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A Test of the Role of Behavioral Factors for Asset Pricing

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A Test of the Role of Behavioral Factors for Asset Pricing

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Management

by

Lin Sun

Dissertation Committee:
Professor David Hirshleifer, Chair
Professor Lu Zheng
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2015

DEDICATION

To my parents,
who have been there for me from day one.
Thank you for all your love and confidence in me.

To my son,
who makes me believe everything is possible.

To my husband,
who has shared my pain and joys, hopes and dreams over the past six years.
Thank you for making everything possible.

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Behavioral Factors in Asset Pricing Models

ABSTRACT OF THE DISSERTATION

A Test of the Role of Behavioral Factors for Asset Pricing

By

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Professor David Hirshleifer, Chair

Theories suggest that both risk and mispricing are associated with commonality in returns, and information associated with this commonality can be used to predict future returns. However, empirically implemented factor pricing models rarely incorporate psychological factors. I propose to augment standard factor models with behavioral factors to capture commonality in mispricing caused by psychological biases. Specifically, I form risk-and-behavioral composite models and examine whether considering jointly both sources of return predictability better explains known return anomalies. I propose two behavioral factors motivated by overconfidence and limited attention, respectively, and show that behavioral factors differ from standard risk factors in several important respects. I find that the risk-and-behavioral composite models outperform both standard models and other recent models and fully explain a number of well-known anomalies, particularly growth-related anomalies. The evidence suggests that behavioral factors play a prominent role in capturing commonality in mispricing and should be incorporated into asset pricing models.

Introduction

In John H. Cochrane's 2011 AFA Presidential Address (Cochrane (2011)), on discussing the zoo of new anomalies, he asks three key questions:

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

This is the agenda we pursue in this paper. We propose two behavioral factors based on firm characteristics that are strong return predictors and are likely to be misvalued by investors because of their own psychological biases. We introduce a parsimonious model that augments standard risk-based factor models with behavioral factors, and examine whether behavioral factors help to explain existing anomalies. We find compelling evidence that, in conjunction with traditional factors, the two behavioral factors subsume many anomalies and provide incremental information about average returns relative to standard risk factors.

There are two alternative theories of return comovement. The traditional theory, derived from economies with rational investors and no frictions, posits that current stock prices closely reflect fundamentals. Hence, comovement in prices arises solely from comovement in fundamental values, with common mispricing playing no role because arbitrageurs readily correct any price inefficiency. In contrast, the alternative theory argues that in economies with irrational investors and limits of arbitrage, comovement in prices can be delinked from comovement in fundamentals.

For example, in the model of Barberis and Shleifer (2003), investors categorize risky assets into different characteristics or "styles", and allocate funds at the style level rather than at individual asset level. If some of the investors using styles are subject to correlated sentiment, when investors move funds from one style to another, their correlated demand could drive return comovement of assets that share the same style, even when these assets' cash flows are uncorrelated. Therefore, shifts in investor sentiment about firm characteristics or styles can cause commonality in mispricing.

Alternatively, in the overconfidence model of Daniel, Hirshleifer, and Subrahmanyam (2001), return comovement can arise when investors misinterpret signals about a fundamental economic factor. In their model, overconfident investors overestimate the precision of signals they receive, and accordingly, overreact to private information about the payoffs of genuine economic factors that influence firms' profits. Thus, sets of stocks (whose cash flows are derived from these factors) move together as information about factors arrives, inducing return comovement due to common mispricing and later correction.

Theories suggest that both risk and mispricing are associated with commonality in returns, and it is important to include behavioral factors in empirical asset pricing models to capture return comovement due to common mispricing.[1] Risk factors describe firms' exposure to systematic risk and the associated risk premium; similarly, behavioral factors describe firms' exposure to common mispricing and later correction. Fama and French (1993) construct risk factors based on firm characteristics proposed to be correlated with risk exposure; similarly, we create behavioral factors based on characteristics that are likely to be misvalued by investors because of their own psychological biases.

Several psychological biases have been shown to affect asset prices, and two pronounced ones are overconfidence and limited attention. Motivated by the overconfidence model of Daniel, Hirshleifer, and Subrahmanyam (2001), Hirshleifer and Jiang (2010) propose a behavioral factor, the underpriced-minus-overpriced (UMO) factor, based on firms' external financing activities.

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

The new issues puzzle is well documented. Though there are possible risk channels,[2] the widely held views are behavioral explanations, such as "market timing" and incitement of misvaluation. The "market timing" hypothesis suggests that managers possess inside information about the true value of their firms and undertake equity (or debt) issuance or repurchase to exploit pre-existing mispricing. Alternatively, managers may manipulate earnings upward to induce overpricing before issuing shares, or manage earnings downward to induce underpricing before a repurchase.[3] In those circumstances, issuing firms would be overpriced and repurchasing firms underpriced. The UMO factor is constructed by going long on firms with debt or equity repurchases and short on firms with IPOs, SEOs, and debt issues over the previous 24 months. They show that UMO indeed captures common mispricing, and loadings on UMO predict the cross-section of stock returns.

We introduce another behavioral factor, the inattention-to-fundamentals (ITF) factor, motivated by investors' limited attention to important information about firm fundamentals. In the fashion of Fama and French (1993), ITF is constructed on a firm characteristic, net operating assets, which is important balance sheet information but is likely to be neglected by investors. According to Hirshleifer et al. (2004), net operating assets measures the relative shortfall between cumulative operating income (the accounting value added) and cumulative free cash flow (the cash value added). When this shortfall is large, the favorable accounting performance receives relatively little affirmation from cash performance. If investors with limited attention focus on accounting profitability but neglect information about cash profitability, then net operating assets measures "the extent to which reporting outcomes provoke over-optimism." Firms with high net operating assets will be overvalued, and firms with low net operating assets will be undervalued.

[2] There are two possible risk explanations for the new issues puzzle. Eckbo, Masulis, and Norli (2000) argue that equity issuance reduces leverage and in turn systematic risk, and thus is followed by lower future returns. Others (Berk, Green, and Naik (1999), Lyandres, Sun, and Zhang (2008), etc.) argue that a lower cost of capital increases planned investment, and firms issue new shares to fund investment. However, Hirshleifer and Jiang (2010) find that the leverage and investment channels do not completely explain the abnormal returns associated with equity and debt financing activities.

[3] See Dong, Hirshleifer, and Teoh (2012), Khan, Kogan, and Serafeim (2012), and Teoh, Welch, and Wong (1998) for recent evidence supporting the behavioral explanations.

ITF is constructed by going long on low net operating assets firms and short on high net operating assets firms, to capture common mispricing due to investors' limited attention to firms' cash flows or fundamentals.[4]

Intuitively, one might ask why there could be a factor associated with net operating assets. One mechanism is that net operating assets is related to economic factors, and innovations in net operating assets are systematic. Owing to limited attention, comovement in net operating assets drives commonality in mispricing and asset returns across firms. Another channel is systematic attention shocks. At a given time, all firms with high (low) net operating assets are overvalued (undervalued) due to limited attention. Shifts in aggregate investor attention, or attention shocks, therefore cause these firms to become more or less misvalued at the same time, generating comovement in returns. Jointly, both systematic innovations in net operating assets and shifts in aggregate investor attention drive return comovement due to common mispricing, in particular among firms with extreme net operating assets. ITF is formed by a long-short strategy on those firms, and therefore captures common mispricing due to investors' limited attention to important information about firm fundamentals. Section 2 provides more discussion about the two channels.

In this paper, we propose to augment the standard factor models (the CAPM, Fama-French, and Carhart models) with behavioral factors to form risk-and-behavioral composite models, with behavioral factors designed to capture common mispricing due to investors' psychological biases. This approach is consistent with theoretical models in which both risk and mispricing proxies predict returns (e.g., Barberis and Shleifer (2003) and Daniel, Hirshleifer, and Subrahmanyam (2001)). We expect the two behavioral factors (UMO and ITF) to be correlated, but to capture

[4]Because net operating assets is related to accruals, which bears potential risk explanations, one argument is that net operating assets may be related to risk. We view limited attention as the primary motivation for net operating assets, given existing counter-evidence for risk or rational explanations for accruals. The original Sloan (1996) study attributes the accruals anomaly to investors' fixation on earnings, which is in line with limited attention hypotheses. Khan (2008) suggests an (unidentified) risk factor explanation, while Hirshleifer, Hou, and Teoh (2012) cast doubts and show that it is the accruals characteristic rather than covariance that predicts returns. Wu, Zhang, and Zhang (2010) propose a growth-based explanation motivated by the q-theory, i.e., firms increase investment (and thus have higher accruals) when discount rates are low. However, Chu (2012) show that accruals is not subsumed by measures of growth, so that investment/growth cannot completely explain the accruals anomaly. Collectively, we argue that mispricing is currently the predominant explanation for the accruals anomaly.

common mispricing in different respects. While UMO is implied by the inside information managers possess about the true value of their firms, ITF is derived from investors' limited attention to important balance sheet information that reveals firm fundamentals. Both UMO and ITF are constructed on firm characteristics related to future growth; thus we further posit that, in particular, UMO and ITF capture common mispricing related to firms' long-term growth prospects.

We empirically assess the incremental contribution of behavioral factors to capturing 21 well-known return anomalies, in particular long-term growth-related anomalies. We compare risk-and-behavioral composite models with standard models (CAPM, FF3 and Carhart) and other recent models, including the profitability factor model of Novy-Marx (2013), the Fama-French five-factor model (FF5) of Fama and French (2014), and the q-factor model of Hou, Xue, and Zhang (2014). We find that across around 20 high-minus-low anomaly portfolios, the average magnitude of alphas is about 0.14% per month under the composite CAPM, FF3 and Carhart models, in contrast to 0.27% under the FF5 model, 0.22% under the profitability model, and 0.20% under the q-factor model. In addition, none of the high-minus-low alphas is significant at the 5% level under the composite CAPM, in contrast to 8 under the FF5 model, 5 under the profitability model, and 5 under the q-factor model. Overall, the risk-and-behavioral composite models outperform standard models and other recent models and fully explain almost all anomalies examined, while showing relatively weak power to the leverage, ROE, and ROA effects. Our evidence suggests that both risk and mispricing are important sources of return comovement and predictability.

There are several other notable findings. First, the Fama-French five-factor model and the q-factor model (with built-in investment factors) do not fully explain several investment-related anomalies, such as the total accruals, investment-to-asset, and inventory changes effects, whereas the risk-and-behavioral composite models do. Second, though neither UMO nor ITF is constructed directly on profitability measures, the composite CAPM performs comparable to the profitability model and the q-factor model (with built-in profitability factors) and fully explains several profitability effects.

If UMO and ITF are indeed behavioral factors that capture common mispricing, then firm loadings on UMO and ITF measure the exposure to systematically mispriced fundamental factors or growth-related characteristics, and therefore should positively predict the cross-section of stock returns. Loadings estimated at firm level are rather imprecise. Instead, we use a portfolio shrinkage method and estimate firms' *conditional* UMO or ITF loadings from annually balanced portfolios sorted by mispricing proxies (external financing or net operating assets, respectively). Using Fama-MacBeth cross-sectional regressions, we show that *conditional* UMO and ITF loadings positively and significantly predict future stock returns, even after controlling for a set of standard return predictors, firm characteristics, and firm loadings on other competing factors.

Next, we show how behavioral factors differ from standard risk factors. If UMO and ITF do account for common mispricing, then firm loadings on UMO and ITF should be fairly unstable over time. A common presumption of many, though not all, studies of risk factors (in tests at the monthly frequency) is that loadings are persistent over periods of 3 to 5 years. However, the same presumption does not apply for behavioral factors. Though a firm characteristic (upon which the behavioral factor is constructed) can be persistently mispriced by the market, for a given firm it will not stay over- or underpriced forever.[5] The stock price fluctuates between mispriced and fairly priced, as mispricing occurs and is corrected. Therefore, unlike standard risk factors, we expect UMO and ITF loadings to be rather unstable over long horizons such as 3 to 5 years, and we find compelling evidence consistent with that hypothesis.

Finally, we conduct a set of robustness tests and provide additional evidence supportive of UMO and ITF as behavioral factors. Specifically, to evaluate ITF as an inattention factor, we examine how ITF factor returns comove with aggregate investors' attention to the stock market. If ITF captures common mispricing due to investors' limited attention, ITF returns measure the extent of mispricing correction. The lower the attention to firm fundamentals, the greater the mispricing, and the larger the ITF returns subsequently. Using two market state variables (sentiment and

[5]This is based on the assumption that mispricing tends to be temporary and reverses out during a period of three to five years.

turnover) as proxies for aggregate investors' attention, we find consistent evidence that ITF returns comove with our attention proxies in expected directions.

On the premise that sophisticated investors help to mitigate or alleviate mispricing, we look at average UMO and ITF loadings across portfolios ranked by investor sophistication proxies, such as institutional ownership and analyst coverage. If UMO and ITF are indeed behavioral factors and loadings on UMO and ITF measure the degree of mispricing, we expect firms with high institutional ownership or analyst coverage to have smaller UMO and ITF loadings (in absolute terms). We find evidence consistent with our hypotheses, particularly among small and medium-sized firms. It seems that sophisticated investors are more efficient in mitigating mispricing for smaller firms, but not much so for larger firms.

This study contributes to a growing literature on asset pricing and return anomalies in several ways. First, we propose a risk-and-behavioral composite model that augments standard risk-based factor models with behavioral factors, and empirically examine the performance of the composite models relative to standard models in explaining existing anomalies. We find that two behavioral factors (UMO and ITF) help to account for around 20 well-known anomalies, especially long-term growth anomalies. Our evidence suggests that investor irrationality can aggregate and affect asset prices systematically, and behavioral factors play a prominent role in capturing return comovement due to common mispricing. Therefore, it is useful to consider both behavior-motivated and risk-based return factors in understanding return comovement and predictability.

Our findings also help to answer the three questions raised by Cochrane's AFA Presidential Address. We show that two factors, formed on external financing and net operating assets, respectively, can subsume many characteristics and provide incremental information about average returns. This suggests that UMO and ITF could serve as a practical benchmark for identifying new anomalies in the future.

Second, our inattention-to-fundamentals (ITF) factor provides a new way of capturing fluctuations in aggregate investor attention. Though the idea is motivated by previous studies, no study has actually constructed an inattention factor and examined its ability in explaining the cross-section of stock returns.

Last, we evaluate how behavioral factors differ from standard risk factors. Following Hirshleifer and Jiang (2010), we show that, unlike the most well known risk factors, firm loadings on behavioral factors are rather unstable over long horizons of 3 to 5 years. In addition, we find that ITF factor returns fluctuate with proxies for aggregate investor attention, justifying it as an inattention factor. We also find that firms with higher investor sophistication have smaller loadings on behavioral factors (in absolute terms), consistent with the notion that sophisticated investors help mitigate mispricing.

1 Motivation for an Inattention-to-Fundamentals Factor

Investors have limited attention and cognitive processing power. Theory predicts that limited investor attention causes systematic errors and affects asset prices (Hirshleifer and Teoh (2003); Peng and Xiong (2006); Hirshleifer, Lim, and Teoh (2011)). Accounting numbers are often associated with firm fundamentals and future asset returns. If investors pay insufficient attention to an accounting number that conveys important information about future cash flows, they will overlook certain aspects of a firm's fundamentals. As a result, all firms sharing similar fundamentals will be misvalued simultaneously, leading to systematic mispricing and return comovement as mispricing occurs and is corrected. In this sense, the inattention-to-fundamentals (ITF) factor is essential to capture return comovement due to investors' limited attention to firms' cash flows or fundamentals.

1.1 Why net operating assets?

To construct the ITF factor, it is useful to look at accounting-based anomalies and find a firm characteristic that both reveals fundamentals and is neglected by investors. We construct

ITF on net operating assets. According to Hirshleifer et al. (2004), a firm's net operating assets measures the cumulative deviation between accounting profitability and cash profitability, or to what extent a firm's balance sheet is "bloated." Good accounting performance is less sustainable than good cash performance. Hence, high net operating assets is an indicator that past accounting performance has been good but is less likely to be sustained in the future. If investors focus on accounting performance but pay insufficient attention to cash performance, they will overestimate the sustainability of accounting performance; therefore, firms with high net operating assets will be overvalued and firms with low net operating assets will be undervalued. Such mispricing can spread systematically and affect all firms with similarly "bloated" balance sheets.

An alternative proxy for investor misperception is accruals, which is also a negative return predictor in line with the limited attention theory. Hirshleifer et al. (2004) show that net operating assets can be decomposed as the sum of cumulative operating accruals and cumulative investments. While accruals provides only a single-period fragment of the degree to which reporting/operating outcomes provoke over-optimism, net operating assets reflects the whole history of flows. Therefore, net operating assets is a more complete proxy for investor misperceptions than the flow measure of accruals. Indeed, Hirshleifer et al. (2004) find that net operating assets has greater power, over a longer horizon, to predict returns than accruals.

Net operating assets is also an accounting number that incorporates many aspects of fundamentals. For example, earnings management, investment activities, and external financing (that is invested in operating assets) all contribute to the growth of net operating assets. Since UMO is formed on external financing activities, ITF to some extent overlaps with UMO, but does not subsume UMO. We expect ITF and UMO to be correlated, but capture common mispricing derived from different aspects. While ITF is derived from investors' limited attention to important balance sheet information that reveals firm fundamentals, UMO is implied by managers' inside information about the true value of their firms.

1.2 Why is net operating assets associated with a factor?

We construct ITF using a long-short strategy on extreme net operating assets firms. On the premise that net operating assets is overvalued by investors with limited attention, ITF captures return comovement through two possible channels.

One channel is systematic shifts in investor attention (or attention shocks). At a given time, all firms with high (low) net operating assets are overvalued (undervalued) because of limited investor attention. Shifts in aggregate investor attention, or attention shocks, therefore cause these firms to become more or less misvalued at the same time, generating return comovement.[6]

Examples of attention shocks include worldwide sports events and holidays. Using Google web search data about sports news, Schmidt (2013) finds that during sporting events, investors reallocate their attention from the stock market toward sports, trading weakens, and stock prices incorporate less firm-specific information. Jacobs and Weber (2012) and Frieder and Subrahmanyam (2004) show that turnover drops during both local and national holidays. Hong and Yu (2009) provide international evidence that aggregate trading activity is lower during summer holiday periods, which they call a "gone fishin" effect. On the other hand, the dot-com bubble may have been a low attention shock, when investors were exuberant about growth opportunities and did not pay attention to cash flows. Publicity about accounting frauds, such as fall of Enron, may serve as high attention shocks, because such events increase accounting concerns and cause investors to look more carefully at accounting information.[7]

The other channel is systematic innovations in net operating assets. If net operating assets is related to fundamental or economic factors, then innovations in net operating assets can be systematic. Owing to limited attention, comovement in net operating assets drives commonality

[6] Formal modeling on this intuition can be provided upon request.

[7] But more generally, many shocks have both fundamental effects and attentional effects. For example, the fall of Enron increases investors' attention to accounting information; on the other hand, it also weakens firms' incentive to manage earnings.

in mispricing and asset returns across firms. There are several possible mechanisms generating systematic innovations in net operating assets.

For example, firms' incentive to manage earnings are correlated. In general, earnings beats/misses are systematic across firms. When the economy is doing well, many firms beat forecasts, and when the economy is falling, many firms miss them. Given the condition of the economy, the incentive to manipulate earnings by accruals is the same for many firms, leading to systematic innovations in net operating assets. Alternatively, at a given time, a group of firms, sharing certain styles or similar sensitivity to technological or economic shocks, may face similarly rich growth opportunities. These firms have a strong need to raise external capital and expand investment, all of which increase net operating assets. In this case, common exposure to growth opportunity leads to systematic innovations in net operating assets across firms.

Collectively, both systematic shifts in investor attention and systematic innovations in net operating assets drive return comovement due to common mispricing, especially among firms with extreme net operating assets. ITF is formed by a long-short strategy on those extreme firms, and therefore captures common mispricing due to investors' limited attention to important information about firm fundamentals, such as net operating assets.

2 Empirical Comparison of Behavioral Factors with Other Factors

2.1 Factor construction

In this section, we compare two behavioral factors (UMO and ITF) with other common factors. UMO is from Hirshleifer and Jiang (2010), constructed by going long on firms with debt or equity repurchases and short on firms with IPOs, SEOs, and debt issuances over the previous 24 months.

ITF is constructed on net operating assets, following Fama and French (1993). Net operating assets is computed using Compustat annual files, following Hirshleifer et al. (2004). In June of each year t, all NYSE, AMEX, and NASDAQ stocks with nonmissing size and net operating assets are assigned to two size groups (small "S" or big "B") based on whether their end-of-June market equity is below or above the NYSE median ME breakpoint. Independently, all stocks are sorted into three net operating assets groups (low "L", middle "M", or high "H") based on their net operating assets for all fiscal years ending in year $t-1$, using the bottom 30%, middle 40%, and top 70% breakpoints for NYSE firms. Six portfolios (SL, SM, SH, BL, BM, and BH) are formed as the intersections. The portfolios are held over the next 12 months (from July of year t to June of year $t+1$) and value-weighted monthly returns of each portfolio are computed. The ITF factor premium is the equal-weighted average return of low net operating assets portfolios (SL and BL) minus the equal-weighted average return of high net operating assets portfolios (SH and BH). That is, $ITF = (SL + BL)/2 - (SH + BH)/2$.

For comparison, we also include standard factors (MKT, SMB, HML, and MOM), the liquidity factor (LIQ) of Pastor and Stambaugh (2003), the profitability factor (PMU) of Novy-Marx (2013), the investment and profitability factors (CMA and RMW) of Fama and French (2014), and the investment and profitability factors (INV and ROE) of Hou, Xue, and Zhang (2014). Monthly returns of MKT, SMB, HML, MOM, CMA, and RMW are downloaded from Kenneth French's website. Monthly series of LIQ and UMO are downloaded from corresponding authors' websites, respectively. PMU is constructed following Novy-Marx (2013), by going long on firms with high gross profit-to-asset ratios and short on firms with low gross profits-to-asset ratios.[8]

INV and ROE are constructed by a triple sort following Hou, Xue, and Zhang (2014). First, all stocks are sorted into two size, three asset growth, and three ROE groups using NYSE breakpoints, resulting in 18 intersection portfolios. Consistent with their paper, size and asset

[8]Here, we use the original PMU factor unadjusted by industry. We did not observe significant improvement on either factor premium or Sharpe ratio for adjusted PMU, HML, and MOM, constructed following Novy-Marx (2013); instead, most factors perform worse after adjustment.

growth are updated annually, while ROE is updated quarterly. INV factor return is the difference between the equal-weighted average returns of six low-asset growth portfolios and six high-asset growth portfolios. Similarly, ROE factor return is the difference between equal-weighted average returns of six high-ROE portfolios and six low-ROE portfolios. In their model, they also include a size factor ME, which is the difference between equal-weighted average returns of nine small-size portfolios and nine large-size portfolios.

2.2 Summary statistics

Table 1 reports summary statistics for factor returns. Panel A describes factor premium, standard deviations, time-series t-statistics, and Sharpe ratios. UMO offers the highest average premium of 91 basis points per month and the highest Sharpe ratio of 0.30. ITF offers an average premium of 32 basis points per month and a Sharpe ratio of 0.20. In comparison with other factors, though INV has a higher Sharpe ratio of 0.23 than ITF (probably due to their high correlation), in Table 3 and Table 4, we show that ITF completely explains INV, but INV does not fully explain ITF, suggesting that ITF carries incremental information to INV.

Panel B reports pairwise correlation between factors. ITF seems to be quite distinct from standard factors, with a correlation of -0.12 with MKT, -0.01 with SMB, -0.19 with HML, and 0.18 with MOM. ITF has moderate correlation with PMU (0.22), INV (0.26), and CMA (0.21). UMO is strongly and positively correlated with HML (0.62), INV (0.56), and CMA (0.62), suggesting that UMO may contain information related to these factors. The correlation between UMO and ITF is only 0.06.[9]

[9]Generally, we expect the correlation between UMO and ITF to be not very high because each is designed to capture a different force of common misvaluation, but a correlation as low as 0.06 is a bit puzzling. In untabulated tests, we check correlation in four subperiods: 1972-1982, 1983-1992, 1993-2002, and 2003-2012. Correlations in the first two subperiods are 0.22 and 0.43; in the latter two subperiods, they are -0.07 and -0.05. Thus, the overall low correlation seems to be attributable to the extremely low (and even negative) correlation after 1993. What happens in the latter periods that drives the distinctive performance of UMO and ITF is still a puzzling question to be further explored.

Panel C describes portfolio weights, returns, and the maximum ex post Sharpe ratios that can be achieved by combining various factors to form the tangency portfolios. Row (1) shows that the maximum Sharpe ratio by combining the Fama-French three factors is 0.22. In row (2), adding MOM and LIQ factors with the Fama-French three factors increases the maximum Sharpe ratio from 0.22 to 0.33; in row (3), adding recent investment and profitability factors (PMU, INV, ROE, RMW, and CMA) increases the maximum Sharpe ratio from 0.22 to 0.41; and in row (4), adding all recent factors (MOM, LIQ, PMU, INV, ROE, RMW, and CMA) increases the maximum Sharpe ratio from 0.22 to 0.44. Row (5) shows that combining the Fama-French three factors with two behavioral factors (UMO and ITF) can increase the maximum Sharpe ratio from 0.22 to 0.47, even higher than in row (3) with all other factors. In row (6), when including all factors, the tangency portfolio places the highest weights on UMO and ITF (21% and 27%). Overall, the evidence suggests that investors can be substantially better off by considering behavioral factors when deriving the optimal tangency portfolio.

2.3 Comparing ITF with accruals and asset growth factors

According to accounting identities, net operating assets relates to accruals and asset growth, and both (especially accruals) are also subject to investors' limited attention. A reasonable question is why we pick net operating assets rather than accruals or asset growth to construct the limited attention factor. Previous studies have shown that the net operating assets anomaly is incremental to, and more persistent than, the accruals and asset growth effect (Hirshleifer et al. (2004); Cao (2011)).[10] To show further evidence, we construct an accruals factor (ACC, as the "CMA" factor in Hirshleifer, Hou, and Teoh (2012)) and an asset growth factor (AG), respectively, and test whether ITF subsumes ACC and AG.

[10] Hirshleifer et al. (2004) decompose net operating assets to cumulative operating accruals plus cumulative investment. Cao (2011) shows that the total asset growth can be decomposed into net operating assets growth and two additional components that have no return predictability, which suggests that the total asset growth anomaly is a noisy manifestation of the net operating assets growth anomaly.

Table 2 reports factor premiums and Sharpe ratios of ACC and AG. Both factors earn lower premiums and lower Sharpe ratios than ITF. The AG factor is rather weak; except for CAPM, standard models like the Fama-French and Carhart models fully explain AG premiums. Adding ITF to the Carhart model further reduces alpha to -0.03% ($t = -0.45$). ACC is stronger than AG, and none of the standard models fully captures ACC premiums. But after adding ITF to the Carhart model, alpha is significantly reduced, from 0.22% ($t = 2.64$) to 0.11% ($t = 1.39$). In contrast, ITF is much stronger than both ACC and AG, earning large and significant alphas under all standard models. Adding AG or ACC to the Carhart model only marginally reduces alphas from 0.39% ($t = 5.20$) to 0.34% ($t = 5.07$) or to 0.35% ($t = 4.97$), respectively. Overall, we see that ITF earns higher premiums and a higher Sharpe ratio than ACC and AG. ITF subsumes ACC and AG, but not vice versa. This suggests that ITF better captures commonality in mispricing than ACC and AG.

2.4 Comparing behavioral factors with other factors

In this section, we examine to what extent standard factors and other recent factors explain the performance of behavioral factors, and to what extent behavioral factors explain other factors. Table 3 shows that the Fama-French three-factor model, the Carhart model, and the liquidity factor do not explain UMO and ITF premiums. Other recent models such as the profitability factor model, the Fama-French five-factor model, and the q-factor model do not explain UMO and ITF either. UMO and ITF earn large and significant alphas under all those models. In a "kitchen sink" model with all standard and recent factors, ITF still earns an alpha of 0.23% per month ($t = 3.29$), and UMO earns an alpha of 0.41% per month ($t = 3.64$). This suggests that UMO and ITF offer abnormally high returns relative to all other factors.

Table 4 shows how behavioral factors explain the performance of other factors. By simply supplementing CAPM with UMO and ITF, most factor premiums are fully explained, except for the liquidity factor (LIQ) and profitability factors (RMW and ROE). For example, the model alpha for HML is driven down from 0.52% ($t = 3.19$) to 0.03% ($t = 0.24$), MOM alpha is reduced from 0.76% ($t = 3.84$) to 0.33% ($t = 1.30$), and INV alpha is down from 0.55% ($t = 5.82$) to 0.08% ($t = 0.92$). Though UMO and ITF do not fully explain RMW and ROE premiums, RMW alpha is significantly reduced from 0.34% ($t = 2.77$) to 0.22% ($t = 1.96$), and ROE alpha is reduced from 0.61% ($t = 4.72$) to 0.36% ($t = 2.10$). On the other hand, behavioral factors show little explanatory power for LIQ and SMB (with merely zero loadings), suggesting that LIQ and SMB may indeed capture some sources of risk.

Collectively, Table 3 and Table 4 show that UMO and ITF are able to fully capture many other common factors, but not vice versa. The evidence suggests that UMO and ITF contain incremental information about return comovement. Therefore, we conjecture that adding UMO and ITF to standard factor models help improve the models' explanatory power.

3 Factor Regressions on Hedged Anomaly Portfolios

Following Fama and French (1993, 1996), we use factor regressions to examine how behavioral factors help to capture various return anomalies. Because UMO is built upon firms' financing activities and ITF is built upon a component of firms' cumulative operating income, both related to firms' long-term growth prospects, we posit that UMO and ITF capture return comovement due to common mispricing on long-term growth. We examine the explanatory power of UMO and ITF for various robust anomalies, in particular growth-related anomalies. We consider 21 anomalies classified into four categories:

Standard anomalies (3): size, book-to-market, and momentum, which are to some extent related to growth and also well-known ingredients in standard factor models.

Investment-related anomalies (9): total accruals (Sloan (1996)), net operating assets (Hirshleifer et al. (2004)), total asset growth (Cooper, Gulen, and Schill (2008)), abnormal capital investment (Titman, Wei, and Xie (2004)), investment-to-asset ratio (Lyandres, Sun, and Zhang

(2008)), investment-to-capital ratio (Polk and Sapienza (2009)), investment growth (Xing (2008)), inventory growth (Belo and Lin (2012)), and inventory changes (Thomas and Zhang (2002)).

Financing-related anomalies (6): external financing (Bradshaw, Richardson, and Sloan (2006)), net composite issuance (Daniel and Titman (2006)), share issuance (Pontiff and Woodgate (2008)), leverage effect (Ferguson and Shockley (2003)), total payout and net payout (Boudoukh et al. (2007)).

Profitability-related anomalies (3): gross profit-to-asset (Novy-Marx (2013)), return-on-equity and return-on-asset effects.[11]

Table 5, Panel A, reports the Pearson correlation coefficients between anomaly characteristics. We confirm that most characteristics are not highly correlated and stand as relatively independent anomalies, except for two groups such as net operating assets/total asset growth/investment-to-asset ratio and leverage/total (net) payout.

3.1 Summary of comparative model performance

To examine the incremental contribution of behavioral factors in explaining various anomalies, we supplement UMO and ITF into standard factor models (CAPM, FF3, and Carhart models) to form risk-and-behavioral composite models. Then, we run factor regressions on test portfolios formed on various anomaly variables. If a model is efficient, the regression alpha of the H-L portfolio should be statistically indistinguishable from zero. We compare the performance of the composite models with both standard models and other recent models, including the profitability factor model of Novy-Marx (2013), the Fama-French five-factor model (FF5) of Fama and French (2014), and the q-factor model of Hou, Xue, and Zhang (2014).[12]

[11] ROE and ROA portfolios are generated by monthly sorts on quarterly updated ROE and ROA. Consistent with the literature, we find that annually updated ROE and ROA do not significantly predict future returns.

[12] In untabulated results, I also check the performance of the liquidity factor model of Pastor and Stambaugh (2003) (adding the traded liquidity factor (LIQ) to the Carhart model), and find that the liquidity factor (LIQ) does not help to explain these anomalies.

Table 5, Panel B, summarizes the comparative performance of the risk-and-behavioral composite models in explaining a number of long-term growth-related anomalies. We report regression alphas of each hedged anomaly portfolio under different factor models. We see that by simply adding two behavioral factors to CAPM, the composite CAPM can fully subsume all investment, financing, and profitability-related anomalies examined here. Comparing the composite CAPM with other recent models, we see that the composite CAPM outperforms the the profitability model, the FF5 model, and the q-factor model in explaining many of these anomalies, such as accruals, investment-to-asset, inventory changes, composite issuance, net share issuance, etc. Adding behavioral factors to FF3 and Carhart models shows similarly strong explanatory power, except for the ROE and ROA effects, because SMB and HML explain the effects in the wrong direction.

At the bottom of Panel B, we report the average alphas of all hedged anomaly portfolios under each factor model, as well as the average absolute alphas ($|\alpha|$). Because both positive and negative alphas indicate meaningful abnormal returns, we particularly look at absolute alphas. We find that average $|\alpha|$ under standard factor models (CAPM, FF3, and Carhart) ranges from 0.32% to 0.58% per month. Among other recent models, the average $|\alpha|$ is 0.27% per month under the FF5 model, 0.22% per month under the profitability model, and 0.20% under the q-factor model. In contrast, the average $|\alpha|$ is only 0.14% under the composite CAPM, 0.15% under the composite FF3, and 0.13% under the composite Carhart model, all substantially smaller than that under standard models and other recent models.

In addition, among the 19 anomalies listed (book-to-market and momentum are excluded because they are tested in two-way sorted portfolios, not in deciles), 8 of them earn significant alphas (at 5% level) under the FF5 model; 5 of them earn significant alphas (at 5% level) under the profitability model and the q-factor models. In contrast, none of them earn significant alphas under the composite CAPM, while 2 of them earn significant alphas (at 5% level) under the composite FF3 and composite Carhart models.

There are several other notable findings. First, the FF5 model and the q-factor model (with built-in investment factors) do not fully explain several investment-related anomalies, such as the total accruals, investment-to-asset and inventory changes effects, whereas the risk-and-behavioral composite models do. Second, though neither UMO nor ITF is constructed directly on profitability measures, the composite CAPM performs comparable to the profitability model and the q-factor model (with built-in profitability factors) and fully explains several profitability effects.

Overall, the risk-and-behavioral composite models dominate other models in explaining almost all anomalies examined here, though showing relatively weak power to the leverage, ROE, and ROA effects.

Next we present detailed factor regression results for each anomaly. For conciseness, we only show statistics for the High-minus-Low (H-L) portfolios. Table 6 reports H-L book-to-market and momentum portfolios in each size quintile, and Table 7 reports H-L portfolios of all other anomalies. Monthly returns of the 25 size and book-to-market portfolios and 25 size and momentum portfolios are downloaded from Kenneth French's website. For all other anomalies except size, composite issuance (IR), ROEQ, and ROAQ, the decile portfolios are formed as follows. In June of each year t, all NYSE, AMEX, and NASDAQ stocks are sorted into deciles based on the anomaly variable measured as of fiscal year ending in year $t-1$ using NYSE breakpoints. Monthly value-weighted portfolio returns are calculated from July of year t to June of year $t+1$, and the portfolios are rebalanced in June of year $t+1$. For size and composite issuance (IR), the decile portfolios are formed similarly each June, but using variables measured at the end of June in year t. ROEQ and ROAQ are computed using quarterly updated Compustat files, and ROEQ and ROAQ portfolios are sorted and rebalanced every month. Anomalies variables are defined in the Appendix.

3.2 Book-to-market, momentum, and size effects

Book-to-market

Table 6, Panel A, reports factor regressions of high-minus-low book-to-market portfolios in each size quintile. Column 2 reports the mean percent excess return (R^e) of each H-L portfolio. On average, the value-minus-growth (or H-L) portfolio return is 1.03% per month ($t = 4.37$) for the smallest size quintile and 0.20% per month ($t = 0.98$) for the largest size quintile. Columns 3, 4, 5 report H-L alphas under the CAPM, the Fama-French three-factor model (FF3), and the Carhart model, none of which fully captures the B/M effect. H-L alphas are large and significantly different from zero in both the small and big quintiles. Columns 6, 7, 8 show that the profitability factor model, the Fama-French five-factor model (FF5), and the q-factor model perform better, but still do not fully explain the B/M effect. Columns 9, 10, 11 show the performance of the risk-and-behavioral composite models. Overall, adding behavioral factors to standard factor models significantly improves explanatory power. In particular, the composite CAPM outperforms all other models and fully captures the value effect, except in the smallest size quintile ($\alpha = 0.38\%$ and $t = 2.10$).

Momentum

Table 6, Panel B, reports factor regressions of high-minus-low momentum portfolios in each size quintile. Column 2 shows that, on average, the H-L portfolio return ranges from 0.66% per month in the biggest size quintile to 1.44% per month in the smallest size quintile, and is statistically significant across all size quintiles. In columns 3, 4 and 5, standard models like the CAPM and FF3 model show no explanatory power at all, and the Carhart model largely explains the momentum effect in medium-sized and big quintiles, but not in the two small quintiles. Columns 6, 7, 8 show that the profitability factor model performs comparably to the Carhart model, owing to the inclusion of the MOM factor; that the FF5 model does not explain the momentum effect at all; and that the q-factor model performs even better than the Carhart model, with H-L alpha significant only for the smallest quintile, probably owing to the high correlation between its ROE factor and the MOM factor ($corr = 0.60$, Table 1). In columns 9, 10, 11, comparing Comp.CAPM and Comp.FF3 with CAPM and FF3, we see that behavioral factors help fully capture the momentum effect among large and medium-sized firms, but not among small firms. Adding UMO and ITF to standard models leads them to outperform the CAPM and FF3 model, but not the Carhart model or q-factor model.

Size or market equity

Table 7, column 2, reports factor regressions on high-minus-low size or market equity portfolios. Banz (1981) documents the size effect and Fama and French (1993) create a size factor, SMB, and use it as a risk factor to explain cross-sectional stock returns. In this section, we test to what extent the size effect can be explained by behavioral factors. Column 2, Panel A, shows the size effect. On average, small firms earn higher returns than big firms, and the big-minus-small or H-L portfolio earns an average return of -0.38% per month, but this is not statistically significant. This is probably because the size effect has become weaker over recent decades. The MKT factor alone in CAPM can reduce H-L alpha to -0.27% with $t = -1.05$. Adding the SMB, HML and MOM factors can further reduce the H-L alphas to 0.11% in the Fama-French model and to -0.01% in the Carhart model. Panels B to G show that the profitability factors (PMU, RMW, and ROE) and behavioral factors (UMO and ITF) have no explanatory power for the size effect, while the investment factor (INV) can partially account for this effect. Overall, the evidence suggests that the two behavioral factors do not explain the size effect. It seems that the SMB factor indeed captures some part of return comovement and predictability that does not overlap with comovement due to common misvaluation.

3.3 Investment-related anomalies

In this section, we examine how behavioral factors help to explain 9 investment-related anomalies, such as total accruals (Sloan (1996)), net operating assets (Hirshleifer et al. (2004)), total asset growth (Cooper, Gulen, and Schill (2008)), abnormal capital investment (Titman, Wei, and Xie (2004)), investment-to-asset ratio (Lyandres, Sun, and Zhang (2008)), investment-to-capital ratio (Polk and Sapienza (2009)), investment growth (Xing (2008)), inventory growth (Belo and Lin (2012)), and inventory changes (Thomas and Zhang (2002)).

Total Accruals

Table 7, Panel A, shows that, on average, high accruals firms earn lower returns than low accruals firms, and the H-L accruals decile earns an average return of -0.29% per month, with $t = -2.13$. The H-L alphas range from -0.36% ($t = -2.56$) under CAPM to -0.25% ($t = -1.63$) under the Carhart model. Panels B, C, and D show that the profitability model, the FF5 model, and the investment model all perform badly, because the profitability factors (PMU, RMW, and ROE) go in the wrong direction in explaining the accruals anomaly. Panels E, F, and G show that behavioral factors completely explain the accruals effect. After adding UMO and ITF to standard models, H-L alphas are reduced to zero. Such strong explanatory power derives mostly from the ITF factor.

Asset Growth (AG)

Table 7, Panel A, shows that firms with higher asset growth, on average, earn lower future returns, and the H-L decile earns an average return of -0.52% per month, which is statistically significant ($t = -2.94$). The CAPM and FF3 models do not explain the asset growth effect, while the Carhart model fully explains it by reducing the H-L alpha to -0.20% ($t = -1.33$). Panels B, C, and D show that the profitability factors (PMU, RMW, and ROE) exhibit no explanatory power at all, while the investment factors (INV and CMA) fully explain the anomaly, which is not surprising as both factors are constructed based on asset growth (or related characteristics). Panels E, F, and G show that behavioral factors completely subsume the asset growth effect. After supplementing UMO and ITF to CAPM, the H-L alpha is close to zero, with $\alpha = 0.08$ ($t = 0.45$). Adding behavioral factors to the Fama-French or Carhart model also significantly improves the models' performance, by reducing H-L alpha to 0.11% and 0.12%, respectively, both of which are insignificant.

Net operating assets (NOA)

Table 7, Panel A, shows that the H-L decile earns a statistically significant average return of -0.42% per month. None of the standard models can fully explain the net operating assets anomaly. The H-L alphas of all standard models are large and significant, ranging from -0.43% ($t = -2.89$) to -0.55% ($t = -3.42$). In Panels B, C, and D, the profitability model and FF5 model do not capture the NOA effect, with H-L alphas equal -0.32% ($t = -2.13$) and -0.49% ($t = -2.59$), respectively. The q-factor model reduce alpha to -0.27% ($t = -1.61$), still large but insignificant. Panels E, F, and G show that behavioral factors can completely subsume the net operating assets anomaly. After adding UMO and ITF to the standard models, H-L alphas are reduced to close to around 0.10%. The superior performance is expected because ITF is constructed on firms' net operating assets characteristics.

Investment-to-asset (IVA)

Table 7, Panel A, confirms that high-IVA firms subsequently earn low average returns, and the H-L portfolio earns an average return of -0.57% ($t = -3.66$). The IVA effect is fairly strong and none of the standard models explains it. Panels B, C, and D show that the profitability factors (PMU, RMW, and ROE) have no explanatory power, or explain it in the wrong direction. The investment factors (INV and CMA) partially capture the effect but do not fully explain it. Panels E, F, and G show that adding behavioral factors to standard models fully captures the IVA effect by reducing the H-L alphas to around -0.10% per month, which is insignificant. Both UMO and ITF contribute to explaining the anomaly,

though ITF shows stronger power. Overall, the IVA effect is robust under both standard models and other recent models, while behavioral factors can fully explain it.

Inventory changes (IvC)

Table 7, Panel A, confirms that high-IvC firms subsequently earn low average returns, and the H-L portfolio earns an average return of -0.44% ($t = -3.16$). None of the standard models captures of IvC effect. Panels B, C, and D show that the investment factors (INV and CMA) help capture the effect, but the profitability factors (PMU, RMW, and ROE) explain it in the wrong direction. Therefore, H-L alphas stay large and significant under the profitability model, the FF5 model, and the q-factor model. Panels E, F, and G show that adding behavioral factors to standard models fully captures the IvC effect by reducing the H-L alphas to close to zero. Overall, the IvC effect is fairly robust under both standard models and other recent models, while behavioral factors fully capture it (mostly by ITF).

ACI, IK, IG, and IvG

We find similar results for abnormal capital investment (ACI), investment-to-capital ratio (IK), investment growth (IG), and inventory growth (IvG). The hedged ACI portfolio earns an excess return of -0.26% ($t = -1.66$), the hedged IG portfolio earns a significant return of -0.46% ($t = -3.12$), the hedged IvG portfolio earns a significant return of -0.46% ($t = -3.30$), while the hedged IK portfolio earns an insignificant return of -0.37% ($t = -1.36$). Adding UMO and ITF to the standard factor models helps to reduce excess returns of all hedged portfolios to close to zero, outperforming or comparable with other recent models.

To summarize, the two behavioral factors show strong explanatory power to the set of investment-related anomalies. Adding behavioral factors to standard factor models help fully subsume all anomalies and reduce H-L alphas toward zero. The risk-and-behavioral composite models outperform other recent models in explaining many of these anomalies. In particular, the FF5 model and q-factor model fail to capture accruals, net operating assets, investment-to-asset, and inventory changes, even with investment factors (INV and CMA) in the models.

3.4 Financing-related anomalies

This section examines how behavioral factors contribute to explaining 6 financing-related anomalies, such as external financing (Bradshaw, Richardson, and Sloan (2006)), net composite issuance (Daniel and Titman (2006)), share issuance (Pontiff and Woodgate (2008)), leverage effect (Ferguson and Shockley (2003)), total payout and net payout (Boudoukh et al. (2007)).

Composite issuance (IR)

Table 7, Panel A, confirms the IR effect, with the H-L IR portfolio earning a highly significant average return of -0.64% per month. None of the standard models captures this anomaly, with H-L alphas ranging from a highly significant -0.40% to -0.86% per month. Panels B, C, and D show that the investment factors (INV and CMA) and profitability factors (PMU, RMW, and ROE) do not fully explain the IR effect, with H-L alpha ranging from a highly significant -0.29% and -0.35% per month. In contrast, the behavioral factors fully subsume this IR effect. Panels E, F, and G show that after incorporating behavioral factors into standard models, the H-L alphas range from -0.13% ($t = -0.95$) to -0.19% ($t = -1.43$). Overall, the behavioral factors fully capture the IR effect, which is not fully accounted for by standard models or other factor models.

EXFIN, NS, O/P, and NO/P

Similar results are found for external financing (EXFIN), net share issuance (NS), total payout (O/P), and net payout (NO/P). The hedged EXFIN portfolio earns an excess return of -0.40% ($t = -1.92$), the hedged NS portfolio earns a negative return of -0.71% ($t = -4.09$), the hedged O/P portfolio earns a positive return of 0.38% ($t = 1.32$), and the hedged NO/P portfolio earns a positive return of 0.66% ($t = 2.99$). All portfolios earn large and significant alphas under standard factor models. Panel B, C, and D show that the profitability model does not capture the NS effect, the FF5 model does not capture the EXFIN and NS effects, and the q-factor model does not explain the NS and NO/P effects. Panel E, F, and G show that behavioral factors help fully subsume all of these anomalies, with small H-L alphas and strictly insignificant. The explanatory power derives from both UMO and ITF.

Leverage (LEV)

Table 7, Panel A, shows that the leverage effect is rather weak. The H-L leverage portfolio earns an average return of 0.37% per month, but is only marginally significant ($t = 1.63$). CAPM does not capture the positive H-L abnormal returns, while the Fama-French model over-explains it, owing to extremely strong and positive loading on HML. Both HML and INV help to capture the leverage effect. UMO shows some explanatory power solely due to its high correlation with HML. However, ITF and profitability factors (PMU and ROE) go in the wrong direction in explaining the effect. Overall, except for HML and INV, none of other factors seems to capture the leverage effect.

To summarize, the two behavioral factors show strong explanatory power on explaining a set of financing-based anomalies. The profitability model, and FF5 model, and the *q*-factor model fail to capture many of these anomalies, while the risk-and-behavioral composite model fully explain all, except for the leverage effect. ITF goes in the wrong direction in explaining the leverage effect, while UMO derives its explanatory power for this effect solely from its correlation with HML. These findings suggest that leverage is indeed a proxy for risk.

3.5 Profitability-related anomalies

This section examines how behavioral factors contribute to explaining 3 profitability-related anomalies, such as gross profit-to-asset (Novy-Marx (2013)), return-on-equity and return-on-asset effects.

Gross profit-to-asset (GP/A)

Novy-Marx (2013) argues that the gross profit-to-asset ratio (GP/A) is the "cleanest" accounting measure of true economic profitability[13] and is a strongly positive return predictor. A

[13]Specifically, Novy-Marx (2013) argues that "Gross profits is the cleanest accounting measure of true economic profitability. The further down the income statement one goes, the more polluted profitability measures become, and the less related they are to true economic profitability." Also, it scales gross profits by book assets, instead of book equity, "because gross profits are an asset level measure of earnings."

profitability factor, PMU, constructed by going long on high GP/A firms and short on low GP/A firms, can account for many well-known return anomalies. In this section, we test whether this GP/A effect can be explained by two behavioral factors.

Table 7, Panel A, shows that high GP/A firms on average earn 0.21% ($t = 1.41$) higher returns than low GP/A firms, which is not statistically significant. H-L alphas from the Fama-French and Carhart models are large and significant, equal to 0.40% ($t = 2.63$) and 0.34% ($t = 2.32$) per month, respectively. Panels B, C, and D show that the profitability model, the FF5 model, and the q-factor model completely explain the GP/A effect, owing to the inclusion of the profitability factors (PMU, CMA, and ROE). Panels E, F, and G show that after adding behavioral factors to the standard models, H-L alphas are reduced to close to zero, ranging from -0.02% ($t = -0.12$) to 0.03% ($t = 0.19$). Both UMO and ITF contribute to capturing the profitability premiums.

Return-on-equity(asset) (ROEQ and ROAQ)

Table 7, Panel A, shows a strong ROEQ (quarterly updated) effect. The H-L hedged ROEQ portfolio earns an excess return of 0.78% per month, highly significantly. None of the standard models captures the ROE effect. Panel B, C, and D show that the profitability model and the q-factor model fully capture the effect, owing to the profitability factors (PMU and ROE). However, the FF5 model fails to explain it, with a large and significant H-L alpha of 0.64% per month ($t = 2.84$). Panel E shows that adding two behavioral factors to CAPM help subsume the ROE effect, with a H-L alpha of 0.47% ($t = 1.59$), still large in magnitude but statistically insignificant. However, in Panels F and G, adding behavioral factors to FF3 and Carhart models yield large and significant alphas again, mostly because SMB and HML explain the effect in the opposite direction. We have similar evidence on ROAQ hedged portfolios.

To summarize, though the behavioral factors are not formed directly on profitability characteristics, they exhibit strong power in explaining several robust profitability effects. By simply adding behavioral factors to CAPM, the composite CAPM performs comparable with the profitability model and the q-factor model in explaining the GP/A, ROE and ROA effects, and outperforms the FF5 model.

4 Stability of Behavioral Factor Loadings

In this section, we examine whether loadings on the two behavioral factors, UMO and ITF, are stable or persistent over different time horizons. This test is important to evaluate whether UMO and ITF are truly behavioral factors. A common presumption for risk factors (such as MKT) in many monthly return tests is that loadings are persistent over periods of 3 to 5 years. As such, when estimating risk factor loadings, the standard method is to run rolling window regressions over the previous 60 months. However, the same presumption may not apply for behavioral factors. Though a firm characteristic (upon which the behavioral factor is constructed) can be persistently mispriced by the market, for any individual firm, it will not stay over- or underpriced forever. The stock price fluctuates between mispriced and fairly priced, as mispricing occurs and is corrected. Therefore, firms' loadings on behavioral factors should not be stable over long horizons, such as 3 to 5 years.

We compare the stability of loadings on behavioral factors with loadings on standard risk factors over a horizon of 3 to 5 years. To test the stability, following Hirshleifer and Jiang (2010), we first estimate individual firms' loadings on a certain factor, rank firms in 100 portfolios based on pre-ranking loadings, estimate each portfolio's post-ranking loading, and then compare patterns of pre-ranking and post-ranking loadings across portfolios. By construction, pre-ranking loadings are monotonically increasing from portfolio 1 to 100. Risk factor loadings are expected to be fairly stable over long horizons; thus post-ranking loadings should be consistent with pre-ranking loadings and monotonically increasing across portfolios. In contrast, behavioral factor loadings are expected to be unstable over time, thus pre-ranking loadings estimated over the past 3 to 5 years should have little power to predict post-ranking loadings.

Specifically, to estimate firm loadings on standard risk factors, we follow the common method of rolling regressions over a 5-year window. First, in each month, firms' loadings on MKT, SMB, and HML are estimated by regressing monthly stock returns over the previous 60 months (at least 36 months required) on the Fama-French three-factor model. Then, in June of each year t, stocks are sorted into 100 portfolios based on their pre-ranking loadings. Each portfolio's pre-ranking loadings are the equal-weighted average of all stocks' pre-ranking loadings within the portfolio. Equal-weighted average returns of each portfolio are calculated from July of year t to June of year $t + 1$, and the portfolios are rebalanced in June of year $t + 1$. This will give a full sample period of monthly returns for each of the 100 portfolios. Finally, portfolios' post-ranking loadings on MKT, SMB, and HML are estimated by regressing the full-sample monthly portfolio returns on the Fama-French three factors. To test the stability of behavioral factors over a horizon of 3 to 5 years, we repeat the procedure. Pre- and post-ranking loadings on UMO (or ITF) are estimated following the same steps, except that returns are regressed on the Fama-French three factors plus the UMO (or ITF) factor.

Figure 1 shows patterns of pre-ranking and post-ranking loadings on behavioral factors, standard risk factors, and other recent factors. We see that post-ranking loadings on standard risk factors (such as MKT, SMB, and HML) are consistent with pre-ranking loadings and monotonically increasing from portfolio 1 to 100, suggesting that risk factors loadings are fairly stable over 3 to 5 years. However, the patterns for behavioral factors are completely different. While pre-ranking loadings on UMO and ITF monotonically increase across portfolios (by construction), post-ranking loadings show no explicit patterns. In fact, the post-ranking loadings are merely flat over 80% of the portfolios. This suggests that UMO and ITF loadings are not persistent over 3 to 5 years, consistent with their being behavioral factors (since we expect misvaluation to correct over time).[14]

[14]Note that for both standard risk factors and behavioral factors, the dispersion of pre-ranking loadings across portfolios is considerably larger than that of post-ranking loadings. Daniel and Titman (1997) find similar results for the HML factor and point out a possible reason that "the preformation factor loading dispersion is due to both measurement error effects and the actual variation in factor-loadings. The post-formation dispersion results almost exclusively from true variation in the loadings."

Figure 1 also shows the stability of other factors, such as the investment and profitability factors (INV and ROE) of Hou, Xue, and Zhang (2014) and the profitability factor (PMU) of Novy-Marx (2013). We see that, over 3 to 5 years, loadings on profitability factors (ROE and PMU) exhibit some degree of persistence (primarily from portfolios with low pre-ranking loadings or less profitable firms). In contrast, loadings on INV show no pattern of persistence at all, and post-ranking loadings are essentially flat across pre-ranking portfolios.

Overall, we find that, unlike standard risk factors, firm loadings on UMO and ITF are rather unstable over a long horizon of 3 to 5 years. This suggests that UMO and ITF are more likely to be behavioral factors capturing systematic mispricing. In untabulated results, we find that UMO and ITF loadings seem to persist over a short horizon of 12 to 18 months. Thus, when estimating firm loadings on UMO and ITF, the common approach for risk factors (rolling regression using monthly returns over the past 3 to 5 years) will not give accurate estimates. Instead, rolling regression using daily or weekly returns over the prior year would work better.

5 Return Predictive Ability of Behavioral Factor Loadings

If UMO and ITF are truly behavioral factors that capture return comovement due to common mispricing, loadings on UMO and ITF measure firms' exposure to systematically underpriced fundamental factors or growth-related characteristics, and should positively predict future returns. In this section, we test how UMO and ITF loadings predict the cross-section of stock returns, using Fama-MacBeth cross-sectional regressions.

Given that behavioral factor loadings are relatively unstable over long horizons of 3 to 5 years, we estimate UMO and ITF loadings using daily stock returns over the previous 12 months (at least 100 trading days required). In untabulated results, we find that firm-level β_{UMO} and β_{ITF} estimated by rolling regressions of daily returns are rather weak in predicting future returns, probably because firm-level loadings are estimated with noise and are relatively imprecise. To mitigate an errors-in-variables problem, following the literature, we estimate *conditional* β_{UMO} and β_{ITF} on portfolio level using a portfolio shrinkage method (see Fama and French (1992), Hou and Moskowitz (2005), and Hirshleifer and Jiang (2010)).

Specifically, to estimate *conditional* β_{ITF}, at the end of June in year t, all stocks are sorted into 100 portfolios based on their end-of-June market value and net operating assets of all fiscal years ending in $t-1$. By sorting stocks based on net operating assets, we create dispersion in the sensitivity to ITF factor. Equal-weighted portfolio returns are calculated from July of year t to June of $t+1$, and portfolios are rebalanced in June of year $t+1$. β_{ITF} of each of the 100 portfolios are estimated by regressing monthly portfolio returns on Fama-French three factors plus the ITF factor, using a rolling window over the previous 60 months (at least 36 months required). Finally, the portfolio β_{ITF} of each month is assigned to all individual stocks belonging to that portfolio in that month, named firms' *conditional* β_{ITF}. *Conditional* β_{UMO} are estimated similarly, except that individual stocks are sorted into 100 portfolios first on market value and then on external financing, and returns are regressed on Fama-French factors plus UMO.

We run Fama-MacBeth cross-sectional regressions of monthly stock returns on *conditional* UMO and ITF loadings (*conditional* β_{UMO} and β_{ITF}) and a set of standard control variables, firm characteristics, and other factor loadings. The standard controls include log(B/M), log(ME), previous 1-month, 1-year, or 3-year returns to control for short-run contrarian, momentum, and long-term reversal. Firm characteristics include accruals, total asset growth (AG), net operating assets (NOA), abnormal capital investment (ACI), investment-to-asset ratio (IVA), net external financing (EXFIN), composite issuance (IR), net share issuance (NS), and gross profit-to-asset ratio (GP/A), all of which are known as strong return predictors. Other factor loadings include *conditional* β_{INV} and β_{ROE} of Hou, Xue, and Zhang (2014), and *conditional* β_{PMU} of Novy-Marx (2013), estimated by the portfolio shrinkage method as well.

Table 8 reports the regression results for *conditional* β_{UMO} in Panel A and *conditional* β_{ITF} in Panel B. Columns (1) and (2) show that both β_{UMO} and β_{ITF} strongly and positively predict stock returns, with or without standard controls. Columns (3) to (11) include several firm characteristics known as strong return predictors, and β_{UMO} and β_{ITF} still retain some predictive ability. For example, the predictability of β_{UMO} is not subsumed by accruals, investments (ACI and IVA), or profitability (GP/A), and β_{ITF} is not subsumed by accruals, investments (ACI), or profitability (GP/A). Columns (12) to (14) run a horse race between *conditional* β_{UMO} or β_{ITF} and other competing factor loadings such as *conditional* β_{INV}, β_{ROE}, and β_{PMU}. The coefficients on β_{UMO} remain significant after controlling for β_{INV} and β_{PMU}, but are insignificant after including β_{ROE}. The coefficients on β_{ITF} stay significant after controlling for all β_{INV}, β_{ROE}, and β_{PMU}. In particular, we see that both β_{UMO} and β_{ITF} drive out the predictive ability of β_{INV}.

Overall, if estimated precisely, firm loadings on UMO and ITF significantly and positively predict future stock returns, and this predictive ability remains robust after controlling for standard return predictors, firm characteristics, and loadings on other recent factors (such as investment and profitability factors). Thus, UMO and ITF truly capture return comovement due to common mispricing.

6 Additional Evidence: Aggregate Attention and Sophisticated Investors

In this section, we conduct a set of robustness tests and provide additional evidence to address whether UMO and ITF are behavioral factors. Specifically, to evaluate ITF as an inattention factor, we show how ITF comoves with aggregate investors' attention to the stock market. Next, on the premise that sophisticated investors help to mitigate or alleviate mispricing, we look at firm loadings on UMO and ITF across portfolios ranked by investor sophistication proxies, such as analyst coverage and institutional ownership.

6.1 Aggregate Investor Attention

Since the inattention-to-fundamentals factor (ITF) captures common mispricing due to investors' limited attention, the ITF premium measures the extent of the mispricing correction. The lower the attention to firm fundamentals, the greater the mispricing and the larger the ITF premium. Thus, we investigate how the ITF premium comoves with investors' attention to the overall stock market. Following the literature, we use two market state variables to proxy for aggregate investor attention. The first attention proxy is investor sentiment, which is broadly defined as "a belief about future cash flows and investment risks that is not justified by the facts at hand" (Baker and Wurgler (2006)). Since stronger sentiment likely leads investors to misvalue or neglect firms' fundamentals, we expect more mispricing during periods in which sentiment is stronger and larger ITF premiums subsequently. The second attention proxy is NYSE turnover. Since active trading likely involves investors' attention to the analysis of asset fundamentals, we expect less mispricing during high turnover periods and smaller ITF premiums subsequently.

Table 9 reports results of time-series regression of annual ITF premiums on each attention proxy. The variables of interest are investor sentiment in the previous year $SENT_{t-1}$, and NYSE turnover in the previous year $TURN_{t-1}$.[15] We are interested in lagged sentiment and turnover because the ITF premium measures price correction *after* high sentiment or turnover increases or reduces mispricing. As control variables, we also include contemporaneous sentiment and turnover, and lagged ITF premium. Consistent with our hypotheses, we find positive coefficients on $SENT_{t-1}$, meaning that the ITF premium is larger after high sentiment periods, when investors are more likely to neglect or misvalue firms' fundamental values, creating greater mispricing and larger price corrections subsequently. In contrast, we observe a negative coefficient on $TURN_{t-1}$, meaning that the ITF premium is smaller after high turnover periods, when actively trading investors are more likely to analyze asset fundamentals, inducing less mispricing and smaller price corrections later. Interestingly, the coefficients on contemporaneous

[15] Annual sentiment index and NYSE turnover data are collected from Professor Jeffrey Wurgler's web page.

$SENT_t$ and $TURN_t$ are of opposite sign. This is because when investors pay greater attention (in a low sentiment or high turnover period), there are more corrections to pre-existing mispricing and thus a larger ITF premium contemporaneously.

For comparison, Table 9 also repeat the regressions on the UMO factor, standard risk factors (MKT, SMB, and HML), and recent investment and profitability factors (RMW, CMA, PMU, INV, and ROE). For standard risk factors, we see largely no association between factor premiums and attention proxies (or in the opposite direction). For UMO and other recent factors premiums, we do not see any sentiment effect, but we observe significant turnover effect for two profitability factors, PMU and ROE. Collectively, we find that the ITF premiums fluctuate with aggregate investor attention to the stock market and firm fundamentals in expected directions, while this is largely not the case for other factors. Though our attention proxies are indirect, the evidence (at least moderately) supports ITF as an inattention factor that captures common mispricing derived from investors' limited attention.

6.2 Analyst Coverage and Institutional Ownership

Next, under the premise that sophisticated investors help to mitigate or alleviate mispricing, we examine how firms with different levels of investor sophistication load differently on the two behavioral factors, UMO and ITF. Following the literature, we use institutional ownership as a direct proxy for sophisticated investors. We also look at analyst coverage, which is correlated with institutional ownership and is often used as a proxy for investor attention. Analyst coverage is the average monthly number of analysts providing current fiscal year earnings estimates, averaged over the previous fiscal year (data provided by I/B/E/S). Institutional ownership is the percentage of shares held by institutions, based on institutions' quarterly 13F filings and averaged over the previous year (data provided by Thomson Reuters).

In Table 10, we examine average UMO and ITF loadings across analyst coverage and institutional ownership portfolios. If UMO and ITF are indeed behavioral factors, then loadings on UMO and ITF (particularly in absolute terms) measure the degree of mispricing; therefore, we expect firms with high analyst coverage or institutional ownership to have smaller (absolute) loadings on UMO and ITF. To test this hypothesis, all sample firms are sorted into 3 size groups (Small, Medium, Large), and within each size group, firms are assigned to 6 groups (0 to 5) based on analyst coverage (AC) or institutional ownership (IO). Firms with no AC or IO are assigned to group 0, and all other firms are placed in groups 1 (low) to 5 (high). We compute average firm loadings on UMO or ITF for each portfolio in each month, which generates a time series of average UMO or ITF loadings for each of the 18 portfolios (using *conditional* β_{UMO} and β_{ITF} from Table 8). Then, within each size group, we examine how average β_{UMO} and β_{ITF} change across AC or IO portfolios.

Table 10 shows the results. Panel A shows average loadings across institutional ownership (IO) portfolios, and in Panel B across analyst coverage (AC) portfolios. For each portfolio, we compute average β_{UMO} and β_{ITF}, as well as average $|\beta_{UMO}|$ and $|\beta_{ITF}|$ in absolute values. Since the absolute magnitude of loadings is more relevant to the degree of mispricing, we pay more attention to absolute loadings.

In Panel A, we see that high IO portfolios have significantly smaller $|\beta_{UMO}|$ and $|\beta_{ITF}|$ than zero or low IO portfolios. This pattern is more pronounced among small and medium-size firms, but seems minimal among large firms. Recall that positive (negative) β_{UMO} and β_{ITF} indicate underpricing (overpricing), and zero loadings indicate fairly priced. Thus, smaller $|\beta_{UMO}|$ and $|\beta_{ITF}|$ in absolute terms means less degree of mispricing. Panel B reports average loadings across AC portfolios. The difference between $|\beta_{UMO}|$ and $|\beta_{ITF}|$ is not as robust as in Panel A, probably because analyst coverage is a less clean proxy for investor sophistication than institutional ownership. Overall, our evidence is consistent with the general notion that sophisticated investors help mitigate mispricing, particularly for small and medium-sized firms.[16]

[16]Interestingly, we also find that small firms on average load positively on UMO and ITF (suggesting underpricing), whereas large firms load negatively (suggesting overpricing).

7 Conclusions

This study supplements the standard asset pricing models with behavioral factors to capture common mispricing caused by psychological biases. Two psychological biases that have been shown to affect asset prices are overconfidence and limited attention. Hirshleifer and Jiang (2010) propose a behavioral factor UMO based on firms' financing activities, motivated by the theory of investor overconfidence. We add to the literature an inattention-to-fundamentals (ITF) factor, derived from the theory of investors' limited attention. Moreover, UMO is built on firms' equity and debt financing activities, and ITF is built on net operating assets, both related to firms' long-term growth prospects. Therefore, we further posit that UMO and ITF capture common mispricing, in particular on long-term growth.

To test the hypotheses, we add behavioral factors (UMO and ITF) to the standard factor models (CAPM, Fama-French, and Carhart models) to form risk-and-behavioral composite models, and examine how well the composite models explain well-known return anomalies, especially long-term growth-related anomalies. This approach is consistent with theoretical models in which both risk and misvaluation proxies predict returns. For comparison, we also test the performance of other recent models, including the profitability factor model of Novy-Marx (2013), the Fama-French five-factor model of Fama and French (2014), and the q-factor model of Hou, Xue, and Zhang (2014). Overall, we find that the risk-and-behavioral composite models outperform standard models and other recent models and fully explain around 20 growth-related anomalies examined, while showing relatively weak power to the leverage, ROE, and ROA effects. Our evidence suggests that both risk and mispricing are important sources of return comovement and predictability.

There are several other notable findings. First, the Fama-French five-factor model and the q-factor model (with built-in investment factors) do not fully explain several investment-related anomalies, such as the total accruals, investment-to-asset, and inventory changes effects, whereas the risk-and-behavioral composite models do. Second, though neither UMO nor ITF is constructed directly on profitability measures, the composite CAPM performs comparable to the profitability model and the q-factor model (with built-in profitability factors) and fully explains several profitability effects.

We conduct additional tests to corroborate whether UMO and ITF are indeed priced behavioral factors that capture return comovement. If UMO and ITF are indeed behavioral factors, then UMO and ITF loadings should be fairly unstable over time. A common presumption for risk factors is that loadings are persistent over periods of 3 to 5 years. However, the same presumption may not apply for behavioral factors. Though a firm characteristic (upon which the behavioral factor is constructed) can be persistently mispriced by the market, for a given firm, it will not stay over- or underpriced forever. The degree of mispricing will fluctuate, with a tendency to correct toward zero. Consistent with our hypotheses, we find that, unlike standard risk factors, UMO and ITF loadings are not stable over long horizons of 3 to 5 years.

If UMO and ITF capture return comovement, then loadings on UMO and ITF measure firms' exposure to systematically underpriced fundamental factors or growth characteristics, and therefore should positively predict the cross-section of stock returns. By both portfolio analysis and firm-level Fama-MacBeth regression, we confirm that *conditional* UMO and ITF loadings (estimated on annually rebalanced portfolios) positively and significantly predict future returns, even after controlling for a set of standard return predictors, firm characteristics, and loadings on competing factors such as the investment and profitability factors.

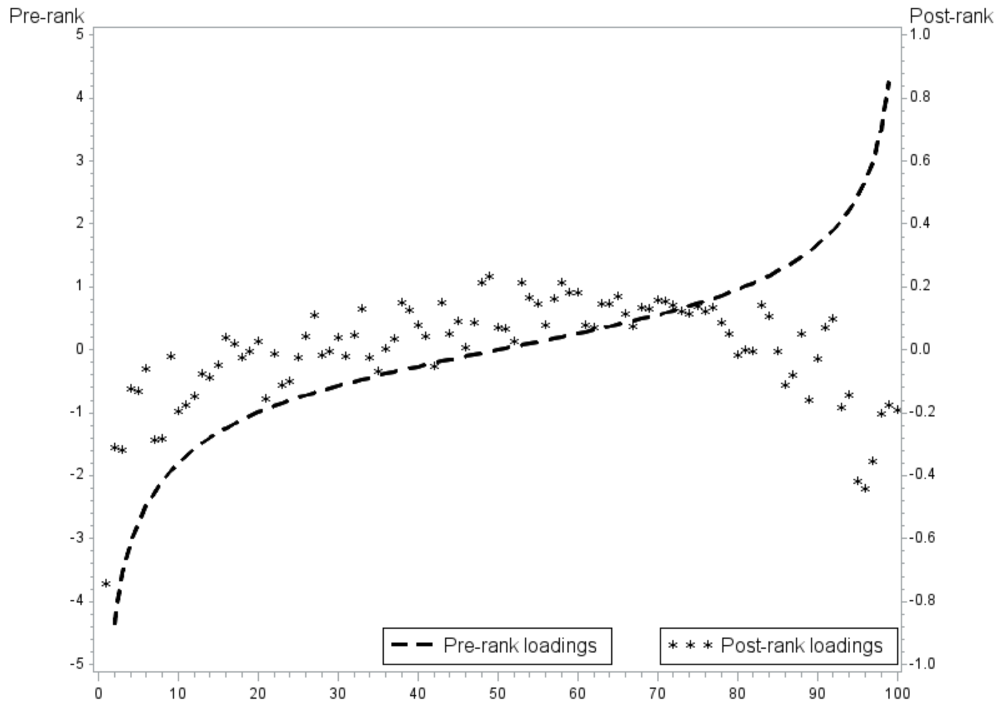
Finally, we conduct a set of robustness tests to provide additional evidence supportive of UMO and ITF as behavioral factors. First, we evaluate ITF as an inattention factor by showing that ITF comoves with aggregate investors' attention to the stock market. Next, on the premise that sophisticated investors help to mitigate or alleviate mispricing, we find that firms with high analyst coverage or institutional ownership have smaller loadings on UMO and ITF in absolute terms (suggesting less degree of mispricing), but only among small and medium-sized firms.

To summarize, in this study, we introduce an inattention-to-fundamentals factor that captures common mispricing due to investors' limited attention. We evaluate how behavioral factors (such as UMO and ITF) differ from standard risk factors on important aspects. More important, we add behavioral factors to standard factor models to form risk-and-behavioral composite models, and find that the composite models can fully explain many robust return anomalies. The broader message of the study is that it is useful to give behavioral-motivated as well as traditional return factors a prominent role in understanding return comovement and predictability. There is strong evidence that behavioral factors are important in capturing common misvaluation and should be incorporated into asset pricing models.

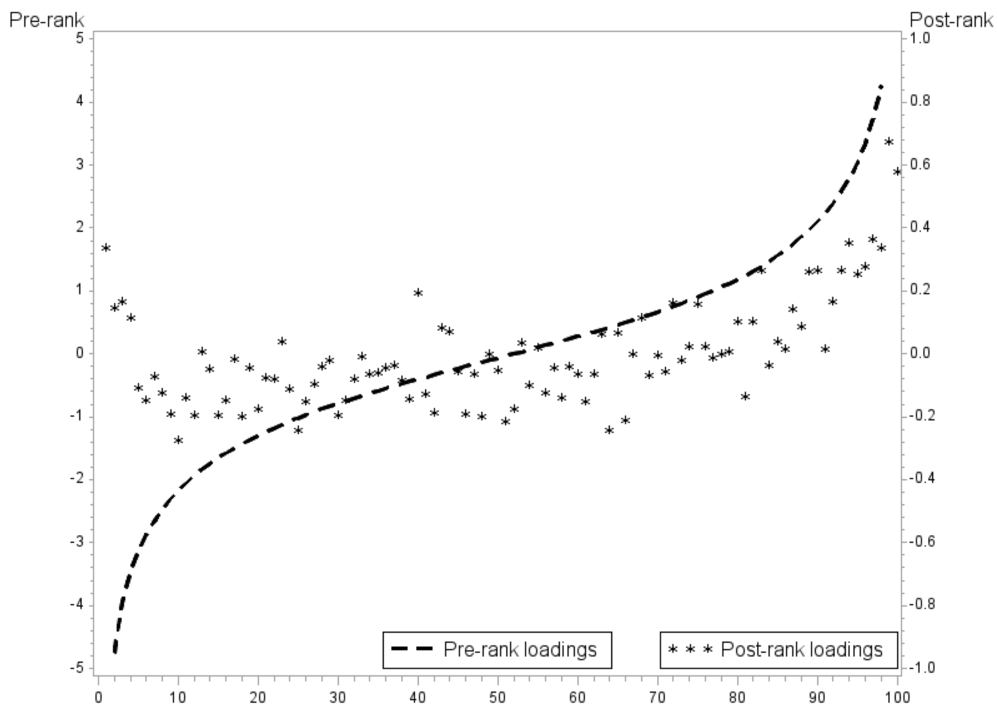
Figure 1: Stability of Factor Loadings over Long Horizons

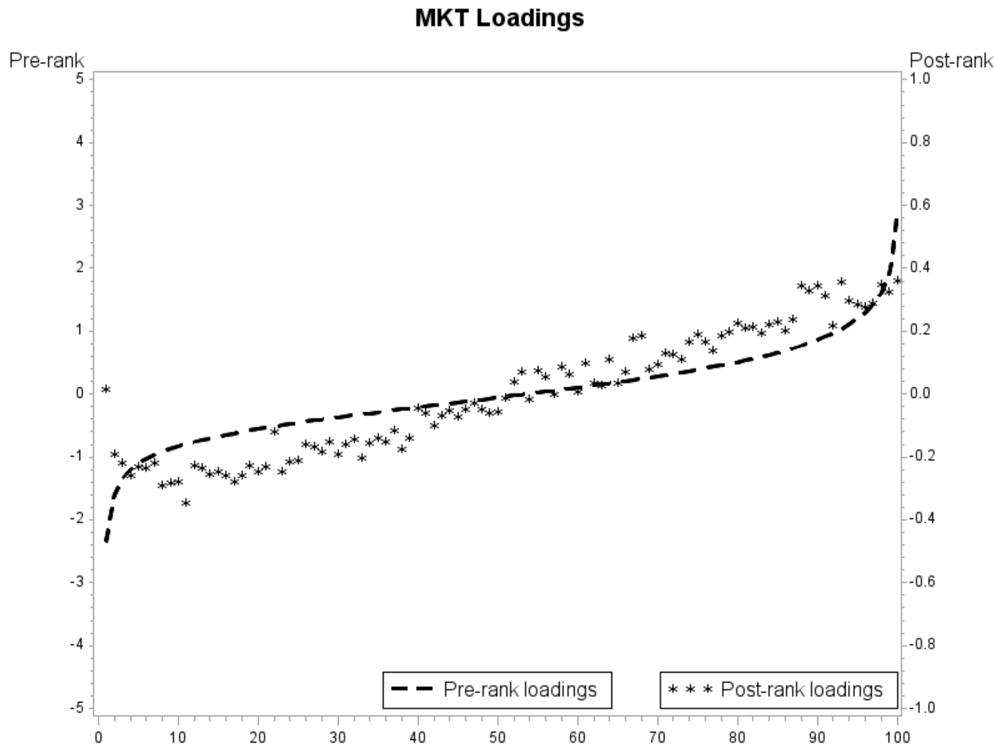
This figure plots pre-ranking and post-ranking loadings of 100 sorted portfolios on behavioral factors (UMO, ITF), standard factors (MKT, SMB, HML), and other recent factors (INV, ROE, PMU). The dashed line represents pre-ranking loadings across 100 portfolios, and the scatter plot represents post-ranking loadings. Pre-ranking loadings on MKT, SMB, and HML are estimated by regressing monthly stocks returns over the previous 60 months (at least 36 months required) on the Fama-French three-factor model. Then, in June of each year t, stocks are sorted into 100 portfolios based on their pre-ranking loadings. Each portfolio's pre-ranking loading is the equal-weighted average of all stocks' pre-ranking loadings within the portfolio. Equal-weighted average returns of each portfolio are calculated from July of year t to June of year $t + 1$, and the portfolios are rebalanced in June of year $t + 1$. This will give a full sample period of monthly returns for each of the 100 portfolios. Finally, portfolios' post-ranking loadings on MKT, SMB and HML are estimated by regressing the full-sample monthly portfolio returns on the Fama-French three-factor model. Pre- and post-ranking loadings on behavioral factors (UMO and ITF) and other recent factors (INV, ROE, and PMU) are estimated similarly, except that returns are regressed on the Fama-French three-factor model plus the target factor. To facilitate comparison across different factors, all pre- and post-ranking loadings are demeaned on a monthly basis. The sample period is from July 1972 to December 2012.

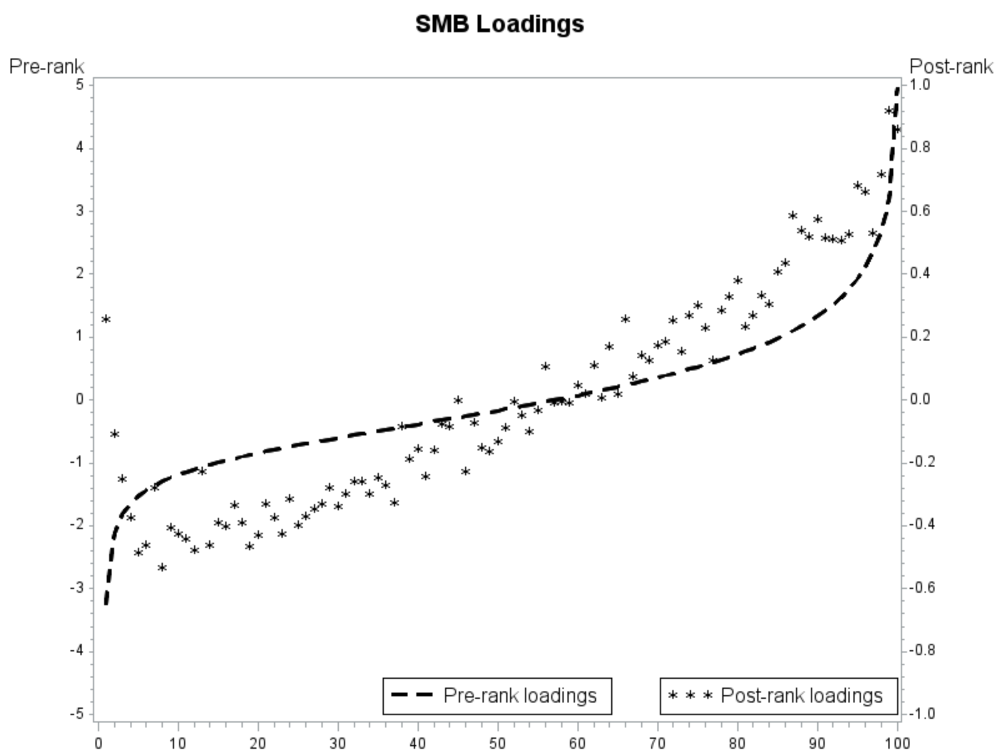
UMO Loadings



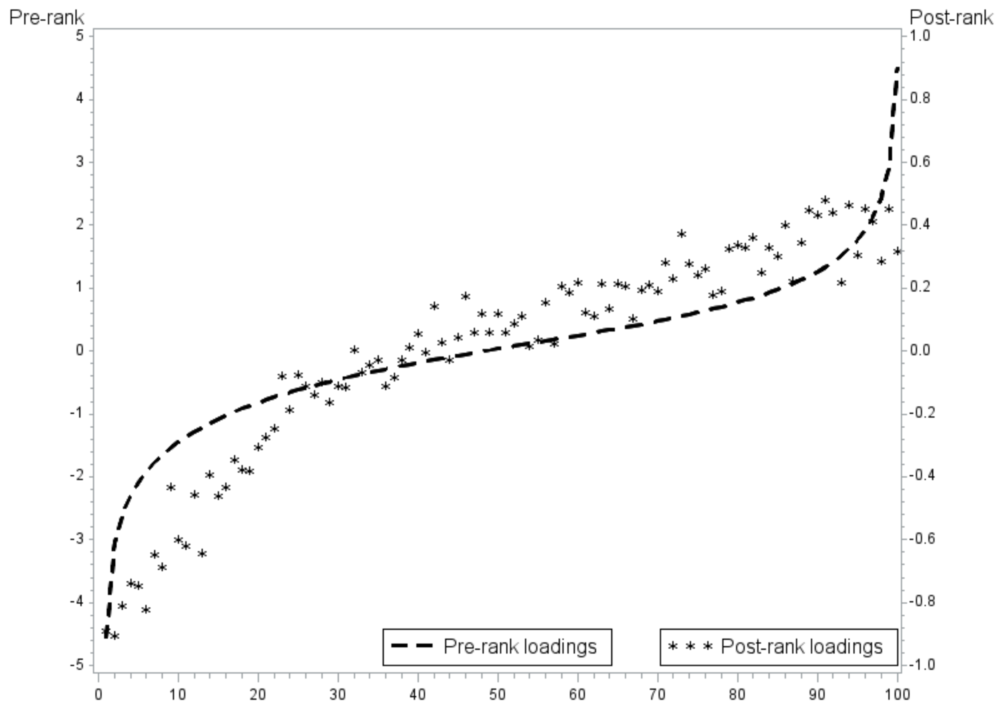
ITF Loadings



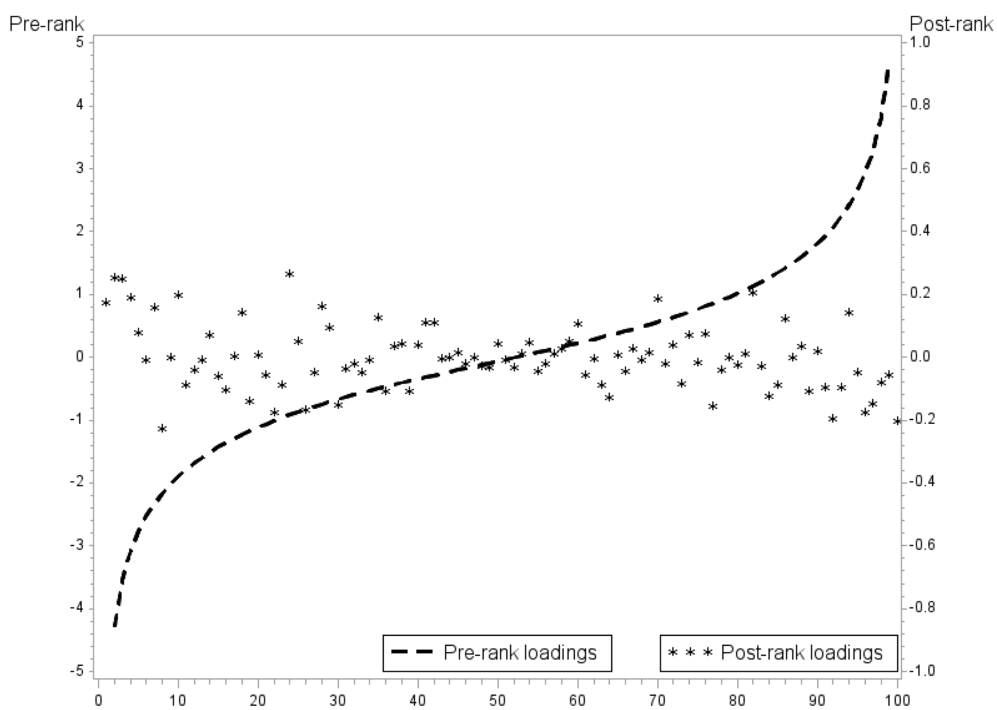

MKT Loadings
Pre-rank
Post-rank
Pre-rank loadings
Post-rank loadings

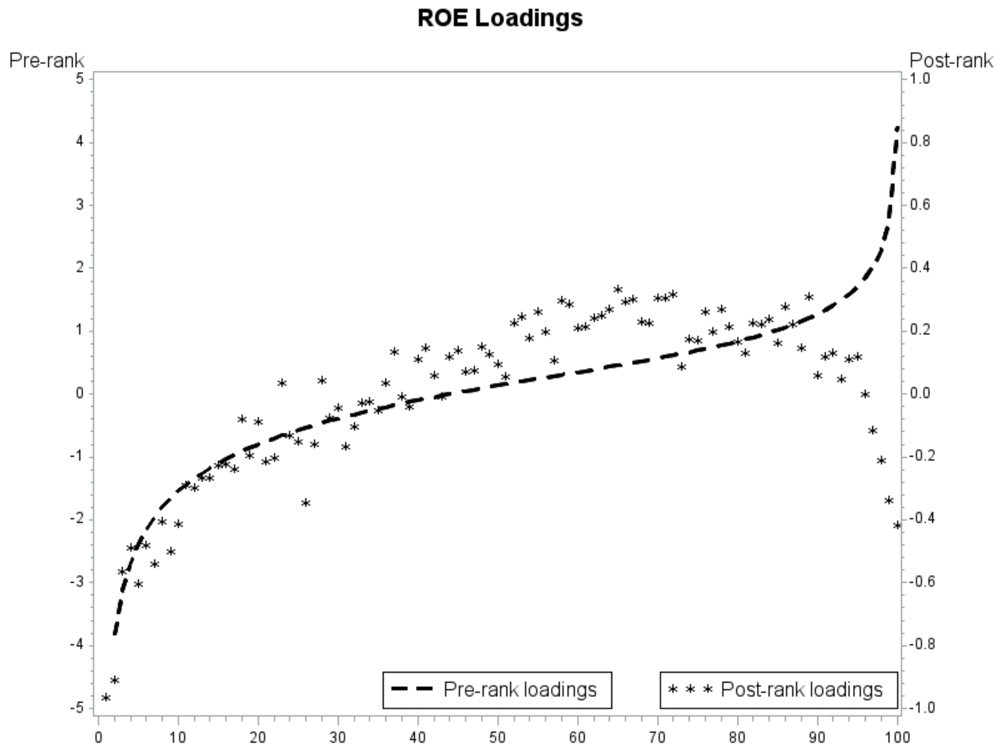

SMB Loadings
Pre-rank
Post-rank
Pre-rank loadings
Post-rank loadings

HML Loadings



INV Loadings




ROE Loadings
Pre-rank
Post-rank
Pre-rank loadings
Post-rank loadings

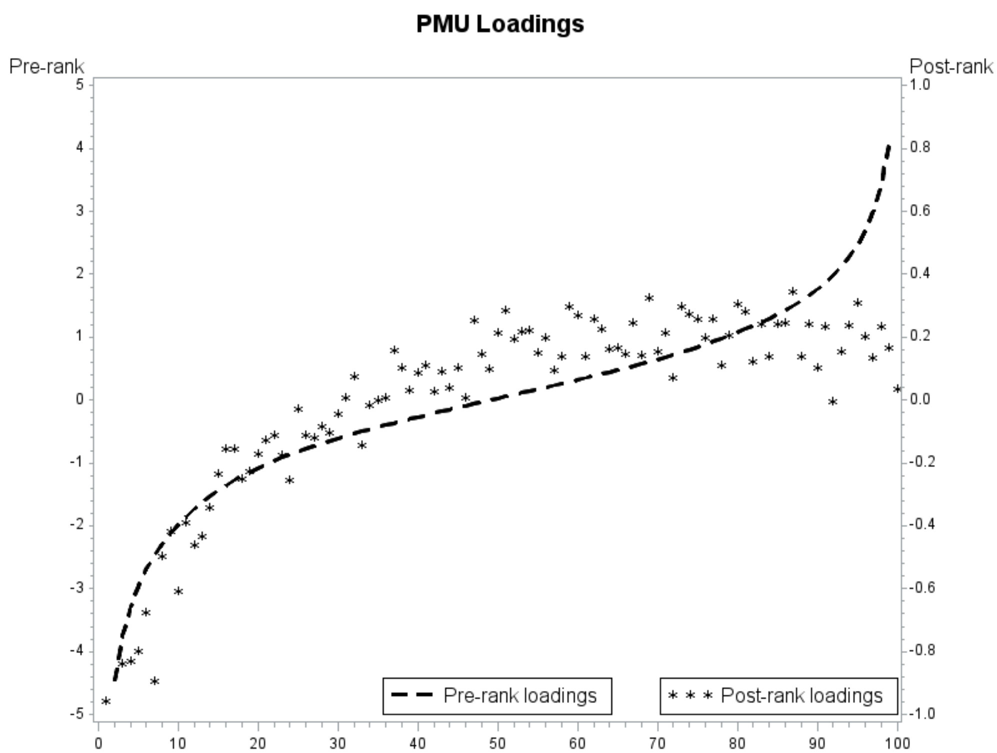

PMU Loadings
Pre-rank
Post-rank
Pre-rank loadings
Post-rank loadings

Table 1: Summary Statistics of Factor Portfolios

Panel A reports summary statistics of standard factors, behavioral factors, and other recent factors. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). PMU is the profitability factor of Novy-Marx (2013). INV and ROE are the investment and profitability factors of Hou, Xue, and Zhang (2014). RMW and CMA are the investment and profitability factors of Fama and French (2014). UMO is the behavioral factor proposed by Hirshleifer and Jiang (2010), and ITF is the inattention factor that we introduce. Monthly returns of MKT, SMB, HML, MOM, RMW, and CMA are from Kenneth French's website. LIQ and UMO premiums are from corresponding authors' websites. Following Novy-Marx (2013), PMU is constructed based on gross profit-to-asset ratios. Following Hou, Xue, and Zhang (2014), INV and ROE are constructed by a triple sort on size, asset growth, and quarterly return on equity. ITF is constructed based on net operating assets. The Sharpe ratio (SR) is the ratio of mean excess return over return standard deviation. Panel B reports Pearson correlations between factor portfolios. Panel C reports summary statistics of ex post tangency portfolios. Portfolio weights are calculated as $(\ell' V^{-1}\mu)^{-1}V^{-1}\mu$, where ℓ is a $k \times 1$ vector of ones, V is the covariance matrix of factor returns, and μ is mean factor return. The sample period is from 1972 to 2012.

Panel A: Factor portfolio premiums

	Premium	Std	t	SR	N. Obs
MKT	0.47	4.66	2.23	0.10	486
SMB	0.19	3.16	1.30	0.06	486
HML	0.42	3.04	3.08	0.14	486
MOM	0.69	4.54	3.37	0.15	486
LIQ	0.46	3.62	2.81	0.13	486
PMU	0.13	2.30	1.23	0.06	486
INV	0.48	2.06	5.11	0.23	486
ROE	0.55	3.10	3.89	0.18	486
RMW	0.29	2.27	2.80	0.13	486
CMA	0.39	1.98	4.33	0.20	486
ITF	0.32	1.57	4.45	0.20	486
UMO	0.91	3.06	6.52	0.30	486

Panel B: Correlation matrix of factor portfolios

	MKT	SMB	HML	MOM	LIQ	PMU	INV	ROE	RMW	CMA	ITF
SMB	0.28										
HML	-0.33	-0.24									
MOM	-0.14	-0.01	-0.15								
LIQ	-0.03	-0.01	0.04	-0.04							
PMU	0.15	0.19	-0.52	0.11	-0.02						
INV	-0.34	-0.21	0.59	0.09	-0.03	-0.30					
ROE	-0.21	-0.35	-0.06	0.60	-0.06	0.24	0.13				
RMW	-0.23	-0.44	0.16	0.09	0.01	0.32	0.10	0.58			
CMA	-0.40	-0.12	0.70	0.02	0.03	-0.39	0.78	-0.03	-0.03		
ITF	-0.12	-0.01	-0.19	0.18	0.02	0.22	0.26	0.07	-0.14	0.21	
UMO	-0.50	-0.20	0.62	0.20	-0.01	-0.14	0.56	0.26	0.31	0.62	0.06

Panel C: Ex post tangency portfolios

	Portfolio Weights												Tangency Portfolios		
	MKT	SMB	HML	MOM	LIQ	PMU	INV	ROE	RMW	CMA	ITF	UMO	Mean	Std	SR
(1)	0.27	0.17	0.56										0.40	1.81	0.22
(2)	0.18	0.09	0.35	0.21	0.16								0.47	1.43	0.33
(3)	0.13	0.12	0.06			0.06	0.17	0.15	0.10	0.21			0.39	0.95	0.41
(4)	0.12	0.10	0.06	0.04	0.08	0.06	0.17	0.10	0.10	0.16			0.40	0.92	0.44
(5)	0.19	0.05	0.03								0.36	0.37	0.56	1.20	0.47
(6)	0.14	0.10	0.02	0.01	0.07	-0.06	0.06	0.07	0.11	-0.02	0.27	0.21	0.50	0.94	0.53

Table 2: Comparing ITF with Asset Growth and Accruals Factors

This table compares ITF with two alternative inattention factors formed on accruals (ACC) and asset growth (AG), respectively. ACC is from Hirshleifer, Hou, and Teoh (2012), constructed by going long on low-accruals firms and short on high-accruals firms. AG is formed by going long on low-asset growth firms and short on high-asset growth firms. The table reports monthly mean factor premiums, Sharpe ratios (SR), and the parameter estimates from time-series factor regressions. The sample period spans from July 1963 to December 2012. Newey-West corrected t-statistics are shown in parentheses.

	Premium	SR	α	MKT	SMB	HML	MOM	ITF	AG	ACC	Adj-R^2
AG	0.25	0.12	0.32***	-0.15***							11.36%
	(3.05)		(3.73)	(-5.02)							
			0.10	-0.06***	0.01	0.46***					49.05%
			(1.40)	(-3.08)	(0.35)	(14.16)					
			0.11	-0.07***	0.01	0.45***	-0.01				49.00%
			(1.41)	(-3.56)	(0.34)	(12.93)	(-0.38)				
			-0.03	-0.04***	0.01	0.49***	-0.03	0.37***			56.62%
			(-0.45)	(-2.77)	(0.45)	(18.74)	(-0.91)	(5.18)			
ACC	0.25	0.14	0.27***	-0.04*							1.06%
	(3.30)		(3.45)	(-1.74)							
			0.25***	-0.01	-0.07*	0.07					3.77%
			(3.29)	(-0.68)	(-1.80)	(1.38)					
			0.22***	-0.01	-0.07*	0.08	0.03				4.16%
			(2.64)	(-0.41)	(-1.93)	(1.42)	(0.72)				
			0.11	0.01	-0.07**	0.11**	0.02	0.27***			8.79%
			(1.39)	(0.41)	(-2.10)	(2.15)	(0.47)	(3.52)			
ITF	0.35	0.23	0.37***	-0.05**							2.01%
	(5.61)		(5.57)	(-2.17)							
			0.43***	-0.07***	-0.01	-0.12***					6.62%
			(6.26)	(-3.18)	(-0.31)	(-3.23)					
			0.39***	-0.06***	-0.01	-0.11***	0.05*				8.07%
			(5.20)	(-3.25)	(-0.35)	(-2.89)	(1.70)				
			0.34***	-0.03**	-0.01	-0.28***	0.05*		0.38***		21.80%
			(5.07)	(-2.01)	(-0.62)	(-5.63)	(1.95)		(5.22)		
			0.35***	-0.06***	0.00	-0.12***	0.04			0.18***	12.51%
			(4.97)	(-3.31)	(0.13)	(-3.69)	(1.49)			(3.38)	

Table 3: Factor Regressions of Behavioral Factors on Other Factors

This table reports time-series regressions of behavioral factor premiums (ITF and UMO) on (1) the Fama-French three-factor model, (2) the Carhart model plus the LIQ factor of Pastor and Stambaugh (2003), (3) the profitability-based model of Novy-Marx (2013), (4) the Fama-French five-factor model of Fama and French (2014), (5) the q-factor model of Hou, Xue, and Zhang (2014), and (6) the "kitchen sink" model with all factors. The sample period is from 1972 to 2012. Newey-West corrected t-statistics are shown in parentheses.

		α	MKT	SMB	HML	MOM	LIQ	PMU	RMW	CMA	ME	INV	ROE	Adj-R^2
ITF	(1)	0.41***	-0.07***	-0.01	-0.13***									6.61%
		(5.10)	(-2.82)	(-0.26)	(-3.28)									
	(2)	0.36***	-0.06***	-0.01	-0.12***	0.04	0.01							7.67%
		(4.25)	(-2.89)	(-0.27)	(-3.02)	(1.40)	(0.40)							
	(3)	0.33***	-0.06***		-0.08	0.04		0.10*						9.50%
		(3.83)	(-3.19)		(-1.49)	(1.35)		(1.88)						
	(4)	0.30***	-0.02	-0.07***	-0.34***				-0.06*	0.51***				28.38%
		(4.33)	(-1.17)	(-2.84)	(-8.51)				(-1.80)	(8.04)				
	(5)	0.24***	-0.00								-0.05	0.19**	0.00	6.64%
		(2.62)	(-0.13)								(-1.01)	(2.28)	(0.03)	
	(6)	0.23***	-0.03*	-0.10***	-0.23***	0.02	0.02	0.25***	-0.21***	0.28***		0.24***	-0.01	37.43%
		(3.29)	(-1.65)	(-4.38)	(-4.93)	(1.12)	(0.87)	(4.85)	(-3.75)	(4.50)		(3.39)	(-0.30)	
UMO	(1)	0.79***	-0.22***	0.01	0.51***									48.15%
		(7.86)	(-6.40)	(0.22)	(7.27)									
	(2)	0.65***	-0.19***	0.02	0.57***	0.16***	-0.02							53.64%
		(6.80)	(-6.41)	(0.30)	(9.05)	(3.36)	(-0.82)							
	(3)	0.55***	-0.18***		0.68***	0.16***		0.30***						57.24%
		(5.26)	(-7.23)		(8.97)	(3.25)		(4.36)						
	(4)	0.54***	-0.15***	0.07	0.26***				0.34***	0.55***				56.57%
		(4.29)	(-4.29)	(1.29)	(3.12)				(2.89)	(4.18)				
	(5)	0.58***	-0.23***								0.11**	0.64***	0.17*	44.92%
		(5.16)	(-5.45)								(2.15)	(5.65)	(1.78)	
	(6)	0.41***	-0.14***	0.05	0.44***	0.11***	-0.02	0.20***	0.15	0.40***		0.07	0.06	61.29%
		(3.64)	(-4.15)	(1.15)	(6.75)	(2.96)	(-0.73)	(2.91)	(1.16)	(3.34)		(0.71)	(0.59)	

Table 4: Factor Regressions of Other Factors on Behavioral Factors

This table reports time-series regressions of other recent factor premiums on CAPM and CAPM plus behavioral factors (UMO and ITF), respectively. SMB, HML, and MOM are size, value, and momentum factors. LIQ is the liquidity factor of Pastor and Stambaugh (2003). PMU is the profitability factor of Novy-Marx (2013). RMW and CMA are the investment and profitability factors of Fama and French (2014). INV and ROE are the investment and profitability factors of Hou, Xue, and Zhang (2014). The sample period is from 1972 to 2012. Newey-West corrected t-statistics are shown in parentheses.

	Premium	α	MKT	Adj-R^2	α	MKT	UMO	ITF	Adj-R^2
SMB	0.19	0.10	0.19***	7.43%	0.17	0.16***	-0.09	0.04	7.61%
	(1.30)	(0.72)	(5.52)		(1.19)	(3.72)	(-1.30)	(0.24)	
HML	0.42***	0.52***	-0.21***	10.44%	0.03	-0.03	0.61***	-0.45***	43.37%
	(3.08)	(3.19)	(-3.63)		(0.24)	(-0.71)	(9.16)	(-3.79)	
MOM	0.69***	0.76***	-0.14	1.82%	0.33	-0.04	0.25	0.48	6.35%
	(3.37)	(3.84)	(-1.48)		(1.30)	(-0.38)	(1.49)	(1.52)	
LIQ	0.46***	0.47***	-0.03	-0.09%	0.50***	-0.04	-0.04	0.03	-0.42%
	(2.81)	(3.08)	(-0.50)		(2.95)	(-0.60)	(-0.51)	(0.19)	
PMU	0.13	0.09	0.07*	1.95%	0.05	0.06*	-0.07	0.35***	7.89%
	(1.23)	(0.78)	(1.96)		(0.48)	(1.83)	(-1.34)	(3.17)	
RMW	0.29***	0.34***	-0.11***	4.96%	0.22*	-0.06*	0.19**	-0.25*	12.52%
	(2.80)	(2.77)	(-2.78)		(1.96)	(-1.74)	(2.47)	(-1.65)	
CMA	0.39***	0.47***	-0.17***	15.91%	0.01	-0.04	0.37***	0.21***	42.28%
	(4.33)	(4.77)	(-5.15)		(0.13)	(-1.52)	(8.12)	(3.06)	
INV	0.48***	0.55***	-0.15***	11.42%	0.08	-0.02	0.35***	0.29***	36.31%
	(5.11)	(5.82)	(-4.52)		(0.92)	(-0.76)	(5.86)	(2.66)	
ROE	0.55***	0.61***	-0.14**	4.24%	0.36**	-0.07	0.22	0.08	7.42%
	(3.89)	(4.72)	(-2.49)		(2.10)	(-1.05)	(1.48)	(0.42)	

Table 5: Comparative Performance of the Risk-and-Behavioral Composite Models

Panel A reports the Pearson correlation coefficients between anomaly characteristics. The correlations are measured on firm-year level. Panel B summarizes the regression alphas of each high-minus-low anomaly portfolio under different factor models. For each factor model, we also compute the average (absolute) magnitude of alphas across all H-L anomaly portfolios, as well as the number of significant alphas at 10% or 5% level, respectively. The sample period is from 1972 to 2012.

Panel A: Correlation matrix between anomaly characteristics

	Accruals	AG	NOA	IVA	ACI	IK	IG	IvG	IvC	IR	EXFIN	NS	O/P	NO/P	LEV
Asset Growth (AG)	0.13														
Net operating assets (NOA)	0.21	0.77													
Investment-to-asset (IVA)	0.24	0.63	0.63												
Abnormal capital invest.(ACI)	0.00	0.00	0.00	0.00											
Investment-to-capital (IK)	0.01	0.05	0.04	0.08	0.01										
Investment growth (IG)	0.00	0.07	0.09	0.13	0.01	0.24									
Inventory growth (IvG)	0.07	0.03	0.02	0.07	0.00	0.01	0.01								
Inventory changes (IvC)	0.49	0.24	0.25	0.41	0.00	0.02	0.01	0.03							
Composite issuance (IR)	0.00	0.09	0.04	0.07	0.01	0.02	0.01	0.00	0.01						
External financing (EXFIN)	0.07	0.37	0.20	0.25	0.01	0.03	0.03	0.03	0.13	0.26					
Net share issuance (NS)	0.06	0.29	0.22	0.23	0.01	0.03	0.03	0.02	0.07	0.29	0.35				
Total payout (O/P)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.07	-0.01	-0.01			
Net payout (NO/P)	-0.01	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	-0.05	-0.04	-0.04	0.69		
Leverage (LEV)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03	0.00	0.00	0.63	0.40	
Gross profit-to-asset (GP/A)	0.04	-0.01	0.02	-0.01	-0.01	0.00	-0.01	-0.01	0.05	-0.11	-0.19	-0.08	-0.01	0.00	0.00

Panel B: Comparative model performance: High-minus-low alphas

List of Anomalies	CAPM	FF3	Carhart	Profit. model	FF5	q-factor model	Comp. CAPM	Comp. FF3	Comp. Carhart
Size	-0.27	0.11	-0.01	-0.23	0.03	-0.08	-0.22	0.04	-0.00
Accruals	-0.36**	-0.31**	-0.25	-0.29*	-0.31**	-0.33**	-0.06	-0.10	-0.08
Asset growth (AG)	-0.62***	-0.28**	-0.20	-0.22	0.00	0.03	0.08	0.11	0.12
Net operating assets (NOA)	-0.43***	-0.55***	-0.43***	-0.32**	-0.49***	-0.27	0.10	0.09	0.11
Investment-to-asset (IVA)	-0.65***	-0.48***	-0.40***	-0.40**	-0.36***	-0.27*	-0.14	-0.10	-0.08
Abnormal capital invest.(ACI)	-0.26	-0.26	-0.14	-0.13	-0.22	-0.08	-0.27	-0.22	-0.16
Investment-to-capital (IK)	-0.63**	-0.11	0.08	0.00	0.29*	0.29	0.07	0.07	0.13
Investment growth (IG)	-0.52***	-0.31**	-0.21	-0.19	-0.08	-0.05	0.00	0.03	0.05
Inventory growth (IvG)	-0.54***	-0.36***	-0.22	-0.24	-0.20*	-0.12	-0.03	-0.02	0.02
Inventory changes (IvC)	-0.50***	-0.37***	-0.28*	-0.37**	-0.36***	-0.28**	-0.08	-0.06	-0.03
Composite issuance (IR)	-0.86***	-0.61***	-0.40***	-0.31**	-0.29**	-0.35**	-0.15	-0.19	-0.13
External financing (EXFIN)	-0.62***	-0.67***	-0.48***	-0.18	-0.30*	-0.25	0.12	0.01	0.05
Net share issuance (NS)	-0.81***	-0.69***	-0.51***	-0.32**	-0.26*	-0.31**	-0.21	-0.24	-0.20
Total payout (O/P)	0.68***	0.27*	0.16	0.03	-0.01	0.17	-0.13	-0.08	-0.10
Net payout (NO/P)	0.86***	0.55***	0.39***	0.20	0.20	0.31**	0.02	0.06	0.02
Leverage (LEV)	0.41*	-0.26*	-0.17	-0.01	-0.32**	-0.06	-0.12	-0.22	-0.18
Gross profit-to-asset (GP/A)	0.22	0.40***	0.34**	0.00	0.05	0.09	-0.02	0.03	0.03
Return on equity (ROEQ)	0.94***	1.22***	0.71***	0.40	0.64***	0.14	0.47	0.63***	0.46**
Return on asset (ROAQ)	0.81***	1.15***	0.67***	0.36*	0.68***	0.23	0.46	0.62***	0.46**
Average α	-0.17	-0.08	-0.07	-0.12	-0.07	-0.06	-0.01	0.02	0.03
Average $\|\alpha\|$	0.58	0.47	0.32	0.22	0.27	0.20	0.14	0.15	0.13
Number of significant α (10%)	16	16	10	7	12	6	0	2	2
Number of significant α (5%)	15	14	9	5	8	5	0	2	2

Table 6: Factor Regressions of High-Minus-Low Book-to-Market and Momentum Portfolios

This table reports time-series factor regressions of the high-minus-low book-to-market (Panel A) and momentum (Panel B) portfolios within each size quintile. Monthly returns of 25 size and book-to-market portfolios and 25 size and momentum portfolios are downloaded from Kenneth French's website. Column 1 shows size quintiles. Column 2 reports mean excess returns (R^e) of the H-L portfolios. Columns 3 to 5 report alphas under standard factor models (CAPM, FF3, and Carhart models). Columns 6 to 8 report alphas under other recent models, such as the profitability factor model of Novy-Marx (2013), the Fama-French five-factor model (FF5) of Fama and French (2014), and the q-factor model of Hou, Xue, and Zhang (2014). The last three columns report alphas under risk-and-behavioral composite models, formed by adding standard models with behavioral factors (UMO and ITF). All portfolio returns are value-weighted. The sample period is 1972 to 2012. Newey-West corrected t-statistics are shown in parentheses.

	R^e	CAPM	FF3	Carhart	Profit. model	FF5	q-factor model	Comp. CAPM	Comp. FF3	Comp. Carhart
					Panel A: H-L book-to-market portfolios					
Small	1.03***	1.19***	0.70***	0.69***	0.50***	0.48***	0.70***	0.38**	0.40***	0.41***
	(4.37)	(5.20)	(5.27)	(5.66)	(3.73)	(4.16)	(3.17)	(2.10)	(3.29)	(3.55)
2	0.56**	0.71***	0.12	0.07	-0.01	0.03	0.25	-0.01	-0.03	-0.04
	(2.49)	(3.18)	(1.25)	(0.71)	(-0.06)	(0.33)	(1.25)	(-0.05)	(-0.34)	(-0.46)
3	0.60**	0.75***	0.15	0.15	0.05	-0.04	0.26	0.09	0.08	0.08
	(2.54)	(3.29)	(1.19)	(1.12)	(0.43)	(-0.36)	(1.38)	(0.41)	(0.62)	(0.62)
4	0.26	0.37	-0.22**	-0.17*	-0.23**	-0.30***	-0.08	-0.22	-0.22**	-0.20*
	(1.19)	(1.63)	(-2.14)	(-1.71)	(-1.99)	(-2.59)	(-0.36)	(-1.14)	(-2.15)	(-1.92)
Big	0.20	0.26	-0.33**	-0.31**	-0.16	-0.18	-0.09	-0.04	-0.11	-0.12
	(0.98)	(1.25)	(-2.54)	(-2.53)	(-1.30)	(-1.63)	(-0.49)	(-0.23)	(-0.86)	(-0.94)
					Panel B: H-L momentum portfolios					
Small	1.44***	1.53***	1.70***	0.76***	0.72***	1.39***	0.79***	0.91***	0.95***	0.62***
	(5.35)	(6.26)	(7.08)	(5.73)	(5.30)	(4.27)	(3.02)	(3.13)	(3.67)	(4.79)
2	1.08***	1.16***	1.36***	0.34**	0.32**	1.09***	0.45	0.63**	0.66**	0.28**
	(3.88)	(4.69)	(5.79)	(2.39)	(2.24)	(3.39)	(1.63)	(2.11)	(2.43)	(2.09)
3	0.91***	0.97***	1.15***	0.05	0.02	0.84**	0.16	0.36	0.37	-0.03
	(3.36)	(3.82)	(4.62)	(0.42)	(0.19)	(2.37)	(0.58)	(1.04)	(1.14)	(-0.25)
4	0.79***	0.90***	1.09***	-0.10	-0.16	0.76**	0.01	0.13	0.14	-0.29**
	(2.73)	(3.27)	(4.11)	(-0.82)	(-1.30)	(2.00)	(0.04)	(0.37)	(0.43)	(-2.02)
Big	0.66**	0.77***	0.96***	-0.20	-0.16	0.72**	0.03	0.33	0.34	-0.10
	(2.24)	(2.66)	(3.46)	(-1.11)	(-0.90)	(1.99)	(0.08)	(0.91)	(0.99)	(-0.61)

Table 7: Factor Regressions of Hedged Portfolios on Anomaly Variables

This table reports results of time-series factor regressions on high-minus-low anomaly portfolios. In June of year t, size and composite issuance (IR) are measured at the end of June in year t; accruals, asset growth (AG), net operating assets (NOA), abnormal capital investment (ACI), investment-to-asset ratio (IVA), investment-to-capital ratio (IK), investment growth (IG), inventory growth (IvG), inventory changes (IvC), net external financing (EXFIN), net share issuance (NS), payout yield (O/P), net payout yield (NO/P), leverage (LEV), and gross profit-to-asset (GP/A) are measured as of all fiscal years ending in year $t-1$. Then, firms are sorted to decile portfolios using NYSE breakpoints, based on each anomaly variable. Monthly value-weighted portfolio returns are calculated from July of year t to June of year $t+1$, and portfolios are rebalanced in June of year $t+1$. High-minus-low portfolio returns are the difference between the top and bottom portfolios. ROEQ and ROAQ are return-on-equity and return-on-asset using quarterly updated Compustat files, respectively. ROEQ and ROAQ portfolios are rebalanced every month. Panel A reports time-series mean excess returns of H-L portfolios and regression alphas under CAPM, Fama-French three factor model (FF3), Carhart model. Panels B, C, and D report alphas and factor loadings under other recent models, such as the profitability factor model of Novy-Marx (2013), the five-factor model of Fama and French (2014), and the q-factor model of Hou, Xue, and Zhang (2014). Panels E, F, and G report alphas and factor loadings under risk-and-behavioral composite models, formed by adding UMO and ITF to standard factor models. All portfolio returns are value-weighted and expressed as percentages. The sample period is 1972 to 2012. Newey-West corrected t-statistics are shown in parentheses.

	Size	Accruals	AG	NOA	IVA	ACI	IK	IG	IvG	IvC
					Panel A: Excess returns and alphas					
R^e	-0.38	-0.29**	-0.52***	-0.42***	-0.57***	-0.26*	-0.37	-0.46***	-0.46***	-0.44***
	(-1.41)	(-2.13)	(-2.94)	(-2.82)	(-3.66)	(-1.66)	(-1.36)	(-3.12)	(-3.30)	(-3.16)
CAPM α	-0.27	-0.36**	-0.62***	-0.43***	-0.65***	-0.26	-0.63**	-0.52***	-0.54***	-0.50***
	(-1.05)	(-2.56)	(-3.43)	(-2.89)	(-4.21)	(-1.52)	(-2.42)	(-3.35)	(-3.94)	(-3.46)
FF3 α	0.11	-0.31**	-0.28**	-0.55***	-0.48***	-0.26	-0.11	-0.31**	-0.36***	-0.37***
	(0.96)	(-2.43)	(-1.98)	(-3.42)	(-3.18)	(-1.63)	(-0.62)	(-2.36)	(-2.84)	(-2.74)
Carhart α	-0.01	-0.25	-0.20	-0.43***	-0.40***	-0.14	0.08	-0.21	-0.22	-0.28*
	(-0.11)	(-1.63)	(-1.33)	(-2.93)	(-2.59)	(-0.81)	(0.50)	(-1.63)	(-1.57)	(-1.91)

	IR	EXFIN	NS	O/P	NO/P	LEV	GP/A	ROEQ	ROAQ
R^e	-0.64***	-0.40*	-0.71***	0.38	0.66***	0.37	0.21	0.78***	0.66***
	(-3.38)	(-1.92)	(-4.09)	(1.32)	(2.99)	(1.63)	(1.41)	(2.97)	(2.80)
CAPM α	-0.86***	-0.62***	-0.81***	0.68***	0.86***	0.41*	0.22	0.94***	0.81***
	(-5.24)	(-3.45)	(-4.94)	(2.72)	(4.18)	(1.74)	(1.43)	(3.82)	(3.80)
FF3 α	-0.61***	-0.67***	-0.69***	0.27*	0.55***	-0.26*	0.40***	1.22***	1.15***
	(-4.71)	(-4.22)	(-4.59)	(1.73)	(3.74)	(-1.92)	(2.63)	(5.46)	(5.98)
Carhart α	-0.40***	-0.48***	-0.51***	0.16	0.39***	-0.17	0.34**	0.71***	0.67***
	(-3.07)	(-3.29)	(-3.41)	(1.08)	(2.82)	(-1.24)	(2.32)	(3.48)	(3.85)

	Size	Accruals	AG	NOA	IVA	ACI	IK	IG	IvG	IvC
Panel B: Profitability factor model										
α	-0.23	-0.29*	-0.22	-0.32**	-0.40**	-0.13	0.00	-0.19	-0.24	-0.37**
	(-0.85)	(-1.84)	(-1.48)	(-2.13)	(-2.41)	(-0.78)	(0.02)	(-1.45)	(-1.63)	(-2.51)
β_{MKT}	-0.24***	0.09**	0.05	0.04	0.09**	-0.02	0.27***	0.02	0.05	0.06*
β_{HML}	-0.26	-0.09	-0.66***	0.04	-0.35***	-0.00	-1.00***	-0.45***	-0.38***	-0.15
β_{MOM}	0.14	-0.07	-0.09	-0.12*	-0.09	-0.13*	-0.21**	-0.11**	-0.15***	-0.11*
β_{PMU}	-0.20	0.31***	0.04	-0.36***	-0.08	-0.21*	0.34***	-0.13	0.12	0.27**
Panel C: Fama-French five-factor model										
α	0.03	-0.31**	0.00	-0.49***	-0.36***	-0.22	0.29*	-0.08	-0.20*	-0.36***
	(0.28)	(-2.56)	(0.03)	(-2.59)	(-2.65)	(-1.44)	(1.67)	(-0.65)	(-1.72)	(-2.80)
β_{MKT}	-0.03	0.04	-0.03	0.02	0.05	0.04	0.19***	-0.02	0.00	0.06*
β_{SMB}	-1.40***	0.36***	-0.01	0.10	0.02	-0.29***	0.02	-0.10*	0.14**	0.06
β_{HML}	-0.28***	-0.05	-0.17**	0.38***	0.06	0.19*	-0.65***	-0.03	-0.03	0.02
β_{RMW}	0.15**	0.24***	-0.03	0.06	0.21***	-0.00	-0.46***	-0.15*	0.08	0.39***
β_{CMA}	-0.03	-0.34**	-1.14***	-0.37**	-0.87***	-0.19	-0.92***	-0.78***	-0.81***	-0.65***
Panel D: q-factor model										
α	-0.08	-0.33**	0.03	-0.27	-0.27*	-0.08	0.29	-0.05	-0.12	-0.28**
	(-0.67)	(-2.53)	(0.27)	(-1.61)	(-1.80)	(-0.48)	(1.47)	(-0.44)	(-0.95)	(-1.99)
β_{MKT}	0.01	0.06	0.05	-0.04	0.08**	0.01	0.32***	0.02	0.03	0.07*
β_{ME}	-1.38***	0.34***	-0.09	0.09	-0.11**	-0.35***	-0.12	-0.13**	0.06	-0.03
β_{INV}	-0.15**	-0.44***	-1.22***	-0.21*	-0.71***	-0.01	-1.26***	-0.72***	-0.81***	-0.59***
β_{ROE}	0.34***	0.24***	0.07	-0.10	0.06	-0.14	-0.31***	-0.05	0.02	0.17*

	Size	Accruals	AG	NOA	IVA	ACI	IK	IG	IvG	IvC
					Panel E: Composite CAPM					
α	-0.22	-0.06	0.08	0.10	-0.14	-0.27	0.07	0.00	-0.03	-0.08
	(-0.77)	(-0.37)	(0.45)	(0.74)	(-0.88)	(-1.53)	(0.36)	(0.01)	(-0.20)	(-0.50)
β_{MKT}	-0.24***	0.08*	0.00	-0.05	0.05	0.01	0.28***	-0.02	0.04	0.04
β_{ITF}	0.18	-0.59***	-0.37**	-1.40***	-0.75***	-0.32	0.61***	-0.32***	-0.52***	-0.61***
β_{UMO}	-0.11	-0.11	-0.57***	-0.04	-0.27***	0.12	-0.87***	-0.40***	-0.31***	-0.21**
					Panel F: Composite FF3 model					
α	0.04	-0.10	0.11	0.09	-0.10	-0.22	0.07	0.03	-0.02	-0.06
	(0.29)	(-0.69)	(0.77)	(0.69)	(-0.75)	(-1.30)	(0.43)	(0.23)	(-0.19)	(-0.35)
β_{MKT}	-0.03	0.03	-0.01	-0.05	0.06	0.06	0.23***	-0.02	0.02	0.04
β_{SMB}	-1.43***	0.27***	-0.06	0.02	-0.11**	-0.31***	0.13*	-0.11**	0.07	-0.10
β_{HML}	-0.50***	-0.28***	-0.66***	0.10	-0.41***	-0.02	-0.84***	-0.34***	-0.43***	-0.31***
β_{ITF}	0.02	-0.73***	-0.66***	-1.35***	-0.93***	-0.32	0.23*	-0.47***	-0.72***	-0.75***
β_{UMO}	0.08	0.08	-0.17**	-0.10	-0.03	0.11	-0.34***	-0.20**	-0.04	-0.03
					Panel G: Composite Carhart model					
α	-0.00	-0.08	0.12	0.11	-0.08	-0.16	0.13	0.05	0.02	-0.03
	(-0.03)	(-0.52)	(0.87)	(0.85)	(-0.62)	(-1.00)	(0.81)	(0.41)	(0.17)	(-0.18)
β_{MKT}	-0.02	0.03	-0.01	-0.05	0.05	0.06	0.22***	-0.02	0.01	0.04
β_{SMB}	-1.42***	0.27***	-0.06	0.02	-0.11**	-0.32***	0.13	-0.11**	0.07	-0.10
β_{HML}	-0.41***	-0.31***	-0.68***	0.07	-0.44***	-0.12	-0.95***	-0.38***	-0.51***	-0.36***
β_{MOM}	0.14***	-0.06	-0.04	-0.05	-0.05	-0.15**	-0.17**	-0.06	-0.13***	-0.08
β_{ITF}	-0.01	-0.72***	-0.65***	-1.34***	-0.92***	-0.29*	0.26**	-0.45***	-0.70***	-0.74***
β_{UMO}	-0.01	0.12	-0.15**	-0.07	0.01	0.20**	-0.24**	-0.16**	0.04	0.02

	IR	EXFIN	NS	O/P	NO/P	LEV	GP/A	ROEQ	ROAQ
Panel B: Profitability factor model									
α	-0.31**	-0.18	-0.32**	0.03	0.20	-0.01	0.00	0.40	0.36*
	(-2.42)	(-1.18)	(-2.39)	(0.20)	(1.40)	(-0.09)	(0.04)	(1.63)	(1.70)
β_{MKT}	0.29***	0.39***	0.12***	-0.41***	-0.24***	0.16***	-0.06	-0.28***	-0.30***
β_{HML}	-0.73***	-0.44***	-0.58***	1.03***	0.94***	1.04***	0.13	0.14	-0.00
β_{MOM}	-0.22***	-0.19***	-0.18***	0.12*	0.17***	-0.08	0.05	0.53***	0.50***
β_{PMU}	-0.10	-0.67***	-0.54***	0.14	0.46***	-0.34***	1.04***	0.58***	0.55***
Panel C: Fama-French five-factor model									
α	-0.29**	-0.30*	-0.26*	-0.01	0.20	-0.32**	0.05	0.64***	0.68***
	(-2.40)	(-1.80)	(-1.84)	(-0.08)	(1.41)	(-2.37)	(0.36)	(2.84)	(3.23)
β_{MKT}	0.20***	0.25***	0.03	-0.29***	-0.15***	0.15***	0.01	-0.18***	-0.21***
β_{SMB}	0.24***	0.50***	0.01	-0.36***	-0.19**	0.34***	0.04	-0.40***	-0.49***
β_{HML}	-0.29***	0.25**	0.04	0.67***	0.39***	1.13***	-0.46***	-0.53***	-0.60***
β_{RMW}	-0.38***	-0.56***	-0.70***	0.39**	0.55***	0.05	0.76***	1.29***	1.08***
β_{CMA}	-0.72***	-0.70***	-0.72***	0.54***	0.62***	0.20	0.28*	0.40	0.29
Panel D: q-factor model									
α	-0.35**	-0.25	-0.31**	0.17	0.31**	-0.06	0.09	0.14	0.23
	(-2.54)	(-1.61)	(-2.22)	(1.02)	(2.14)	(-0.31)	(0.64)	(1.02)	(1.53)
β_{MKT}	0.29***	0.28***	0.09**	-0.42***	-0.24***	-0.02	0.02	-0.11**	-0.13***
β_{ME}	0.18**	0.46***	0.06	-0.35***	-0.20**	0.37***	-0.04	-0.24***	-0.35***
β_{INV}	-0.81***	-0.44***	-0.59***	1.04***	0.90***	1.01***	-0.14	0.02	-0.19*
β_{ROE}	-0.18***	-0.39***	-0.31***	0.03	0.16*	-0.30***	0.35***	1.40***	1.27***

	IR	EXFIN	NS	O/P	NO/P	LEV	GP/A	ROEQ	ROAQ
Panel E: Composite CAPM									
α	-0.15	0.12	-0.21	-0.13	0.02	-0.12	-0.02	0.47	0.46
	(-0.97)	(0.68)	(-1.37)	(-0.68)	(0.13)	(-0.58)	(-0.12)	(1.59)	(1.64)
β_{MKT}	0.26***	0.29***	0.06	-0.38***	-0.18***	0.15***	0.03	-0.22**	-0.23***
β_{ITF}	-0.22	-0.85***	-0.30**	-0.05	0.16	-0.79***	0.32***	0.24	0.31
β_{UMO}	-0.60***	-0.42***	-0.48***	0.78***	0.74***	0.77***	0.10	0.35	0.25
Panel F: Composite FF3 model									
α	-0.19	0.01	-0.24	-0.08	0.06	-0.22	0.03	0.63***	0.62***
	(-1.43)	(0.07)	(-1.52)	(-0.51)	(0.46)	(-1.43)	(0.16)	(2.59)	(2.90)
β_{MKT}	0.19***	0.20***	0.03	-0.28***	-0.11***	0.13***	0.04	-0.12*	-0.13**
β_{SMB}	0.31***	0.59***	0.17***	-0.44***	-0.31***	0.33***	-0.16***	-0.75***	-0.77***
β_{HML}	-0.50***	0.11*	-0.12*	0.77***	0.47***	1.18***	-0.51***	-0.78***	-0.89***
β_{ITF}	-0.46***	-0.82***	-0.36***	0.32***	0.39***	-0.27***	0.10	-0.09	-0.06
β_{UMO}	-0.27***	-0.44***	-0.39***	0.27***	0.43***	0.09	0.39***	0.76***	0.73***
Panel G: Composite Carhart model									
α	-0.13	0.05	-0.20	-0.10	0.02	-0.18	0.03	0.46**	0.46**
	(-0.95)	(0.36)	(-1.26)	(-0.66)	(0.19)	(-1.19)	(0.19)	(2.19)	(2.49)
β_{MKT}	0.18***	0.20***	0.02	-0.28***	-0.11***	0.13***	0.04	-0.10	-0.11**
β_{SMB}	0.31***	0.59***	0.17**	-0.44***	-0.31***	0.33***	-0.16***	-0.75***	-0.76***
β_{HML}	-0.61***	0.04	-0.20**	0.81***	0.54***	1.11***	-0.51***	-0.49***	-0.61***
β_{MOM}	-0.18***	-0.10*	-0.12**	0.07	0.10**	-0.10**	-0.01	0.47***	0.45***
β_{ITF}	-0.43***	-0.80***	-0.34***	0.30***	0.37***	-0.25***	0.10	-0.18	-0.15
β_{UMO}	-0.16*	-0.37***	-0.31***	0.23**	0.37***	0.15	0.40***	0.46***	0.44***

Table 8: Firm-Level Fama-MacBeth Regressions on Conditional Behavioral Factor Loadings

This table reports firm-level Fama-MacBeth regressions from 1975 to 2012. The dependent variable is individual stock returns in month t, and the independent variables are firm-level *conditional* UMO or ITF loadings estimated at month $t-1$, a set of standard control variables, firm characteristics, and *conditional* loadings on other factors such as INV, ROE, and PMU. All *conditional* factor loadings are estimated using the portfolio shrinkage method following Fama and French (1992) and Hirshleifer and Jiang (2010). All Controls include log(B/M) as of fiscal year end in year $t-1$, log(ME) by the end of June in year t, 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 cumulative past returns are converted on a monthly basis. Firm characteristics include accruals, total asset growth (AG), net operating assets (NOA), abnormal capital investment (ACI), investment-to-asset ratio (IVA), net external financing (EXFIN), composite issuance (IR), net share issuance (NS), and gross profit-to-asset ratio (GP/A). Except for composite issuance (IR), all characteristics variables are measured at the end of June in year t using accounting information from fiscal year end in year $t-1$ and updated each June. IR is measured at the end of June in year t and updated every June. Intercepts are included in all regressions but not reported here. Newey-West corrected t-statistics are reported in parentheses.

Panel A: Conditional UMO loadings predicting returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$Cond.\beta_{UMO}$	0.483***	0.204**	0.197**	0.124	0.136	0.207**	0.174*	0.076	0.139	0.146	0.173*	0.192**	0.152	0.180*
	(3.35)	(2.10)	(2.03)	(1.31)	(1.40)	(2.14)	(1.79)	(0.75)	(1.46)	(1.51)	(1.76)	(1.98)	(1.60)	(1.84)
Accruals			-0.383											
			(-1.54)											
AG				-0.395***										
				(-4.55)										
NOA					-0.429***									
					(-4.47)									
ACI						-0.025								
						(-1.00)								
IVA							-0.350**							
							(-2.23)							
EXFIN								-0.947***						
								(-3.94)						
IR									-0.357***					
									(-3.58)					
NS										-0.935***				
										(-3.85)				
GP/A											0.329**			
											(2.11)			
$Cond.\beta_{INV}$												0.088		
												(1.18)		
$Cond.\beta_{ROE}$													0.840***	
													(8.54)	
$Cond.\beta_{PMU}$														0.206**
														(2.15)
All Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.50%	4.60%	4.70%	4.70%	4.70%	4.70%	4.70%	4.70%	4.80%	4.70%	4.80%	4.70%	4.90%	4.80%

Panel B: Conditional ITF loadings predicting returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$Cond.\beta_{ITF}$	0.375***	0.143**	0.129*	0.076	0.011	0.143**	0.109	0.086	0.102	0.107	0.118*	0.136*	0.153**	0.122*
	(3.09)	(2.04)	(1.84)	(1.07)	(0.16)	(2.05)	(1.55)	(1.13)	(1.41)	(1.49)	(1.70)	(1.92)	(2.26)	(1.76)
Accruals			-0.380											
			(-1.51)											
AG				-0.400***										
				(-4.66)										
NOA					-0.436***									
					(-4.38)									
ACI						-0.025								
						(-1.01)								
IVA							-0.363**							
							(-2.29)							
EXFIN								-0.961***						
								(-3.89)						
IR									-0.357***					
									(-3.48)					
NS										-0.923***				
										(-3.70)				
GP/A											0.331**			
											(2.12)			
$Cond.\beta_{INV}$												0.061		
												(0.82)		
$Cond.\beta_{ROE}$													0.849***	
													(8.63)	
$Cond.\beta_{PMU}$														0.200**
														(2.09)
All Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.50%	4.60%	4.70%	4.70%	4.70%	4.70%	4.70%	4.70%	4.80%	4.70%	4.80%	4.70%	4.80%	4.80%

Table 9: Aggregate Investor Attention and the Inattention Factor Premiums

This table reports time-series regressions of the ITF premiums on two attention proxies: investor sentiment and NYSE turnover. For comparison, we also show regression results for the UMO factor, standard risk factors (MKT, SMB, and HML), and other recent factors such as RMW and CMA of Fama and French (2014), PMU of Novy-Marx (2013), and INV and ROE of Hou, Xue, and Zhang (2014). The dependent variable is annualized ITF (or other factor) premium in year t. $SENT_{t-1}$ and $TURN_{t-1}$ are the investor sentiment index (orthogonalized to macro variables) and NYSE turnover from Baker and Wurgler (2006) over the prior year $t-1$, respectively. We also include contemporaneous $SENT_t$ and $TURN_t$ and lagged factor premium $Premium_{t-1}$ as controls. All variables are measured on an annual basis. Intercepts are included in all regressions but not reported here. The sample period is from 1973 to 2012. Newey-West corrected t-statistics are shown in parentheses.

	ITF		UMO		MKT		SMB		HML	
$SENT_{t-1}$	5.20***		2.99		-7.75		-4.15		-1.24	
	(5.03)		(0.55)		(-1.33)		(-1.14)		(-0.42)	
$SENT_t$	-3.07***		0.05		5.60		1.06		3.77	
	(-3.15)		(0.01)		(0.95)		(0.34)		(0.88)	
$TURN_{t-1}$		-9.70*		-53.60*		21.27		30.35**		-15.00
		(-1.82)		(-1.85)		(0.63)		(2.39)		(-0.81)
$TURN_t$		10.43**		46.92		-26.01		-34.07**		10.93
		(2.05)		(1.38)		(-0.70)		(-2.68)		(0.53)
$Premium_{t-1}$	0.20	0.27***	-0.23	-0.22***	-0.12	-0.04	0.18**	0.24*	0.07	-0.02
	(1.53)	(2.82)	(-1.33)	(-2.99)	(-0.90)	(-0.30)	(2.16)	(1.86)	(0.67)	(-0.24)

	RMW		CMA		PMU		INV		ROE	
$SENT_{t-1}$	5.17		4.01		2.06		5.02*		2.06	
	(1.32)		(1.03)		(0.54)		(1.95)		(0.54)	
$SENT_t$	-2.07		-2.08		1.68		-2.60		1.68	
	(-0.71)		(-0.36)		(0.48)		(-0.80)		(0.48)	
$TURN_{t-1}$		-17.57		-6.38		-76.42**		-18.79		-76.42**
		(-1.55)		(-0.33)		(-2.54)		(-0.99)		(-2.54)
$TURN_t$		22.14*		5.27		67.61**		16.43		67.61**
		(1.79)		(0.23)		(2.30)		(0.75)		(2.30)
$Premium_{t-1}$	-0.08	0.03	0.00	0.08	-0.24	-0.28*	-0.09	0.01	-0.24	-0.28*
	(-0.51)	(0.29)	(0.02)	(0.99)	(-1.02)	(-1.70)	(-0.94)	(0.17)	(-1.02)	(-1.70)

Table 10: Institutional Ownership and Analyst Coverage

This table reports average UMO and ITF loadings across analyst coverage or institutional ownership portfolios. First, all sample firms are sorted into 3 size groups (Small, Medium, Large), and then within each size group, firms are assigned to 6 groups (0 to 5) based on analyst coverage (AC) and institutional ownership (IO). Firms with no AC or IO are assigned to group 0, and all other firms are assigned to group 1 (low) to 5 (high). Analyst coverage is the average monthly number of analysts providing current fiscal year earnings estimates, averaged over the previous fiscal year. Institutional ownership is the percentage of shares held by institutions, based on institutions' quarterly 13F filings and averaged over the previous year. Then, for each portfolio in each month, we compute average firm loadings on UMO and ITF and average "absolute" loadings, using *conditional* β_{UMO} and β_{ITF} from Table 8. Panel A reports average (absolute) firm loadings on UMO and ITF across institutional ownership portfolios, and in Panel B across analyst coverage portfolios. The sample period starts from 1982/07 to 2012/12 for analyst coverage and from 1981/01 to 2012/12 for institutional ownership, restricted by data availability. Newey-West corrected t-statistics are reported in parentheses.

Panel A: Institutional Ownership Portfolios								
	0	1	2	3	4	5	High-Low	High-Zero
				Average β_{UMO}				
Small	0.11	0.14	0.16	0.13	0.12	0.10	-0.05*	-0.02
	(2.08)	(2.68)	(3.18)	(2.86)	(2.74)	(2.42)	(-1.68)	(-0.67)
Medium	-0.11	-0.08	-0.06	-0.07	-0.07	-0.07	0.01	0.04***
	(-3.81)	(-2.76)	(-2.33)	(-2.54)	(-2.54)	(-2.62)	(0.84)	(4.18)
Large	-0.08	-0.08	-0.07	-0.07	-0.07	-0.08	-0.00	0.00
	(-3.71)	(-3.59)	(-3.14)	(-3.04)	(-3.42)	(-3.43)	(-0.06)	(0.65)
				Average β_{ITF}				
Small	0.24	0.20	0.20	0.21	0.18	0.17	-0.04*	-0.08***
	(3.63)	(2.92)	(2.98)	(3.24)	(3.12)	(3.18)	(-1.76)	(-4.28)
Medium	0.08	0.11	0.08	0.06	0.03	-0.02	-0.13***	-0.10***
	(2.29)	(2.98)	(2.94)	(2.12)	(1.50)	(-0.99)	(-5.59)	(-5.36)
Large	-0.27	-0.20	-0.22	-0.24	-0.23	-0.25	-0.05***	0.02
	(-12.94)	(-11.06)	(-12.08)	(-12.40)	(-12.36)	(-13.60)	(-4.41)	(1.60)
				Average $\lvert\beta_{UMO}\rvert$				
Small	0.55	0.56	0.52	0.48	0.44	0.40	-0.16***	-0.15***
	(21.87)	(18.17)	(20.26)	(20.67)	(24.56)	(25.17)	(-7.76)	(-9.83)
Medium	0.32	0.33	0.30	0.29	0.29	0.29	-0.04***	-0.04***
	(22.64)	(23.91)	(25.54)	(24.29)	(22.86)	(21.68)	(-5.95)	(-8.24)
Large	0.22	0.23	0.22	0.21	0.21	0.22	-0.02**	0.00
	(16.66)	(18.96)	(19.83)	(19.31)	(18.80)	(16.79)	(-2.43)	(0.40)
				Average $\lvert\beta_{ITF}\rvert$				
Small	0.59	0.59	0.58	0.55	0.51	0.47	-0.12***	-0.12***
	(20.04)	(18.63)	(19.12)	(18.09)	(19.75)	(19.50)	(-9.95)	(-12.49)
Medium	0.41	0.42	0.38	0.36	0.34	0.34	-0.08***	-0.07***
	(37.17)	(33.11)	(39.48)	(45.09)	(55.32)	(50.96)	(-6.91)	(-9.28)
Large	0.41	0.37	0.37	0.37	0.37	0.39	0.03***	-0.01*
	(33.39)	(36.52)	(33.57)	(31.71)	(31.63)	(31.86)	(4.38)	(-1.96)

Panel B: Analyst Coverage Portfolios								
	0	1	2	3	4	5	High-Low	High-Zero
				Average β_{UMO}				
Small	0.14	0.06	-0.11	0.02	-0.01	-0.03	-0.09***	-0.17***
	(2.98)	(1.46)	(-1.64)	(0.39)	(-0.20)	(-0.66)	(-7.39)	(-9.91)
Medium	-0.04	-0.06	-0.09	-0.11	-0.13	-0.17	-0.12***	-0.13***
	(-1.53)	(-2.22)	(-3.18)	(-3.76)	(-4.49)	(-5.95)	(-12.29)	(-11.04)
Large	-0.07	-0.06	-0.09	-0.10	-0.09	-0.08	-0.02***	-0.01
	(-3.10)	(-2.39)	(-3.68)	(-4.05)	(-4.00)	(-3.81)	(-3.19)	(-1.31)
				Average β_{ITF}				
Small	0.20	0.17	-0.32	0.15	0.11	0.13	-0.04**	-0.07***
	(2.83)	(2.73)	(-2.69)	(2.31)	(1.67)	(2.43)	(-2.24)	(-2.86)
Medium	0.10	0.09	0.07	0.05	0.02	-0.04	-0.14***	-0.14***
	(2.44)	(2.92)	(2.41)	(2.15)	(0.69)	(-1.73)	(-7.76)	(-5.77)
Large	-0.16	-0.18	-0.26	-0.27	-0.29	-0.26	-0.09***	-0.10***
	(-6.65)	(-9.43)	(-11.55)	(-13.76)	(-15.84)	(-13.43)	(-6.28)	(-5.71)
				Average $\lvert\beta_{UMO}\rvert$				
Small	0.52	0.43	0.35	0.43	0.44	0.41	-0.02	-0.11***
	(18.75)	(22.95)	(16.25)	(23.75)	(26.95)	(23.88)	(-1.21)	(-4.07)
Medium	0.30	0.30	0.30	0.31	0.32	0.33	0.03***	0.03**
	(24.10)	(25.27)	(23.25)	(21.74)	(21.67)	(18.71)	(3.06)	(2.40)
Large	0.23	0.24	0.24	0.23	0.22	0.19	-0.05***	-0.04***
	(19.18)	(20.19)	(18.30)	(17.43)	(17.24)	(15.84)	(-6.52)	(-3.24)
				Average $\lvert\beta_{ITF}\rvert$				
Small	0.58	0.53	0.56	0.50	0.46	0.46	-0.07***	-0.12***
	(18.58)	(18.19)	(12.29)	(17.73)	(15.41)	(18.11)	(-6.64)	(-9.40)
Medium	0.41	0.38	0.37	0.37	0.37	0.37	-0.01	-0.04***
	(32.44)	(38.00)	(48.56)	(49.90)	(48.60)	(39.02)	(-0.88)	(-2.89)
Large	0.35	0.34	0.40	0.40	0.40	0.39	0.05***	0.03***
	(26.04)	(30.05)	(26.75)	(32.53)	(35.84)	(31.58)	(5.90)	(2.93)

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Appendix

A Definition of Anomaly Variables

Accruals: Following Sloan (1996), we measure operating accruals as *Accruals* = [(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 ACT (Compustat item #4), *Cash* is CHE (Compustat item #1), *Current Liabilities* is LCT (Compustat item #5), *Short-term Debt* is DLC (Compustat item #34), *Taxes Payable* is TXP (Compustat item #71), *Depreciation and Amortization Expense* is DP (Compustat item #14), and *Total Assets* is AT (Compustat item #6).

Asset Growth (*AG*): Following Cooper, Gulen, and Schill (2008), asset growth is defined percentage change in total asset (Compustat item #6), scaled by beginning total asset.

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, #6) – *Cash and Short-term Investment* (CHE, #1), and *Operating Liabilities* = *Total Assets* (AT, #6) – *Short-term Debt* (DLC, #34) – *Long-term Debt* (DLTT, #9) – *Minority Interest* (MIB, #38) – *Preferred Stock* (PSTK, #130) - *Common Equity* (CEQ, #60).

Abnormal capital investment (*ACI*): Following Titman, Wei, and Xie (2004), we measure abnormal capital investment as a firm's capital expenditures scaled by the moving-average of its past capital expenditures over the previous three years. Specifically, $ACI_{t-1} = CE_{t-1}/[(CE_{t-2} + CE_{t-3} + CE_{t-4})/3] - 1$, where CE is capital expenditure (CAPX, #128) scaled by sales (SALE, #12).

Investment-to-asset ratio (*IVA*): Following Lyandres, Sun, and Zhang (2008), we measure the investment-to-asset ratio as the annual change in gross property, plant, and equipment (PPEGT, #7) plus the annual change in inventories (INVT, #3) divided by the lagged total assets (AT, #6).

Investment-to-capital (*IK*): Following Polk and Sapienza (2009), we measure the investment-to-capital ratio as capital expenditure (CAPX, #128) over beginning-of-year net property, plant, and equipment (PPENT, #8).

Investment growth (*IG*): Following Xing (2008), we measure investment growth as the percentage change in capital expenditure (CAPX, #128).

Inventory growth (*IvG*): Following Belo and Lin (2012), we measure inventory growth as the ratio of inventory (Compustat item INVT) of fiscal year ending in year $t-1$ over inventory of the fiscal year ending in $t-2$.

Inventory changes (*IvC*): Following Thomas and Zhang (2002), we measure inventory changes as the change in inventory (Compustat item INVT) from the fiscal year ending in year $t-2$ to the fiscal year ending in $t-1$, scaled by the average of total assets (Compustat item AT) for fiscal years ending in $t-2$ and $t-1$.

Total payout (*O/P*) and net payout (*NO/P*): Following Boudoukh et al. (2007), total payout (O) is dividend on common stock (Compustat item 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). P is the market value of equity at the end of December of the fiscal year end.

External financing (*EXFIN*): Following Bradshaw, Richardson, and Sloan (2006), external financing is defined as the net amount of cash flow received from external financing activities, including net equity and debt financing, scaled by total assets. Specifically, net equity financing is defined as the sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTKC) minus cash dividends paid (DV). Net debt financing is defined as the issuance of long-term debt (DLTIS) minus the reduction in long-term debt (DLTR). But different from Bradshaw, Richardson, and Sloan (2006), we do not include change in current debt in calculating net debt financing to avoid including natural retirement of short-term debt which is not a market timing choice[17]. Thus, $EXFIN_{t-1}$ is measured as net equity financing in year $t-1$ plus net debt financing in year $t-1$, scaled by the average of beginning and ending total assets of year $t-1$.

[17] This revised definition of EXFIN is consistent with Hirshleifer and Jiang (2010).

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

Net stock issues (*NS*): Following Pontiff and Woodgate (2008), we measure net stock issues 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, #25) times the adjustment factor (AJEX, #27).

Leverage (*LEV*): Following Ferguson and Shockley (2003), we measure a firm's leverage of year $t-1$ as the book value of total liabilities (LT, #181) of fiscal year ending in year $t-1$ over the market value of equity at the end of December of year $t-1$.

Gross profit-to-asset ratio (GP/A**)**: Following Novy-Marx (2013), we define a firm's gross profit-to-asset ratio (GP/A_t) as total revenue ($REVT_t$) minus cost of goods sold ($COGS_t$) adjusted by total asset (AT_t).

ROAQ and ROEQ: ROAQ and ROEQ are computed using Compustat quarterly files.

ROAQ is income before extraordinary items (IBQ) divided by one-quarter lagged total assets (ATQ). ROEQ is income before extraordinary items (IBQ) divided by one-quarter lagged book equity. 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).