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Short- and Long-Horizon Behavioral Factors

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We propose a theoretically motivated factor model based on investor psychology and assess its ability to explain the cross-section of U.S. equity returns. Our factor model augments the market factor with two factors that capture long- and short-horizon mispricing. The long-horizon factor exploits the information in managers' decisions to issue or repurchase equity in response to persistent mispricing. The short-horizon earnings surprise factor, which is motivated by investor inattention and evidence of short-horizon underreaction, captures short-horizon anomalies. This 3-factor risk-and-behavioral model outperforms other proposed models in explaining a broad range of return anomalies. (*JEL* G12, G14)

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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)?

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Several approaches to developing a parsimonious factor model have been proposed in the literature. One approach is based on rational asset pricing theory in an efficient market (Fama and French 2015, 2018; Hou, Xue, and Zhang 2015). A second approach is to extract factors using a statistical analysis of the returns to assets or characteristic-sorted portfolios, while potentially imposing structural constraints implied by rational asset pricing theory (Kelly, Pruitt, and Su 2017; Freyberger, Neuhierl, and Weber 2017; Kozak, Nagel, and Santosh 2017; Lettau and Pelger 2018). Finally, Stambaugh and Yuan (2017) develop a set of “mispricing factors” using a purely empirical approach of averaging characteristics known from previous research to predict the cross-section of returns. They construct their two factors by averaging rankings across two clusters of the eleven well-documented anomalies examined by averaging characteristics known, from extant empirical research, to have power to forecast the cross-section of average returns. As Stambaugh and Yuan (2017, p. 1271) put it, “Rather than construct a factor using stocks’ rankings on a single anomaly variable, such as investment, we construct a factor by averaging rankings across multiple anomalies.” They construct their two factors using the eleven well-documented anomalies examined by Stambaugh, Yu, and Yuan (2012, 2014, 2015).

In contrast with these approaches, we propose a model that supplements the market factor with just two theory-based behavioral factors, and show that this model does a good job of explaining the cross-section of average realized returns. Building on past literature, our two behavioral factors are designed to capture long- and short-horizon mispricing.

The novelty of our approach comes from motivating the factor model based on different forms of mispricing. Behavioral theories suggest distinct mispricing mechanisms that will correct at shorter or longer horizons. For example, investors with limited attention underreact to public information that arrives at a fairly high frequency, such as quarterly earnings announcements. Specifically, the evidence in Bernard and Thomas (1990) and the models of Hirshleifer and Teoh (2003), DellaVigna and Pollet (2009), and Hirshleifer, Lim, and Teoh (2011) suggest that a subset of investors fails to fully incorporate the information contained in the most recent earnings surprises. As a consequence, stock prices underreact to earnings surprises, resulting in predictable future abnormal returns (the post-earnings announcement drift anomaly, or PEAD). Such misperceptions about the subsequent earnings should be corrected at reasonably short time horizons when new earnings are reported. Consistent with this hypothesis, Bernard and Thomas find evidence suggesting that the resultant mispricing is corrected over the next few quarterly earnings announcements.

In contrast, some biases should lead to 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 the correction of overconfidence-driven mispricing will take place over a much longer time horizon than mispricing that derives solely from limited attention. The persistence associated with the value effect, for example, suggests that this process can last for many years.[1]

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 expected. In contrast their overextrapolative ("trending") regime is more persistent, because a brief trend-opposing sequence of earnings surprises does not provide sufficient evidence to overcome the extrapolative expectations investors have formed about more distant earnings.

Therefore, we propose a short-horizon and a long-horizon behavioral factor which, respectively, capture short- and long-horizon mispricing. Our long-horizon factor is based on the intuition from the model of Stein (1996), who argues that when a firm becomes over- or underpriced, the optimal response for the firm is to issue or repurchase its own stock, while not necessarily changing its level of investment. Managers have superior information about the intrinsic value of their firms, so they are well positioned to lead their firms to act as arbitrageurs of their own stock. If investors were fully rational, they would fully impound the information contained in a firm's decision to issue or repurchase equity (Myers and Majluf 1984), so that the financing decision would not predict future returns. However, in models of investor overconfidence, the market does not fully impound this information, so market timing leads to return predictability (Daniel, Hirshleifer, and Subrahmanyam 1998).

Empirically, on average, persistent and strong negative abnormal returns follow issuance activity, and positive abnormal returns follow repurchases.[2] Precisely because the market underreacts to issuance/repurchase activity, it is in firms' interests to engage in "market timing," that is, issuing or repurchasing

[1] 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.

[2] See Loughran and Ritter (1995, 2000), Spiess and Affleck-Graves (1995), Brav, Geczy, and Gompers (2000), and 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.

equity to exploit preexisting mispricing.[3,4] In essence, the argument here is that managers who do not fully share the market's biased expectations observe mispricing and exploit it in the interest of the existing shareholders who do not participate in either the firm's new issues or repurchases.

The intuition that issuance/repurchase activity is a catchall for many possible sources of "stubborn" investor misperceptions (those that are unlikely to be corrected by just a few more earnings announcements) is a key motivation for our financing-based mispricing factor. This hypothesis is supported by the evidence of Greenwood and Hanson (2012) suggesting that managers exploit mispricing that derives from many possible sources. Their measure of characteristic mispricing, the issuer-repurchaser spread, is defined as the difference in a given characteristic (e.g., size) between recent stock issuers and repurchasers. They find that this characteristic-spread measure forecasts the corresponding characteristic-based factor returns for most of the characteristics they examine, including book-to-market (i.e., HML) and size (i.e., SMB). For example, large firms underperform after years when issuing firms are large relative to repurchasing firms.[5] Our approach is instead to form a financing factor (constructed as the *return* spread between recent issuers and repurchasers), and see whether this factor, together with a second behavioral factor, can price a wide range of anomalies.

Our financing factor FIN is a composite of the 1-year net-share-issuance (NSI) and 5-year composite-share-issuance (CSI) measures of Pontiff and Woodgate (2008) and Daniel and Titman (2006), respectively. Following the approach of Fama and French (1993), our FIN factor portfolio is based on two-by-three sort on size and the financing characteristic which is a 50/50 combination of the NSI and CSI measures, and goes long the two value-weighted low-issuance portfolios and short the two high-issuance portfolios. The choice of an (ad hoc) 50/50 combination of NSI and CSI is based on a desire to avoid overfitting.

Consistent with its theoretical motivation, we find that our FIN factor captures predominantly longer-term mispricing and correction (1 year or longer). For several reasons, it is much less likely to capture shorter-horizon mispricing. Equity issuance and repurchase have disclosure, legal, underwriting, and

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[3] Ritter (1991) and many others argue that firms may issue and repurchase shares to "time" share mispricing. Stein (1996) develops a theoretical model of market timing. Empirical evidence suggests that firms issue equity when their price-to-book ratios are high and repurchase when they are low (Dong, Hirshleifer, and Teoh 2012, Khan, Kogan, and Serafeim 2012); that these sales and repurchases forecast the firms' future returns in a way consistent with market timing; that earnings surprises tend to be more negative following equity issues (Denis and Sarin 2001); and, in surveys, that managers state that their issuance and repurchase activity is designed to exploit mispricing (Graham and Harvey 2001). Baker and Wurgler (2002) provide a good summary of the evidence about market timing.

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

[5] Greenwood and Hanson (2012) examine seven characteristics: book-to-market, size, nominal share price, distress, payout policy, profitability, and industry.

other costs that likely constrain firms from issuing to exploit very short-horizon mispricing. There are also informational barriers to high-frequency issuance/repurchase strategies. Owing to these frictions, such corporate events tend to occur only occasionally, rather than as continuously updated responses to even transient changes in market conditions.[6] In addition, the fixed costs associated with initiating any issuance or repurchase program would constrain firms from exploiting short-horizon mispricing.[7]

To capture the shorter-horizon mispricing that FIN is likely to miss, we introduce a second behavioral factor, PEAD. Motivated by the theory that limited investor attention induces stock market underreaction to new earnings information (Hirshleifer and Teoh 2003; DellaVigna and Pollet 2009; Hirshleifer, Lim, and Teoh 2011), our PEAD factor is based on the eponymous post-earnings announcement drift (PEAD) phenomenon, the observation that firms that experience positive earnings surprises subsequently earn higher returns than those with negative earnings surprises. Bernard and Thomas (1989) argue that this return differential is not a rational risk premium, and instead reflects delayed price response to information. A recent empirical literature suggests that this delayed response derives from limited investor attention.[8] If the source of PEAD is that 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 (Bernard and Thomas 1989).

Therefore, we 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, and because all value-relevant news is ultimately manifested in earnings. Our PEAD factor is constructed by going long firms with positive earnings surprises and short

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 a 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 firms to exploit even transient private information, but, by the same token, investors are likely to be especially skeptical when firms maintain such flexibility.

7 The larger the total mispricing, the greater the benefit to a firm of trading to exploit it. An anomaly in which abnormal returns continue for 5 years represents a greater total mispricing than if a similar (or even somewhat smaller) per-year abnormal return only persists for a year.

8 For example, market reactions to earnings surprises are muted when earnings announcements are released during low-attention periods, such as nontrading hours (Francis, Pagach, and Stephan 1992; Bagnoli, Clement, and Watts 2005), Fridays (DellaVigna and Pollet 2009), and days with many same-day earnings announcements by other firms (Hirshleifer, Lim, and Teoh 2009), and in down markets 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.

firms with negative surprises. For robustness, PEAD, like FIN, is based on two-by-three sort on size and earning-announcement returns, with value-weighted portfolios.

Our factor model supplements the market factor from the capital asset pricing model (CAPM) with these two behavioral factors to form a 3-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; Kozak, Nagel, and Santosh 2017). 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 motivate the use of a behavioral factor model based on long- and short-horizon mispricing in more depth in Section 1.

We empirically assess the incremental ability of behavioral factors to explain expected returns relative to the factors used in other models, including both traditional factors (such as the market, size, value, and return momentum factors) and other recently prominent factors (such as the investment and profitability factors). Barillas and Shanken (2017, p. 1317) suggest that when comparing models with traded factors, "... 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 many of the traded factors proposed in the literature, including several of the new factors proposed in Fama and French (2015), Hou, Xue, and Zhang (2015), and Stambaugh and Yuan (2017). In sharp contrast, reverse regressions show that 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). FIN and PEAD are designed to capture mispricing over different horizons, so we are especially interested in how well FIN captures long-horizon anomalies and how well PEAD captures short-horizon anomalies. Therefore, we categorize the thirty-four anomalies into two groups: twelve short-horizon anomalies, including price momentum, earnings momentum, and short-term profitability, and twenty-two long-horizon anomalies, including long-term profitability, value, investment and financing, and intangibles. We compare the performance of our 3-factor composite model built on three firm characteristics with recently proposed factor models: the 4-factor model of Novy-Marx (2013, NM4) built on five characteristics, the 5-factor model of Fama and French (2015, FF5) built on four characteristics, the 4-factor model of Hou, Xue, and Zhang (2015, HXZ4) built on three characteristics, and the 4-factor model of Stambaugh and Yuan (2017, SY4) built on twelve characteristics.[9]

We find that across the twelve short-horizon anomalies, the composite model fully captures all anomalies at the 5% significance level (i.e., none have significant alphas). In contrast, 11 anomalies have significant FF5 alphas, 2 have significant NM4 alphas, 1 has a significant HXZ4 alpha, and 4 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 twelve composite-model alphas are jointly zero, but rejects each of the four alternative models at a 1% significance level.

The composite model also does a good job explaining the twenty-two long-horizon anomaly portfolios, but for these portfolios the SY4 and NM4 models also perform well. For the composite model, 3 of the 22 alphas are significant at the 5% significance level. For competing models, the numbers of significant alphas are 7 (FF5), 3 (NM4), 5 (HXZ4), 3 (SY4), etc. The GRS F-test that the 22 long-horizon anomaly portfolio alphas are jointly zero is not rejected for the SY4 model, and only rejected at a 10% level for our composite model or the NM4 model. The GRS test does, however, reject this null at a 1% significance level for both the FF5 and HXZ4 models. The good performance of the SY4 model appears to result primarily from the inclusion of their MGMT factor, which is constructed from six characteristics associated with investment and financing.

Overall, across all 34 long- and short-horizon anomalies, our 3-factor composite model performs well. Only three anomalies have 5% significant composite-model alphas. In comparison, there are 18 significant FF5 alphas, 5 significant NM4 alphas, 6 significant HXZ4 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.

Thus, relative to other proposed factor models, our composite model prices both short- and long-horizon anomalies at least as well. Our model is motivated by theory and is arguably more parsimonious.[10] Because our composite model

9 Consistent with convention in this literature since Fama and French (1993), both our FIN and PEAD factor portfolios are based on bivariate (3×2) sorts on the relevant characteristic and firm size (i.e., Market Equity). In addition to keeping in mind how many factors are in each model, to assess parsimony it is useful to bear in mind the number of firm characteristics used to construct each factor model. Therefore, we provide characteristic counts for each model.

10 Evaluating parsimony requires care, because it is well known that any pattern of returns can be “explained” ex post by a single-factor model in which the factor is the ex post mean-variance efficient portfolio (see also the discussion of Novy-Marx (2016)). Still, when factors are built from characteristics, it is likely that the use of

is motivated by just two hypotheses—that firm managers time issuance to arbitrage longer-horizon mispricing and that shorter-horizon mispricing results from inattention—our model requires just two behavioral factors in addition to the market factor. The competing models we examine all use either more factors, more characteristics, or both.

To further evaluate the performance of 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 and PEAD should be proxies for underpricing. In particular, FIN loadings are proxies for persistent underpricing and PEAD loadings for transient underpricing. In consequence, these loadings should positively predict the cross-section of stock returns.

The dynamic nature of mispricing implies that any given firm's loadings on behavioral factors will vary substantially over time. Therefore, we estimate firms' loadings on these factors using daily stock returns over a short horizon, for example, 1 month. Using Fama and MacBeth (1973) cross-sectional regressions, we find that FIN loadings significantly predict future stock returns, even after controlling for most of the thirty-four anomaly characteristics that we examine. In contrast, estimated PEAD loadings have no incremental power to forecast future returns. As we discuss in Section 4, the problems are estimation error when PEAD loadings are unstable, and the heavy influence of small illiquid firms in Fama-MacBeth regression tests.

Furthermore, we find that consistent with behavioral models, the return predictability associated with FIN and PEAD factors is increasing with proxies for limits to arbitrage. These implications do not hold for effects in rational frictionless models of risk premiums.

A growing literature seeks to explain a wide set of anomalies with a small set of factors. This is the motivation for the tests of Fama and French (1996) and more recently Novy-Marx (2013), Fama and French (2015, 2018), Hou, Xue, and Zhang (2015), and Stambaugh and Yuan (2017). Our paper goes further 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 approach is distinct from this literature, in that our behavioral factors are based on theoretical arguments as to what variables should capture long- and short-horizon mispricing. Finally, as noted earlier, our factor model provides a better fit to a wide set of anomalies and factors.

more characteristics and/or more factors tends to grant greater freedom to a researcher overfit the cross-section of returns. Certainly, a focus of the empirical factor pricing literature since Fama and French (1992) has been on identifying models that explain the cross-section of returns with a small number of factors, presumably owing to a preference for parsimony.

1. Motivation for the Behavioral Factor Model

In behavioral models, return comovement can result from commonality in stock mispricing (Barberis and Shleifer 2003), as well as commonality in investor errors in interpreting signals about fundamental economic factors (Daniel, Hirshleifer, and Subrahmanyam 2001). That mispricing predicts future returns owing to subsequent correction implies that behavioral factors can be used to construct a factor model that better describes the cross-section of expected returns.[11] Just as firms that are exposed to systematic risk factors earn an associated risk premium, firms that are heavily exposed to behavioral factors earn a conditional return premium (see, e.g., the model of Hirshleifer and Jiang 2010). Fama and French (1993, 2015) construct risk factors based on firm characteristics that they argue capture risk exposures; we instead supplement the market factor with two behaviorally motivated factors.

Furthermore, in the setting of Daniel, Hirshleifer, and Subrahmanyam (2001) and Kozak, Nagel, and Santosh (2018), investors with biased expectations coexist with unbiased (rational) arbitrageurs, and the presence of the arbitrageurs ensures 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 fundamental risks, as would the risk factors in a fully rational setting with no biased investors.

The potential explanatory power of behavioral factors derives from expectations that are correlated with fundamentals, and from fluctuating sentiment that induces commonality in mispricing and return. This leads biased investors to expose themselves to behavioral factors because they think they will be compensated for these "risks." In contrast arbitrageurs will take the other side of these bets, and the factors will be negatively correlated with innovations in marginal utility for the subset of arbitrageurs in the economy. For example, to the extent that broker-dealers act as rational arbitrageurs, broker-dealer leverage should price behavioral anomalies, in that it captures "risk" for these agents (He and Krishnamurthy 2013; Adrian, Etula, and Muir 2014; He, Kelly, and Manela 2017). Indeed, one interpretation of our financing factor is that it captures the first-order condition for a rational optimizing firm in a setting such as that of Stein (1996), in which mispricing of a firm's issued securities is driven by behavioral biases.

[11] Several other studies have also suggested that behavioral biases 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) find that retail investor sentiment leads to stock return comovement incremental to market, size, value and momentum factors. Stambaugh and Yuan (2017) develop a behavioral factor model based on commonality in mispricing.

We argue that the mispricing effects of numerous behavioral biases, occurring at both long- and short-horizons, can be captured by two behavioral factors: a financing factor FIN that captures long-horizon mispricing, and an inattention factor PEAD that captures short-horizon mispricing. Why do just two proxies for mispricing (external financing and earnings surprises) capture a wide set of anomalies? These proxies can capture misperceptions deriving from multiple behavioral biases, each somewhat different. To the extent that a firm's manager is aware of that firm's total mispricing—resulting from a 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), our long-horizon behavioral factor FIN can provide a good summary of the various sources of longer-term mispricing.[12] Similarly, to the extent that short-horizon anomalies derive from 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.

The observed premiums of the behavioral factors we propose could alternatively be interpreted as rational risk premiums. This mirrors the fact that the factors in traditional models (other than the market factor) can instead be interpreted as reflecting mispricing. However, we motivate our two behavioral factors with behavioral/mispricing arguments. The premium on the PEAD factor is unlikely to be mainly a rational risk premium, given the extensive evidence in the literature that the PEAD effect reflects delayed price response to information owing to limited investor attention (see footnote 8). As for the financing factor, there are risk- or rational-based explanations (e.g., firms issue equity when cost of capital is low), and there is debate about rational versus behavioral explanations. But there are both theoretical models and empirical and survey evidence supporting the mispricing arguments (see footnotes 3 and 4).

We are not the first to construct a PEAD factor or a financing factor. Our contribution is to use these factors in a theoretically motivated and parsimonious factor pricing model, and to show that such a model explains a broad range of both short- and long-horizon anomalies.[13]

12 Although models of overconfidence offer a motivation for seeking a factor based on long-horizon mispricing, the market timing motivation for the FIN factor means that it does not directly pinpoint what investor psychological bias is driving mispricing.

13 Chordia and Shivakumar (2006) and Novy-Marx (2015a) construct PEAD factors 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). Hirshleifer and Jiang (2010) propose a behavioral factor, the underpriced-minus-overpriced (UMO) factor, based on firms' external financing activities, such as debt/equity repurchase and issuance events over the previous 24 months.

2. Comparison of Behavioral Factors with Other Factors

2.1 Factor definitions

We construct the financing factor (FIN) based on the 1-year net share issuance (NSI) and 5-year composite share issuance (CSI) measures of Pontiff and Woodgate (2008) and Daniel and Titman (2006), respectively. Daniel and Titman's 5-year CSI measure is simply the firm's 5-year growth in market equity, minus the 5-year equity return, in logs. Thus, any issuance activity, such as seasoned issues, the exercise of employee stock options, and equity-financed acquisitions, will increase the issuance measure, whereas activity such as share repurchases, cash dividends, and other actions that pay cash out of the firm will decrease the issuance measure. Note that corporate actions, such as splits and stock dividends, don't affect the market capitalization or the return, and thus leave the composite issuance measure unchanged. Pontiff and Woodgate's NSI measure is identical to CSI, except that NSI uses a 1-year horizon and excludes cash dividends. Both issuance measures earn significant abnormal returns (incremental to each other) during our sample period of 1972 to 2014. The appendix provides details on variable construction.[14]

As noted above, the key differences between CSI and NSI are the horizons and the treatment of cash dividends. It seems plausible that managers might adjust dividend policy to respond to mispricing at a roughly 5-year horizon, but that frictions would constrain managers from adjusting dividends to respond to mispricing at annual horizon. Empirically, dividend yields do in fact forecast returns at longer horizons. To minimize data mining, we have elected to construct FIN based on NSI and CSI measures identical to those used in the Pontiff and Woodgate (2008) and Daniel and Titman (2006) studies. Our procedure of combining two existing financing measures off the shelf from existing papers eliminates numerous potential degrees of freedom in how a researcher might potentially form a FIN factor by tweaking existing financing measures.

The FIN factor is constructed using all NYSE, AMEX, and NASDAQ common stocks with CRSP share codes of 10 or 11. Following Hou, Xue, and Zhang (2015), we exclude financial firms and firms with negative book equity. 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 1-year NSI and 5-year CSI, 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

[14] 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 (see also Daniel and Titman 2016).

when sorting firms into NSI groups, because 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. Similarly, on the issuance side, using a simple NSI sort would cause no distinction between large and small issuances in some formation years. To address this, 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 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 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, which is intended to capture investor limited attention. It is again constructed in the fashion of Fama and French (1993). Following Chan, Jegadeesh, and Lakonishok (1996), earnings surprise is measured as the 4-day cumulative abnormal return around the most recent quarterly earnings announcement date (Compustat quarterly item RDQ).[15] Specifically,

[15] If investors underreact to fundamental news by a fixed percentage, then a greater announcement date return implies a proportional future alpha. Previous studies of earnings momentum have used return-based surprise measures, such as CAR, and earnings-based measures, such as the standardized unexpected earnings (SUE) (Chan, Jegadeesh, and Lakonishok 1996). Several advantages motivate our choice of a return-based measure. First, an earnings-based measure of surprise necessarily compares announced earnings to analyst-forecasted earnings or to a time-series historical proxy for the earnings expectation, either of which is a noisy proxy for the true expected earnings. In addition, the degree of earnings persistence affects the information content in any given earnings surprise. SUE does not account for this, whereas a return-based measure does. Moreover, previous literature indicates that return-based measures, such as CAR, better forecast future stock returns than do earnings-based measures (see, e.g., Brandt et al. 2008).

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

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 of the trading days in this 4-day window. We also require the Compustat earnings date (RDQ) to be at least two trading days prior to the month end. In forming the PEAD portfolio, we sort on CAR_i from the most recent earnings announcement. If, however, there is no earnings announcement in the past 6 months, then firm i is excluded from the PEAD portfolio.

To construct the PEAD factor portfolio in month t, we begin with 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 also independently sorted into one of three earnings surprise groups (low "L", middle "M", or high "H") based on CAR_i 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 return of the high earnings surprise portfolios (SH and BH) minus the average return of the low earnings surprise portfolios (SL and BL), that is, $PEAD=(r_{SH}+r_{BH})/2-(r_{SL}+r_{BL})/2$.

2.2 Competing factor models

We compare our behavioral factors and the 3-factor composite model, which is built on three firm characteristics, with traditional factor models, such as the CAPM (Sharpe 1964; Lintner 1965; Black 1972), 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.[16] Monthly factor returns are either downloaded from Kenneth French's Web site or provided by the relevant authors.[17]

Novy-Marx (2013, NM4) proposes a 4-factor model consisting of 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

[16] The three characteristics of our composite model are external financing, earnings surprises, and size. When firm size is used in a model to form a factor, as is the case in forming our FIN and PEAD factors and factors in other models, size is counted as one of the model's characteristics, regardless of whether the model includes a size factor.

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

hedge the factor returns for industry exposure. Thus, the model is built on five characteristics: value, momentum, gross profits-to-assets, size, and industry. To differentiate from their standard versions, we label the industry-adjusted value and momentum factors as HML(NM4) and MOM(NM4). All factor portfolios are annually rebalanced at the end of each June.

Fama and French (2015, FF5) propose a 5-factor model built on four characteristics. It consists of 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 based on operating profitability. The size, investment, and profitability factors are formed by a triple sort on size, change in total assets, and operating profitability. All factor portfolios are annually rebalanced at the end of each June.

Hou, Xue, and Zhang (2015, HXZ4) propose a q-factor model consisting of four factors built on three characteristics: 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(HXZ4). The size and IVA factor portfolios are annually rebalanced at the end of each June, and the ROE factor is rebalanced each month.

The proxy for investment used in the Fama and French (2015) and Hou, Xue, and Zhang (2015) is the annual change in total assets, scaled by the 1-year lagged total assets. Cooper, Gulen, and Ion (2017) argue that the use of asset growth as a proxy for investment is problematic, in that the use of an investment factor based on investment measures, such as CAPX or PPE growth, renders these factor models far less effective in explaining the cross-section of returns.

Lastly, Stambaugh and Yuan (2017, SY4) propose a 4-factor model built on twelve characteristics. The four factors are a market factor, a size factor, and two mispricing factors (MGMT and PERF). The MGMT factor is 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. The size factor is formed using only stocks least likely to be mispriced (based on the above eleven characteristics), to reduce the effect of arbitrage asymmetry. We label it SMB(SY4). The SMB(SY4), MGMT, and PERF factors are rebalanced each month.

2.3 Summary statistics

Table 1 reports summary statistics for our zero-investment behavioral factor portfolios, and for a set of factor portfolios proposed in previous literature. Panel A of Table 1 shows that, over our sample period, FIN offers the highest

Table 1
Summary statistics of factor portfolios

A. Factor premiums

	Mean	SD	*t*-value	*SR*	N	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(HXZ4)	0.29	3.14	2.06	0.09	510	1972:07–2014:12
SMB(SY4)	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(NM4)	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(NM4)	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

B. Correlation matrix

	MKT	SMB	SMB (HXZ4)	SMB (SY4)	HML	HML (NM4)	MOM	MOM (NM4)	CMA	IVA	PMU	RMW	ROE	MGMT	PERF	FIN
SMB	0.26															
SMB(HXZ4)	0.25	**0.95**														
SMB(SY4)	0.21	**0.92**	**0.93**													
HML	−0.28	−0.22	−0.05	−0.05												
HML(NM4)	−0.19	−0.04	0.09	0.10	**0.81**											
MOM	−0.14	0.01	0.01	0.03	−0.17	−0.12										
MOM(NM4)	−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

Table 1
Continued

C. Ex post tangency portfolios

	Portfolio weights													Tangency portfolios		
	MKT	SMB*	HML*	MOM*	RMW	CMA	PMU	IVA	ROE	MGMT	PERF	FIN	PEAD	Mean	SD	*SR*
(1) FF3	0.29	0.15	0.56											0.41	1.86	0.22
(2) Carhart4	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) NM4*	0.10		0.40	0.11			0.39							0.40	0.70	**0.57**
(5) HXZ4*	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**

Panel A reports the mean and standard deviations of monthly factor returns for a set of traded factors. In addition, we report the t-statistic testing whether 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, and MOM factors proposed by Fama and French (1993) and Carhart (1997) and modified versions of these factors proposed by Novy-Marx (2013, NM4), Fama and French (2015, FF5), Hou, Xue, and Zhang (2015, HXZ4), and Stambaugh and Yuan (2017, SY4). We additionally 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 (2017). 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 on two financing characteristics, net share issuance and composite issuance. PEAD is the post-earnings announcement drift factor, constructed based on earnings surprises (measured as the 4-day cumulative abnormal returns around quarterly earnings announcements). In panel C, the asterisk after factors SMB, HML, and MOM indicates these factors have modified versions, and the asterisk after models NM4, FF5, HXZ4, and SY4 indicates these models use modified factors.

average premium of 0.80% per month and a monthly Sharpe ratio of 0.20. The t-statistic testing whether the FIN premium is zero is 4.6, well above the hurdle of 3.0 for new factors proposed by Harvey, Liu, and Zhu (2016). PEAD offers an average premium of 0.65% per month and the highest monthly 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 the factors.[18]

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.[19]

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(NM4)) 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(NM4)) are about 0.5.

Not surprisingly, the composite MGMT factor, constructed on six investment and financing characteristics, is highly correlated with value factors (HML, HML(NM4)) and investment factors (CMA, IVA), with ρ ranging from 0.59 to 0.76. The PERF factor, which is constructed on five characteristics including price momentum and profitability, is highly correlated with both momentum factors (MOM, MOM(NM4)) and profitability factors (PMU, RMW, ROE), with ρ ranging from 0.48 to 0.72.

Lastly, although FIN is constructed using only external financing, its returns are correlated with both value factors (HML, HML(NM4)) and investment factors (CMA, IVA), with ρ between 0.50 and 0.66, consistent with issuing firms having both 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 component in the

[18] The share issuance effect is slightly stronger among large firms, and the PEAD effect much stronger among small firms. A FIN factor built on large firms, $FIN_B = r_{BL} - r_{BH}$, earns an average premium of 0.83% per month, whereas FIN built on small firms, $FIN_S = r_{SL} - r_{SH}$, earns 0.77% per month. A PEAD factor built on large firms, $PEAD_B = r_{BH} - r_{BL}$, earns an average premium of 0.38% per month, whereas PEAD built on small firms, $PEAD_S = r_{SH} - r_{SL}$, earns 0.94% per month. This is consistent with evidence in the literature.

[19] In Internet Appendix Table A1, we report factor means and t-values for the 1972–1990 and 1991–2014 subperiods, respectively. Sample sizes are, of course, smaller in subperiods, reducing t-values. In the earlier subperiod, FIN has a mean return of 1.12% per month (t = 5.75), and PEAD has a mean of 0.77% per month (t = 7.32). Both point estimates are extremely large. In the later subperiod, FIN has a mean return of 0.56% per month (t = 2.09), and PEAD has a mean of 0.55% per month (t = 4.59). Both point estimates are large, though smaller than in the earlier time period. It is possible that the underlying effects are weakening over time (see McLean and Pontiff 2016). On the other hand, we expect subperiod variation by chance.

composition of the MGMT factor. This suggests that it may not be necessary to use such a large number of characteristics to obtain a factor that is effective in explaining the cross-section of expected returns. FIN is moderately correlated with profitability factors (PMU, RMW, ROE) and the composite PERF factor, with ρ around 0.35. As we would expect, PEAD is strongly correlated with momentum factors (MOM, MOM(NM4)) 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 correlated, apparently driven at least in part by market underreaction to latest earnings news (Chan, Jegadeesh, and Lakonishok 1996). Finally, the correlation between FIN and PEAD is -0.05, suggesting that the two behavioral factors capture different sources of mispricing.

Panel C summarizes 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 the optimal combination of factors from the Fama and French (2015), Novy-Marx (2013), Hou, Xue, and Zhang (2015), and Stambaugh and Yuan (2017) models achieve realized monthly Sharpe ratios 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. Thus, the 3-factor 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 3-factor composite model as a baseline, 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 (2017) 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.

2.4 Comparing behavioral factors with other factors

When comparing models with traded factors, it is important to compare their ability to price all returns, that is, both test assets and traded factors (Barillas and Shanken 2017). 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 one factor on other proposed factors and examine the regression intercepts (alphas). If a factor is subsumed by a set of other factors, we expect the regression alpha to be close to zero.

In interpreting tests between factors, it is important to keep in mind that winning the horse race is not the only criterion for a good model. It is always possible to construct an overfitted model that will "beat" all other factors ex post. It is therefore crucial for a model to have a strong combination of theoretical motivation, parsimony, and good fit.

Table 2 reports the results of regressions of behavioral factor returns on other sets of factor returns. The significant intercepts from the Fama-French 3-factor model, the Carhart model, the Fama and French (2015) 5-factor model and the Hou, Xue, and Zhang (2015) q-factor model suggest that the factors in these models do not explain the FIN premium. However, the profitability-based model of Novy-Marx (2013) and the 4-factor mispricing model of Stambaugh and Yuan (2017) are able to fully capture the FIN premium. 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 fully explain the PEAD premium. The "kitchen sink" regression of the PEAD factor returns on all alternative model factors shows that PEAD continues to earn 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* the other factors we examine, including the investment, profitability and mispricing factors of Stambaugh and Yuan (2017). 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 (2017).

Table 3 reports the results of regressions of other factors on our two behavioral factors.[20] With just FIN and PEAD, our 2-factor behavioral model fully explains 7 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 (2017). 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 3-factor composite model does not explain CMA and MGMT factors either, which load negatively on the market factor and therefore earn significant alphas under the model. However, for the factors other than SMB for which the alphas remain statistically significant, on average 48% of

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

Table 2
Factor regressions of behavioral factors on other factors

	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) Carhart4	0.59***	−0.21***	−0.38***	0.72***	0.13***								63.2%
			(4.64)	(−5.74)	(−4.92)	(10.54)	(2.93)								
		(3) NM4*	−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) HXZ4*	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) Carhart4	0.56***	−0.03	0.01	−0.06	0.18***								19.2%
			(7.34)	(−1.27)	(0.40)	(−1.47)	(6.31)								
		(3) NM4*	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) HXZ4*	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)	

This table reports the results of time-series regressions of behavioral factors on the sets of factors incorporated in other factor models: (1) the Fama-French 3-factor model (FF3), (2) the Carhart 4-factor model (Carhart4), (3) the profitability-based model of Novy-Marx (2013, NM4), (4) the 5-factor model of Fama and French (2015, FF5), (5) the q-factor model of Hou, Xue, and Zhang (2015, HXZ4), (6) the 4-factor mispricing model of Stambaugh and Yuan (2017, SY4), and (7) the "kitchen sink" model with all factors. The asterisk after factors SMB, HML and MOM indicates that these factors have modified versions, and the asterisk after models NM4, FF5, HXZ4, and SY4 indicates 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 six lags) are shown in parentheses.

Table 3
Factor regressions of other factors on behavioral factors

	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)	

This table reports the results of 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 (2017). The sample period is from 1972:07 to 2014:12, depending on data availability. Newey-West corrected t-statistics (with six lags) are shown in parentheses.

the premium earned by these factors is explained by exposure to the factors in the BF3 model.[21]

This significant t-statistic on SMB shows that, at least ex post, the BF3 model could have been improved by the addition of SMB as a fourth factor. However, while statistically significant, the economic improvement that would result from adding SMB to the model is small. Specifically, the Sharpe ratio of the optimal ex post combination of the three BF3 factors is 0.52 (in panel C of Table 1). We find that adding a SMB factor to our BF3 model only increases the Sharpe ratio from 0.52 to 0.54.[22]

Also, if managers time their issuance and repurchase, then our factor model should capture all long-horizon mispricing without recourse to a size factor. It is important for a factor model to have a theoretical motivation rather than just an ex post empirical one. Our BF3 model comes close to pricing all long-horizon anomalies (as shown in Section 3), and additional inclusion of SMB

[21] In Internet Appendix Tables A2 and A3, we report spanning regressions for the 1972–1990 and 1991–2014 subperiods, respectively. The results are generally consistent with those in the whole sample period. In particular, in the latter subperiod, no other factors can explain our PEAD factor. The only models that can explain our FIN factor are NM4, HXZ4, and SY4. In contrast, our factor model explains all factors from competing models, with three exceptions: SMB, PMU, and RMW.

[22] The improvement in the squared Sharpe ratio is the Treynor-Black squared information ratio, which also can be calculated using $t(\alpha)$ from the regression of SMB on the BF3 factors in Table 3.

does not help the model come much closer, as evidenced by the small change in the Sharpe ratio when we add in an SMB factor.

Overall, we find that FIN and PEAD capture a large fraction of the premiums of the factors from the alternative models, but not vice versa. The evidence suggests that FIN and PEAD contain important incremental information about average returns relative to existing factors. This motivates further testing of their ability to explain well-known return anomalies, which we do in the next section.

3. Explaining Anomaly Returns with Behavioral Factors

3.1 Anomaly magnitudes and correlations

Next, we examine whether our composite model explains the various return anomalies documented in the academic literature. We focus on thirty-four robust anomalies based on the list of anomalies considered in Hou, Xue, and Zhang (2015) that earn significant excess returns over their sample period of 1972 to 2012. We exclude the systematic volatility (Svol) of Ang et al. (2006) and the revisions in analysts' earnings forecasts (6-month holding period, RE-6) of Chan, Jegadeesh, and Lakonishok (1996) from the set of anomalies considered by Hou, Xue, and Zhang (2015), as these two portfolios do not earn statistically significant excess returns over our sample period. In addition to the remaining HXZ anomalies, we also consider the cash-based operating profitability (CbOP) of Ball et al. (2016). Although our strong inclination is to stick with the HXZ anomalies, to minimize our own discretion, we make an exception in this case given the evidence in Fama and French (2018) that an anomaly portfolio based on cash-based operating profitability dominates one based on operating profitability.

FIN is constructed using a firm's financing activities and PEAD using the firm's quarterly earnings surprises. Thus, we further posit that FIN captures longer-term predictability and that PEAD captures short-term underreaction to recent earnings news and the correction to such high-frequency mispricing. Given that FIN and PEAD are designed to capture mispricing over different horizons, we are especially interested in how well FIN captures long-horizon anomalies and how well PEAD captures short-horizon anomalies.

We define as *long-horizon* those anomalies which continue to earn statistically significant positive excess returns for 1 to 3 years after portfolio formation. The trading strategies for each of these long-horizon anomaly portfolios are annually rebalanced. In contrast, *short-horizon* anomalies are those based on quarterly accounting reports or high-frequency price information. Such anomalies typically have a higher decay rate of return predictability as the forecast horizon is extended. The premiums 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, 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. The appendix defines the anomaly characteristics.

To further validate our classification of long- versus 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 premiums 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 a portfolio's formation.[23]

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

3.2 Summary of comparative model performance

To examine how well behavioral factors account for various return anomalies, we run anomaly portfolio regressions of the long/short (L/S) portfolio returns on FIN alone, PEAD alone, a 2-factor model with FIN and PEAD (BF2), and a 3-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

[23] 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 on annual accounting reports, and it makes more sense to form annually rebalanced trading strategies based on them.

Table 4
List of anomalies

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

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 et al. (2016)	0.42	0.10
Value	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 et al. (2007)	0.65	0.17
	DUR	Equity duration, Dechow, Sloan, and Soliman (2004)	0.64	0.15
Investment and financing	AG	Asset growth, Cooper, Gulen, and Schill (2008)	0.43	0.12
	NOA	Net operating assets, Hirshleifer et al. (2004)	0.38	0.12
	IVA	Investment-to-assets, Lyandres, Sun, and Zhang (2008)	0.50	0.17
	IG	Investment growth, Xing (2008)	0.38	0.13
	IvG	Inventory growth, Belo and Lin (2012)	0.33	0.10
	IvC	Inventory changes, Thomas and Zhang (2002)	0.45	0.14
	OA	Operating accruals, Sloan (1996) and Hribar and Collins (2002)	0.24	0.08
	POA	Percent operating accruals, Hafzalla, Lundholm, and Van Winkle (2011)	0.39	0.13
	PTA	Percent total accruals, Hafzalla, Lundholm, and Van Winkle (2011)	0.40	0.12
	NSI	Net share issuance, Pontiff and Woodgate (2008)	0.69	0.22
	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

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 thirty-four total anomalies into two groups: twelve short-horizon anomalies and twenty-two long-horizon anomalies. Short-horizon anomalies include earning momentum, price momentum, and short-term profitability. Long-horizon anomalies include long-horizon profitability, value, investment and financing, and intangibles. The last two columns report the monthly mean returns (expressed as a percentage) of the long/short anomaly portfolios and the Sharpe ratios. The sample period runs from 1972:07 to 2014:12, depending on data availability.

Table 5
Decay rate of anomaly portfolio returns

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)

(Continued)

Table 5
Continued

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)

Table 5
Continued

B. Long-horizon anomalies

	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)

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 (six lags for monthly or quarterly window, twelve lags for annual window). When a long/short portfolio earns significant returns in predicted direction over a return window, we mark this case in bold. The sample period runs from 1972:07 to 2014:12, depending on data availability.

Table 6
Correlations between anomaly portfolios

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**

(continued)

Table 6
Continued

B. Long-horizon anomalies

	GP/A	CbOP	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																					
CbOP	**0.43**																				
Value																					
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

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 twelve short-horizon anomalies, and panel B reports correlations among twenty-two long-horizon anomalies. Correlation coefficients greater than 0.30 are marked in bold. The sample period runs from 1972:07 to 2014:12, depending on data availability.

CAPM, the Fama-French 3-factor model (FF3), and the Carhart 4-factor model (Carhart4), and recent prominent models, such as the profitability-based factor model of Novy-Marx (2013, NM4), the 5-factor model of Fama and French (2015, FF5), the *q*-factor model of Hou, Xue, and Zhang (2015, HXZ4), and the 4-factor mispricing model of Stambaugh and Yuan (2017, SY4).[24]

Table 7 summarizes the comparative performance of competing factor models in explaining the set of thirty-four 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.[25] 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 statistics: (1) the number of significant alphas at the 5% level; (2) the average absolute alphas; (3) the average absolute t-values of alphas; (4) the GRS F-statistics and p-values, which test the null hypothesis that all alphas are jointly zero (Gibbons, Ross, and Shanken 1989); (5) the Hansen and Jagannathan (1997, HJ) distance, which measures the maximum pricing error generated by a model on a set of testing portfolios; and (6) the F-statistics and p-values that test whether the average t^2 of alphas under a given model is larger than the average t^2 of the composite-model alphas.[26]

3.2.1 Fitting short-horizon anomalies. Panel A of Table 7 compares different models on explaining the list of twelve short-horizon anomalies. We first look at the number of significant alphas at the 5% level. Among standard factor models, the CAPM and FF3 models do not capture most of these anomalies and the Carhart4 model 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

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

[25] 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 underlying characteristic of the profitability factor (PMU) of the Novy-Marx (2013) model.

[26] 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 obtain 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 $M = 5,000$ random draws.

Table 7
Comparative model performance

A. Short-horizon anomalies

	List of anomalies		H-L ret	CAPM	FF3	Carhart4	FF5	NM4	HXZ4	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	1	0
	Average $\lvert\alpha\rvert$		0.58	0.67	0.82	0.36	0.57	0.29	0.19	0.22	0.47	0.16	0.15	0.10
	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
	$F\text{-stat} = \frac{Average\ t^2}{Average\ t^2_{BF3}}$		34.84***	47.46***	73.99***	25.28***	37.45***	11.85***	8.75***	11.13***	23.07***	2.54*	2.31*	
	p-value		(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.06)	(.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		(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.01)	(.00)	(.00)	(.02)	(.01)	(.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			(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.09)	(.00)	(.02)	(.03)	(.49)

(continued)

Table 7
Continued

B. Long-horizon anomalies

	List of anomalies		H-L ret	CAPM	FF3	Carhart4	FF5	NM4	HXZ4	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	CbOP	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 (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%		19	20	12	8	7	3	5	3	6	16	4	3
	Average $\lvert\alpha\rvert$		0.47	0.54	0.32	0.27	0.19	0.19	0.23	0.11	0.24	0.50	0.27	0.25
	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		(.01)	(.00)	(.01)	(.05)	(.24)	(.81)	(.34)	(.97)	(.23)	(.00)	(.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		(.00)	(.00)	(.00)	(.00)	(.01)	(.05)	(.00)	(.80)	(.00)	(.00)	(.01)	(.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			(.00)	(.07)	(.90)	(.16)	(.73)	(.05)	(.90)	(.00)	(.00)	(.01)	(.35)

(continued)

Table 7
(Continued)

C. All anomalies

		H-L ret	CAPM	FF3	Carhart4	FF5	NM4	HXZ4	SY4	FIN	PEAD	BF2	BF3
All anomalies (34)	N. significant α at 5%	29	32	24	15	18	5	6	7	14	16	5	3
	Average $\lvert\alpha\rvert$	0.51	0.58	0.50	0.30	0.33	0.22	0.22	0.15	0.32	0.38	0.23	0.20
	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	(.00)	(.00)	(.00)	(.00)	(.00)	(.16)	(.07)	(.34)	(.00)	(.00)	(.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	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.01)	(.00)	(.00)	(.00)	(.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		(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.01)	(.00)	(.00)	(.00)	(.01)

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 3-factor model (FF3), and Carhart 4-factor model (Carhart4). The second set includes four recent models: the 5-factor model of Fama and French (2015, FF5), the profitability-based model of Novy-Marx (2013, NM4), the q-factor model of Hou, Xue, and Zhang (2015, HXZ4), and the 4-factor mispricing model of Stambaugh and Yuan (2017, SY4). The last set includes our behavioral-motivated models: a single factor FIN, a single factor PEAD, a 2-factor model with FIN and PEAD (BF2), and a 3-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 (six 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.

shorter-horizon momentum-like anomalies. The NM4, HXZ4, 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 market factor 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 statistics confirm the superior performance of the PEAD factor and our BF3 model. The BF3 model gives the smallest average absolute alpha ($|\alpha|=0.10\%$) 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 $F=1.15$, $p=.32$). It also gives the smallest HJ distance and does not reject the null hypothesis that the composite model is specified correctly (HJ $=14.66$, $p=.49$). In contrast, all other models give substantially larger average absolute alphas and t, their GRS F-tests reject the null hypotheses at the 1% level, and the HJ tests reject the null hypotheses that these models are specified correctly at the 1% level (except for SY4 model which rejects the null at the 10% level).

Although the PERF factor of the SY4 model is constructed on five characteristics related to price momentum and profitability, our PEAD factor, which is constructed on just two characteristics, size and earnings surprises, outperforms the composite PERF factor in capturing the twelve short-horizon anomalies.

3.2.2 Fitting long-horizon anomalies. We have argued that our FIN factor should be especially helpful for fitting long-horizon anomalies, and that a factor model that disentangles long-horizon mispricing with the FIN factor and short-horizon mispricing with the PEAD factor should help provide a parsimonious fit to anomalies more generally.[27] To test the effectiveness of our factor model, panel B of Table 7 compares different models on explaining the list of twenty-two long-horizon anomalies. We first consider the number of significant alphas at the 5% level. Among standard factor models, the CAPM does not capture most of these anomalies, the FF3 model gives 12 significant alphas, and the Carhart4 model gives 8 significant alphas. For competing models, the numbers

[27] A subtle argument for why the PEAD factor may help capture even long-horizon anomalies to some extent goes like this: consider a stock that is underpriced based on a long-horizon anomaly characteristic, which implies high expected returns. If that characteristic is persistent, the stock was on average also underpriced one quarter ago; the latest earnings surprise (relative to market expectations) was on average probably positive; and some portion of the high expected return of the asset is likely to reflect post-earning announcement drift. This suggests that the PEAD factor can, to some extent, help capture long-horizon anomalies.

of significant alphas are 7 (FF5), 3 (NM4), 5 (HXZ4), and 3 (SY4), respectively. Among our behavioral-motivated models, a single FIN factor gives 6 significant alphas, performing as well as the FF5 and HXZ4 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 HXZ4 models and performing equally well as the NM4 and SY4 models.

Other statistics confirm the good performance of the NM4, BF3, and SY4 models. The SY4 model gives the smallest average absolute alpha ($|\alpha|=0.11\%$) 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, NM4, and HXZ4 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 $F=0.74$, $p=.80$). The GRS F-tests only reject the null at a 10% significance level for NM4 and BF3 models, while rejecting the null at a 1% significance level for all other models including the FF5 and HXZ4 models. Lastly, the HJ tests cannot reject the null hypotheses that the FF5, NM4, SY4, and BF3 models are specified correctly, while rejecting the null at 10% significance level for the HXZ4 model.

While the FF5 and HXZ4 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 HXZ4 models, each with a profitability factor, do not capture the cash-based operating profitability (CbOP) effect, whereas our BF3 model does, even though neither FIN nor PEAD is directly constructed on investment or profitability characteristics.

The good performance of the SY4 model appears to result from the inclusion of its MGMT factor, which is constructed on six long-horizon characteristics related to investment and financing, allowing it to price investment-related anomalies. Interestingly our single long-horizon factor (FIN) performs almost as well as the MGMT factor in capturing abnormal returns associated with 22 firm characteristics. This is consistent with the fact that the two factors have a correlation of about 0.8.

3.2.3 Fitting all anomalies. Panel C of Table 7 summarizes model performance on the 34 anomalies. Our BF3 model gives just 3 significant alphas at the 5% level, while the FF5, NM4, HXZ4, and SY4 models give 18, 5, 6, and 7 significant alphas, respectively. 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 NM4 and SY4 models are not significantly different from average t^2 of BF3 alphas, but the average t^2 of FF5 and HXZ4 alphas are significantly larger than that of BF3 alphas at 1% and 10% significance levels, respectively. Unlike in panels 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.[28] [29] [30]

Overall, a 3-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 the thirty-four robust anomalies.[31] Our findings suggest that many of the existing anomalies, such as price and earnings momentum, profitability, value, investment and financing, and intangibles, can be attributed to systematic mispricing.

One criticism of characteristic-based factor models is that the factors are built on the same characteristics as the anomalies to be explained. Such models can have high explanatory power for such anomalies for purely mechanical reasons (Daniel and Titman 1997). As a robustness check, we rerun our tests where, for each factor model, we exclude the anomalies whose characteristics are used to build the factors of that model. The results are very similar to our main results, and the BF3 model continues to outperform the other models.

Next, we present detailed factor regression results for each anomaly. For brevity, we show statistics only for the long/short (L/S) hedged anomaly portfolios (not for decile portfolios). The appendix defines anomaly variables

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28 In Internet Appendix Table A4, we perform split sample tests that divide the sample into two roughly equal subperiods: 1972–1990 and 1991–2014. The conclusion that our 3-factor composite model explains anomalies extremely well is highly robust. The model explains *all* thirty-four anomalies during the earlier subperiod, in sharp contrast with the other factor models we examine here. In the later subperiod, it explains all of the short-horizon anomalies and all but 4 of the 22 long-horizon anomalies; it has lower number of significant alphas, except for the SY4 model (which has only two significant alphas).

29 In all tests, we use value-weighted test asset portfolios, so microcaps should have relatively little influence. For robustness, we exclude microcaps (firms with size below the 20th percentile of NYSE firms) from the test assets and from our factor portfolios. Internet Appendix Table A5 shows that our factor model performs about equally well. As a further robustness check, we exclude from our factors and the test assets all stocks with prices $<$ \$5. Internet Appendix Table A6 shows that the results are almost unchanged.

30 A referee inquired whether adding the SMB, HML, or PMU factors to the BF3 model would change its ability to explain anomalies. Internet Appendix Table 7A shows that adding SMB or HML has almost no effect on the model's performance. However, the BF3+PMU model's performance is worse in explaining longer-horizon anomalies and, in particular, the performance of several value, investment, and accrual-based portfolios. This is consistent with existing evidence that some of these anomalies become stronger after controlling for profitability (see, e.g., Novy-Marx 2013). A firm's profitability is likely associated with its investment opportunities, so the inability of the FIN factor to fully explain these portfolios may result from an interaction of FIN with profitability. The resolution of this issue is a topic for future research.

31 Going beyond the Hou, Xue, and Zhang (2015) list of anomalies, referees of this paper inquired whether our model prices the long-term reversal effect of DeBondt and Thaler (1985), the 1-month industry momentum effect of Moskowitz and Grinblatt (1999), and the industry relative reversal effect of Da, Liu, and Schaumburg (2014). We find that our model fully prices the first two and that neither our model nor any of the competing models prices the last of these. So including these in our main tests would improve the relative performance of our factor model. However, to avoid cherry-picking, in our overall tests we stick to the Hou, Xue, and Zhang (2015) anomalies list.

Table 8
Factor regressions of long/short anomaly portfolios

	Earnings momentum					Return momentum			Profitability						Value		
	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
A. 5-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**
B. Profitability-based model of Novy-Marx (2013, NM4)																	
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
C. q-factor model of Hou, Xue, and Zhang (2015, HXZ4)																	
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
D. 4-factor mispricing model of Stambaugh and Yuan (2017, 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*
E. 3-factor composite 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)

Table 8
Continued

	Value		Investment and financing											Intangibles			
	NPY	DUR	AG	NOA	IVA	IG	IvG	IvC	OA	POA	PTA	NSI	CSI	OC/A	AD/M	RD/M	OL
A. 5-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
B. Profitability-based model of Novy-Marx (2013, NM4)																	
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***
C. q-factor model of Hou, Xue, and Zhang (2015, HXZ4)																	
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***
D. 4-factor mispricing model of Stambaugh and Yuan (2017, 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***
E. 3-factor composite 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

This table reports alphas and factor betas from time-series regressions of long/short anomaly portfolio returns on recent prominent factor models. Panels A, B, C, and D report regression alphas and factor betas under the 5-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 4-factor mispricing model of Stambaugh and Yuan (2017), respectively. Panel E reports the alphas and betas under our 3-factor risk-and-behavioral composite model (BF3). Newey-West corrected t-statistics (with six lags) are shown in parentheses. The sample period runs from 1972:07 to 2014:12, depending on data availability.

and describes portfolio constructions. 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 into which factors contribute to explaining which anomalies.

3.2.4 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. Panels B and C show that the momentum factor (MOM) of the NM4 model and the ROE factor of the HXZ4 model help fully explain 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 does 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.

3.2.5 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 annually rebalanced.

Panel A of Table 8 shows that despite inclusion of the profitability factor RMW, the FF5 model fails to fully explain the premiums 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 NM4 model fully explains all but the failure probability effect (FP). Panel C shows that the short-term profitability (ROE) factor of the HXZ4 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), or 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, NM4, and HXZ4 models and the PERF factor of the SY4 model based on price momentum, distress, and profitability.

3.2.6 Value. Our test assets include five value anomaly portfolios: B/M, E/P, CF/P, NPY, and DUR. Panels A and B of Table 8 show that the FF5 and NM4 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 HXZ4 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, successfully captures all anomalies as well.

3.2.7 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 NM4 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 HXZ4 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) all 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 just two return predictors (external financing and firm size), delivers equally good performance as the composite MGMT factor.

3.2.8 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 NM4 model explains all but one anomaly (OC/A), which loads negatively on the PMU factor. Panel C shows that the SMB factor of the HXZ4 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 wrong direction. Overall, our 3-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.

4. Forecasting Returns with Behavioral Factor Loadings

4.1 Estimation methods and results

If FIN and PEAD are behavioral factors that capture return comovement associated with common mispricing, then 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 mispricing to shift over time, owing to correction of past mispricing and innovations to mispricing. Correspondingly, we 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 should be 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 has been to run rolling window regressions over the previous 60 months.[32] However, for our behavioral factors, this presumption is unlikely to apply. Though a firm characteristic (on 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 individual 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 1-month horizon.[33]

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 fifteen valid daily returns is required). The estimated coefficients on FIN and PEAD (β_{FIN} and β_{PEAD}) at the end of month $t-1$ are then used to forecast firm-level stock returns in month t in a Fama and MacBeth (1973) regression, with

32 However, some recent papers have utilitized daily data over different horizons for estimating the correlation and volatility components of firm loadings. (See, e.g., Frazzini and Pedersen 2014.)

33 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.

standard control variables and a broad set of firm characteristics underlying the list of thirty-four robust anomalies that we examine. Standard controls include log(ME), log(B/M), and the previous 1-month, 1-year, and 3-year returns to control for short-run contrarian, momentum, and long-term reversal, respectively. All regressors are winsorized at the 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 estimated firm β_{FIN} loadings positively and significantly forecast the following month's 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 tests. This suggesting that the return predictive ability of β_{FIN} is incremental to these short-horizon anomaly characteristics.

In models (11)−(13), we include two financing characteristics used to construct FIN. 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. The coefficients 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 marginally 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, and intangibles. Consistent with earlier evidence, the return predictive ability of β_{FIN} stays robust and incremental to profitability and value characteristics. When controlling for intangibles, the coefficients on β_{FIN} become weaker or statistically insignificant. This is consistent with the evidence in Tables 7 and 8 indicating that our behavioral factors exhibit weak pricing power for the intangibles-related anomalies, in particular R&D.

Overall, our findings suggest that estimated firm loadings on FIN positively and significantly forecast future stock returns. This predictive power is robust to controlling for many well-known return predictors in the literature. The evidence supports our hypothesis that FIN captures return comovement resulting from common mispricing.

While the predictive power of β_{FIN} for future returns is statistically strong, 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

Table 9
Firm-level Fama-MacBeth regressions on behavioral factor loadings

	(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%
$No.\ obs$	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)

Table 9
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%
$No.\ obs$	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)

Table 9
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 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%
$No.\ obs$	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

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 3-factor composite 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 the top and bottom 1% and standardized to have zero mean and unit standard deviation. Newey-West corrected t-statistics are reported in parentheses (with six lags). The sample period runs from 1972:08 to 2014:12, depending on data availability.

mispricing. PEAD is built on cumulative abnormal returns during the 4-day window around earnings announcement (CAR as defined above, or ABR-1 as defined in Table 4). Table 5 shows that the return predictive ability of ABR portfolios becomes much weaker or insignificant just 2 quarters after portfolio formation.[34]

4.2 Discussion

These cross-sectional tests generally confirm the predictive power of FIN factor loadings for future returns, but not PEAD factor loadings. However, for several reasons, we place less weight on the cross-sectional tests than the time-series tests, particularly for the higher-frequency PEAD factor. First, each month, the cross-sectional regression (Fama and MacBeth 1973) coefficient is the return of a zero-investment portfolio (weighted by the corresponding regressor) in that month. These portfolios can have large weights on microcap stocks which are costly to trade, and for which microstructure noise can bias coefficient estimates. Second, factor loadings are estimated with noise, so coefficients are prone to an errors-in-variables bias. As discussed earlier, such bias is likely to be especially severe for the loadings on short-horizon behavioral factors. We discuss each of these points in turn.

The intuition for the bias in the Fama-MacBeth coefficient estimates is as follows. In a setting like ours where the characteristics (regressors) are relatively stable, the regression coefficient portfolio will implicitly place relatively constant weight on securities from month to month, much like an equal-weighted portfolio. Maintaining this approximate constant-weighting requires rebalancing the portfolio each month, buying firms that have fallen in value and selling firms that have risen. Thus, any microstructure noise (or bid-ask bounce) that results in negative serial correlation in measured returns will result in strong positive average returns for such portfolios as a result of this rebalancing. However, these returns are not achievable, as even small transaction costs will tremendously reduce the actual returns from such a strategy, especially for portfolios tilted toward small and illiquid firms.[35]

In addition, as noted above, the PEAD factor loadings are proxies for transient mispricing and are therefore estimated with substantial noise. The resultant errors-in-variables problem will reduce the ability of these loadings to subsume the effect of characteristics in predicting returns.

Overall, the results for FIN loadings confirm our hypothesis that loadings on behavioral factors are underpricing proxies. The lack of a finding for PEAD loadings is neither confirmation nor disconfirmation, because the theory

[34] The correlation between PEAD characteristic (CAR) and estimated PEAD beta is very low at below 0.05. This suggests that the PEAD-beta estimates are too noisy to predict the cross-section of stock returns. Regressions by calendar month show that PEAD betas do not predict stock returns in most months (apart from May and September).

[35] Hou, Xue, and Zhang (2017, p. 12) also discuss the biases inherent in the cross-sectional regression method.

suggests that such loadings are likely to be unstable and difficult to estimate. Indeed, most papers that introduce new factor models do not perform Fama-Macbeth regressions, in part because of the errors-in-variables estimation challenges of such tests. The errors-in-variables problem in cross-sectional regressions severely biases in favor of null findings, so it is notable that these tests do work for our FIN loadings.

5. Effects of Limits to Arbitrage

Next, we conduct additional tests of the effects of limits to arbitrage to refine our understanding of where FIN and PEAD are most effective. 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.

5.1 Loadings on behavioral factors of long- and short-leg portfolios

To exploit anomaly profits, it is standard to form a zero-investment portfolio by going long underpriced stocks and short overpriced stocks. Owing to short-sale constraints, overpriced stocks in the short-leg portfolios are more difficult to correct and therefore more subject to 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 the negative loadings of the short legs to be larger in absolute magnitude than the positive loadings of the long legs. Moreover, PEAD primarily captures high-frequency mispricing and FIN captures low-frequency mispricing, so we expect the result for PEAD loadings to be more pronounced among short-horizon anomalies and the result for FIN loadings more pronounced among long-horizon anomalies.

We run time-series regressions of the long- and short-leg portfolio returns on our composite model. We count how many short-horizon anomalies have more negative (larger in absolute magnitude) PEAD loadings in the short legs than the positive loadings in the long legs, and we mark these cases in bold. Similarly for long-horizon anomalies, we highlight the cases where the negative loadings on the FIN factor in the short legs are larger (in absolute magnitude) than the positive loadings in the long legs. 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

Table 10
Behavioral factor loadings of the long- and short-leg portfolios

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

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

This table reports time-series regressions of the long- and short-leg portfolio returns on the 3-factor composite model. Panel A shows PEAD factor betas of the long- and short-leg portfolios for each of the 12 short-horizon anomalies, and panel B shows FIN factor betas for long-horizon anomalies. At the bottom of each panel, we summarize the average FIN or PEAD betas, and count how many anomalies have larger (in absolute terms) and significant FIN or PEAD betas in the short legs than in the long legs (marked in bold), and vice versa. The sample period runs from 1972:07 to 2014:12, depending on data availability.

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 have 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.

5.2 Market frictions and the beta-return relation

We have hypothesized that firm loadings or betas on FIN and PEAD are proxies for the degree of mispricing, implying a positive relation between FIN or PEAD betas and future stock returns. In Section 4, we confirm the strong return predictive ability of FIN betas, but find that PEAD betas have no statistically significant power to forecast future returns, potentially as a result of estimation issues involving betas on transient mispricing among small illiquid firms.

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. Mispricing, as proxied by factor betas on FIN, is measured with noise. For stocks with low frictions and low mispricing (either over- 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 large frictions and thus greater potential under- or overpricing, 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 4) and market friction proxies. Portfolios are held for the current month and rebalanced at the beginning of the next month. We calculate value-weighted returns for each portfolio, and corresponding Newey and West (1987) corrected t-statistics. 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

Table 11
Market frictions and sensitivity of beta-return relation

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)

(continued)

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 the 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 (in low IO or RIO ranks) have greater beta-return sensitivity.

Overall, the evidence from portfolio sorts and cross-sectional regressions is largely consistent with our hypothesis that the sensitivity of FIN-beta/return

Table 11
continued

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%
$No.\ obs$	634,529	634,529	477,847	477,847	477,847	477,847

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 twenty-five 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 three 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 the 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 using ILLIQ and from 1980:02 to 2014:12 using IO and RIO.

relation is stronger among stocks with higher arbitrage frictions, indicating that FIN betas capture mispricing.

6. 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 longer-horizon mispricing, and that managers time share issuance and repurchase to exploit this mispricing (Stein 1996; Daniel, Hirshleifer, and Subrahmanyam 1998, 2001), we create a financing factor (FIN) based on external financing. Motivated by the theory that limited investor attention induces stock market underreaction to public news arrival, we consider a post-earnings announcement drift factor (PEAD) constructed based on earnings surprises. We further hypothesize that FIN especially reflects the returns associated with long-term ($>$ 1 year) mispricing, while PEAD predominately captures 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 3-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 for short-horizon 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 5-factor model of Fama and French (2015), the *q*-factor model of Hou, Xue, and Zhang (2015), and the mispricing model of Stambaugh and Yuan (2017). Our composite model outperforms all other models in explaining the returns of thirty-four anomaly portfolios, based on the list of anomalies considered in Hou, Xue, and Zhang (2015). In addition to its simple conceptual motivation, the composite model is parsimonious in the sense that, along with the market, two behavioral factors built on only three economic characteristics−size, financing, and earnings surprise−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. Notably, this predictive power remains robust even after controlling for most of the 34 anomaly characteristics that we examine. In contrast, estimated PEAD loadings have no return predictive ability. The interpretation of the PEAD finding is unclear because of the econometric issues associated with the instability of the PEAD loadings as proxies for transient mispricing and the heavy influence of small illiquid firms on the Fama-MacBeth regression tests.

Finally, we conduct several tests related to limits to arbitrage and provide additional evidence suggesting that FIN and PEAD indeed capture 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 underpriced stocks, and stocks with greater trading frictions.

Our paper contributes to a large literature on factor pricing models and anomalies. It is a mathematical fact that a 1-factor model always exists that perfectly explains average returns, ex post. But without theoretical motivation, such a model represents meaningless overfitting. The factor model we offer has an attractive behavioral motivation and a better fit than existing factor models. So our conceptual contribution here is not in devising novel factors. It is to suggest that based on theoretical considerations, behavioral effects should be captured well by two behavioral factors that reflect short- and long-horizon mispricing; and that when these are combined with the market factor (to capture rational risk premiums), the resultant factor model should capture the cross-section of stock returns very effectively. Our empirical contribution is to show that this is indeed the case.

Our paper also partially addresses the prevalent data-mining concern in the anomaly literature. McLean and Pontiff (2016), Harvey, Liu, and Zhu (2016), and Linnainmaa and Roberts (2018) each argue that some fraction of the return premiums associated with various anomalies is a result of overfitting rather than actual mispricing. In contrast, Lu, Stambaugh, and Yuan (2017) show that anomalies previously identified in U.S. cross-sectional equity data are also significant in five non-U.S. markets, suggesting that the characteristics underlying these anomalies robustly identify mispricing.

That our model fits very well and that the two behavioral factors heavily contribute to fitting many well-known anomalies suggest that many important anomalies are about mispricing. Furthermore, if anomalies can be explained by just a few economically motivated factors, it suggests to us that they are far from wholly spurious. In particular, the strong performance of our financing factor in explaining anomalies suggests that corporate managers are issuing and repurchasing to exploit many of the well-known anomalies. This also suggests that these effects have some basis in reality.

Appendix

Definition of Anomaly Variables

A.1 Short-Horizon Anomalies

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

Following Foster, Olsen, and Shevlin (1984), we calculate SUE as the change in quarterly earnings per share (Compustat quarterly item EPSPXQ) from its value 4 quarters ago divided by the standard deviation of this change over the prior 8 quarters (6 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 6 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 6-month holding period, in each month, a given SUE-6 decile has six subdeciles that are initiated in the prior 6-month period. We then take the simple average of the six subdeciles 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 4-day cumulative abnormal returns ($t-2, t+1$) around the latest quarterly earnings announcement date (Compustat quarterly item RDQ):

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

where R_{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 6 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 6-month holding period, in each month, a given ABR-6 decile has six subdeciles that are initiated in the prior 6-month period. We then take the simple average of the six subdeciles 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 6-month moving average of past changes in analysts' forecasts:

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

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 6-month holding period, in each month, a given R6-6 decile has six subdeciles that are initiated in the prior 6-month period. Following Hou, Xue, and Zhang (2015), we take the simple average of the six subdeciles 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 forty-five industries. For each industry, we calculate its prior 6-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 forty-five industries into nine I-MOM portfolios (each with five industries) based on their prior 6-month returns from month $t-6$ to $t-1$. Monthly portfolio returns are calculated for the subsequent 6 months from t to $t+5$, by taking the simple average of the five industry returns within each portfolio, and the portfolios are rebalanced at the beginning of month $t+1$. Because of the 6-month holding period, in each month, a given I-MOM portfolio has six subportfolios that are initiated in the prior 6-month period. Following Hou, Xue, and Zhang (2015), we take the simple average of the six subportfolios 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 8 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 closely follow those 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 6 months after the quarterly earnings announcement date (RDQ). We impose the 4-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 6 months from month t to $t+5$ and rebalance the deciles at the beginning of month $t+1$. Because of the 6-month holding period, in each month, a given FP decile has six subdeciles that are initiated in the prior 6-month period. Following Hou, Xue, and Zhang (2015), we take the simple average of the six subdecile returns as the monthly return of each FP decile.

A.2 Long-Horizon Anomalies

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

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

Cash-based operating profitability (CbOP)

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

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

Book-to-market equity (B/M)

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

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

Earnings-to-price (E/P)

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

Cash flow-to-price (CF/P)

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

Net payout yield (NPY)

Following Boudoukh et al. (2007), total payout (O) is dividend on common stock (DVC) plus repurchase, where repurchase is the purchase of common and preferred stock (PRSTKC) plus any reduction (negative change over the prior year) in the value of the net number of preferred stocks outstanding (PSTKRV). Net payout (NO) is total payout minus equity issuance, which is the sale of common and preferred stock (SSTK) minus any increase (positive change over the prior year) in the value of the net number of preferred stocks outstanding (PSTKRV). Net payout yield (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 et al. (2004), we define net operating assets as *NOA* = (*Operating Assets* – *Operating Liabilities*)/*Lagged Total Assets*, where *Operating Assets* = *Total Assets*(AT) – *Cash and Short-term Investment* (CHE), and *Operating Liabilities* = *Total Assets* (AT) – *Short-term Debt* (DLC) – *Long-term Debt* (DLTT) – *Minority Interest* (MIB) – *Preferred Stock* (PSTK) – *Common Equity* (CEQ).

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

Investment-to-asset ratio (IVA)

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

Investment growth (IG)

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

Net 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 3 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 et al. (2005) and measure TA as ΔWC + ΔNCO + ΔFIN. ΔWC is the change in net noncash 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 noncurrent operating assets (NCO). NCO is noncurrent operating assets (NCOA) minus noncurrent 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. We closely follow Hou, Xue, and Zhang (2015) for detailed definition of each variable.

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 $t+1$.

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