R&D-to-market (RD/M):

Following Chan, Lakonishok, and Sougiannis (2001), we measure RD/M as R&D expenses (Compustat item XRD) for the fiscal year ending in year $t-1$ divided by the market equity at the end of December of year $t-1$. We keep only firms with positive R&D expenses. At the end of June of each year t, we sort stocks into deciles based on RD/M for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.

Operating leverage (OL):

Following Novy-Marx (2011), OL is measured as cost of goods sold (Compustat item COGS) plus selling, general, and administrative expenses (Compustat item XSGA) for the fiscal year ending in year $t-1$, adjusted by current (not lagged) total assets (Compustat item AT). At the end of June of each year t, we sort stocks into deciles based on OL for all fiscal years ending in year $t-1$. Monthly decile returns are calculated from July of year t to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$.