Short and Long Horizon Behavioral Factors

Kent Daniel, David Hirshleifer and Lin Sun*

November 30, 2017

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.

*Daniel: Columbia Business School and NBER; Hirshleifer: Merage School of Business, UC Irvine and NBER; Sun: Florida State University. We appreciate helpful comments from Jawad Addoum (FIRS discussant), Chong Huang, Danling Jiang, Frank Weikai Li (CICF discussant), Anthony Lynch (SFS-Cavalcade discussant), Stefan Nagel, Christopher Schwarz, Zheng Sun, Siew Hong Teoh, Yi Zhang (FMA discussant), Lu Zheng, seminar participants at UC Irvine, University of Nebraska, Lincoln, Florida State University, Arizona State University, and from participants in the FIRS meeting at Quebec City, Canada, the FMA meeting at Nashville, TN, the SFS Cavalcade North America meeting at Vanderbilt University, and the China International Conference in Finance at Hangzhou.

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 generally-better description of the cross-section of expected returns than other factor models proposed in the literature.[1]

Consistent with much of the literature (Fama and French, 1993, 2015), we seek to explain the expected returns of different firms by their factors exposures as opposed to characteristics (Daniel and Titman, 1997). However, we consider behaviorally-motivated factors that might be expected to be related to short- or long-term mispricing.

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. Sentiment shocks can induce comovement of

[1] A tempting but fallacious way to evaluate parsimony is to simply count 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. So radical overfitting is entirely compatible with having a small number of factors. This is consistent with the argument in Novy-Marx (2016).

assets that share the same style, even when news about the assets' underlying cash flows is uncorrelated.

Alternatively, return comovement can result from commonality in investor errors in interpreting signals 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 economic factors that influence profits. (These economic factors, such as industry, are not necessarily priced risk factors in the rational asset pricing sense.) As a result, shocks to these factors lead to comovement among stocks with similar levels of mispricing, as such stocks share similar exposures to the economic factors.

Thus in behavioral models there will be comovement associated with common levels of mispricing, as well as with common exposure to fundamental risk factors. Since mispricing predicts future returns owing to subsequent correction of the mispricing, this implies that behavioral factors can be used to construct a factor model that better describes the cross-section of expected returns.[2] Just as firms which are exposed to systematic risk factors earn an associated risk premium, firms which are heavily exposed to behavioral factors earn a conditional return premia (see, e.g., the model of Hirshleifer and Jiang (2010)). Fama and French (1993) construct risk factors based on firm characteristics that they argue capture risk exposure; we use behavioral factors based on characteristics that are expected to be associated with misvaluation.

One goal of this paper is to identify common return factors based on insights from behavioral theories of securities price formation. In particular, some theories suggest mispricing that will persist a relatively short period of time, and others suggest more persistent mispricing. We therefore seek to identify both short-horizon behavioral factors that capture comovement associated with short-horizon return anomalies, and long-horizon factors for long-horizon anomalies.

A second goal of this paper is to use a factor model to provide a more parsimonious description of return anomalies. Specifically, by combining behavioral factors with the market factor (to capture rational risk premia) we seek to describe parsimoniously anomalies at both short- and long-horizons.

[2]Several other studies also suggest that behavioral biases could systematically affect asset prices. 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. Stambaugh and Yuan (2016) develop a behavioral factor model based on commonality in mispricing.

We expect anomalies resulting from limited attention to higher-frequency information—such as quarterly earnings announcements—to be corrected at reasonably short time horizons. For example, building on insights of Bernard and Thomas (1990), in the models of Hirshleifer and Teoh (2003), DellaVigna and Pollet (2009), and Hirshleifer, Lim, and Teoh (2011), a subset of investors fail to take into account the implications of the latest earnings surprise for future earnings. As a consequence, stock prices underreact to earnings surprises. This results in abnormal returns in the form of post-earnings announcement drift (PEAD) when this mispricing is corrected upon the arrival of the next few earnings announcements (Ball and Brown, 1968).

In contrast, theory suggests that other biases may result in more persistent, longer-horizon mispricing. For example, investors who are overconfident about their private information signals will overreact to these signals, leading to a value effect wherein firms with high stock valuations relative to fundamental measures subsequently experience low returns. Owing to overconfidence in their private signals, investors are relatively unwilling to correct their perceptions as further (public) earnings news arrives. Indeed, in the models of Daniel, Hirshleifer, and Subrahmanyam (1998) and Gervais and Odean (2001), the arrival of new public information can temporarily *increase* overconfidence and mispricing. So in contrast with a limited-attention-driven anomaly, the correction of overconfidence-driven mispricing will take place over a much longer time horizon.

Furthermore, in the model of Barberis, Shleifer, and Vishny (1998), there are regime shifting beliefs about the nature of the earnings time series. An under-extrapolative belief regime (their "mean-reverting" regime) leads to post-earnings announcement drift and momentum. In this regime the positive returns that follow a positive earnings surprise dissipate rapidly when the next few earnings surprises prove earnings to be higher than was expected. In contrast their over-extrapolative ("trending") regime can be more persistent, because a brief sequence of earnings surprises may not provide enough evidence to fully disprove the extrapolative expectations investors have formed about more distant earnings.

Overall, then, behavioral theories suggest that different mechanisms can lead to different types of mispricing that correct at either long or short horizons. Based on these considerations, we develop distinct long- and short-horizon behavioral factors.[3]

Our long-horizon behavioral 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 complementary repurchase puzzle that repurchases positively predict future returns.[4] Under the market timing hypothesis, managers possess inside information about the true value of their firms and issue or repurchase equity (or debt) to exploit pre-existing mispricing (Stein, 1996).[5] Firms undertaking share issues will generally be overpriced and repurchasing firms underpriced. Furthermore, issuance and repurchase should be powerful indicators of mispricing, because firms can benefit from trading against mispricing that derives from many possible sources. Furthermore, under this hypothesis, investors hold stubbornly to their mistaken beliefs upon observing the new issue or repurchase, perhaps owing to overconfidence (Daniel, Hirshleifer, and Subrahmanyam, 1998). If investors are overconfident, a few corrective earnings announcements may not be enough to fully eliminate misperceptions, so abnormal performance can persistent for a long period of time.

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 portfolio takes long positions in firms which repurchased debt or equity over the previous 24 months, and short positions in firms which issued either debt or equity through an IPO or SEO over the same time frame. 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

[3]A complicating issue is that some behavioral theories also use overconfidence to explain price momentum, which is a short-horizon anomaly (lasting about a year). Empirically, part of the price momentum effect is explained by earnings momentum (Chan, Jegadeesh, and Lakonishok, 1996), which is much like post-earnings announcement drift. The remaining part of the price momentum effect, according to the Daniel, Hirshleifer, and Subrahmanyam (1998) model, derives from dynamic patterns of shifts in overconfidence. This mechanism differs from both the short-run mechanism of the limited attention theory for PEAD, and the long-run static overconfidence mechanism for the value effect and financing anomalies.

[4]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 a firm's total issuances and repurchases.

[5]Alternatively, Eckbo, Masulis, and Norli (2000), Berk, Green, and Naik (1999) and Lyandres, Sun, and Zhang (2008) propose or test risk-based explanations for the new-issues anomaly. Dong, Hirshleifer, and Teoh (2012), Khan, Kogan, and Serafeim (2012), and Teoh, Welch, and Wong (1998) for recent evidence supporting the behavioral explanations.

it in the interest 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 portfolio is based on 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 on composite issuance exhibits stronger pricing power for the cross-section of stock returns than a factor based solely on external financing events.

FIN is designed to capture longer-term mispricing and correction, as opposed to short-term mispricing (though it could contain some short-term mispricing as well). Overconfidence offers a possible explanation for the long horizon of the effects FIN captures, but other institutional features relating to issuance and repurchase further contribute to the ability of FIN to capture long-term mispricing. Equity issuance and repurchase have disclosure, legal, underwriting, and other costs, and as a consequence such corporate events tend to occur only occasionally, rather than as immediate responses to even transient mispricing. There are also informational barriers to high-frequency issuance/repurchase strategies.[6]

Our second behavioral factor is designed to capture short-term mispricing, such as underreaction to earnings information. Post-earnings announcement drift (PEAD) is the finding that firms that experience positive earnings surprises subsequently outperform those with negative earnings surprises. Bernard and Thomas (1989) argue that the premium earned by a PEAD is not a rational risk premium, and instead reflects delayed price response to information. A recent empirical literature suggests that this delayed response is attributable to limited investor attention.[7] If the source of PEAD is that

[6]U.S. regulation potentially creates substantial time lags in registering security issues. Issuance also subjects the firm to possible investor skepticism about the possibility that firms with high value of assets in place are issuing to exploit private information, as modeled by Myers and Majluf (1984). Flexibility in issuance timing can be increased through shelf-registration, allowing the firm to exploit even transient private information, but by the same token, investors are likely to be especially skeptical when firms maintain such flexibility.

[7]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.

some investors neglect the implications of current earnings news for future earnings, any mispricing is likely to be corrected as the next few earnings are announced. Indeed, the evidence indicates that this correction is complete within a year.

We therefore hypothesize that PEAD reflects 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.

Our PEAD factor is constructed by going long firms with positive earnings surprises and short firms with negative surprises. We are not the first to construct a PEAD factor; our contribution is to use this factor in a parsimonious factor pricing model, to show that it explains a broad range of short-horizon anomalies.[8,9]

Our factor model augments the CAPM with these 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). By using both long- and short-horizon behavioral factors, we seek to capture both long-term mispricing that takes a few years to correct and short-term mispricing that takes a few quarters to correct.

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

[8] Chordia and Shivakumar (2006) and Novy-Marx (2015a) construct a PEAD factor and argue that the predictive power of past returns is subsumed by a zero-investment portfolio based on earnings surprises. Novy-Marx (2015b) uses a PEAD factor to price the ROE factor of Hou, Xue, and Zhang (2015).

[9] We note that the evidence Kothari, Lewellen, and Warner (2006) suggest that the relation between *aggregate* earnings surprises and market returns is negative rather than positive. This is not inconsistent with our hypothesis: we are arguing that there is likely to be some commonality in the factor loadings of the set of firms which experienced both positive and negative earnings surprises. Based on the arguments in Daniel, Hirshleifer, and Subrahmanyam (2001) and Kozak, Nagel, and Santosh (2017a), this will result in a high premium becoming associated with the firms that load on the resulting PEAD factor.

and profitability factors). Barillas and Shanken (2017) 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 run spanning tests to 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 price 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 built on 3 firm characteristics with recently proposed factor models: the four-factor model of Novy-Marx (2013, NM) built on 5 characteristics, the five-factor model of Fama and French (2015, FF5) built on 4 characteristics, the four-factor model of Hou, Xue, and Zhang (2015, HXZ) built on 3 characteristics, and the four-factor model of Stambaugh and Yuan (2016, SY4) built on 12 characteristics.[10]

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, eleven anomalies

[10]Consistent with convention in this literature since Fama and French (1993), both our FIN and PEAD factor portfolios are based on multivariate (3×2) sorts on the relevant characteristic and on firm size (i.e., Market Equity). The next step is to go long both the small- and large-high-characteristic portfolio, and short the small- and large-low-characteristic portfolio (see Section 1.1 for a detailed discussion of our portfolio formation procedure). Since firm size is used in forming these portfolios, we count size as a separate characteristic for our FIN and PEAD factors. We count similarly for all other factors for which size is used in factor construction. Similarly, we count industry as a separate characteristic for Novy-Marx factors as those factors are industry-adjusted. We then count the total number of firm characteristics used in each model (excluding the market factor). For example, the 3 characteristics of our composite model are external financing, earnings surprises, and size. The 5 characteristics of Novy-Marx (2013) model are value, momentum, gross profits-to-assets, size, and industry.

have significant FF5 alphas, two have significant NM alphas, one has a significant HXZ alpha, and four have significant SY4 alphas. The mean $|\hat{\alpha}|$ is lower for the composite model than for any of the four alternative models. Finally, the Gibbons, Ross, and Shanken (1989, GRS) F-test fails to reject the hypothesis that the 12 composite-model alphas are jointly zero, but allows rejection of each of the four alternative models at a 1% significance level.

The composite model also does a good job explaining the 22 long-horizon anomaly portfolios, but for these portfolios the SY4 and NM models also perform well. For the behavioral-composite model, 3 of the 22 alphas are significant at the 5% significance level, compared to 7, 3, 5 and 3 for the FF5, NM, HXZ, and SY4 models respectively. The GRS F-test that the 22 long-horizon anomaly portfolio alphas are jointly zero is not rejected at a 10% level for the SY4 model, or at a 5% level for our behavioral-composite model or the NM model. The GRS test does, however, reject this null at a 1% significance level for both the FF5 and HXZ models. The superior performance of the SY4 model appears to result primarily from the inclusion of their MGMT factor, which is constructed from the characteristics of *six* long-horizon anomalies related to investment and financing.

Overall, across all 34 long- and short-horizon anomalies, our three-factor behavioral-composite model performs well. Only 3 anomalies have 5% significant composite-model 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 large set of anomalies studied in Hou, Xue, and Zhang (2015). 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.

Along with its superior pricing power, the composite model is more parsimonious in that it includes factors built upon just three characteristics. Some recent models are built based upon larger numbers of characteristics (see footnote 1). Despite using fewer factors and characteristics, the composite model tends to have as strong or stronger explanatory power for existing return anomalies as the other models we examine. These other models use either more factors, more characteristics, or both.

Why do just two return predictors (external financing and earnings surprises) capture a wide set of anomalies? This result does not imply that anomalies derive from just two psychological sources. Rather, it is plausible that there are many behavioral biases, each somewhat different. However, to the extent that each firm's manager is aware of that firm's total mispricing—resulting from this variety of biases—and attempts to arbitrage this mispricing via issuance/repurchase activities the scale of which is proportional to the magnitude of the mispricing, we would expect our long-horizon behavioral factor FIN to provide a good summary of the various sources of longer-term mispricing. Similarly, to the extent that short-horizon anomalies are related to psychological biases that induce underreaction to fundamentals, a firm's earnings information may be a good summary of higher-frequency information about firm value that investors misvalue, in which case loadings on the PEAD factor may do a good job of capturing such mispricing.

To further evaluate our composite factor model, we perform cross-sectional tests. If FIN and PEAD are indeed priced behavioral factors that capture commonality in mispricing, then behavioral models imply that firm loadings on FIN should be proxies for persistent underpricing, and loadings on PEAD should be proxies for transient underpricing. In consequence, these loadings should positively predict the cross-section of stock 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 that underlie the 34 anomalies that we examine. In contrast, estimated PEAD loadings have no return predictive ability. As we discuss below, a possible explanation is econometric issues associated with the instability of the PEAD loadings as proxies for transient mispricing, and to the estimation of the characteristic premium.

The observed premia of the behavioral factors we propose could alternatively be interpreted as rational risk premia. (This mirrors the fact that traditional rational factor models might instead be interpreted as reflecting mispricing.) However, we motivate our two behavioral factors with behavioral/mispricing arguments. Following Daniel, Hirshleifer, and Subrahmanyam (2001) and Kozak, Nagel, and Santosh (2017a), in a setting in which investors with biased expectations co-exist with unbiased (rational) arbitrageurs, the presence of the arbitrageurs will ensure that there are no pure arbitrage opportunities. This will necessarily link the covariance structure and the expected returns of the individual assets; that is, *behavioral factors* will be priced, and the Sharpe Ratios associated with the behavioral factors will be bounded. The loadings on the behavioral factors will correctly price individual securities, but the factors themselves will not necessarily covary with aggregate macroeconomic risks, as would the risk-factors in setting with no biased investors. Furthermore, the returns associated with behavioral factors should be related to market frictions; these implications do not follow for effects that derive from a rational frictionless model of risk premia.

We therefore conduct several robustness tests to provide additional evidence regarding the performance of the FIN and PEAD factors. We focus on market frictions, 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 overpriced stocks in the short-leg of anomaly portfolios (Stambaugh, Yu, and Yuan, 2012). Consistent with this hypothesis, we find the short-side of the anomaly portfolios (i.e., overpriced firms) load far more strongly on the relevant behavioral factors than do the long sides of the portfolios (i.e., the underpriced firms).

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.

A growing literature seeks to explain wide sets of anomalies with a small set of factors. This is the motivation behind the work of Fama and French (1996), and more recently Novy-Marx (2013), Fama and French (2015, 2016b), Hou, Xue, and Zhang (2015), and Stambaugh and Yuan (2016). Our paper builds on this earlier work in three key ways. First, 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. Second, our behavioral factors are constructed on the basis of three economic characteristics which are not obviously related to the set of anomalies we seek to explain.[11] Finally, as noted earlier, our factor model provides a better fit to a wide set of anomalies and factors.

A key criterion for choosing among factor models is parsimony. Less parsimonious models are more subject to overfitting. 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, there is always a single ex post mean-variance efficient factor-portfolio that will price all assets.

A more relevant parsimony criterion for a factor model is the number of economically distinct characteristics 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, for parsimony it is valuable to have a factor model which strictly limits the set of characteristics drawn upon. A key strength of our model is that it explains a wide range of anomalies using just three economic characteristics, and that these characteristics are distinct from most of those used to construct the anomaly portfolios themselves.

1 Comparison of Behavioral Factors with Other Factors

1.1 Factor definitions

We construct the financing-based mispricing factor (FIN) based on the 1-year net share issuance and 5-year composite share issuance measures of Pontiff and Woodgate (2008) and Daniel and Titman (2006), respectively. Daniel and Titman's 5-year composite share issuance (CSI) measures the part of a firm's growth in market value that is not attributed to stock returns. As such, corporate actions such as splits and stock dividends leave the composite issuance measure unchanged. However, issuance activity such as seasoned issues, employee stock option plans, and share-based acquisitions increases the issuance measure. In contrast, repurchase activity such as actual share repurchases, dividends, and

[11] A recent set of papers explore factor selection using machine learning techniques (Freyberger, Neuhierl, and Weber, 2017; Kozak, Nagel, and Santosh, 2017b; Feng, Giglio, and Xiu, 2017).

other actions that pay cash out of the firm decreases the issuance measure. Pontiff and Woodgate's net share issuance (NSI) is constructed using the same method as Daniel and Titman, while focusing on an annual horizon. It measures a firm's annual share issuance as change in shares outstanding, adjusted for distribution events such as splits and rights offerings. Both issuance measures earn significant abnormal returns (incremental to each other) during our sample period of 1972 to 2014. Details on variable constructions are provided in Appendix A.[12]

The FIN factor is constructed as follows. We use all NYSE, AMEX, and NASDAQ common stocks with CRSP share codes of 10 or 11, excluding financial firms. At the end of 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 is below or above the NYSE median size breakpoint. Independently, we sort firms into one of the three financing groups (low "L", middle "M", or high "H") based on the 1-year net share issuance (NSI) measure of Pontiff and Woodgate (2008)) and the corresponding 5-year composite share issuance (CSI) measure of Daniel and Titman (2006), respectively. The three financing groups are created based on an index of NSI and CSI rankings.

Specifically, we first sort firms into three CSI groups (low, middle, or high) using 20% and 80% breakpoints for NYSE firms. Special care is needed when sorting firms into NSI groups: about one quarter of our NSI observations are negative (i.e., are repurchasing firms). If we were to use NYSE 20% and 80% breakpoints to assign NSI groups, then in some formation years we would have all repurchasing firms in the bottom 20% group, without differentiating between firms with high and low repurchases. To address this concern, each June we separately sort all repurchasing firms (with negative NSI) into two groups using the NYSE median breakpoint, and sort all issuing firms (with positive NSI) into three groups using NYSE 30% and 70% breakpoints. We then assign the repurchasing firms with the most negative NSI to the low NSI group, the issuing firms in the top group to the high NSI group, and all other firms to the middle group.

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

[12] 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. This is also consistent with the discussion in Daniel and Titman (2016).

low group by both NSI and CSI 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, again 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 return ($t-2$, $t+1$) around the most recent 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.[13]

The set of firms which are used in calculating 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, and value-weighted portfolio returns are calculated for the current month. The month t PEAD factor return is then the average of the high earnings surprise portfolio

[13] 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).

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

1.2 Competing factor models

We compare our behavioral factors and the three-factor composite model with traditional factor models, such as the CAPM (Sharpe, 1964; Lintner, 1965; Black, 1972), and models that include the Mkt-Rf, SMB, HML, and MOM factors proposed by Fama and French (1993) and Carhart (1997), as well as a set of recently proposed factors and models. Monthly factor returns are either downloaded from Kenneth French's web site or provided by the relevant authors.[14]

Novy-Marx (2013) proposes a four-factor model including a market factor, a value factor, a momentum factor, and a profitability factor (PMU). The profitability factor is constructed based on gross profits-to-assets from Compustat annual files. The value, momentum, and profitability characteristics are demeaned by the average characteristic for firms in the same industry to hedge the factor returns for industry exposure. To differentiate from their standard versions, we label the industry-adjusted value and momentum factors as HML(NM) and MOM(NM). All factor portfolios are annually rebalanced at the end of each June.

Fama and French (2015) propose a five-factor model that includes a market factor, a size factor, a value factor, an investment factor (CMA), and a profitability factor (RMW). The investment factor is formed based on annual change in total assets and the profitability factor is based on operating profitability. All factor portfolios are annually rebalanced at the end of each June.

Hou, Xue, and Zhang (2015) propose a q-factor model including four factors: a market factor, a size factor, an investment factor (IVA), and a profitability factor (ROE). The size, investment, and profitability factors are formed by a triple sort on size, change in total assets from Compustat annual files, and ROE from Compustat quarterly files. To differentiate from the standard size factor, we label the size factor in this model as SMB(HXZ). The size and IVA factor portfolios are rebalanced annually at the end of each June, and the ROE factor is rebalanced each month.

Lastly, Stambaugh and Yuan (2016) propose a four-factor model that includes a market factor, a

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

size factor, and two mispricing factors (MGMT and PERF). The size factor is formed using only stocks least likely to be mispriced, to reduce the effect of arbitrage asymmetry, and we label it as SMB(SY4). The MGMT factor is a composite factor constructed based on six characteristics related to investment and financing: net share issuance, composite issuance, operating accruals, net operating assets, asset growth, and investment-to-assets. The PERF factor is a composite factor based on five characteristics including price momentum and profitability: distress, O-Score, momentum, gross profitability, and return on assets. Both MGMT and PERF factors are rebalanced each month.

1.3 Summary statistics

Table 1 reports summary statistics for our zero-investment behavioral factors, and for a set of factors proposed in previous literature. 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 investment and profitability factors (e.g., CMA, IVA, PMU, RMW) and the composite mispricing factor MGMT shows that 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, 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. Also, the correlations of ROE with the two momentum factors (MOM, MOM(NM)) are about 0.5.

Not surprisingly, the composite 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, which is constructed on five anomalies including price momentum and profitability, is highly correlated with both momentum factors (MOM, MOM(NM)) and with the profitability factors (PMU, RMW, ROE), with ρ ranging from 0.48 to 0.72.

Lastly, although FIN is constructed using only share issuance, its returns are correlated with both value factors (HML, HML(NM)) and investment factors (CMA, IVA), with ρ between 0.50 and 0.66, consistent with issuing firms both having high valuation ratios and substantial investment levels. FIN is highly correlated with the composite MGMT factor with $\rho = 0.80$, suggesting that financing characteristics might be a dominant principal 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. 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 ROE, with $\rho = 0.22$. This is consistent with the finding in the literature that earnings momentum, price 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. Finally, 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.

1.4 Comparing behavioral factors with other factors

As discussed in the introduction, Barillas and Shanken (2017) point out that in comparing traded factor models it is important to compared their abilities to price traded factors as well as assets. Here, using spanning tests, we assess the power of our behavioral factors to price each of the factors from the alternative models, and vice versa. Specifically, we run time-series regressions of the monthly returns of FIN and PEAD on returns of other proposed factors, and vice versa, and examine the regression intercepts (alphas). If a factor is subsumed by a set of other factors, we expect the regression alpha to statistically indistinguishable from zero.

Table 2 reports the results of regressions of our behavioral factors on other sets of factors proposed in the literature. The significant intercepts from the Fama-French three-factor model, the Carhart model, the Fama and French (2015) five-factor model and the Hou, Xue, and Zhang (2015) q-factor show that the factors in these models do not explain FIN premia. 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 premia. 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 premia. The 'kitchen sink' regression of the PEAD factor returns on all alternative model factors shows that PEAD continues to earns a significant alpha of 0.58% per month ($t = 6.76$) even after controlling for the exposure to all other proposed factors from the alternative models.

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.[15] With 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 factors from the alternative models, 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, Hodrick, Xing, and Zhang (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 to the remaining HXZ anomalies, we also consider the cash-based operating

[15] 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.

profitability (CbOP) of Ball, Gerakos, Linnainmaa, and Nikolaev (2016). We do this based on the evidence in Fama and French (2016a) suggesting that an anomaly portfolio based upon cash-based operating profitability dominates one based upon operating profitability.

Because FIN is constructed using a firm's financing activities, and PEAD using the firm's 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 price 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 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.[16]

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 price 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*-

[16]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.

factor model of Hou, Xue, and Zhang (2015, HXZ), and the four-factor mispricing model of Stambaugh and Yuan (2016, SY4).[17]

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. Not suprisingly, most anomalies earn large and statistically significant excess returns.[18] 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 several comparative statistics: (1) the number of significant alphas at 5% significance level, (2) the average absolute alphas, (3) the average absolute t-values of alphas, (4) the F-statistics and p-values that test whether the average t^2 of alphas under a given model is significantly larger than the average t^2 of the composite-model alphas, (5) the GRS F-statistics and p-values which test the null hypothesis that all alphas are jointly zero (Gibbons, Ross, and Shanken, 1989), and (6) the Hansen and Jagannathan (1997, HJ) distance which measures the maximum pricing error generated by a model on a set of testing portfolios.[19]

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

[17]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.

[18]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.

[19]The HJ-distance is estimated as follows. Consider a portfolio of N assets, with a (gross) return vector R_t at month t. Let 1_N be an N-dimensional vector of ones, and Y_t a K-dimensional vector of (gross) factor returns including one. Following Hansen and Jagannathan (1997), the HJ-distance is estimated by $Dist(\delta_T)=\sqrt{w'(\delta_T)\ G_T^{-1}\ w(\delta_T)}$, where $\delta_T = (D_T' G_T^{-1} D_T)^{-1} D_T' G_T^{-1} 1_N$ is a GMM estimator that minimizes the distance $Dist(\delta)$, $D_T = \frac{1}{T}\ \sum_{t=1}^{T} R_t Y_t'$, the weighting matrix $G_T = \frac{1}{T} \sum_{t=1}^{T} R_t R_t'$, T is the number of sample months, and the pricing error vector $w(\delta_T) = D_T \delta_T - 1_N$. Jagannathan and Wang (1996) prove that the asymptotic distribution of $T[Dist(\delta_T)]^2$ is a weighted sum of $\chi^2(1)$ distributed random variables. To get the critical value for $T[Dist(\delta_T)]^2$, they suggest an algorithm that first draws $M \times (N - K)$ random variables from $\chi^2(1)$ distribution, and then computes the simulated p-value that tests the null hypothesis that the underlying factor model is specified correctly. We set $M = 5000$ random draws.

with a momentum factor explains about half of them. Not surprisingly, the FF3 and FF5 models perform poorly 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 inability of the MOM factor, the ROE factor, and the PERF factor, respectively, to explain the short-horizon anomaly portfolio returns. 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 price momentum, earnings momentum, and short-term profitability.

Other comparative statistics confirm the superior performance of the PEAD factor and our BF3 model. The BF3 model gives the smallest average absolute alpha ($|\alpha| = 0.09\%$) and absolute t ($|t| = 0.49\%$) among all models. The F-tests suggest that the average of the squared t-statistics for the estimated alphas (t^2) under all other models are significantly larger than average t^2 of BF3 alphas. Furthermore, the BF3 model gives the smallest GRS F-statistic and does not reject the null hypothesis that all alphas are jointly zero (GRS $F = 1.15$ and $p = 0.32$). It also gives the smallest HJ-distance and does not reject the null hypothesis that the composite model is specified correctly (HJ $= 14.66$ and $p = 0.49$). In contrast, all other models give substantially larger average absolute alphas and t, their GRS F-tests reject the null hypotheses at 1% significance level, and the HJ tests reject the null hypotheses that these models are specified correctly at 1% significance level (except for SY4 model which rejects the null at 10% significance level).

Although the PERF factor of the SY4 model is constructed on five return predictors related to price momentum and profitability, our PEAD factor, which is constructed on a *single* return predictor, earnings surprises (along with size), outperforms the composite PERF factor in capturing the 12 short-horizon anomalies.[20]

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 consider the number of significant alphas at 5% significance level. Among standard factor

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

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 comparative statistics confirm the superior performance of the NM, BF3, and particularly the SY4 models. The SY4 model gives the smallest average absolute alpha ($|\alpha| = 0.12\%$) and absolute t ($|t| = 0.70\%$) among all models. The F-tests suggest that the average of the squared t-statistics for the estimated alphas (t^2) under FF5, NM, and HXZ models are not significantly different from average t^2 of BF3 alphas, but the average t^2 of SY4 alphas is significantly smaller than that of BF3 alphas. Furthermore, the SY4 model gives the smallest GRS F-statistic and does not reject the null hypothesis that all alphas are jointly zero (GRS $F = 0.74$ and $p = 0.80$). The GRS F-tests cannot reject the null under 5% significance level for NM and BF3 models, while rejecting the null at 1% significance level for all other models including the FF5 and HXZ models. Lastly, the HJ tests cannot reject the null hypotheses that the FF5, NM, SY4 and BF3 models are specified correctly, while rejecting the null at 10% significance level for the HXZ model.

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, such as net operating assets (NOA), investment-to-asset ratio (IVA), inventory changes (IvC), and operating accruals (OA). 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 appears to result from the inclusion of its MGMT factor, which is constructed on six long-horizon return predictors related to investment and financing, allowing it to price investment-related anomalies.[21] Interestingly FIN and PEAD, constructed on just

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

two return predictors, are able to perform almost 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, the SY4 model gives the smallest, and the BF3 model gives the second smallest, average absolute alpha and absolute t among all models. The F-tests suggest that the average of the squared t-statistics for the estimated alphas (t^2) under NM and SY4 models are not significantly different from average t^2 of BF3 alphas, but the average t^2 of FF5 and HXZ alphas are significantly larger than that of BF3 alphas at 1% and 10% significance levels, respectively. Unlike in Panel A and B, the GRS F-tests reject the null hypotheses of all alphas jointly zero under all models, while the BF3 model achieves the smallest GRS F-statistic. Similarly, the HJ tests reject the null hypotheses under all models, while the BF3 model gives the smallest HJ-distance measure.

Overall, a three-factor risk-and-behavioral composite model (BF3) with a market factor and two behavioral factors outperforms both traditional 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.

Next, we present detailed factor regression results for each anomaly. For brevity, 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 price momentum

Our test assets include five earnings momentum portfolios (SUE-1, SUE-6, ABR-1, ABR-6, RE-1) and three price momentum portfolios (R6-6, R11-1, I-MOM). Panel A of Table 8 shows that, likely owing to the lack of a momentum factor, the FF5 model does not capture any of these anomalies. Panel B and C show that the momentum factor (MOM) 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 price 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 fully captures *all* anomalies.

Overall, the PEAD factor, constructed on earnings surprises, exhibits stronger pricing power for price 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

Our test assets include six profitability anomaly portfolios. Four are based on short-term profitability metrics from quarterly COMPUSTAT files or based on earnings realizations (ROAQ, ROEQ, NEI, FP), and two are based on longer-term profitability metrics from annual COMPUSTAT files (GP/A, CbOP). The short-term profitability portfolios are rebalanced monthly, and the long-term profitability portfolios are rebalanced annually.

Panel A of Table 8 shows that despite inclusion of the profitability factor RMW, the FF5 model fails to fully explain the premia earned by the profitability portfolios; most of these anomalies have large and significant alphas after controlling for exposure to RMW. Panel B shows that the profitability (PMU) factor of the NM model fully explains all but the failure probability effect (FP). Panel C shows that the short-term profitability (ROE) factor 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 fully captures *all* these profitability anomalies.

Overall, it is notable that 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 price momentum, distress, and profitability.

2.2.6 Value anomalies

Our test assets include five value anomaly portfolios: B/M, E/P, CF/P, NPY, 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 (HML) factor. In Panel C, without a value factor, the investment (IVA) factor of the HXZ model explains all these anomalies except for the net payout yield effect (NPY). In Panel D, the MGMT factor of the SY4 model, constructed on six anomaly variables related to investment and financing, fully captures *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

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

Overall, the value factor (HML) and the investment factors (CMA and IVA) play a role in successfully pricing many, but not all, investment and financing anomaly portfolios. The profitability factors (RMW, PMU, and ROE) to some extent help explain financing anomalies, but go in the wrong direction for many investment anomalies. Not surprisingly, the MGMT factor, constructed on six investment and financing return predictors, delivers the best performance. Interestingly, our FIN factor, constructed on a *single* return predictor, external financing, delivers equally good performance as the composite MGMT factor.

2.2.8 Intangibles

Our test assets include four intangibles anomaly portfolios: OC/A, AD/M, RD/M, and OL. Panel A of Table 8 shows that the size (SMB) factor of the FF5 model plays a role in successfully pricing all but one anomaly portfolio (OC/A), which loads negatively on the HML and RMW factors and earns a significant positive FF5 alpha. In Panel B, the HML factor of the NM model explains all but one anomaly (OC/A), which loads negatively on the HML and PMU factors. Panel C shows that the SMB factor of the HXZ model explains all but one anomaly (RD/M), which loads negatively on the ROE factor. Panel D shows that, with a modified size factor, the SY4 model captures all but one anomaly (OC/A), which loads negatively on the MGMT factor. Lastly, Panel E shows that without a size factor, our BF3 model fails to explain two anomalies (OC/A and RD/M).

The evidence suggests that a size factor contributes greatly to capturing intangibles-related anomalies, whereas profitability factors and financing factors tend to "explain" some of these anomalies, such as OC/A and RD/M, in the opposite direction. Overall, our three-factor risk-and-behavioral composite model has only a limited ability to explain the set of intangibles-related anomalies, perhaps partly as a result of the lack of a size factor in the model.

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.

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-term 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, especially short-horizon factors, should not be stable over longer horizons. We therefore estimate firms' loadings on behavioral factors using daily excess returns over a one month horizon.[22]

Specifically, estimated firm factor loadings at the start of month t come from regressions of each firm's daily (excess) returns on daily (excess) market, FIN, and PEAD factor returns over month $t-1$ (a minimum of 15 valid daily returns is required). The estimated coefficients on FIN and PEAD (β_{FIN} and β_{PEAD}) at the end of month $t-1$ and are then used to forecast firm level stock returns in month t in a Fama and MacBeth (1973) regression, 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

[22]The daily FIN and PEAD factor construction is identical to the construction of the corresponding monthly factors: each (value-weighted) component portfolio is rebalanced each year at June month end for FIN, and at the end of each month for PEAD.

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), but is only marginally significant after controlling for composite share issuance (CSI). When including both NSI and CSI, 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 share issuance (CSI). 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 Tables 7 and 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 likely explanation is that the PEAD loadings, β_{PEAD}, are estimated with substantial noise owing to the fact that these are estimates of a transient source of mispricing. 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 two quarters after portfolio formation. This may explain the inability of β_{PEAD} to predict the next month stock returns.

3.2 Discussion

The cross-sectional tests generally confirm the value of the FIN factor, but not the PEAD factor. For two reasons, we place less weight on the cross-sectional tests. First each cross-sectional coefficient in a Fama and MacBeth (1973) regression represents the return on a portfolio. However, as discussed by Daniel and Titman (2006), these portfolios place extremely heavy weights on small illiquid stocks, yet the tests assume that these portfolios can be rebalanced monthly at zero cost. Second is the well-known errors-in-variables problem in estimating factor loadings. As discussed above, this is likely to be especially severe for the loadings on short-horizon behavioral factors. We discuss each of these points in turn.

With respect to heavy weights on small illiquid stocks, in a setting where the characteristics (the independent variables in the cross-sectional regressions) are fairly stable, the regression coefficient portfolios implicitly place relatively constant weight on high- and low-characteristic securities from month to month, much like an equal-weighted portfolio. In practice, market frictions make it hard to achieve such returns. To maintain approximate equal-weighting requires rebalancing the portfolio each month, buying firms that fell in value and selling firms that rose. Bid-ask bounce, illiquidity, and transaction costs can tremendously reduce the actual returns from such a strategy, especially for portfolios tilted towards small (and illiquid) firms. This implies upwardly-biased estimates of the returns of illiquid firms.

This can help explain the differences between the Fama-MacBeth tests and the factor-regressions tests of Section 2. The ability of factor models to explain anomalies is consistently better in the factor-regressions tests than in the Fama-MacBeth tests. A plausible reason is that factor models may do better in explaining implementable anomalies than non-implementable ones. For example, in the factor-regressions tests the PEAD factor captures short-horizon anomalies extremely well, whereas in the Fama-MacBeth tests it does so more imperfectly. 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), any mispricing of the idiosyncratic components of security payoffs is almost completely arbitraged away, because competitive rational arbitrageurs can diversify away the risk associated with bets on idiosyncratic mispricing, and therefore eliminate this mispricing. In contrast, the only way to arbitrage factor mispricing is to bear substantial non-diversifiable risk, so factor mispricing persists. So in factor regression tests, which focus primarily on liquid stocks, we expect factor-derived mispricing, as reflected in loadings on mispricing factors, to explain the return-prediction ability of characteristics (which reflect both factor-derived and idiosyncratic mispricing) In contrast, in tests that focus on illiquid stocks, we expect characteristics to be important return predictors, as idiosyncratic mispricing is not arbitraged away for such stocks.

Consistent with these arguments, in our factor-regressions tests, which focus on large liquid stocks, factor loadings (a measure of systematic mispricing) almost completely explain characteristic-based anomalies. This suggests that almost all firm-level mispricing is 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 among small illiquid stocks, idiosyncratic mispricing remains important. This explains why the PEAD factor is successful in the factor-regressions tests, but loadings on this factor fail to predict returns in the Fama-MacBeth tests when controlling for the short-horizon anomaly characteristics.

With respect to the second point, the errors-in-variables problem, the small illiquid stocks that dominate in Fama-MacBeth regressions (again, especially for short-horizon anomalies) are traded by investors less frequently. Owing to asynchronous trading, their factor loadings are estimated poorly. Greater measurement error in estimating PEAD factor loadings would reduce the ability of these loadings to subsume the effect of characteristics 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, which 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.

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. Owing 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 the idea that FIN and PEAD capture commonality in 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-term 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 thereby affect the *sensitivity* of the FIN-beta/return relation. Owing to limits to arbitrage and short-sale constraints, we expect high friction stocks to have greater mispricing, but this does not in itself imply greater sensitivity of expected returns to any given amount of mispricing. However, mispricing, as proxied by factor betas on FIN, is measured with noise. For stocks with low frictions and with low mispricing (either overpricing or underpricing), most of the variation in the mispricing proxies (factor betas) would be noise. For such stocks, we should observe low sensitivity of expected returns to estimated factor betas. In contrast, for stocks with high friction and high mispricing, we expect less noise in the mispricing proxies and therefore high sensitivity of expected returns to estimated factor betas. Therefore, we hypothesize that the FIN-beta/return relation should be stronger for high friction stocks.

We first test this hypothesis using 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.

5 Conclusion

We supplement the market factor of the CAPM with behavioral factors intended to capture commonality in mispricing associated with psychological biases. We focus on two psychological biases that are likely to affect asset prices: overconfidence and limited attention. Motivated by the idea that investor overconfidence induces commonality in mispricing, and building on the idea of capturing this via a misvaluation factor constructed based on firms' financing events (Hirshleifer and Jiang, 2010), we create a modified financing factor (FIN) using two prominent financing-related firm characteristics, net share issuance and composite issuance. Motivated by the theory that limited investor attention induces stock market underreaction to public information, we consider a post-earnings announcement drift factor (PEAD) constructed based upon earnings surprises. We further hypothesize that FIN especially reflects the returns associated with long-term (>1 year) mispricing, and that PEAD especially 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 three economic characteristics capture a wide range of anomalies.

If FIN and PEAD are indeed priced behavioral factors that capture commonality in mispricing, then behavioral models imply that firm loadings on FIN should be proxies for persistent underpricing, and loadings on PEAD should be proxies for transient underpricing. In consequence, these loadings should positively predict the cross-section of stock returns. Using Fama-MacBeth cross-sectional regressions, we confirm that estimated FIN loadings strongly forecast future returns, even after controlling for the firm characteristics that underlie 34 anomalies that we examine. In contrast, estimated PEAD loadings have no return predictive ability. It is not clear how to interpret the PEAD finding, since there are econometric issues related to instability of the firm loadings on the higher-frequency PEAD factor, and to the estimation of the characteristic premium.

Finally, we conduct several robustness tests and provide additional evidence suggesting that FIN and PEAD are indeed capturing mispricing effects. If these are behavioral factors, we expect the mispricing that they identify to be stronger when limits to arbitrage, including short-sale constraints, are more binding. We find that FIN and PEAD are particularly useful for predicting the returns of stocks with high arbitrage frictions, such as over- rather than under-priced stocks, and stocks with greater trading frictions.

The broader message of this study is that it is useful to use behaviorally-motivated factors in explaining asset mispricing, comovement and return predictability at short- versus long-horizons.

References

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Bagnoli, Mark, Michael B. Clement, and Susan G. Watts, 2005, Around-the-clock media coverage and the timing of earnings announcements, Working paper, Purdue University.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645–1680.

Balakrishnan, Karthik, Eli Bartov, and Lucile Faurel, 2010, Post loss/profit announcement drift, *Journal of Accounting and Economics* 50, 20–41.

Ball, Ray, and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159–178.

Ball, Ray, Joseph Gerakos, Juhani T. Linnainmaa, and Valeri Nikolaev, 2016, Accruals, cash flows, and operating profitability in the cross section of stock returns, *Journal of Financial Economics* 121, 28–45.

Barberis, Nicholas, and Ming Huang, 2001, Mental accounting, loss aversion, and individual stock returns, *Journal of Finance* 56, 1247–1292.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161–199.

——— , and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Barillas, Francisco, and Jay A. Shanken, 2017, Which alpha?, *Review of Financial Studies,* forthcoming.

Barth, Mary E., John A. Elliott, and Mark W. Finn, 1999, Market rewards associated with patterns of increasing earnings, *Journal of Accounting Research* 37, 387–413.

Basu, Sanjoy, 1983, The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence, *Journal of Financial Economics* 12, 129–156.

Belo, Frederico, and Xiaoji Lin, 2012, The inventory growth spread, *Review of Financial Studies* 25, 278–313.

Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1607.

Bernard, Victor L., and Jacob K. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or risk premium?, *Journal of Accounting Research* 27, 1–36.

——— , 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305–340.

Black, Fischer, 1972, Capital market equilibrium with restricted borrowing, *Journal of Business* 45, 444–455.

Boudoukh, Jacob, Roni Michaely, Matthew Richardson, and Michael Roberts, 2007, On the importance of measuring payout yield: Implications for empirical asset pricing, *Journal of Finance* 62, 877–915.

Bradshaw, Mark T., Scott A. Richardson, and Richard G. Sloan, 2006, The relation between corporate financing activities, analysts' forecasts, and stock returns, *Journal of Accounting and Economics* 42, 53–85.

Brav, Alon, Christopher Geczy, and Paul A. Gompers, 2000, Is the abnormal return following equity issuances anomalous?, *Journal of Financial Economics* 56, 209–249.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899–2939.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chan, Louis K.C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681–1713.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *Journal of Finance* 56, 2431–2456.

Chordia, Tarun, and Lakshmanan Shivakumar, 2006, Earnings and price momentum, *Journal of Financial Economics* 80, 627–656.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609–1651.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839–1885.

——— , 2001, Overconfidence, arbitrage, and equilibrium asset pricing, *Journal of Finance* 56, 921–965.

Daniel, Kent D., and Sheridan Titman, 1997, Evidence on the characteristics of cross-sectional variation in stock returns, *Journal of Finance* 52, 1–33.

——— , 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605–1643.

——— , 2016, Another look at market responses to tangible and intangible information, *Critical Finance Review* 5, 165–175.

Davis, James L., Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389–406.

Dechow, Patricia M., Richard G. Sloan, and Mark T. Soliman, 2004, Implied equity duration: A new measure of equity risk, *Review of Accounting Studies* 9, 197–228.

DellaVigna, Stefano, and Joshua Pollet, 2009, Investor inattention and friday earnings announcements, *Journal of Finance* 64, 709–749.

Dong, Ming, David A. Hirshleifer, and Siew Hong Teoh, 2012, Overvalued equity and financing decisions, *Review of Financial Studies* 25, 3645–3683.

Eckbo, B. Espen, Ronald W. Masulis, and Oyvind Norli, 2000, Seasoned public offerings: Resolution of the 'new issues puzzle', *Journal of Financial Economics* 56, 251–291.

Eisfeldt, Andrea L., and Dimitris Papanikolaou, 2013, Organization capital and the cross-section of expected returns, *Journal of Finance* 68, 1365–1406.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

———, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

———, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

———, 2016a, Choosing factors, University of Chicago Working Paper.

———, 2016b, Dissecting anomalies with a five-factor model, *Review of Financial Studies* 29, 69–103.

Fama, Eugene F., and James MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Feng, Guanhao, Stefano Giglio, and Dacheng Xiu, 2017, Taming the factor zoo, Working paper, University of Chicago.

Foster, George, Chris Olsen, and Terry Shevlin, 1984, Earnings releases, anomalies, and the behavior of security returns, *Accounting Review* 59, 574–603.

Francis, Jennifer, Donald Pagach, and Jens Stephan, 1992, The stock market response to earnings announcements released during trading versus nontrading periods, *Journal of Accounting Research* 30, 165–184.

Freyberger, Joachim, Andreas Neuhierl, and Michael Weber, 2017, Dissecting characteristics nonparametrically, Working paper, University of Wisconsin-Madison.

Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident, *Review of Financial Studies* 14, 1–27.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121–1152.

Goetzmann, William N ., and Massimo Massa, 2008, Disposition matters: Volume, volatility, and price impact of a behavioral bias, *Journal of Portfolio Management* 34, 103–125.

Green, Jeremiah, John R. M. Hand, and X. Frank Zhang, 2013, The supraview of return predictive signals, *Review of Accounting Studies* 18, 692–730.

Hafzalla, Nader, Russell Lundholm, and E. Matthew Van Winkle, 2011, Percent accruals, *Accounting Review* 86, 209–236.

Hansen, Lars Peter, and Ravi Jagannathan, 1997, Assessing specification errors in stochastic discount factor models, *Journal of Finance* 52, 557–590.

Harvey, Campbell R, Yan Liu, and Heqing Zhu, 2016, ... and the cross-section of expected returns, *Review of Financial Studies* 29, 5–68.

Haugen, Robert A., and Nardin L. Baker, 1996, Commonality in the determinants of expected stock returns, *Journal of Financial Economics* 41, 401–439.

Hirshleifer, David, Kewei Hou, Siew Hong Teoh, and Yinglei Zhang, 2004, Do investors overvalue firms with bloated balance sheets?, *Journal of Accounting and Economics* 38, 297–331.

Hirshleifer, David, and Danling Jiang, 2010, A financing-based misvaluation factor and the cross section of expected returns, *Review of Financial Studies* 23, 3401–3436.

Hirshleifer, David, Sonya S. Lim, and Siew Hong Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news, *Journal of Finance* 64, 2289–2325.

——— , 2011, Limited investor attention and stock market misreactions to accounting information, *Review of Asset Pricing Studies* 1, 35–73.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337–386.

Hou, Kewei, Lin Peng, and Wei Xiong, 2009, A tale of two anomalies: The implication of investor attention for price and earnings momentum, Working paper, Ohio State University.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650–705.

Hribar, Paul, and Daniel W. Collins, 2002, Errors in estimating accruals: Implications for empirical research, *Journal of Accounting Research* 40, 105–134.

Ikenberry, David, Josef Lakonishok, and Theo Vermaelen, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181–208.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional capm and the cross-section of expected returns, *Journal of Finance* 51, 3–53.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Khan, Mozaffar, Leonid Kogan, and George Serafeim, 2012, Mutual fund trading pressure: Firm-level stock price impact and timing of SEOs, *Journal of Finance* 67, 1371–1395.

Kothari, S.P., Jonathan Lewellen, and Jerold B. Warner, 2006, Stock returns, aggregate earnings surprises, and behavioral finance, *Journal of Financial Economics* 79, 537–568.

Kozak, Serhiy, Stefan Nagel, and Shrihari Santosh, 2017a, Interpreting factor models, *Journal of Finance,* forthcoming.

——— , 2017b, Shrinking the cross section, Working paper, University of Michigan.

Kumar, Alok, and Charles M.C. Lee, 2006, Retail investor sentiment and return comovements, *Journal of Finance* 61, 2451–2486.

Lakonishok, Josef, Andrei Shleifer, and Robert Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–1578.

Lakonishok, Josef, and Theo Vermaelen, 1990, Anomalous price behavior around repurchase tender offers, *Journal of Finance* 45, 455–477.

Lintner, John, 1965, Security prices, risk, and maximal gains from diversification, *Journal of Finance* 20, 587–615.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23–51.

——— , 2000, Uniformly least powerful tests of market efficiency, *Journal of Financial Economics* 55, 361–389.

Lyandres, Evgeny, Le Sun, and Lu Zhang, 2008, The new issues puzzle: Testing the investment-based explanation, *Review of Financial Studies* 21, 2825–2855.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249–1290.

Myers, Stewart C., and Nicholas S. Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* 13, 187–221.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive, semi-definite, heteroskedasticity and autocorrelation consistent covaiance matrix, *Econometrica* 55, 703–708.

Novy-Marx, Robert, 2011, Operating leverage, *Review of Finance* 15, 103–134.

——— , 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

——— , 2015a, Fundamentally, momentum is fundamental momentum, Working paper, University of Rochester.

——— , 2015b, How can a q-theoretic model price momentum?, Working paper, University of Rochester.

——— , 2016, Backtesting strategies based on multiple signals, University of Rochester working paper.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity risk and expect stock returns, *Journal of Political Economy* 111, 642–685.

Pontiff, Jeffrey, and Artemiza Woodgate, 2008, Share issuance and cross-sectional returns, *The Journal of Finance* 63, 921–945.

Richardson, Scott A., Richard G. Sloan, Mark T. Soliman, and Irem Tuna, 2005, Accrual reliability, earnings persistence and stock prices, *Journal of Accounting and Economics* 39, 437–485.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985, Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9–16.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Sloan, Richard, 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *Accounting Review* 71, 289–315.

Spiess, Katherine, and John Affleck-Graves, 1995, Underperformance in long-run stock returns following seasoned equity offerings, *Journal of Financial Economics* 38, 243–267.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288–302.

Stambaugh, Robert F., and Yu Yuan, 2016, Mispricing factors, *Review of Financial Studies,* forthcoming.

Stein, Jeremy C., 1996, Rational capital budgeting in an irrational world, *Journal of Business* 69, 429–455.

Teoh, Siew Hong, Ivo Welch, and T. J. Wong, 1998, Earnings management and the underperformance of seasoned equity offerings, *Journal of Financial Economics* 50, 63–99.

Thomas, Jacob K., and Huai Zhang, 2002, Inventory changes and future returns, *Review of Accounting Studies* 7, 163–187.

Xing, Yuhang, 2008, Interpreting the value effect through the q-theory: An empirical investigation, *Review of Financial Studies* 21, 1767–1795.

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). In Panel C, we add asterisk after factors SMB, HML and MOM, meaning these factors have modified versions, and asterisk after models NM, HXZ and SY4, meaning these models use modified factors. 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 asterisk after factors SMB, HML and MOM means that these factors have modified versions and the asterisk after models NM, HXZ and SY4 means these models use modified 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, price 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 returns (in percent) of the long/short anomaly portfolios and the Sharpe ratios. 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	L-S Ret(%)	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, Jegadeesh, and Lakonishok (1996)	0.79	0.25
	ABR-6	Cumulative abnormal returns around earnings announcements (6-month holding period), Chan, Jegadeesh, and Lakonishok (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, Elliott, and Finn (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	L-S Ret(%)	Sharpe ratio
Profitability	GP/A	Gross profits-to-assets ratio, Novy-Marx (2013)	0.22	0.06
	CbOP	Cash-based operating profitability, Ball, Gerakos, Linnainmaa, and Nikolaev (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
	NPY	Net payout yield, Boudoukh, Michaely, Richardson, and Roberts (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, Hou, Teoh, and Zhang (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
	CSI	Composite share 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	NPY	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	CSI	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	NPY	DUR	AG	NOA	IVA	IG	NSI	CSI	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**																	
NPY	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**										
CSI	-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 t-values, the F-statistics and p-values that test whether the average t^2 of alphas under a given model is significantly larger than the average t^2 of the composite-model alphas, the GRS F-statistics and p-values following Gibbons, Ross, and Shanken (1989), and the HJ-distance following Hansen and Jagannathan (1997). 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
	Average $\lvert t\rvert$		3.11	3.70	4.68	2.40	3.21	1.58	1.08	1.39	2.32	0.78	0.67	0.49
	F-stat $= \frac{Average\ t^2}{Average\ t^2_{BF3}}$		34.84***	47.46***	73.99***	25.28***	37.45***	11.85***	8.75***	11.13***	23.07***	2.54*	2.31*	
	p-value		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.08)	
	GRS F-stat		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)
	HJ-distance			44.20***	43.44***	30.99***	36.50***	32.20***	34.12***	26.73*	44.12***	26.04**	23.39**	14.66
	p-value			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)	(0.02)	(0.03)	(0.49)

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 yield	NPY	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	CSI	-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
	Average $\lvert t\rvert$		2.63	3.09	2.19	1.84	1.38	0.96	1.36	0.70	1.41	2.61	1.48	1.33
	F-stat $= \frac{Average\ t^2}{Average\ t^2_{BF3}}$		3.00***	4.31***	2.86***	2.01*	1.35	0.68	1.20	0.45	1.37	3.17***	1.27	
	p-value		(0.01)	(0.00)	(0.01)	(0.05)	(0.24)	(0.81)	(0.34)	(0.97)	(0.23)	(0.00)	(0.29)	
	GRS F-stat		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)
	HJ-distance			63.58***	38.76*	16.78	29.49	24.15	34.34*	13.89	57.79***	56.67***	47.96**	35.72
	p-value			(0.00)	(0.07)	(0.90)	(0.16)	(0.73)	(0.05)	(0.90)	(0.00)	(0.00)	(0.01)	(0.35)

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
	Average $\lvert t\rvert$	2.80	3.31	3.07	2.04	2.03	1.18	1.26	0.95	1.73	1.96	1.19	1.03
	F-stat $= \frac{Average\ t^2}{Average\ t^2_{BF3}}$	5.08***	7.13***	7.52***	3.54***	3.71***	1.41	1.69*	1.15	2.79***	3.13***	1.34	
	p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.07)	(0.34)	(0.00)	(0.00)	(0.20)	
	GRS F-stat	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)
	HJ-distance		131.18***	123.65***	105.47***	108.66***	107.69***	103.59***	77.14**	123.13***	102.96***	89.74***	76.39**
	p-value		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	0.00	(0.00)	(0.00)	(0.01)

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_{MOM}	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_{SMB}	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			
	NPY	DUR	AG	NOA	IVA	IG	IvG	IvC	OA	POA	PTA	NSI	CSI	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_{MOM}	-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_{SMB}	-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														
NSI	-0.237***		-0.101***											-0.041
	(-6.48)		(-3.20)											(-1.07)
CSI		-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)
NPY						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

	Long legs	Short legs		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

	Long legs	Short legs		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)**
NPY	0.36	**-0.40**	NSI	0.29	**-0.33**
	(5.49)	**(-7.36)**		(6.17)	**(-8.64)**
DUR	**0.23**	-0.21	CSI	**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

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, Gerakos, Linnainmaa, and Nikolaev (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 (NPY):

Following Boudoukh, Michaely, Richardson, and Roberts (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 (NPY) 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 NPY 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, Hou, Teoh, and Zhang (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 share issuance (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 share issuance (CSI):

Following Daniel and Titman (2006), we measure CSI as the growth rate in market equity that is not attributable to the stock returns, $CSI_t = log(ME_t/ME_{t-5}) - r(t-5,t)$. Specifically, for CSI 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 CSI 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 = [(Δ*Current Assets* – Δ*Cash*) – (Δ*Current Liabilities* – Δ*Short-term Debt* – Δ*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, Sloan, Soliman, and Tuna (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 $t+1$.