# The Use of Asset Growth in Empirical Asset Pricing Models*


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**Abstract**

We provide evidence that the empirical performance of the new factor models proposed by Hou, Xue, and Zhang (2015) and Fama and French (2015) depends crucially on how their investment factor is constructed. Specifically, we call attention to the fact that, in both models, the investment factor is based on the measure of growth in total assets from Cooper, Gulen, and Schill (2008) and not on what most researchers would view as traditional measures of corporate investment. For both models, we show that there are large decreases in their ability to price the cross-section of returns when the investment factor is instead constructed using the traditional investment measures, or when it is constructed using arguably more complete measures that account for investment in intangibles. Additionally, we do not find a significant decrease in performance when we replace the asset-growth factor with a factor based on growth in noncash current assets or long-term debt (which cannot be complete measures of investment). Our results challenge the idea that traditional investment models can fully account for the explanatory power of the asset-growth factor used in the Hou, Xue, and Zhang (2015) and Fama and French (2015) models.



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# 1 Introduction

Recent advances in empirical factor models such as the four-factor model of Hou, Xue, and Zhang (2015) and the five-factor model of Fama and French (2015) have improved our ability to explain the cross-section of equity returns, including the returns of many anomalies. In these new models, the improvement relative to prior models such as the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model has come in part from the addition of new factors related to firm-level profitability and investment. In both Fama and French (2015) and Hou, Xue, and Zhang (2015), the motivation to use profitability and investment factors is based on theoretical arguments (a dividend discount model for the five factor model and a production based model of Cochrane (1991) for the four factor model) that profitability and investment are inextricably linked to expected returns.

Using theory to identify empirical asset pricing factors is important, since there are many return anomalies that could serve as factors, and some of these potential factors may be better at explaining returns than those in widely accepted empirical asset pricing models.[1] Without economic motivation from theory, a purely data-driven approach to find new factors may lead to problems, as discussed on page 7 of Fama and French (2017): "...opening the game to factors that seem empirically robust but lack theoretical motivation has a destructive downside – the end of the discipline that produces parsimonious models and the beginning of the dark age of data dredging that produces a long list of factors with little hope of sifting through them in a statistically reliable way."

[1] A number of papers show that factor models developed using previously documented predictors of stock returns perform well in explaining sorted portfolios and related spread portfolios. For example, Kogan and Tian (2017) conduct a "model-mining experiment" whereby they construct all possible three- and four-factor models using factors based on 27 previously proposed (firm-level) predictors of stock returns. They find that, in the absence of theoretical constraints, it is relatively easy to construct a factor model that performs well in sample. For example, 48% of their models outperformed the Fama and French (1993) three factor model. Stambaugh and Yuan (2016) develop a factor model using"mispricing" factors based on aggregate information across 11 successful anomalies and show that their model explains returns better than Hou, Xue, and Zhang (2015) and Fama and French (2015). The search for firm level characteristics that predict the cross-section of returns is an important part of the finance literature, and to the extent that new characteristics are used to construct new factors in asset pricing models, some researchers point out that caution should be exercised to guard against "data mining" of these characteristics and resultant factors. Recent papers highlighting the potential dangers of empirical-based predictability searches include Hou, Xue, and Zhang (2017), Chordia, Goyal, and Saretto (2017), and Novy-Marx (2015). Moreover, Harvey, Liu, and Zhu (2016) point out that the continued search for pricing factors implies researchers should have adjusted significance thresholds upward to account for the presence of multiple testing. They also argue that "A factor derived from a theory should have a lower hurdle than a factor discovered from a purely empirical exercise." In his presidential address, Harvey (2017) shows how to adjust the standard test statistic to incorporate priors implied by a theoretical model.

Our paper examines the efficacy of the link between the empirical specification and theoretical motivation of the investment factors in Hou, Xue, and Zhang (2015; hereafter HXZ) and Fama and French (2015; hereafter FF5F). Specifically, we call attention to the fact that the investment factors used in the empirical tests of both HXZ and FF5F are not based on traditional measures of firm investment (such as measures based on capital expenditures and the growth in property, plant, and equipment (PPE)) as one might expect from their theoretical arguments.[2] Instead, both papers use "asset growth" (i.e., the year-on-year percentage change in total assets) from Cooper, Gulen, and Schill (2008) as a measure of investment. We show that both HXZ and FF5 factor models derive much of their explanatory power from their nonconventional empirical specification for investment (i.e., asset growth). That is, the models are no more powerful than prior models they are purported to replace when conventional measures of investment are employed. Thus, despite the empirical power of these models, and their potential relevance to performance evaluation, their relevance to asset pricing is potentially limited by their (lack of) theoretical justification, as is the case with many other firm characteristics associated with anomalous returns.

We argue that it is difficult to justify asset growth as the preferred measure of a firm's investment activity for several reasons. First, asset growth does not include off-balance sheet intangible capital, such as knowledge capital and organizational capital, an increasingly important type of capital that arguably should be included in an investment measure given recent evidence in Peters and Taylor (2017). Second, asset growth confounds investments with the financing used for them. For example, if a firm uses cash to finance an investment in PPE, we would observe zero growth in total assets when an investment was clearly made. Third, it is not clear to what extent growth in certain components of total assets, such as growth in current assets, can be classified as an investment activity. While increases in current assets could be indicative of the firm growing its operations, they can also be a result of the firm stagnating. Cash balances can increase in the absence of investment opportunities, inventory can increase if the firm is not able to sell its products at the same rate, and accounts receivables can increase if the firm is not able to recover the trade credit extended to its customers. Essentially, the main issue is that asset growth is not investment, especially as considered by the q-theory related motivation of HXZ and in the Gordon dividend

[2]See Appendix B for a partial but representative list of related investment papers and the measures used in those papers.

discount model framework of FF5F. We conduct tests to determine how well these new models perform when using theory implied investment factors instead of an asset growth factor.

Our empirical work proceeds as follows. In Section 2, we briefly review the asset growth anomaly of Cooper, Gulen, and Schill (2008) and provide out-of-sample evidence on how well the anomaly performs over the full period of our sample. In Section 3, we provide background on the factor models of HXZ and FF5F, with special attention to the theory and empirical implementation of their investment factors. Throughout the paper, we examine the performance of the FF5F and HXZ models using test assets from both papers. We first discuss tests of the FF5F and HXZ models on a set of 35 anomaly spread portfolios from HXZ and compare their ability to explain the anomaly spread portfolio returns to more established asset pricing models in the literature [i.e., CAPM, the Fama and French (1993) three-factor model (FF3F), and the Carhart (1997) four-factor model (C4F)]. We find that the HXZ model outperforms all the others, yielding insignificant spread portfolio alphas on all but 5 of the 35 anomalies. In contrast, the Carhart (1997), and FF5F models fail to explain 16 and 21 anomalies, respectively. Next, we test versions of FF5F and HXZ in which we drop their asset-growth based factor but retain their other factors. We find that the models perform uniformly worse; the HXZ model fails to explain 21 anomalies, and the FF5F model fails to explain 24. Clearly, in our sample, the asset growth factor, in both the FF5F and HXZ models, play a key role in explaining anomaly spread portfolio returns.

In Section 4, we compare the performance of the FF5F and HXZ models using alternative (more conventional) measures of investment. We are particularly interested in the performance of investment factors related to the theoretical motivations of these models. The most common measure employed in empirical tests of the q-theory focus on investment in physical capital, which is measured using either the capital expenditure (CAPX) figure from the statement of cash flows or the growth in property, plant, and equipment (PPE). We also consider investment measures that incorporate intangible capital into the investment factors based on the capital decomposition measures in Peters and Taylor (2017). For the HXZ model, replacing the asset growth factor with alternative investment factors results in significantly worse performance. When using CAPX (PPE), the model fails to explain 15 (14) out of 35 anomalies, and when using "total capital" from Peters and Taylor (2017), the model fails to explain 14 anomalies. For the FF5F model, replacing the asset growth factor with alternative investment factors also results in worse model performance.

When using CAPX (PPE), the model fails to explain 23 (24) out of 35 anomalies, and when using "total capital," the model fails to explain 24 anomalies. In sum, both the HXZ and FF5F models perform markedly better using an asset growth factor rather than investment factors. In some cases, especially for the FF5F model, the alternative investment models do not improve on a model with no investment factor.

In Section 5, we study why the asset growth factor works well in explaining anomaly returns by implementing an asset growth decomposition from Cooper, Gulen, and Schill (2008). We decompose the asset growth factor into factors that come from changes in items from both the left-hand side and the right-hand side of the balance sheet. On the left-hand-side, we create factors based on changes in cash, noncash current assets, gross PPE, and other assets (i.e., total assets minus the previous three categories). On the right-hand-side, we develop factors using changes in long-term debt, common equity, retained earnings, and operating liabilities (i.e., total assets minus the previous three categories). The decomposition suggests that it is difficult to justify growth in total assets as an accurate measure of a firm's investment activity since other arguably "non-investment" related firm activities play important roles in the asset growth of most firms. For example, we find that growth in PPE, a common measure of investment in the literature, is not the largest component of asset growth. Growth in noncash current assets is the largest component in most of the asset growth deciles.

We then analyze the performance of variations of the HXZ model, where the asset growth factor is replaced with a factor based on a subcomponent of asset growth from the left-hand side or the right-hand side of the balance sheet. Our results suggest that the performance of the asset growth factor in the HXZ model is driven in part by the factor based on noncash current assets. When replacing the asset-growth factor with a factor based on growth in noncash current assets, we obtain a factor model that performs almost as well as the original HXZ model; the noncash current assets model explains all but 8 anomalies (as opposed to 5 for the asset growth based model). We then perform the same tests for the FF5F model. As with the HXZ model, we find that a FF5F model based on growth in noncash current assets performs just as well as the original FF5F model using asset growth. Also, the FF5F model, using a factor based on long-term debt, performs as well as the FF5F model using asset growth.

We repeat all previous tests using various sets of 25 and 32 portfolio combinations (formed by sorting on size, book-to-market (BM), asset growth (AG), and profitability), which is similar to portfolios used in FF5F. We consider a total of 171 portfolios. With these test assets, the HXZ model with asset growth fails to explain the average returns of 21 of 171 portfolios, and the FF5F fails to explain 36 of 171 portfolios. The performance of both models drops when we exclude asset growth as a factor; the HXZ model fails to explain 88 portfolios, and the FF5F model fails to explain 37 portfolios. When we swap the asset growth risk premium with premiums based on CAPX and PPE, both models experience worse performance in explaining the portfolio returns. As we previously found with the anomaly spread portfolios, when we examine the balance sheet components of asset growth, the HXZ model performs reasonably well, relative to the other components, using noncash current assets as the investment factor, and the FF5F model performs well using a long-term debt factor. These results (suggesting that the HXZ and FF5F models perform just as well if variables such as growth in noncash current assets and growth in long-term debt are used to form the investment factor) will likely come as a surprise to many readers, since these variables ignore obvious measures of investments such as PPE spending.

Finally, we perform "model mining" tests where we construct factors using combinations of possible investment measures and subcomponents of asset growth for a total of 220 different investment factors. These tests let us evaluate the performance of the asset growth based investment models relative to many other investment models that a researcher with no strong prior on the exact construction of the investment factor may consider. We evaluate how these alternative investment factors perform in explaining the 35 anomalies and compare their performance to the HXZ and FF5F models. Consistent with our previous results, we find for the HXZ (FF5F) model that using asset growth as the investment factor outperforms almost all (the majority) of the other investment factors. Traditional measures of investment, such as CAPX and PPE, do not perform as well in explaining the anomalies as a factor based on asset growth, factors related to asset growth, and factors composed primarily of non-CAPX or non-PPE related components. These findings suggest that if an ex-post econometrician were asked to pick an "investment-type" variable with the most explanatory power in-sample (with a benefit of hindsight), asset growth would likely emerge as one of the obvious variables.

Overall, we view our results as casting doubt on the idea that these models' ability to explain asset pricing anomalies can be attributed to the fact that total asset growth is an appropriate measure of investment. Asset growth contains investment, but it also captures many other aspects of balance sheet expansion and contraction that arguably have little to do with most researchers' definitions of firm investment. These non-investment components of asset growth appear to drive the empirical success of the current popular asset pricing models. More generally, our study points out that, while having theoretical underpinnings for new factor models is important, forging a tight link between those theories and their empirical implementation is equally important, especially when it comes to interpreting results. Our findings suggest that the appropriate use of asset-growth based return premiums is in performance benchmarking models, much like many researchers' adaptation of the Carhart (1997) four-factor model, rather than in asset pricing models.

## 2 The Asset Growth Anomaly

We begin our analysis by revisiting the asset growth anomaly of Cooper, Gulen, and Schill (2008). In June of every year $t$ from 1968 to 2016, we sort firms into deciles based on their year-over-year growth in total assets, measured in the fiscal year ending in calendar year $t-1$.[3] In Table I, we present time-series means of several portfolio-level average characteristics: asset growth, market capitalization, book-to-market ratio ("BM"), buy-and-hold returns over the past 12 and 36 months ("RET12" and "RET36), gross profitability ("GP), return on equity ("ROE"), net equity issuance over the past 1 and 5 years ("Issuance 1 year" and "Issuance 5 years"), and accruals.[4] In the last five columns of Table I, we also break down the composition of each decile-portfolio into firms of various sizes and ages. Specifically, we first present the percentage of firms in each decile that are classified as "micro", "small", and "large", based on the 20th and 50th NYSE market cap percentiles, following Fama and French (2008). Second, in the last two columns, we present the average firm age for each decile, as well as the percentage of firms younger than five years.[5]

In the bottom two rows of Table I, we present the average differences in firm characteristics between decile 10 and decile 1, along with their respective t-statistics. The results show significant differences between the extreme asset growth deciles along all dimensions reported in the table; high asset growth firms are significantly larger, have lower book-to-market ratios, better past returns,

[3]Consistent with the extant literature, our sample excludes financials and firms with negative book equity.
[4]See Appendix A for a detailed description of how these variables were calculated.
[5]Firm age is measured as the number of years since the firm appears in CRSP.

better profitability, more equity issuance, and higher accruals than low asset growth firms. The high asset growth portfolio also has significantly fewer micro firms, more small and large firms, and more young firms than the low asset growth portfolio. Interestingly, several of these characteristics do not change monotonically across the ten asset growth deciles; the firms in the first and tenth decile are smaller, younger, less profitable, and issue more equity than the firms in the remaining eight deciles. Overall, Table I documents substantial cross-sectional differences among firms with varying levels of asset growth.

We next investigate if the previously documented predictive power of asset growth over future stock returns survives when controlling for many of these other firm characteristics in a regression setting. In Table II, we present Fama-MacBeth (1973) regressions of future 12-month buy-and-hold returns on asset growth and other firm characteristics. The sample period in Table II is from July 1968 to June 2016, which extends the original July 1968 to June 2003 sample of Cooper, Gulen, and Schill (2008). In Panel A, we gradually introduce controls for size (market capitalization as of June of each year), book-to-market equity ("BM"), past 12 months buy-and-hold returns ("RET12"), and gross profitability ("GP").[6] In the last three columns, we run these regressions separately for micro, small, and large firms. Across the board, we find that asset growth is strongly negatively associated with future 12-month stock returns.[7] Overall, this table shows that asset growth remains a strong predictor of the cross-section of returns.

In Panel B of Table II, we investigate if the predictive power of the asset growth variable survives the inclusion of other anomaly variables proposed in the literature. In all specifications, we estimate Fama-MacBeth (1973) regressions in which the dependent variable is future 12-month buy-and-hold returns and the control variables include size, BM, past 12-month buy-and-hold returns (i.e., momentum), asset growth, and an additional anomaly variable taken from the following representative list: net operating assets ("NOA"), common equity issuance ("CEI"), operating accruals ("OA"), gross profitability ("GP"), return on assets ("ROA"), standardized unexpected earnings ("SUE"), and abnormal returns around earnings announcements ("ABR"). As a whole, the results show that all of these variables have significant predictive power over future returns,

[6]We restricted our attention to these firm characteristics for brevity. In unreported tests, we verify that our results hold if we simultaneously include a large set of controls, including, but not limited to accruals, firm age, and equity issuance. Panel B provides further robustness tests.

[7]Standard errors are corrected for autocorrelation using the Newey-West (1987) procedure with three lags.

but none of them explains the predictive power of asset growth.

# 3 New Factor Models

## 3.1 The Hou, Xue, and Zhang (2015) four-factor model

HXZ propose a factor model that includes investment and profitability factors alongside more traditional market and size factors. As theoretical support for this choice of factors, the authors use a production-based asset pricing model with an exogenous stochastic discount factor and solve for the optimal investment policy. The equilibrium conditions of the model suggest a negative relationship between expected returns and investment, and a positive relationship between expected returns and expected profitability. The intuition proposed by the authors is that, controlling for profitability, firms that invest more are the firms with lower discount rates (i.e., expected returns). Similarly, controlling for investment levels, firms with higher expected profits should have higher discount rates.

The HXZ four-factor model is given by:

$$R^i_t - R_{f,t} = \alpha^i + \beta^i_{MKT} R_{MKT,t} + \beta^i_{ME} R_{ME,t} + \beta^i_{I/A} R_{I/A,t} + \beta^i_{ROE} R_{ROE,t} \tag{1}$$

The market factor ("MKT") is the excess return on the CRSP value-weighted return index, and $R_{f,t}$ is the yield on the one-month Treasury bill. Firm size ("ME") is calculated as price times number of shares using CRSP data. Importantly, the authors measure corporate investment ("I/A") as the annual percentage growth in total assets and offer, as far as we can determine, no explanation for why this is more appropriate than the traditional measures based on capital expenditures and PPE growth found in the investments literature. Finally, profitability ("ROE") is measured as income before extraordinary items divided by one quarter lagged book equity (using quarterly Compustat data).

To construct the size, investment, and profitability factors, HXZ use a 2-by-3-by-3 independent sort on market capitalization, asset growth, and ROE. Specifically, at the end of every June, the authors sort firms into two groups based on how their market cap compares to the median NYSE market cap that month. Independently, every June, the authors sort firms into three groups based on how their asset growth compares to the 30th and 70th NYSE asset growth percentiles.[8] Finally, every month, the authors independently sort firms into three groups based on how their ROE compares to the 30th and 70th NYSE ROE percentiles that month.[9] The intersection of these three independent sorts yields 18 portfolios. Every month, the three factors are calculated using the value-weighted returns on these 18 portfolios. The return on the size factor equals the simple average of the returns on the 9 small portfolios minus the simple average of the returns on the 9 large portfolios. The return on the "investment factor" equals the simple average of the returns on the 6 low asset growth portfolios minus the simple average of the returns on the 6 high asset growth portfolios. The return on the profitability factor is the simple average of the returns on the 6 high ROE portfolios minus the simple average of the returns on the 6 low ROE portfolios.

### 3.2 The Fama and French (2015) five-factor model

FF5F propose a model that augments their Fama and French (1993) three-factor model with an investment factor and a profitability factor. To justify this model, the authors start with a dividend discount model and use a clean-surplus assumption to write market value as discounted expected profits minus discounted expected growth in book equity (which they call investment). Hence, keeping valuations and expected investments constant, higher profitability should be associated with higher discount rates. Similarly, keeping valuations and expected profits constant, higher expected investment should imply lower discount rates.

The FF5F model is given by:

$$R_t^i - R_{f,t} = \alpha^i + \beta^i_{MKT} R_{MKT,t} + \beta^i_{SMB} R_{SMB,t} + \beta^i_{HML} R_{HML,t} + \beta^i_{RMW} R_{RMW,t} + \beta^i_{CMA} R_{CMA,t} \quad (2)$$

Once again, the market factor ("MKT") is the excess return on the CRSP value-weighted return index, and $R_{f,t}$ is the yield on the one-month Treasury bill. SMB (small-minus-big) and HML (high-minus-low) are size and value factors analogous to those from the Fama and French (1993) three-factor model. RMW (robust-minus-weak) is a factor based on operating profitability, which is measured as revenues minus COGS, interest expense, and SG&A, all divided by book

[8] Asset growth in year $t$ is measured using total assets in fiscal years ending in calendar years $t-1$ and $t-2$.

[9] To calculate ROE in a given month $m$, the authors use the most recently announced earnings prior to month $m$ divided by the book equity in the quarter prior to those earnings. To avoid stale data, the earnings figure must correspond to a fiscal quarter ending within 6 months of month $m$.

equity. CMA (conservative minus aggressive) is a factor based on corporate investment, measured again as annual growth in total assets.[10] While their model speaks to growth in book-equity as the measure of investment, the authors allude to choosing asset growth instead because sorts on asset growth produce larger spreads in mean returns.

The value (HML), profitability (RMW), and investment (CMA) factors are constructed using three different 2-by-3 independent sorts, each based on size and either book-to-market equity (for HML), operating profitability (for RMW), or asset growth (for CMA). For example, to build the HML factor, every June, firms are sorted into two groups based on how their market cap compares to the NYSE median market cap that month. They also are independently sorted into three groups based on how their book-to-market ratio compares to the 30th and 70th NYSE book-to-market percentiles. Using this 2-by-3 sort, the return on the HML factor in any given month is the simple average of the returns on the two high book-to-market portfolios minus the simple average of the returns on the two low book-to-market portfolios. The RMW and CMA factors are created analogously. Notice, however, that each 2-by-3 sort creates its own size factor.[11] The return on the overall SMB factor is calculated as the simple average of the returns on the three size factors resulting from these individuals 2-by-3 sorts.[12]

It is important to note that the valuation model used as motivation in FF5F predicts a negative relation between (long-run) expected returns and *expected* investment, while the q-theoretic model in HXZ predicts a negative relation between (one-period) expected returns and *realized* investment. Hence, in FF5F, asset-growth is used as a proxy for expected investment while in HXZ it is used as a proxy for realized investment. We refrain from analyzing the relation between asset-growth and expected investment for the simple fact that any such analysis must be preceded by a determination of an appropriate measure of realized investment. The main argument of our study is that this is by no means a trivial matter. In the absence of a generally agreed upon measure of realized investment, any discussion of expected investment would be speculative at best.[13]

[10] In June, of every year $t$, operating profitability and asset growth are measured using annual Compustat data from fiscal year ending in calendar year $t-1$.

[11] For example, in the 2-by-3 sort based on size and book-to-market, the return on the size factor equals the average return on the three small portfolios minus the average return on the three big portfolios.

[12] Fama and French (2015) also form factors based on three 2-by-2 sorts (instead of 2-by-3) as well as on a single 2-by-2-by-2-by-2 sort. At the end of their paper, they suggest that they prefer the 2-by-3 sorts because they follow the approach in Fama and French (1993) and the resulting factors perform no worse than those based on the alternative sorting strategies.

[13] That being said, in unreported results, we test whether various measures of investment (e.g. asset growth,

In addition to the empirical difficulties of analyzing the relation between asset growth and expected investment, there are also theoretical challenges to the idea that asset growth explains expected returns because it is a good proxy for expected investment. As discussed in Hou, Xue, and Zhang (2014), q-theory predicts a positive relation between one-period-ahead expected returns and expected investment. In addition, Hou, Xue, and Zhang (2014) show that, while the valuation model used in FF5F predicts a negative relation between expected investment and long-run expected returns, a reformulation of the model yields a positive relation between expected investment and one-period-ahead expected returns.

### 3.3 Empirical performance of asset-growth based models

To examine the performance of the various factor models used in this study, we use the same set of anomaly variables as HXZ. They start with a broad set of 80 anomaly variables and form portfolios based on NYSE cutoffs for each of these variables to prevent micro stocks from dominating the extreme portfolios. They then focus only on the anomaly variables that generate value-weighted spread portfolios with significant CAPM alphas. This yields a list of 35 anomaly variables which we focus on in this study. Following HXZ, we also form portfolios based on NYSE cutoffs and report results only for value-weighted portfolio returns. Our sample period starts in January 1972 and ends in December 2016.[14] Appendix A describes how each of the 35 anomalies used in this study is constructed.

In Table III, we use five different factor models to calculate alphas and t-statistics for the spread portfolios of the 35 anomalies. Specifically, we use the capital asset pricing model (CAPM), the Fama and French (1993) three-factor model (FF3F), the Carhart (1997) four-factor model (C4F), the HXZ four-factor model, and the FF5F five-factor model. The bottom four rows of the table summarize how these models fare at explaining the anomaly returns. In the row titled "Mean $|\alpha|$: spread" for each of the five models, we take the average of the absolute values of the 35 spread-portfolio alphas corresponding to that model. Here the HXZ model performs significantly better

change in PPE, the total investment measure of Peters and Taylor (2017)), have predictive power over future levels of investment and we find that this is not the case. For example, a regression of future asset growth on current asset growth yields an $R^2$ of 2.5% and a regression of future PPE growth on current PPE growth has an $R^2$ of 8.9%. Similarly, a regression of future PPE growth on current asset growth has an $R^2$ of 7.8%. All these $R^2$ statistics fall drastically (in the range of 1-3%) if we use two-years-ahead predictive regressions. This suggests that asset growth and several measures of realized investment are likely poor proxies for expected investment.

[14]The sample period in Hou, Xue, and Zhang (2015) is from January 1972 to December 2012.

than the rest. It yields an average absolute spread alphas of 19 bps per month, whereas the FF5F model and the Carhart (1997) model yield average absolute spread alphas of 38 and 29 bps per month, respectively. The same cannot be said when looking at the average absolute alphas of all decile portfolios (as opposed to just the spread portfolios). As shown in the "Mean $|\alpha|$: all" row, there is little difference in the average absolute alphas of the Carhart (1997), HXZ, and FF5F models.

Moving on to more formal testing methods, we count, for each model, the number of anomalies with spread-portfolio alphas with t-statistics larger than 2 in absolute value. The results, reported in the "N($|t| > 2$)" row, show that the HXZ model significantly outperforms all the others, explaining all but 5 of the 35 anomalies. In contrast, the Carhart (1997) and FF5F models explain all but 16 and 21 anomalies respectively. Finally, for each model, we count the number of anomalies for which the model is rejected by the Gibbons, Ross, and Shanken (1989, GRS) test at the 5% level.[15] As seen in the "N($p < 5\%$)" row, the HXZ and FF5F models get rejected by the GRS test for 18 and 23 anomalies respectively.

Overall, Table III provides two main conclusions about the performance of the new investment– and profitability–based factor models. First, while the FF5F five-factor model performs significantly better than the Fama and French (1993) three-factor model, it does not provide significant improvements over the Carhart (1997) model. Second, the HXZ model performs significantly better than both the traditional CAPM, Fama and French (1993), and Carhart (1997) models, as well as the new FF5F model, regardless of which test metric we use.

FF5F test the performance of variations of their five factor model using several sets of tests assets (portfolios). In Table IV, we use the same test assets to test the performance of the models from Table III. Specifically, the test assets consist of 25 Size-Book to Market portfolios (Panel B), 25 Size-Asset Growth portfolios (Panel C), 25 Size-Profitability portfolios (Panel D), 32 Size-Book to Market - Asset Growth portfolios (Panel E), 32 Size-Book to Market-Profitability portfolios (Panel F), and 32 Size-Asset Growth-Profitability portfolios (Panel G). In Panel A, we use a set of test assets consisting of all the portfolios used in panels B through G. For each model (i.e., column), we present the average of the absolute alphas corresponding to each set of portfolios ("Mean $|\alpha|$"), the

[15]The Gibbons, Ross, and Shanken (1989) model tests the null hypothesis that the alphas of all the decile portfolios formed on a particular anomaly variable are jointly zero.

number of alpha t-statistics with absolute value larger than 2 ("N($|t| > 2$)") and the GRS statistic.

The results in Panel A of Table IV show that the HXZ and FF5F models outperform the CAPM, Fama and French (1993), and Carhart (1997) models on all three metrics. However, the HXZ model seems to significantly outperform the FF5F only with respect to the number of t-statistics larger than 2. These two basic results hold regardless of which set of tests assets we use (Panels B through G). Moreover, the HXZ and FF5F models seem to perform the best in explaining the 25 Size–Profitability portfolios (Panel D), and they perform the worst in explaining the 32 Size–AG–Profitability portfolios (Panel G).

## 4 Alternative Measures of Corporate Investment

Both HXZ and FF5F suggest adding investment-based factors to factor pricing models using the basic intuition that, in equilibrium, firms with higher investments must be firms with lower discount rates (holding everything else constant). We argue that, if the cross-sectional dispersion in corporate investment explains much of the cross-sectional dispersion in average returns observed when sorting stocks on other anomaly variables, then this result should be reasonably robust to changes in how corporate investments are calculated. In this section, we test if this is the case using several different measures of investment used in previous studies.

The corporate investment literature is vast, and any survey of it is bound to be incomplete. With this caveat in mind, our broad review of the literature reveals that empirical studies of corporate investment (including tests of the q-theory) most commonly focus on investment in physical capital, measured either using the capital expenditure (CAPX) figure from the statement of cash flows or growth in property, plant, and equipment (PPE). Appendix B provides a sample of studies using CAPX or PPE growth to measure investment. This list is by no means exhaustive. Our only intent is to point out that, at least from our reading of the literature, standard practice seems to measure investment using CAPX and PPE-based variables.[16] Hence, we use CAPX and change in PPE, both divided by lagged PPE, as our two traditional measures of investment. In unreported tests, we verify that our results are qualitatively unchanged if we use variations of these two measures,

[16]For comparison, in our search, we found only three studies that use growth in total assets to measure corporate investment – Alti and Tetlock (2014), Li and Zhang (2010), and Baker, Stein, and Wurgler (2003). The latter two use it as part of a larger set of investment measures.

such as (1) normalizing by lagged total assets instead of PPE (e.g. Warusawitharana and Whited (2016)) (2) normalizing by replacement value of capital calculated using a perpetual inventory method (e.g. Fazzari, Hubbard, and Petersen (1988)) (3) subtracting the sale of PPE to obtain measures of net investment instead of gross investment (e.g. Liu, Whited, and Zhang (2009)) (4) adding R&D expense to all investment measures (e.g. Asker, Farre-Mensa, and Ljungqvist (2015)) (5) adding change in inventory to all investment measures (e.g. Lyandres, Sun, and Zhang (2008)) and (6) using capital expenditures net of depreciation (e.g. Denis and Sibilkov (2010)).

In a recent study, Peters and Taylor (2017) point out that although firms mainly owned physical capital when the neoclassical theory of investment was developed more than three decades ago, intangible capital has become an increasingly important factor of production and should be included in measures of corporate investment. They calculate total intangible capital as the sum of intangible capital on the balance sheet (goodwill) plus intangible capital off the balance sheet. The latter is calculated as capitalized knowledge capital (R&D) plus capitalized organizational capital (30% of SG&A).[17] The total capital of a firm is calculated as the sum of physical capital (gross PPE) plus intangible capital. In our analysis below, we use the annual change in these measures of total, tangible and intangible capital as additional measures of investment.[18]

### 4.1 Relationship between asset growth and alternative investment measures

In Panel A of Table V, for each asset-growth decile, we show the average decomposition of firms' total capital into its various components (expressed as percentages of contemporaneous total capital). The first two columns show how total capital decomposes into physical and intangible capital. Across the 10 asset growth deciles, we see that a large portion of firms' capital is intangible, which suggests that focusing on growth in physical assets misses a significant component of firms' investment activity. The next two columns show how total intangible capital decomposes into on- and off-balance sheet intangible capital. This shows that off-balance-sheet intangible capital represents, on average, more than a third of a firm's total capital and most of their total intangible capital. This means that measures of investment based only on balance sheet items also ignore a significant

[17]The assumption that firms on average use 30% of SG&A as an investment in human capital and the rest for operating expenses has been used in several other studies e.g. Eisfeldt and Papanikolaou (2014), Hulten and Hao (2008), and Zhang (2014).

[18]All three change variables are normalized by lagged total capital.

component of corporate investment. This seems to be particularly important for firms with the lowest asset growth (decile 1), where almost half of the capital (49.5%) is in the form of off-balance items. The last two columns in the panel show how off-balance sheet intangible capital decomposes into knowledge capital (R&D) and organizational capital (SG&A). Across the 10 deciles, we find that organizational capital accounts for the largest portion of intangible capital. Finally, looking at the differences between the extreme asset growth deciles (bottom two rows in the panel), we find that high asset growth firms tend to invest more in on-balance sheet intangible capital (goodwill) but less in off-balance-sheet capital (mostly coming from organizational capital).

In Panel B of Table V, using several different measures of investment, we show average investment levels for each asset growth decile. In the first two columns, we use the traditional measures described above: CAPX divided by lagged PPE and percentage change in PPE. The third column reports averages in the percentage change in total capital, as measured by Peters and Taylor (2017). The last six columns use changes in the different types of capital discussed in Peters and Taylor (2017), normalized by lagged total capital. The bottom two rows show that regardless of which investment measure we choose, firms in the highest asset growth decile invest significantly more than those in the lowest asset growth decile. However, looking at the last three columns, we notice that the relationship is not monotonic. In fact, the bottom asset growth decile invests more in off balance sheet capital than the next five to six asset growth deciles. This suggests that measures of investment based on balance sheet items (including asset growth) provide an incomplete picture of corporate investment activity. To further illustrate this point, in Panel C, we present correlation coefficients between asset growth and each investment measure. We find that these correlations are moderate when using measures of investment in physical capital (around 0.55), but they are quite low when using measures of investment in intangible capital, particularly off-balance-sheet capital (around 0.17 to 0.30).

### 4.2 Explaining anomaly returns

In Table VI, we investigate how the HXZ and FF5F models perform if the investment factor is constructed using alternative measures of corporate investment (as opposed to asset growth). Panel A presents results using variations of the HXZ model. The first column ("AG") uses asset growth to measure investment (hence this is just the HXZ model). In the second column ("None"), we reconstruct the HXZ model using no investment factor whatsoever. The following five columns correspond to different versions of the HXZ model in which the investment is not measured as asset growth but as either CAPX divided by lagged PPE ("CAPX"), percentage growth in PPE ("PPE"), percentage growth in the total capital ("TOTK"), change in physical capital divided by lagged capital ("PHK"), or change in intangible capital divided by lagged total capital ("INTK"). The last three measures are based on the capital decomposition measures of Peters and Taylor (2017).[19]

The bottom four rows of Panel A summarize the performance of all these alternative models. Comparing the first two columns ("AG" and "None"), we notice that the HXZ model performs significantly better (as judged by the number of anomalies with spread-portfolio alphas with t-statistics larger than 2 in absolute value ("N($|t| > 2$)") with the investment (asset growth) factor than without the investment (asset growth) factor. However, as seen in the following five columns, the same cannot be said if the investment factor is constructed using any other measure than asset growth. PPE and CAPX perform better than no investment factor, but worse than asset growth. The TOTK, PHK, and INTK factors also do not perform as well as asset growth. In fact, INTK performs about as well as the model with no investment factor. Note that there is not much evidence of model performance differences as judged by the average absolute alphas of all decile portfolios ("Mean $|\alpha|$: all") and the associated GRS tests. In fact, the model with no investment factor ("None") performs about as well as all models with investment factors as judged by these two metrics. The success of the HXZ model is most evident using the test on spread portfolio alphas ("Mean $|\alpha|$: spread"). Overall in this panel, even though in some cases the alternative investment measures do perform somewhat better than the model without an investment factor, their performance does not come near the performance of the asset-growth based model.

In Panel B, we perform the same analysis using variations on the FF5F model.[20] Here the difference between the asset-growth-based FF5F model and its variants using alternative investment measures is not as stark. Nevertheless, we notice that many of the alternative investment models do not even improve on a model with no investment factor (the "None" column).

[19]Note that because each of the factors in the HXZ model depends on the multivariate sort on size, investment, and profitability, when we change the measure of investment, this changes not only the investment factor, but also the size and profitability factors.

[20]Note that changing the way we measure investment in the Fama and French (2015) model will change not only the investment factor but also the size factor, because this factor depends on the 2-by-3 sort on size and investment.

### 4.3 Explaining test-asset returns

In Table VII, we summarize the ability of the alternative models described above to explain returns on various sets of test assets (portfolios). We use the same groups of portfolios as in Table IV, and the same models as in Table VI. Panel A of Table VII shows the performance of models based on HXZ. Panel A1, in which we use all 171 test assets together, shows that all the models obtained by substituting the asset-growth based factor with alternative measures of investment significantly underperform with respect to the asset-growth based HXZ model (AG). This holds true even when we use the complete measure of investment of Peters and Taylor (2017) (TOTK) and is valid regardless of which set of test assets we look at (Panels A1 through A7). For example, the base HXZ model ("AG" in Column 1) can explain the average returns of all but 21 of the 171 portfolios. In contrast, the other models with substitute investment factors range from failing to explain 35 portfolios (total capital (TOTK)) to 61 portfolios (intangible capital (INTK)).

In Panel B of Table VII, we show the performance of models based on the FF5F model. Once again, the models based on alternative measures of investment perform worse than the asset-growth based FF5F model (AG), even though the difference is not as pronounced as for the HXZ model. It is important to note that the models based on alternative investment factors often do not outperform the model with no investment factor whatsoever ("None").

To reiterate, the two main findings of Table VI and Table VII are that (1) using alternative measures of corporate investment to create the investment factor in HXZ yields models that perform significantly worse than the original model based on asset-growth and (2) using different measures of investment in the FF5F model generally does not improve on a version of the model with no investment factor. These findings hold even when we consider a much larger set of investment measures, as explained at the beginning of this section. In fact, of all the measures we use, none of them comes close to the performance of the HXZ model with asset growth. The fact that no other measure of investment provides similar performance as the asset-growth based model of HXZ, and that no other measure of investment provides significant improvements on a version of the FF5F model with no investment factor, raises serious concerns about whether these models truly identify the negative theoretical relation between investment and expected returns.

# 5 Decomposing Asset Growth

We find it difficult to justify growth in total assets as the most accurate measure of a firm's investment activity. First, as mentioned above, the asset growth measure ignores investments in off-balance sheet intangible capital, such as knowledge capital and organizational capital. Second, growth in total assets confounds investments with the financing used for them. For example, if a firm uses cash to finance and invest in PPE, we would observe zero growth in total assets when an investment was clearly made. Third, it is not clear if growth in current assets tells us much about the firm's investment activities. While increases in current assets *could* be a result of the firm growing its operations, they can also be a result of the firm stagnating. Cash balances can increase in the absence of investment opportunities, inventory can increase if the firm is not able to sell its products at the same rate, and accounts receivables can increase if the firm is not able to recover the trade credit extended to its customers.

While the asset growth measure may have the benefit of aggregating several different types of investment made by the firm, as argued above, this aggregation may just as easily introduce noise into the process of measuring corporate investments. In fact, studies such as Peters and Taylor (2017), detail exactly how this aggregation should be done and what types of investments should be included in the calculation. Nevertheless, the data shows strong evidence that the asset growth factor helps explain the cross-sectional dispersion of expected stock returns. If this is indeed because asset growth is a better aggregator of all the firm's investment activities, then if we restrict ourselves to specific subcomponents of asset growth and use them to form our investment factor, we should obtain factor models that do not perform nearly as well as the asset-growth based models. We investigate this prediction in the remainder of this section.

We decompose a firm's growth in total assets into changes in items from both the left-hand side and the right-hand side of the balance sheet. On the left-hand side, we use changes in cash, noncash current assets, gross PPE, and other assets (i.e., total assets minus the previous three categories). On the right-hand side, we use changes in long-term debt, common equity, retained earnings, and operating liabilities (i.e., total assets minus the previous three categories). All eight growth measures are normalized by lagged total assets. As a result, the sum of all the subcomponents on each side of the balance sheet amounts to the firm's percentage growth in total assets.

In Panel A of Table VIII, for each asset growth decile, we present averages of asset growth as well as averages of its subcomponents. Looking at the subcomponents on the left-hand side of the balance sheet, we notice that growth in PPE – a common measure of investment in the literature – is not the largest component of asset growth. Growth in noncash current assets seems to play that role across almost all asset growth deciles. On the right-hand side of the balance sheet, the largest component of asset growth seems to be the change in retained earnings for firms with low asset growth, and common equity for firms with high asset growth. Panel B shows the correlations between asset growth and its various subcomponents. While unsurprisingly high, these correlations are nowhere near perfect, which means that sorting on asset growth will not yield the same portfolios as sorting on its subcomponents.

## 5.1 Fama-MacBeth regressions

To investigate the explanatory power of the different asset-growth components, in Table IX, we run Fama and MacBeth (1973) regressions of future 12 month returns on size (ME), book-to-market (BM), gross-profitability (GP) and components of asset growth. In Panel A, we use items from the left-hand-side of the balance sheet as predictors. In the first five columns, we use all firms in our sample. We find that both when introduced separately (columns 1-4), and together (column 5), all components except for growth in cash have statistically significant predictive power over returns. In the last five columns, we address the issue that the previous results overweight small firms by running the same regressions excluding the micro firms (i.e. market capitalization below the 20th NYSE cutoff). We find that in this sample, when introduced together (last column), the only subcomponent that has predictive power over returns is growth in noncash current assets.

In Panel B, we use items from the right-hand-side of the balance sheet as predictors. Here the results are qualitatively identical if we use the full sample (first five columns) or the all-but-micro subsample (last five columns). When introduced separately, all components except for growth in retained earnings (RE) are significant predictors of returns. However, when introduced together, only the growth in long term debt (DEBT) and growth in book equity (EQ) are statistically significant.[21]

[21] Daniel and Titman (2006), using an equity issuance measure, find similar results as we do for growth in book equity in predicting the cross-section of returns.

Overall, the results in Table IX provide two important takeaways. First, they highlight the fact that several different sources of growth in total assets have predictive power over future returns. Second, the subcomponents that are reliable predictors of returns (growth in noncash current assets, debt, and equity) are not the most direct measures of investment activity in a firm. This calls into question the idea that the negative relation between asset growth and future returns is solely a reflection of the negative relation between corporate investment and expected returns predicted by $q$-theory.

## 5.2 Explaining anomaly returns

In Panel A1 of Table X, we analyze the performance of variations of the HXZ model, where the asset growth factor is replaced with a factor based on a subcomponent of asset growth from the left-hand side of the balance sheet. As before, the first two columns replicate the results using the original HXZ model ("AG") and a version of it with no investment factor ("None"). The summary results from the bottom four rows of the table indicate that, when replacing the asset-growth factor with a factor based on growth in noncash current assets ("NCCA"), we obtain a factor model that seems to perform about as well as the original HXZ model. Indeed, the noncash current assets model explains all but 8 anomalies based on spread portfolio alphas (as opposed to 5 for the asset growth based model) and is only rejected 16 times by the GRS test (as opposed to 18 times for the asset growth based model). Furthermore, based on the GRS test, the model based on growth in other assets ("Other") performs better than the asset-growth based model. In Panel A2, we perform a similar exercise using subcomponents of asset growth from the right-hand side of the balance sheet to construct the investment factor. Here we find that, based on the GRS test, the model based on growth in operating liabilities ("OLIAB") performs just as well as the original asset-growth based model.

In Panels B1 and B2 of Table X, we repeat the analysis in Panels A1 and A2, using variations of the FF5F model instead of the HXZ model. The bottom four rows in Panel B1 reveal that the model based on growth in noncash current assets ("NCCA"), as judged by the number of insignificant spread portfolio alphas, performs as well as the original FF5F model ("AG"). Similarly, from Panel B2, we see that the model based on growth in long-term debt ("DBT") performs about the same as the FF5F model as judged by the spread portfolio alpha tests, and performs better using the

GRS test.

The results in Table X show that the HXZ and FF5F models would perform just as well if variables such as growth in noncash current assets and growth in long-term debt were used to form the investment factor. Since these variables ignore obvious measures of investments, such as PPE spending, our results cast serious doubts on the idea that these models' ability to explain asset pricing anomalies can be attributed to the fact that total asset growth is a comprehensive measure of investment.

### 5.3 Explaining test-asset returns

In Panel A of Table XI, we summarize the ability of the alternative models based on the asset growth left-hand side of the balance sheet decomposition to explain the returns on 171 test portfolios for the HXZ model. As we showed previously in Table VII, the HXZ model (AG) can explain, as judged by portfolio alphas, all but 21 out of 171 portfolios. When we examine the ability of factors based on the asset side of the balance sheet decomposition of asset growth in Panel A, we see that the property, plant, and equipment (PPE) factor, which arguably is the most investment-like part of the decomposition, performs much worse than asset growth by failing to explain the returns of 54 portfolios. In fact, the best performing subcomponent factor is based on growth in noncash current assets ("NCCA"). The NCCA model fails to explain 31 of the portfolios and has a mean absolute alpha across all 171 portfolios of only slightly more than the asset growth model. In Panel B, which contains the decomposed right-hand side of the balance sheet, none of the subcomponents comes close to the performance of the asset growth model in explaining the portfolio alphas.

In Panels C and D of Table XI, we summarize the ability of the alternative models based on the asset growth decomposition to explain the returns on 171 test portfolios for the FF5F model. In Panel C, which contains the decomposition of assets, we see that relative to the FF5F model (AG), there is not much ability to explain the test portfolio returns using other components. As we have seen before in other tables, the factors based on the components of left-hand side of the balance sheet do not perform much better than the "None" model without an investment factor. When we examine decomposed liabilities in Panel D, we see that the model based on growth in long-term debt ("DBT") performs better than the FF5F model, as judged by the spread portfolio alpha tests and the GRS test. Overall, the results from Table XI provide similar conclusions as with the spread portfolios in Table X. There is evidence that traditional investment factors do not perform as well as asset growth, and models using growth in noncash current assets for HXZ tests and growth in long-term debt for FF5F tests also perform well.

## 6 A Data–Mining Approach

In the previous two sections, we analyzed how the performance on the HXZ and FF5F models would change if the asset-growth-based investment factor in these models was instead constructed using several key alternative measures of corporate investment (Section 4) or subcomponents of asset growth (Section 5). In this section, we verify that the main findings of our analysis are not driven by our particular choice of alternative investment measures or subcomponents of asset growth. To this end, we extend the analysis in the previous two sections by considering 144 different measures of investment and 76 different asset growth subcomponents with which to construct alternative investment factors.

To construct our set of investment measures, we start with three different measures of investment in physical capital (CAPX, change in gross PPE and CAPX net of PPE sales). We then consider several other investments that the firm could make: change in inventory, change in goodwill, change in capitalized knowledge capital, and change in capitalized organizational capital (the latter three measures are calculated as in Peters and Taylor (2017)). For each of the three choices of physical capital investment, we add every possible combination of the additional four types of investment. This yields $3 \times 2 \times 2 \times 2 \times 2 = 48$ different investment measures. Finally, we use three different lagged normalizing variables (total assets, gross PPE and total capital as measured in Peters and Taylor (2017)), which leads us to $48 \times 3 = 144$ investment variables.

To construct our set of asset growth subcomponents, we consider all the possible combinations of several key items from the left-hand-side or the right-hand-side of the balance sheet. On the left-hand-side, we consider all the possible combinations of growth in cash holdings, inventory, accounts receivable, net PPE, goodwill and "other" (i.e. total assets minus the other five items). This yields $2^6 = 64$ possibilities, of which one equals 0 and one equals total asset growth. This leaves us with 62 well defined subcomponents. On the right-hand-side, we use all the combinations of the same basic components we use in Section 5: operating liabilities, long-term debt, retained earnings, and shareholders equity minus retained earnings. Following the same logic, this leaves us with $2^4 - 2 = 14$ well defined subcomponents (and $62 + 14 = 76$ in total). All subcomponents are normalized by lagged total assets.

Next, we follow the same approach as in Sections 4 and 5, and we analyze how the performance of the HXZ and FF5F models changes if the asset-growth factor is replaced with a factor based on one of our 144 different measures of investment or one of our 76 subcomponents of asset growth. For brevity, we restrict our attention to two performance measures: the average absolute alpha of the 35 anomaly spread portfolios, and the number of spread-portfolio alpha t-statistics greater than two. Hence, for both performance metrics, lower values represent better performance.

Figure 1 shows our results for HXZ-like models. In the top two panels, we report histograms of average spread alphas (left) and number of t-statistics greater than 2 (right) for the 144 HXZ-like models obtained from replacing the asset growth factor with an alternative investment measure. The bottom two panels do the same for the 76 HXZ-like models obtained by using subcomponents of asset growth as the investment factor. In all panels, the red vertical line shows the performance of the HXZ model, using asset growth as investment. As a reference, the blue vertical line shows the performance of the HXZ model obtained using the percentage change in PPE to construct the investment factor.

The top two panels in Figure 1 show that constructing the HXZ model using any of our 144 different measures of corporate investment results in models with strictly worse performance than HXZ. The bottom two panels show that the performance of the HXZ model can in fact be matched, in many cases, by using subcomponents of asset growth to construct the investment factor. This is inconsistent with the notion that the superior performance of the HXZ model displayed in the top two panels is a result of asset growth being a more complete or less noisy measure of corporate investment. If this were the case, then we should not be able to create models that perform just as well as HXZ by simply ignoring some components of asset growth.

Figure 2 shows the performance of the alternative FF5F-like models. The structure is the same as in Figure 1. The results in the top two panels differ from Figure 1 in that they show that one *can* use alternative measures of investment to construct FF5F-like models that perform better than the original, asset-growth-based model. However, this is not surprising given the poor performance of the FF5F model to begin with. The more striking result is in the bottom two panels, which show that there are many ways to *improve* on the FF5F model by simply ignoring some components of asset growth. Once again, this is inconsistent with the idea that the explanatory power of the asset growth factor in the FF5F model can be attributed to asset growth being an accurate measure of investment.

## 7 Conclusion

The Hou, Xue, and Zhang (2015) and Fama and French (2015) factor models describe the cross-section of expected stock returns better than pre-existing factor models. However, the success of these models is difficult to interpret. As Kozak, Nagel, and Santosh (2017) point out, factor models in themselves cannot help distinguish between behavioral and rational determinants of expected return variation.[22] Apart from performance-evaluation applications, the usefulness of the new factor models must lie in the fact that they may have uncovered new sources of comovement between stock returns that previous factor models did not pick up.

Our study aims to improve our understanding of the sources of comovement underlying the Hou, Xue, and Zhang (2015) and Fama and French (2015) models. We do so by asking whether the "investment factor" in these models explains anomalies because it picks up comovement in returns of firms with similar investment levels. We provide two main pieces of evidence that suggest this may not be the case. First, we point out that the investment factor used in Hou, Xue, and Zhang (2015) and Fama and French (2015) is measured using firm-level growth in total assets which is difficult to justify as the most accurate available measure of investment. We find that when we construct it using many other (arguably more direct) measures of corporate investment, the explanatory power of the Hou, Xue, and Zhang (2015) and Fama and French (2015) models is greatly reduced. Second, we show that using some subcomponents of asset growth (e.g. growth in noncash current assets or growth in long-term debt) to construct the investment factor, we obtain models that perform virtually as well as the Hou, Xue, and Zhang (2015) and Fama and French (2015) models.

To sum, the performance of these new factor models can be replicated using measures of investment that are arguably incomplete, but cannot be replicated using traditional measures used in the

[22]To do so, one must at least specify investor beliefs and preferences.

literature (e.g. CAPX or growth in PPE) or more complete measures that include investment in intangible capital (e.g. Peters and Taylor (2017)). This raises serious doubts about the possibility that the investment factor's explanatory power is derived from the fact that it captures comovement in returns of firms with similar investment levels. Our findings suggest that much more needs to be done to understand what drives the explanatory power of the asset growth factor in Hou, Xue, and Zhang (2015) and Fama and French (2015). As such, we view these models as more appropriate for performance benchmarking purposes, and we caution against using them to estimate expected returns or to investigate the risk-return tradeoff.

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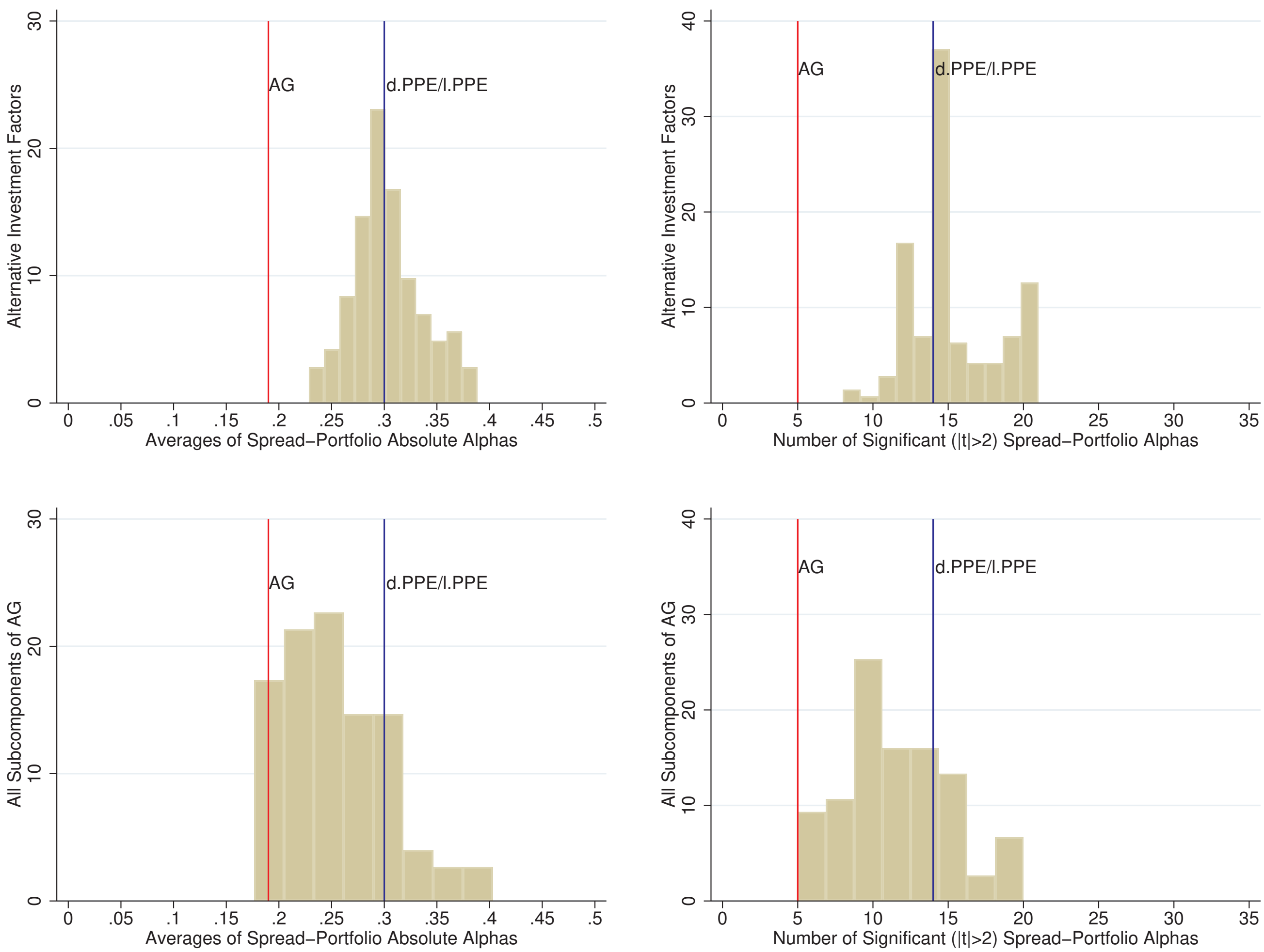


**Figure 1**
**Performance of Alternative HXZ-Style Models**
This figure plots the performance of HXZ-style models obtained by replacing the asset-growth based investment factor in HXZ, with a factor based on one of 144 different measures of investment (top two panels) or one of 76 different subcomponents of asset growth. For these alternative models, the left two panels report histograms of average spread alphas, and the right two panels report histograms of the number of t-statistics greater than 2. As reference points, the red vertical line shows the performance of the original, asset-growth-based HXZ model, and the blue line shows the performance of the HXZ model obtained using the percentage change in PPE to construct the investment factor.

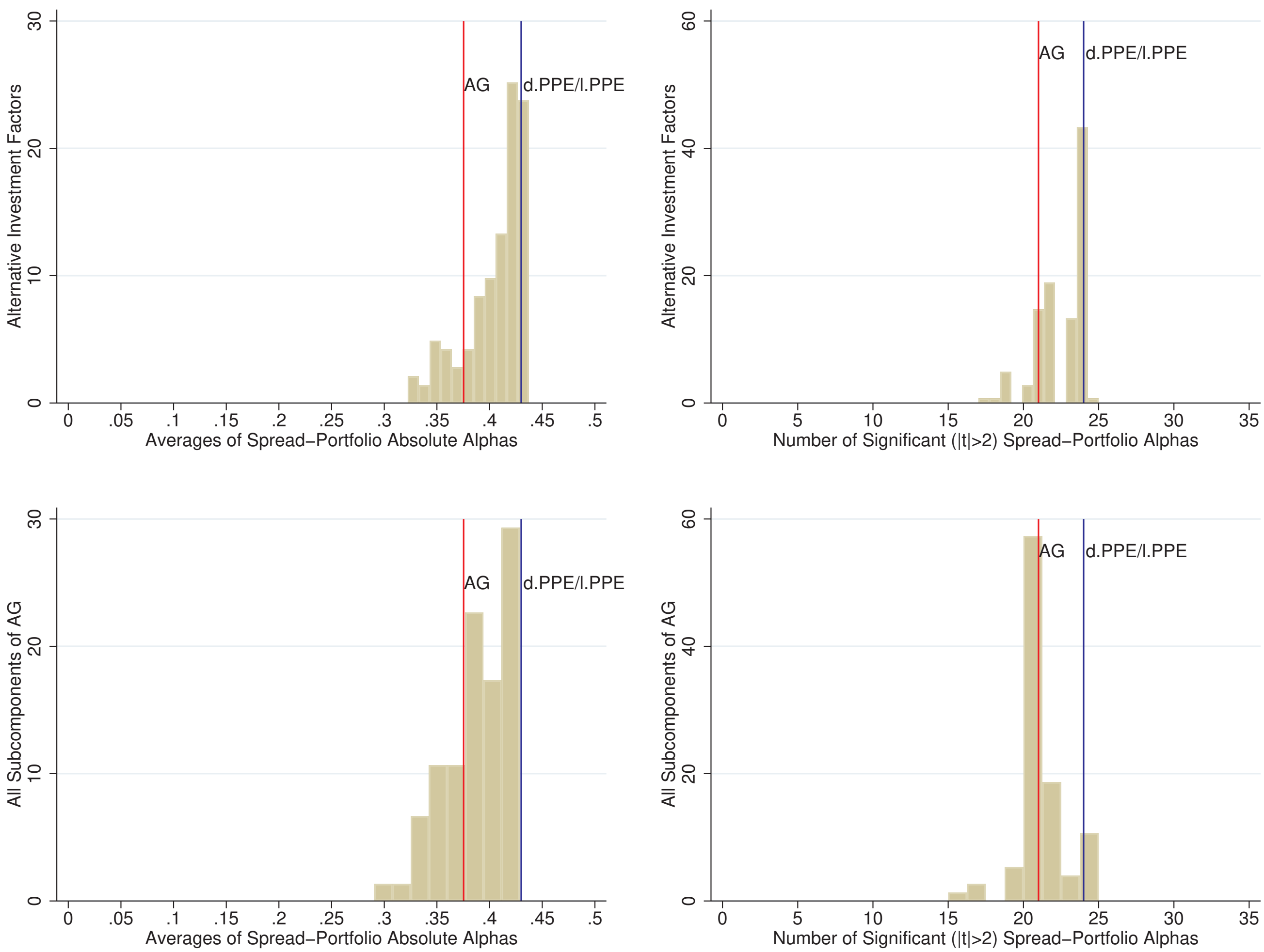


**Figure 2**
**Performance of Alternative FF5F-Style Models**
This figure plots the performance of FF5F-style models obtained by replacing the asset-growth based investment factor in FF5F, with a factor based on one of 144 different measures of investment (top two panels) or one of 76 different subcomponents of asset growth. For these alternative models, the left two panels report histograms of average spread alphas, and the right two panels report histograms of the number of t-statistics greater than 2. As reference points, the red vertical line shows the performance of the original, asset-growth-based FF5F model, and the blue line shows the performance of the FF5F model obtained using the percentage change in PPE to construct the investment factor.

## Table I
## Characteristics of Asset Growth Portfolios

This table presents characteristics of portfolios formed based on firm-level annual percentage growth in total assets. Every June from 1968 to 2016, firms are split into ten portfolios (deciles) based on their asset growth ranking in the fiscal year ending in the previous calendar year. The sample excludes financials and firms with negative book equity. For each characteristic (column), the numbers reported are time-series averages of annual portfolio-level cross-sectional means. In the last column, "young" refers to firms younger than 5 years. Please see Section 2 for more details on how each characteristic is constructed.

| AG decile | Asset growth | Market cap. | BM | RET12 | RET36 | GP | ROE | Issuance 1 year | Issuance 5 years | Accruals | Percent micro | Percent small | Percent large | Age | Percent young |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1(Low) | -0.224 | 587.2 | 1.080 | 0.065 | -0.078 | 0.285 | -0.268 | 0.027 | 0.152 | -0.110 | 0.780 | 0.101 | 0.066 | 10.25 | 0.354 |
| 2 | -0.066 | 1068.8 | 1.167 | 0.108 | 0.111 | 0.345 | 0.075 | 0.014 | 0.041 | -0.066 | 0.638 | 0.157 | 0.152 | 12.41 | 0.274 |
| 3 | -0.010 | 1851.4 | 1.079 | 0.128 | 0.237 | 0.354 | 0.173 | 0.009 | -0.018 | -0.050 | 0.521 | 0.191 | 0.236 | 13.86 | 0.239 |
| 4 | 0.026 | 2523.2 | 0.984 | 0.147 | 0.343 | 0.368 | 0.214 | 0.010 | -0.039 | -0.041 | 0.451 | 0.202 | 0.294 | 14.70 | 0.231 |
| 5 | 0.057 | 2892.8 | 0.909 | 0.147 | 0.431 | 0.379 | 0.231 | 0.013 | -0.035 | -0.034 | 0.418 | 0.209 | 0.320 | 15.00 | 0.233 |
| 6 | 0.091 | 3022.1 | 0.839 | 0.156 | 0.510 | 0.391 | 0.246 | 0.017 | -0.010 | -0.030 | 0.400 | 0.214 | 0.333 | 14.55 | 0.239 |
| 7 | 0.132 | 2987.9 | 0.763 | 0.159 | 0.606 | 0.413 | 0.255 | 0.023 | 0.022 | -0.024 | 0.399 | 0.222 | 0.327 | 13.55 | 0.265 |
| 8 | 0.194 | 2558.8 | 0.704 | 0.167 | 0.732 | 0.417 | 0.250 | 0.033 | 0.077 | -0.014 | 0.428 | 0.234 | 0.285 | 12.05 | 0.305 |
| 9 | 0.319 | 2000.0 | 0.638 | 0.159 | 0.916 | 0.403 | 0.235 | 0.061 | 0.172 | -0.004 | 0.456 | 0.240 | 0.251 | 10.47 | 0.366 |
| 10(High) | 0.906 | 1500.1 | 0.576 | 0.140 | 1.160 | 0.319 | 0.160 | 0.164 | 0.382 | 0.010 | 0.517 | 0.239 | 0.192 | 8.61 | 0.463 |
| Spread(10-1) | 1.130 | 912.9 | -0.504 | 0.075 | 1.238 | 0.034 | 0.428 | 0.137 | 0.230 | 0.121 | -0.263 | 0.137 | 0.126 | -1.64 | 0.110 |
| t(spread) | 24.599 | 5.991 | -7.124 | 1.417 | 11.868 | 2.494 | 9.249 | 13.382 | 5.964 | 9.166 | -7.528 | 12.302 | 8.545 | -2.433 | 2.542 |

## Table II
## Asset Growth and The Cross-Sectional Predictability of Stock Returns

This table presents Fama-MacBeth (1973) regressions of future 12 months buy-and-hold returns on asset growth and other known predictors of expected returns. The estimates are obtained by running cross-sectional regressions every year from 1968 to 2016 and averaging over the resulting time-series of cross-sectional coefficients. The dependent variable measures the cumulative returns from July of the current year to June of the following year. In panel A, the independent variables include asset growth ("AG"), market capitalization of equity ("ME"), book-to-market equity ("BM"), cumulative returns in the past 12 months ("RET12") and gross profitability ("GP"). Columns 1 through 5 use all firms in our sample, and columns 6 through 8 are restricted to micro firms (market cap smaller than 20th NYSE percentile), small firms (market cap between 20th and 50th NYSE percentiles), and large firms (market cap larger than 50th NYSE percentiles) respectively. In Panel B, we use our full sample of firms and we introduce controls for the following anomaly variables: net operating assets ("NOA"), common equity issuance ("CEI"), operating accruals ("OA"), gross profitability ("GP"), return on assets ("ROA"), standardized unexpected earnings ("SUE"), and abnormal returns around earnings announcements ("ABR"). Standard errors are corrected for serial correlation using the Newey-West (1987) procedure. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A

| | (1) All Firms | (2) All Firms | (3) All Firms | (4) All Firms | (5) All Firms | (6) Micro Firms | (7) Small Firms | (8) Large Firms |
|---|---|---|---|---|---|---|---|---|
| AG | -0.118*** | -0.107*** | -0.093*** | -0.092*** | -0.087*** | -0.097*** | -0.072*** | -0.041*** |
| | (-7.90) | (-7.55) | (-7.60) | (-7.62) | (-7.67) | (-7.12) | (-5.68) | (-3.28) |
| Size | | -0.013** | -0.009 | -0.009 | -0.008 | -0.028*** | 0.007 | -0.003 |
| | | (-2.03) | (-1.36) | (-1.32) | (-1.18) | (-3.16) | (0.87) | (-0.42) |
| BM | | | 0.040*** | 0.038*** | 0.045*** | 0.044*** | 0.026** | 0.037*** |
| | | | (3.99) | (3.93) | (4.12) | (3.73) | (2.08) | (3.57) |
| RET12 | | | | -0.001 | -0.007 | -0.013 | 0.012 | 0.036* |
| | | | | (-0.07) | (-0.38) | (-0.69) | (0.55) | (1.75) |
| GP | | | | | 0.076*** | 0.077** | 0.069** | 0.062** |
| | | | | | (2.70) | (2.68) | (2.15) | (2.31) |
| Constant | 0.162*** | 0.226*** | 0.166*** | 0.162** | 0.123* | 0.204*** | 0.034 | 0.086 |
| | (5.69) | (3.94) | (2.79) | (2.58) | (1.91) | (3.03) | (0.49) | (1.45) |

**Table II**
**Asset Growth and The Cross-Sectional Predictability of Stock Returns (continued)**

| Panel B | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| AG | -0.056*** | -0.065*** | -0.080*** | -0.087*** | -0.090*** | -0.088*** | -0.090*** |
| | (-4.99) | (-4.46) | (-5.88) | (-7.67) | (-7.23) | (-6.57) | (-6.60) |
| ME | -0.008 | -0.011* | -0.009 | -0.008 | -0.012* | -0.011* | -0.010 |
| | (-1.22) | (-1.71) | (-1.32) | (-1.18) | (-1.98) | (-1.73) | (-1.61) |
| BM | 0.041*** | 0.027*** | 0.038*** | 0.045*** | 0.036*** | 0.033*** | 0.033*** |
| | (4.62) | (3.05) | (3.89) | (4.12) | (3.64) | (3.03) | (3.21) |
| RET12 | -0.001 | -0.011 | 0.000 | -0.007 | 0.002 | -0.002 | 0.004 |
| | (-0.07) | (-0.64) | (0.02) | (-0.38) | (0.09) | (-0.10) | (0.21) |
| NOA | -0.063** | | | | | | |
| | (-2.37) | | | | | | |
| CEI | | -0.057*** | | | | | |
| | | (-3.79) | | | | | |
| ACC | | | -0.073* | | | | |
| | | | (-1.73) | | | | |
| GP | | | | 0.076*** | | | |
| | | | | (2.70) | | | |
| OCA | | | | | 0.690*** | | |
| | | | | | (3.73) | | |
| SVOL | | | | | | 0.011*** | |
| | | | | | | (5.21) | |
| ABR | | | | | | | 0.245*** |
| | | | | | | | (7.40) |
| Constant | 0.196*** | 0.187*** | 0.159** | 0.123* | 0.191*** | 0.195*** | 0.185*** |
| | (2.99) | (3.00) | (2.58) | (1.91) | (3.22) | (3.11) | (3.05) |

## Table III
## Anomaly Spread-Portfolio Alphas: Performance of New Factor Models

This table presents alphas (left) and corresponding t-statistics (right) of spread portfolios (high minus low) of 35 anomalies. The alphas are calculated using the CAPM, the Fama and French (1993) three factor model (FF3F), the Carhart (1997) four factor model (C4F), the Hou, Xue, and Zhang (2015) four factor model (HXZ), and the Fama and French (2015) five factor model (FF5F). The sample period is 1972-2016. Please see Section 3 for details on the HXZ and FF5F models and Appendix A for details on how the anomalies are constructed. The bottom panel of the table summarizes the performance of the five models employed. "Mean $|\alpha|$: spread" is the mean absolute values of the 35 spread-portfolio alphas. "Mean $|\alpha|$: all" is the mean absolute value of all the decile-portfolio alphas of all anomalies. "N($|t| > 2$)" counts how many of the 35 anomalies have spread-portfolio alphas with t-statistics greater than 2 in absolute value. "N($p < 5\%$)" counts for how many of the 35 anomalies the model employed is rejected by the Gibbons, Ross, and Shanken (1989) test at the 5% level.

| | Alphas of spread portfolios | | | | | T-statistics of spread portfolios | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Anomaly | CAPM | FF3F | C4F | HXZ | FF5F | CAPM | FF3F | C4F | HXZ | FF5F |
| SUE | 0.46 | 0.51 | 0.30 | 0.13 | 0.48 | 4.33 | 4.59 | 2.57 | 1.02 | 4.15 |
| SUE6 | 0.23 | 0.33 | 0.13 | 0.00 | 0.31 | 2.50 | 3.45 | 1.28 | -0.01 | 2.79 |
| Abr | 0.82 | 0.91 | 0.69 | 0.74 | 0.98 | 6.57 | 6.57 | 4.97 | 4.90 | 7.09 |
| Abr6 | 0.36 | 0.43 | 0.24 | 0.31 | 0.49 | 4.09 | 4.52 | 2.83 | 2.84 | 5.13 |
| RE | 0.75 | 0.95 | 0.30 | -0.13 | 0.66 | 3.44 | 4.43 | 1.70 | -0.62 | 2.77 |
| RE6 | 0.51 | 0.75 | 0.16 | -0.17 | 0.52 | 2.62 | 4.05 | 1.04 | -0.79 | 2.40 |
| R6_6 | 0.87 | 1.08 | 0.04 | 0.22 | 1.04 | 3.61 | 4.51 | 0.34 | 0.71 | 3.55 |
| R11_1 | 1.18 | 1.43 | 0.04 | 0.24 | 1.31 | 4.21 | 5.21 | 0.33 | 0.62 | 3.68 |
| Imom | 0.66 | 0.77 | -0.05 | 0.12 | 0.75 | 3.15 | 3.57 | -0.34 | 0.42 | 2.63 |
| BM | 0.69 | -0.01 | -0.01 | 0.21 | 0.02 | 2.80 | -0.06 | -0.09 | 1.26 | 0.15 |
| EP | 0.62 | 0.03 | -0.01 | 0.15 | -0.04 | 2.90 | 0.22 | -0.10 | 0.69 | -0.33 |
| CFP | 0.56 | -0.02 | -0.06 | 0.20 | -0.05 | 2.67 | -0.16 | -0.45 | 1.02 | -0.40 |
| NOP | 0.83 | 0.56 | 0.49 | 0.20 | 0.13 | 3.77 | 3.83 | 3.38 | 1.30 | 1.09 |
| Dur | -0.54 | -0.03 | -0.04 | -0.21 | -0.01 | -2.73 | -0.19 | -0.31 | -1.10 | -0.05 |
| AG | -0.52 | -0.19 | -0.12 | 0.06 | 0.02 | -3.12 | -1.41 | -0.86 | 0.47 | 0.17 |
| NOA | -0.43 | -0.55 | -0.43 | -0.43 | -0.53 | -2.92 | -3.56 | -3.08 | -2.25 | -3.11 |
| dPIA | -0.56 | -0.40 | -0.34 | -0.23 | -0.34 | -3.98 | -2.90 | -2.43 | -1.71 | -2.88 |
| IG | -0.47 | -0.30 | -0.24 | -0.07 | -0.17 | -3.54 | -2.48 | -1.97 | -0.57 | -1.50 |
| NSI | -0.77 | -0.63 | -0.54 | -0.27 | -0.31 | -4.81 | -4.36 | -3.79 | -1.98 | -2.47 |
| CEI | -0.79 | -0.54 | -0.43 | -0.26 | -0.29 | -5.20 | -4.40 | -3.39 | -1.92 | -2.67 |
| IvG | -0.39 | -0.21 | -0.12 | 0.00 | -0.09 | -2.87 | -1.55 | -0.89 | -0.02 | -0.74 |
| IvC | -0.51 | -0.35 | -0.28 | -0.27 | -0.34 | -3.68 | -2.70 | -2.21 | -1.84 | -2.62 |
| OA | -0.23 | -0.26 | -0.24 | -0.46 | -0.41 | -1.91 | -2.17 | -1.81 | -3.44 | -3.41 |
| POA | -0.46 | -0.28 | -0.25 | -0.19 | -0.17 | -3.32 | -2.19 | -1.90 | -1.42 | -1.36 |
| PTA | -0.44 | -0.25 | -0.28 | -0.13 | -0.05 | -3.24 | -1.77 | -2.09 | -0.85 | -0.32 |
| ROE | 0.89 | 1.08 | 0.78 | 0.00 | 0.57 | 4.01 | 5.44 | 4.20 | -0.03 | 4.23 |
| ROA | 0.75 | 0.99 | 0.67 | 0.05 | 0.58 | 3.81 | 5.72 | 4.10 | 0.53 | 4.59 |
| GPA | 0.28 | 0.44 | 0.40 | 0.04 | 0.15 | 1.90 | 3.15 | 3.00 | 0.32 | 1.22 |
| NEI | 0.33 | 0.53 | 0.34 | 0.10 | 0.40 | 2.95 | 5.45 | 3.27 | 0.99 | 4.25 |
| FP6 | -0.70 | -1.10 | -0.63 | -0.11 | -0.60 | -2.85 | -5.56 | -3.79 | -0.80 | -3.74 |
| OCA | 0.56 | 0.50 | 0.34 | 0.08 | 0.28 | 4.51 | 4.48 | 3.00 | 0.66 | 2.52 |
| AdM | 0.63 | 0.08 | 0.19 | -0.04 | -0.27 | 2.38 | 0.45 | 0.82 | -0.14 | -1.51 |
| RDM | 0.45 | 0.23 | 0.31 | 0.63 | 0.50 | 1.92 | 1.04 | 1.53 | 2.79 | 2.33 |
| OL | 0.43 | 0.38 | 0.32 | -0.04 | 0.08 | 2.28 | 2.06 | 1.88 | -0.25 | 0.50 |
| Svol | -0.47 | -0.46 | -0.38 | -0.14 | -0.20 | -2.38 | -2.38 | -1.79 | -0.67 | -1.00 |
| Mean $\lvert\alpha\rvert$: spread | 0.58 | 0.50 | 0.29 | 0.19 | 0.38 | | | | | |
| Mean $\lvert\alpha\rvert$: all | 0.15 | 0.15 | 0.11 | 0.10 | 0.12 | | | | | |
| N($\lvert t\rvert > 2$) | 32 | 26 | 16 | 5 | 21 | | | | | |
| N($p < 5\%$) | 25 | 28 | 25 | 18 | 23 | | | | | |

## Table IV
## Performance of New Factor Models Using Various Test Assets

This table summarizes the ability of various factor models to explain monthly excess returns on 25 Size-Book to Market portfolios (Panel B), 25 Size-Asset Growth portfolios (Panel C), 25 Size-Profitability portfolios (Panel D), 32 Size-Book to Market - Asset Growth portfolios (Panel E), 32 Size-Book to Market-Asset Growth portfolios (Panel F), and 32 Size-Asset Growth-Profitability portfolios (Panel G). The sample period is 1972-2016. In Panel A, we use a set of test assets consisting of all the portfolios used in panels B through G. The models use to explain these expected returns are the CAPM, the Fama and French (1993) three factor model (FF3F), the Carhart (1997) four factor model (C4F), the Hou, Xue, and Zhang (2015) four factor model (HXZ), and the Fama and French (2015) five factor model (FF5F). Please see Section 3 for details on the HXZ and FF5F models. "Mean $|\alpha|$" is the average of the absolute alphas corresponding to each set of portfolios. "N($|t| > 2$) " is the number of alpha t-statistics with absolute value greater than 2. "GRS test statistic" is the Gibbons, Ross, and Shanken (1989) statistic testing that the alpha estimates corresponding to each set of portfolios are jointly 0.

| | CAPM | FF3F | C4F | HXZ | FF5F |
|---|---|---|---|---|---|
| *Panel A: All 171 portfolios* | | | | | |
| Mean $|\alpha|$ | 0.261 | 0.135 | 0.124 | 0.098 | 0.099 |
| N($|t| > 2$) | 78 | 50 | 49 | 21 | 36 |
| GRS test statistic | 2.212 | 2.118 | 1.935 | 1.887 | 1.901 |
| *Panel B: 25 Size-BM portoflios* | | | | | |
| Mean $|\alpha|$ | 0.26 | 0.104 | 0.092 | 0.104 | 0.105 |
| N($|t| > 2$) | 10 | 6 | 6 | 4 | 6 |
| GRS test statistic | 4.356 | 3.61 | 3.019 | 3.191 | 3.369 |
| *Panel C: 25 Size-AG Portfolios* | | | | | |
| Mean $|\alpha|$ | 0.263 | 0.117 | 0.108 | 0.087 | 0.095 |
| N($|t| > 2$) | 16 | 8 | 7 | 5 | 5 |
| GRS test statistic | 5.026 | 4.26 | 3.674 | 3.256 | 3.674 |
| *Panel D: 25 Size-Profitability portfolios* | | | | | |
| Mean $|\alpha|$ | 0.208 | 0.119 | 0.109 | 0.051 | 0.051 |
| N($|t| > 2$) | 9 | 5 | 5 | 0 | 1 |
| GRS test statistic | 2.672 | 2.464 | 2.235 | 1.497 | 1.669 |
| *Panel E: 32 Size-BM-AG portfolios* | | | | | |
| Mean $|\alpha|$ | 0.255 | 0.139 | 0.123 | 0.097 | 0.108 |
| N($|t| > 2$) | 13 | 9 | 9 | 4 | 9 |
| GRS test statistic | 3.667 | 3.198 | 2.581 | 2.185 | 2.597 |
| *Panel F: 32 Size-BM-Profitability portfolios* | | | | | |
| Mean $|\alpha|$ | 0.294 | 0.138 | 0.139 | 0.13 | 0.11 |
| N($|t| > 2$) | 13 | 6 | 8 | 3 | 5 |
| GRS test statistic | 2.768 | 2.496 | 2.142 | 1.968 | 2.138 |
| *Panel G: 32 Size-AG-Profitability portfolios* | | | | | |
| Mean $|\alpha|$ | 0.273 | 0.18 | 0.158 | 0.108 | 0.113 |
| N($|t| > 2$) | 17 | 16 | 14 | 5 | 10 |
| GRS test statistic | 4.573 | 4.038 | 3.285 | 2.411 | 3.357 |

## Table V
## Investment Characteristics of Asset Growth Portfolios

In this table, we summarize capital decompositions (Panel A) and investment levels (Panel B) of asset growth portfolios over 1972-2016. In Panel A, we use the Peters and Taylor (2017) measure of firm-level total capital which we decompose it into physical capital (gross PPE) in the first column and intangible capital in the second column. The latter is the sum of intangible capital on the balance sheet (goodwill), shown in column three, and intangible capital off the balance sheet (column four), which in turn is the sum of knowledge capital (capitalized R&D) and organizational capital (capitalized 30% of SG&A). We normalize each type of capital by total capital (which is the sum of gross PPE and total intangible capital). The numbers reported are time-series averages of cross-sectional means of these normalized measures. In Panel B, we present average portfolio investment levels. The first two columns show the standard measures of investment: CAPX divided by lagged PPE and percentage growth in PPE. The last seven columns use investment measures based on the Peters and Taylor (2017) measure of total capital. Column 3 shows the percentage growth in total capital and the following six columns show changes in the six types of capital from Panel A, normalized by total capital. Please see Section 4 for details on these investment measures. Panel C presents correlation correlation coefficients between asset growth and each of the investment measures used in Panel B.

Panel A: Decomposition of capital

| AG decile | Physical capital | Intan. capital | Intan. capital on B.S. | Intan. capital off B.S. | Know. capital (R&D) | Org. capital (SG&A) |
|---|---|---|---|---|---|---|
| 1(Low) | 0.457 | 0.543 | 0.048 | 0.495 | 0.178 | 0.317 |
| 2 | 0.540 | 0.460 | 0.064 | 0.396 | 0.111 | 0.285 |
| 3 | 0.586 | 0.414 | 0.070 | 0.344 | 0.086 | 0.258 |
| 4 | 0.598 | 0.402 | 0.070 | 0.332 | 0.078 | 0.254 |
| 5 | 0.601 | 0.399 | 0.070 | 0.329 | 0.075 | 0.255 |
| 6 | 0.591 | 0.409 | 0.069 | 0.340 | 0.082 | 0.257 |
| 7 | 0.571 | 0.429 | 0.069 | 0.360 | 0.088 | 0.272 |
| 8 | 0.548 | 0.452 | 0.075 | 0.377 | 0.097 | 0.280 |
| 9 | 0.531 | 0.469 | 0.082 | 0.387 | 0.114 | 0.274 |
| 10(High) | 0.503 | 0.497 | 0.119 | 0.378 | 0.143 | 0.235 |
| Spread(10-1) | 0.046 | -0.046 | 0.071 | -0.117 | -0.035 | -0.082 |
| t(spread) | 1.719 | -1.719 | 5.941 | -6.101 | -1.833 | -8.552 |

Panel B: Investment measures

| AG decile | CAPX | PPE | Total capital | Physical capital | Intan. capital | Intan. capital on B.S. | Intan. capital off B.S. | Know. capital (R&D) | Org. capital (SG&A) |
|---|---|---|---|---|---|---|---|---|---|
| 1(Low) | 0.124 | -0.005 | 0.031 | -0.014 | 0.049 | -0.014 | 0.061 | 0.027 | 0.032 |
| 2 | 0.111 | 0.046 | 0.059 | 0.017 | 0.041 | -0.004 | 0.045 | 0.015 | 0.029 |
| 3 | 0.112 | 0.062 | 0.069 | 0.030 | 0.039 | 0.000 | 0.039 | 0.011 | 0.027 |
| 4 | 0.116 | 0.075 | 0.081 | 0.040 | 0.040 | 0.001 | 0.038 | 0.010 | 0.028 |
| 5 | 0.127 | 0.091 | 0.094 | 0.050 | 0.045 | 0.004 | 0.040 | 0.010 | 0.030 |
| 6 | 0.146 | 0.116 | 0.117 | 0.063 | 0.054 | 0.008 | 0.046 | 0.012 | 0.034 |
| 7 | 0.172 | 0.149 | 0.147 | 0.079 | 0.068 | 0.011 | 0.056 | 0.015 | 0.040 |
| 8 | 0.211 | 0.200 | 0.194 | 0.101 | 0.092 | 0.020 | 0.071 | 0.019 | 0.050 |
| 9 | 0.279 | 0.305 | 0.288 | 0.151 | 0.134 | 0.041 | 0.092 | 0.027 | 0.063 |
| 10(High) | 0.438 | 0.678 | 0.649 | 0.318 | 0.291 | 0.137 | 0.140 | 0.044 | 0.089 |
| Spread(10-1) | 0.313 | 0.683 | 0.618 | 0.332 | 0.242 | 0.151 | 0.080 | 0.017 | 0.058 |
| t(spread) | 14.982 | 20.622 | 20.447 | 21.142 | 12.454 | 10.721 | 11.093 | 4.157 | 13.627 |

Panel C: Correlations with asset growth

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Full sample correlation | 0.417 | 0.568 | 0.644 | 0.550 | 0.498 | 0.461 | 0.308 | 0.166 | 0.296 |
| Mean TS correlation | 0.442 | 0.582 | 0.635 | 0.583 | 0.476 | 0.382 | 0.354 | 0.209 | 0.351 |
| Mean CS correlation | 0.426 | 0.574 | 0.657 | 0.561 | 0.483 | 0.431 | 0.308 | 0.165 | 0.293 |

## Table VI
## Replacing Asset Growth With Alternative Measures of Investment

This table presents alphas (left) and corresponding t-statistics (right) of spread portfolios (high minus low) of 35 anomalies. The sample period is 1972-2016. In Panel A, the alphas are calculated using a version of the Hou, Xue, and Zhang (2015) four factor model (HXZ), in which the asset growth factor has been replaced with an analogous factor based on a different measure of investment. In Panel B, we make the same adjustment to the Fama and French (2015) five factor model (FF5F). We use investment measures based on CAPX, growth in PPE, growth in total capital (TOTK), investment in physical capital (PHK), and investment in intangible capital (INTK). The last three measures are based on Peters and Taylor (2017): intangible capital (INTK) is the sum of intangible capital on the balance sheet (goodwill) plus intangible capital off the balance sheet (capitalized knowledge capital (R&D) plus capitalized organizational capital (30% of SG&A)). Physical capital (PHK) is gross PPE and total capital (TOTK) is the sum of physical capital plus intangible capital. Please see Appendix A for details on how the anomalies are constructed. For comparison purposes, the table also reports results using the original HXZ and FF5F models (columns titled "AG") and versions of these models without an investment factor (columns titled "none"). "Mean $|\alpha|$: spread" is the mean absolute values of the 35 spread-portfolio alphas. "Mean $|\alpha|$: all" is the mean absolute value of all the decile-portfolio alphas of all anomalies. "N($|t| > 2$)" counts how many of the 35 anomalies have spread-portfolio alphas with t-statistics greater than 2 in absolute value. "N($p < 5\%$)" counts for how many of the 35 anomalies the model employed are rejected by the Gibbons, Ross, and Shanken (1989) test at the 5% level.

Panel A: Alphas obtained using HXZ-like models

| | Alphas of spread portfolios | | | | | | | T-statistics of spread portfolios | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anomaly | AG | None | CAPX | PPE | TOTK | PHK | INTK | AG | None | CAPX | PPE | TOTK | PHK | INTK |
| SUE | 0.13 | 0.19 | 0.17 | 0.18 | 0.18 | 0.17 | 0.16 | 1.02 | 1.64 | 1.36 | 1.42 | 1.41 | 1.46 | 1.31 |
| SUE6 | 0.00 | 0.00 | -0.01 | 0.01 | 0.01 | 0.00 | -0.02 | -0.01 | -0.04 | -0.11 | 0.04 | 0.10 | -0.03 | -0.22 |
| Abr | 0.74 | 0.70 | 0.74 | 0.77 | 0.77 | 0.75 | 0.71 | 4.90 | 5.12 | 5.07 | 5.29 | 5.27 | 5.34 | 4.96 |
| Abr6 | 0.31 | 0.27 | 0.29 | 0.32 | 0.33 | 0.31 | 0.28 | 2.84 | 2.74 | 2.73 | 3.02 | 3.14 | 3.03 | 2.70 |
| RE | -0.13 | -0.01 | -0.17 | -0.05 | -0.04 | 0.06 | -0.12 | -0.62 | -0.03 | -0.84 | -0.28 | -0.21 | 0.30 | -0.58 |
| RE6 | -0.17 | -0.12 | -0.26 | -0.15 | -0.13 | -0.06 | -0.21 | -0.79 | -0.63 | -1.36 | -0.78 | -0.66 | -0.31 | -1.09 |
| R6_6 | 0.22 | 0.32 | 0.20 | 0.31 | 0.31 | 0.37 | 0.19 | 0.71 | 1.10 | 0.68 | 1.01 | 1.01 | 1.22 | 0.65 |
| R11_1 | 0.24 | 0.41 | 0.24 | 0.39 | 0.37 | 0.44 | 0.22 | 0.62 | 1.18 | 0.65 | 1.02 | 1.00 | 1.20 | 0.64 |
| Imom | 0.12 | 0.24 | 0.13 | 0.24 | 0.20 | 0.28 | 0.09 | 0.42 | 0.92 | 0.46 | 0.83 | 0.71 | 1.02 | 0.36 |
| BM | 0.21 | 0.88 | 0.51 | 0.50 | 0.43 | 0.70 | 0.63 | 1.26 | 4.20 | 3.15 | 3.20 | 2.77 | 3.58 | 3.75 |
| EP | 0.15 | 0.61 | 0.29 | 0.27 | 0.23 | 0.48 | 0.41 | 0.69 | 2.86 | 1.46 | 1.44 | 1.24 | 2.27 | 2.14 |
| CFP | 0.20 | 0.67 | 0.36 | 0.35 | 0.29 | 0.59 | 0.43 | 1.02 | 3.24 | 1.91 | 1.92 | 1.64 | 2.81 | 2.46 |
| NOP | 0.20 | 0.69 | 0.53 | 0.51 | 0.50 | 0.52 | 0.71 | 1.30 | 3.68 | 3.09 | 3.23 | 3.21 | 3.21 | 3.87 |
| Dur | -0.21 | -0.61 | -0.31 | -0.31 | -0.27 | -0.52 | -0.45 | -1.10 | -2.95 | -1.79 | -1.77 | -1.56 | -2.58 | -2.48 |
| AG | 0.06 | -0.57 | -0.35 | -0.29 | -0.26 | -0.35 | -0.46 | 0.47 | -3.49 | -2.03 | -1.83 | -1.74 | -2.30 | -2.80 |
| NOA | -0.43 | -0.43 | -0.55 | -0.52 | -0.54 | -0.39 | -0.55 | -2.25 | -2.70 | -3.25 | -2.91 | -3.12 | -2.17 | -3.83 |
| dPIA | -0.23 | -0.64 | -0.46 | -0.40 | -0.41 | -0.40 | -0.60 | -1.71 | -4.35 | -3.05 | -2.67 | -2.74 | -2.97 | -3.93 |
| IG | -0.07 | -0.44 | -0.27 | -0.24 | -0.24 | -0.27 | -0.37 | -0.57 | -3.56 | -2.23 | -2.10 | -2.10 | -2.39 | -3.06 |
| NSI | -0.27 | -0.60 | -0.51 | -0.46 | -0.46 | -0.49 | -0.60 | -1.98 | -4.17 | -3.36 | -3.14 | -3.22 | -3.48 | -4.01 |
| CEI | -0.26 | -0.76 | -0.50 | -0.49 | -0.47 | -0.59 | -0.65 | -1.92 | -4.83 | -3.58 | -3.55 | -3.35 | -3.97 | -4.33 |
| IvG | 0.00 | -0.45 | -0.26 | -0.24 | -0.23 | -0.32 | -0.36 | -0.02 | -3.19 | -1.79 | -1.71 | -1.67 | -2.33 | -2.50 |
| IvC | -0.27 | -0.61 | -0.51 | -0.47 | -0.45 | -0.51 | -0.53 | -1.84 | -4.04 | -3.22 | -3.04 | -2.99 | -3.29 | -3.54 |
| OA | -0.46 | -0.45 | -0.51 | -0.52 | -0.49 | -0.54 | -0.43 | -3.44 | -3.80 | -4.10 | -4.12 | -3.88 | -4.40 | -3.45 |
| POA | -0.19 | -0.56 | -0.41 | -0.40 | -0.37 | -0.48 | -0.46 | -1.42 | -4.03 | -3.12 | -3.08 | -2.87 | -3.49 | -3.56 |
| PTA | -0.13 | -0.50 | -0.37 | -0.31 | -0.31 | -0.32 | -0.49 | -0.85 | -3.27 | -2.29 | -2.05 | -2.04 | -2.27 | -2.94 |
| ROE | 0.00 | 0.12 | 0.01 | 0.04 | 0.07 | 0.11 | 0.09 | -0.03 | 1.10 | 0.07 | 0.34 | 0.56 | 0.90 | 0.68 |
| ROA | 0.05 | 0.04 | 0.03 | 0.05 | 0.08 | 0.08 | 0.07 | 0.53 | 0.44 | 0.26 | 0.43 | 0.72 | 0.74 | 0.60 |
| GPA | 0.04 | -0.04 | 0.11 | 0.05 | 0.09 | -0.08 | 0.12 | 0.32 | -0.29 | 0.79 | 0.36 | 0.67 | -0.53 | 0.94 |
| NEI | 0.10 | 0.00 | 0.06 | 0.08 | 0.11 | 0.04 | 0.08 | 0.99 | 0.02 | 0.64 | 0.86 | 1.13 | 0.41 | 0.78 |
| FP6 | -0.11 | -0.01 | -0.01 | -0.06 | -0.12 | -0.05 | -0.06 | -0.80 | -0.04 | -0.08 | -0.43 | -0.89 | -0.39 | -0.42 |
| OCA | 0.08 | 0.30 | 0.15 | 0.16 | 0.17 | 0.18 | 0.24 | 0.66 | 2.74 | 1.31 | 1.37 | 1.46 | 1.63 | 2.14 |
| AdM | -0.04 | 0.59 | 0.31 | 0.30 | 0.27 | 0.35 | 0.55 | -0.14 | 2.06 | 1.27 | 1.19 | 1.09 | 1.29 | 2.08 |
| RDM | 0.63 | 0.69 | 0.83 | 0.74 | 0.71 | 0.59 | 0.76 | 2.79 | 3.37 | 3.94 | 3.41 | 3.28 | 2.67 | 3.91 |
| OL | -0.04 | 0.06 | 0.08 | 0.02 | 0.06 | -0.05 | 0.18 | -0.25 | 0.38 | 0.45 | 0.12 | 0.34 | -0.31 | 1.02 |
| Svol | -0.14 | -0.16 | -0.19 | -0.20 | -0.20 | -0.19 | -0.21 | -0.67 | -0.84 | -0.93 | -1.01 | -1.00 | -1.01 | -1.09 |
| Mean $\|\alpha\|$: spread | 0.19 | 0.39 | 0.31 | 0.30 | 0.29 | 0.33 | 0.36 | | | | | | | |
| Mean $\|\alpha\|$: all | 0.10 | 0.12 | 0.11 | 0.11 | 0.10 | 0.11 | 0.11 | | | | | | | |
| N($\|t\| > 2$) | 5 | 21 | 15 | 14 | 14 | 19 | 21 | | | | | | | |
| N($p < 5\%$) | 18 | 23 | 20 | 18 | 17 | 23 | 22 | | | | | | | |

## Table VI
## Replacing Asset Growth With Alternative Measures of Investment (continued)

Panel B: Alphas obtained using FF5F-like models

| | Alphas of spread portfolios | | | | | | | T-statistics of spread portfolios | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anomaly | AG | None | CAPX | PPE | TOTK | PHK | INTK | AG | None | CAPX | PPE | TOTK | PHK | INTK |
| SUE | 0.48 | 0.49 | 0.47 | 0.49 | 0.48 | 0.48 | 0.50 | 4.15 | 4.14 | 4.05 | 4.13 | 4.13 | 4.08 | 4.31 |
| SUE6 | 0.31 | 0.33 | 0.31 | 0.33 | 0.33 | 0.32 | 0.34 | 2.79 | 3.02 | 2.70 | 2.92 | 2.88 | 2.80 | 3.14 |
| Abr | 0.98 | 0.97 | 0.98 | 0.98 | 0.98 | 0.98 | 0.97 | 7.09 | 6.83 | 6.78 | 6.96 | 6.96 | 7.01 | 6.87 |
| Abr6 | 0.49 | 0.47 | 0.47 | 0.48 | 0.48 | 0.48 | 0.47 | 5.13 | 5.00 | 4.87 | 5.14 | 5.13 | 5.11 | 5.05 |
| RE | 0.66 | 0.66 | 0.63 | 0.66 | 0.66 | 0.68 | 0.81 | 2.77 | 2.90 | 2.66 | 2.90 | 2.91 | 2.97 | 3.56 |
| RE6 | 0.52 | 0.51 | 0.48 | 0.51 | 0.52 | 0.53 | 0.64 | 2.40 | 2.53 | 2.23 | 2.53 | 2.54 | 2.58 | 3.23 |
| R6_6 | 1.04 | 1.06 | 1.02 | 1.07 | 1.07 | 1.08 | 1.10 | 3.55 | 3.65 | 3.27 | 3.66 | 3.61 | 3.66 | 3.79 |
| R11_1 | 1.31 | 1.37 | 1.31 | 1.38 | 1.37 | 1.38 | 1.43 | 3.68 | 3.99 | 3.49 | 3.96 | 3.89 | 3.92 | 4.16 |
| Imom | 0.75 | 0.77 | 0.75 | 0.78 | 0.77 | 0.79 | 0.81 | 2.63 | 2.72 | 2.45 | 2.76 | 2.69 | 2.74 | 2.82 |
| BM | 0.02 | 0.03 | 0.04 | 0.04 | 0.04 | 0.04 | 0.05 | 0.15 | 0.30 | 0.31 | 0.33 | 0.31 | 0.37 | 0.43 |
| EP | -0.04 | -0.11 | -0.10 | -0.10 | -0.10 | -0.09 | -0.10 | -0.33 | -0.85 | -0.79 | -0.82 | -0.81 | -0.68 | -0.78 |
| CFP | -0.05 | -0.11 | -0.10 | -0.11 | -0.11 | -0.07 | -0.09 | -0.40 | -0.88 | -0.77 | -0.84 | -0.84 | -0.57 | -0.74 |
| NOP | 0.13 | 0.25 | 0.25 | 0.25 | 0.25 | 0.21 | 0.22 | 1.09 | 2.07 | 2.00 | 2.06 | 2.09 | 1.80 | 1.78 |
| Dur | -0.01 | 0.06 | 0.06 | 0.06 | 0.05 | 0.03 | 0.06 | -0.05 | 0.47 | 0.46 | 0.45 | 0.43 | 0.25 | 0.49 |
| AG | 0.02 | -0.21 | -0.18 | -0.20 | -0.19 | -0.16 | -0.22 | 0.17 | -1.46 | -1.21 | -1.42 | -1.40 | -1.13 | -1.57 |
| NOA | -0.53 | -0.62 | -0.64 | -0.62 | -0.62 | -0.59 | -0.59 | -3.11 | -3.71 | -3.85 | -3.69 | -3.68 | -3.39 | -3.96 |
| dPIA | -0.34 | -0.52 | -0.47 | -0.50 | -0.50 | -0.44 | -0.51 | -2.88 | -3.68 | -3.52 | -4.02 | -3.88 | -3.70 | -3.69 |
| IG | -0.17 | -0.31 | -0.27 | -0.30 | -0.29 | -0.26 | -0.32 | -1.50 | -2.64 | -2.40 | -2.79 | -2.71 | -2.37 | -2.76 |
| NSI | -0.31 | -0.41 | -0.41 | -0.41 | -0.41 | -0.39 | -0.40 | -2.47 | -3.17 | -3.12 | -3.11 | -3.13 | -2.98 | -3.13 |
| CEI | -0.29 | -0.40 | -0.37 | -0.39 | -0.39 | -0.38 | -0.41 | -2.67 | -3.40 | -3.25 | -3.47 | -3.40 | -3.25 | -3.52 |
| IvG | -0.09 | -0.23 | -0.20 | -0.22 | -0.22 | -0.20 | -0.24 | -0.74 | -1.68 | -1.51 | -1.68 | -1.63 | -1.51 | -1.74 |
| IvC | -0.34 | -0.46 | -0.45 | -0.45 | -0.45 | -0.43 | -0.47 | -2.62 | -3.39 | -3.28 | -3.44 | -3.35 | -3.22 | -3.48 |
| OA | -0.41 | -0.38 | -0.42 | -0.39 | -0.39 | -0.41 | -0.38 | -3.41 | -3.30 | -3.66 | -3.32 | -3.36 | -3.54 | -3.27 |
| POA | -0.17 | -0.27 | -0.26 | -0.26 | -0.26 | -0.25 | -0.28 | -1.36 | -2.10 | -2.02 | -2.09 | -2.07 | -1.98 | -2.18 |
| PTA | -0.05 | -0.17 | -0.16 | -0.16 | -0.16 | -0.12 | -0.15 | -0.32 | -1.15 | -1.05 | -1.15 | -1.12 | -0.87 | -1.03 |
| ROE | 0.57 | 0.58 | 0.54 | 0.57 | 0.57 | 0.57 | 0.61 | 4.23 | 4.36 | 4.12 | 4.31 | 4.33 | 4.27 | 4.66 |
| ROA | 0.58 | 0.55 | 0.54 | 0.55 | 0.55 | 0.55 | 0.56 | 4.59 | 4.49 | 4.26 | 4.46 | 4.46 | 4.40 | 4.56 |
| GPA | 0.15 | 0.21 | 0.23 | 0.21 | 0.21 | 0.18 | 0.16 | 1.22 | 1.65 | 1.90 | 1.67 | 1.68 | 1.40 | 1.42 |
| NEI | 0.40 | 0.39 | 0.38 | 0.39 | 0.39 | 0.38 | 0.38 | 4.25 | 4.21 | 4.12 | 4.21 | 4.22 | 4.07 | 4.08 |
| FP6 | -0.60 | -0.63 | -0.59 | -0.62 | -0.63 | -0.60 | -0.64 | -3.74 | -3.89 | -3.46 | -3.80 | -3.83 | -3.64 | -4.10 |
| OCA | 0.28 | 0.37 | 0.33 | 0.36 | 0.36 | 0.33 | 0.39 | 2.52 | 3.21 | 2.64 | 3.04 | 3.05 | 2.85 | 3.35 |
| AdM | -0.27 | -0.15 | -0.16 | -0.15 | -0.15 | -0.19 | -0.20 | -1.51 | -0.86 | -0.91 | -0.85 | -0.87 | -1.12 | -1.15 |
| RDM | 0.50 | 0.56 | 0.61 | 0.57 | 0.56 | 0.54 | 0.39 | 2.33 | 2.62 | 2.99 | 2.67 | 2.64 | 2.44 | 2.00 |
| OL | 0.08 | 0.12 | 0.12 | 0.13 | 0.13 | 0.10 | 0.09 | 0.50 | 0.76 | 0.76 | 0.78 | 0.78 | 0.63 | 0.57 |
| Svol | -0.20 | -0.23 | -0.23 | -0.22 | -0.23 | -0.23 | -0.26 | -1.00 | -1.15 | -1.13 | -1.14 | -1.18 | -1.15 | -1.34 |
| Mean $\|\alpha\|$: spread | 0.38 | 0.43 | 0.42 | 0.43 | 0.43 | 0.41 | 0.44 | | | | | | | |
| Mean $\|\alpha\|$: all | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | | | | | | | |
| N($\|t\| > 2$) | 21 | 24 | 23 | 24 | 24 | 22 | 22 | | | | | | | |
| N($p < 5\%$) | 23 | 24 | 25 | 24 | 25 | 25 | 25 | | | | | | | |

## Table VII
## Replacing Asset Growth With Other Measures of Investment: Performance Using Various Test Assets

This table summarizes the ability of various factor models to explain monthly excess returns on several sets of test assets (the same ones used in Table IV). The sample period is 1972-2016. In Panel A, we use factor models that are variations of the Hou, Xue, and Zhang (2015) four factor model (HXZ), in which the asset growth factor has been replaced with an analogous factor based on a different measure of investment. In Panel B, we make the same adjustment to the Fama and French (2015) five factor model (FF5F). In both panels, we use investment measures based on CAPX, growth in PPE, growth in total capital (TOTK), investment in physical capital (PHK), and investment in intangible capital (INTK). The last three measures are based on Peters and Taylor (2017): intangible capital (INTK) is the sum of intangible capital on the balance sheet (goodwill) plus intangible capital off the balance sheet (capitalized knowledge capital (R&D) plus capitalized organizational capital (30% of SG&A)). Physical capital (PHK) is gross PPE and total capital (TOTK) is the sum of physical capital plus intangible capital. For comparison purposes, the table also reports results using the original HXZ and FF5F models (columns titled "AG") and versions of these models without an investment factor (columns titled "none"). "Mean $|\alpha|$" is the average of the absolute alphas corresponding to each set of portfolios. "N($|t| > 2$)" is the number of alpha t-statistics with absolute value greater than 2. "GRS test statistic" is the Gibbons, Ross, and Shanken (1989) statistic testing that the alpha estimates corresponding to each set of portfolios are jointly 0.

| Panel A: Performance of HXZ-like models | | | | | | | |
|---|---|---|---|---|---|---|---|
| | AG | None | CAPX | PPE | TOTK | PHK | INTK |
| *Panel A1: All 171 portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.098 | 0.221 | 0.137 | 0.132 | 0.123 | 0.159 | 0.169 |
| N($\lvert t\rvert > 2$) | 21 | 88 | 44 | 39 | 35 | 50 | 61 |
| GRS test statistic | 1.887 | 2.18 | 2.108 | 2.082 | 2.039 | 2.096 | 2.086 |
| *Panel A2: 25 Size-BM portoflios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.104 | 0.25 | 0.144 | 0.136 | 0.13 | 0.178 | 0.185 |
| N($\lvert t\rvert > 2$) | 4 | 14 | 8 | 7 | 6 | 10 | 11 |
| GRS test statistic | 3.191 | 4.28 | 3.637 | 3.534 | 3.473 | 3.626 | 3.839 |
| *Panel A3: 25 Size-AG Portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.087 | 0.232 | 0.139 | 0.134 | 0.12 | 0.16 | 0.178 |
| N($\lvert t\rvert > 2$) | 5 | 20 | 10 | 8 | 8 | 9 | 11 |
| GRS test statistic | 3.256 | 4.846 | 4.114 | 4.006 | 3.881 | 4.228 | 4.274 |
| *Panel A4: 25 Size-Profitability portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.051 | 0.085 | 0.048 | 0.046 | 0.048 | 0.057 | 0.059 |
| N($\lvert t\rvert > 2$) | 0 | 4 | 1 | 1 | 0 | 2 | 2 |
| GRS test statistic | 1.497 | 2.129 | 1.654 | 1.62 | 1.643 | 1.682 | 1.883 |
| *Panel A5: 32 Size-BM-AG portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.097 | 0.229 | 0.138 | 0.133 | 0.121 | 0.162 | 0.171 |
| N($\lvert t\rvert > 2$) | 4 | 16 | 7 | 7 | 7 | 8 | 10 |
| GRS test statistic | 2.185 | 3.261 | 2.859 | 2.808 | 2.73 | 2.905 | 3.073 |
| *Panel A6: 32 Size-BM-Profitability portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.13 | 0.269 | 0.17 | 0.162 | 0.15 | 0.202 | 0.206 |
| N($\lvert t\rvert > 2$) | 3 | 16 | 8 | 8 | 6 | 9 | 12 |
| GRS test statistic | 1.968 | 2.568 | 2.229 | 2.232 | 2.189 | 2.341 | 2.542 |
| *Panel A7: 32 Size-AG-Profitability portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.108 | 0.239 | 0.165 | 0.16 | 0.151 | 0.179 | 0.198 |
| N($\lvert t\rvert > 2$) | 5 | 18 | 10 | 8 | 8 | 12 | 15 |
| GRS test statistic | 2.411 | 3.825 | 3.269 | 3.231 | 3.194 | 3.349 | 3.594 |

**Table VII**
**Replacing Asset Growth With Other Measures of Investment: Performance Using Various Test Assets (continued)**

| Panel B: Performance of FF5F-like models | | | | | | | |
|---|---|---|---|---|---|---|---|
| | AG | None | CAPX | PPE | TOTK | PHK | INTK |
| *Panel B1: All 171 portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.099 | 0.107 | 0.107 | 0.108 | 0.108 | 0.106 | 0.109 |
| N($\lvert t\rvert > 2$) | 36 | 37 | 37 | 39 | 38 | 38 | 39 |
| GRS test statistic | 1.901 | 1.969 | 2.052 | 2.026 | 2.007 | 2.005 | 1.975 |
| *Panel B2: 25 Size-BM portoflios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.105 | 0.102 | 0.106 | 0.104 | 0.105 | 0.104 | 0.1 |
| N($\lvert t\rvert > 2$) | 6 | 5 | 6 | 5 | 5 | 6 | 5 |
| GRS test statistic | 3.369 | 3.323 | 3.403 | 3.332 | 3.358 | 3.3 | 3.319 |
| *Panel B3: 25 Size-AG Portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.095 | 0.111 | 0.108 | 0.112 | 0.111 | 0.108 | 0.117 |
| N($\lvert t\rvert > 2$) | 5 | 7 | 7 | 8 | 8 | 7 | 7 |
| GRS test statistic | 3.674 | 4.04 | 4.027 | 4.033 | 4.015 | 4.013 | 3.99 |
| *Panel B4: 25 Size-Profitability portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.051 | 0.047 | 0.045 | 0.048 | 0.047 | 0.048 | 0.05 |
| N($\lvert t\rvert > 2$) | 1 | 2 | 2 | 2 | 2 | 2 | 2 |
| GRS test statistic | 1.669 | 1.713 | 1.655 | 1.699 | 1.691 | 1.638 | 1.669 |
| *Panel B5: 32 Size-BM-AG portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.108 | 0.129 | 0.128 | 0.13 | 0.129 | 0.125 | 0.132 |
| N($\lvert t\rvert > 2$) | 9 | 10 | 10 | 10 | 10 | 10 | 10 |
| GRS test statistic | 2.597 | 2.812 | 2.827 | 2.826 | 2.826 | 2.811 | 2.802 |
| *Panel B6: 32 Size-BM-Profitability portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.11 | 0.103 | 0.109 | 0.105 | 0.105 | 0.106 | 0.099 |
| N($\lvert t\rvert > 2$) | 5 | 3 | 4 | 4 | 4 | 4 | 3 |
| GRS test statistic | 2.138 | 1.943 | 2.078 | 1.986 | 1.998 | 2.023 | 1.871 |
| *Panel B7: 32 Size-AG-Profitability portfolios* | | | | | | | |
| Mean $\lvert\alpha\rvert$ | 0.113 | 0.137 | 0.131 | 0.137 | 0.136 | 0.131 | 0.141 |
| N($\lvert t\rvert > 2$) | 10 | 10 | 8 | 10 | 9 | 9 | 12 |
| GRS test statistic | 3.357 | 3.678 | 3.628 | 3.703 | 3.711 | 3.644 | 3.663 |

## Table VIII
## Decomposing Asset Growth

In this table, we decompose growth in total assets into subcomponents based on the growth of items on the left hand side of the balance sheet (growth in cash, noncash current assets, PPE and other assets) and the right hand side of the balance sheet (growth in liabilities, long-term debt, common equity and retained earnings). The sample period is 1972-2016. In Panel A, the numbers reported are time series averages of the cross-sectional means of each subcomponent for each asset growth decile. In the first column, we also present average asset growth levels for each decile. Please see Appendix A for details on how each subcomponent is calculated. In Panel B, we present correlation coefficients between asset growth and each of its subcomponents.

Panel A: Asset growth components

| AG decile | Asset growth | Cash | Noncash current assets | PPE | Other assets | Operating liabilities | Long-term debt | Common equity | Retained earnings |
|---|---|---|---|---|---|---|---|---|---|
| 1(Low) | -0.224 | -0.073 | -0.066 | -0.033 | -0.032 | -0.036 | -0.051 | 0.036 | -0.167 |
| 2 | -0.066 | -0.024 | -0.021 | -0.010 | -0.009 | -0.012 | -0.024 | 0.020 | -0.049 |
| 3 | -0.010 | -0.010 | 0.000 | 0.002 | -0.001 | 0.000 | -0.013 | 0.011 | -0.009 |
| 4 | 0.026 | -0.003 | 0.015 | 0.012 | 0.003 | 0.009 | -0.002 | 0.012 | 0.008 |
| 5 | 0.057 | 0.002 | 0.028 | 0.022 | 0.007 | 0.018 | 0.007 | 0.013 | 0.020 |
| 6 | 0.091 | 0.007 | 0.041 | 0.032 | 0.012 | 0.027 | 0.016 | 0.018 | 0.031 |
| 7 | 0.132 | 0.014 | 0.057 | 0.043 | 0.019 | 0.037 | 0.031 | 0.027 | 0.039 |
| 8 | 0.194 | 0.023 | 0.083 | 0.058 | 0.031 | 0.053 | 0.052 | 0.047 | 0.046 |
| 9 | 0.319 | 0.047 | 0.123 | 0.091 | 0.057 | 0.080 | 0.097 | 0.102 | 0.045 |
| 10(High) | 0.906 | 0.166 | 0.243 | 0.189 | 0.189 | 0.183 | 0.268 | 0.426 | -0.007 |
| Spread(10-1) | 1.130 | 0.239 | 0.309 | 0.222 | 0.221 | 0.219 | 0.319 | 0.390 | 0.161 |
| t(spread) | 24.599 | 14.988 | 28.235 | 25.530 | 13.050 | 34.362 | 25.879 | 9.955 | 7.225 |

Panel B: Correlations with asset growth

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Full sample correlation | 1.000 | 0.522 | 0.643 | 0.581 | 0.619 | 0.661 | 0.615 | 0.618 | 0.070 |
| Mean TS correlation | 1.000 | 0.311 | 0.696 | 0.635 | 0.467 | 0.641 | 0.588 | 0.466 | 0.402 |
| Mean CS correlation | 1.000 | 0.479 | 0.662 | 0.592 | 0.564 | 0.663 | 0.633 | 0.578 | 0.181 |

**Table IX**

**Cross-Sectional Predictability of Returns Using Subcomponents of Asset Growth**

This table presents Fama-MacBeth (1973) regressions of future 12 months buy-and-hold returns on subcomponents of asset growth and other known predictors of expected returns. In panel A, we use predictors based on growth in the items on the left-hand-side of the balance sheet: cash, noncash current assets (NCCA), PPE and other assets (all divided by lagged total assets). In panel B, we use predictors based on growth in the items on the right-hand-side of the balance sheet: operating liabilities (OLIAB), long-term debt (DEBT), common equity (EQ) and retained earnings (RE). The predictors common to all regressions are market equity (ME), book-to-market (BM) and gross profitability (GP). The estimates are obtained by running cross-sectional regressions every year from 1968 to 2016 and averaging over the resulting time-series of cross-sectional coefficients. The dependent variable measures the cumulative returns from July of the current year to June of the following year. In each panel, the first five columns use all firms in our sample, and the last five columns use all but the micro firms (market cap smaller than 20th NYSE percentile). Standard errors are corrected for serial correlation using the Newey-West (1987) procedure. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Components of asset growth on the left-hand-side of the balance sheet

| | All firms | | | | | All-but-micro firms | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| ME | -0.008 | -0.009 | -0.008 | -0.008 | -0.008 | -0.000 | -0.001 | -0.001 | -0.000 | -0.001 |
| | (-1.32) | (-1.39) | (-1.27) | (-1.31) | (-1.29) | (-0.05) | (-0.24) | (-0.10) | (-0.03) | (-0.22) |
| BM | 0.054*** | 0.048*** | 0.051*** | 0.053*** | 0.045*** | 0.041*** | 0.035*** | 0.039*** | 0.042*** | 0.033*** |
| | (4.86) | (4.29) | (4.61) | (4.68) | (4.21) | (3.49) | (2.83) | (3.22) | (3.29) | (2.95) |
| GP | 0.081*** | 0.088*** | 0.074*** | 0.077** | 0.077*** | 0.072** | 0.078** | 0.070** | 0.069** | 0.068** |
| | (2.85) | (2.98) | (2.77) | (2.56) | (2.73) | (2.43) | (2.43) | (2.42) | (2.13) | (2.19) |
| CASH | -0.032 | | | | -0.020 | -0.024 | | | | -0.005 |
| | (-1.43) | | | | (-0.97) | (-1.10) | | | | (-0.24) |
| NCCA | | -0.205*** | | | -0.146*** | | -0.156*** | | | -0.114*** |
| | | (-5.97) | | | (-5.40) | | (-4.37) | | | (-3.17) |
| PPE | | | -0.180*** | | -0.098** | | | -0.093** | | -0.027 |
| | | | (-4.10) | | (-2.48) | | | (-2.26) | | (-0.67) |
| Other | | | | -0.148*** | -0.080*** | | | | -0.081** | -0.039 |
| | | | | (-4.76) | (-3.20) | | | | (-2.31) | (-1.06) |
| Constant | 0.110* | 0.123** | 0.121* | 0.115* | 0.132** | 0.067 | 0.083 | 0.074 | 0.069 | 0.090* |
| | (1.83) | (2.06) | (1.99) | (1.90) | (2.18) | (1.24) | (1.56) | (1.44) | (1.27) | (1.73) |

## Table IX
## Cross-Sectional Predictability of Returns Using Subcomponents of Asset Growth (continued)

| Panel B: Components of asset growth on the right-hand-side of the balance sheet | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | All firms | | | | | All-but-micro firms | | | | |
| ME | -0.008 | -0.009 | -0.010 | -0.010 | -0.010 | -0.001 | -0.001 | -0.003 | -0.001 | -0.003 |
| | (-1.34) | (-1.40) | (-1.65) | (-1.56) | (-1.61) | (-0.09) | (-0.15) | (-0.45) | (-0.25) | (-0.60) |
| BM | 0.050*** | 0.051*** | 0.044*** | 0.051*** | 0.041*** | 0.037*** | 0.039*** | 0.029** | 0.038*** | 0.025** |
| | (4.53) | (4.61) | (4.17) | (4.86) | (4.10) | (2.99) | (3.12) | (2.51) | (3.12) | (2.22) |
| GP | 0.081*** | 0.073** | 0.059** | 0.072** | 0.055** | 0.073** | 0.069** | 0.054* | 0.061* | 0.040 |
| | (2.88) | (2.59) | (2.13) | (2.55) | (2.02) | (2.51) | (2.29) | (1.94) | (1.94) | (1.35) |
| OLIAB | -0.156*** | | | | -0.032 | -0.103*** | | | | 0.007 |
| | (-4.57) | | | | (-1.18) | (-3.01) | | | | (0.20) |
| DEBT | | -0.133*** | | | -0.110*** | | -0.079*** | | | -0.071*** |
| | | (-7.11) | | | (-6.07) | | (-3.79) | | | (-3.26) |
| EQ | | | -0.128*** | | -0.116*** | | | -0.110*** | | -0.098*** |
| | | | (-9.85) | | (-8.89) | | | (-5.98) | | (-5.44) |
| RE | | | | 0.030 | -0.011 | | | | 0.055 | 0.037 |
| | | | | (0.91) | (-0.29) | | | | (1.38) | (1.06) |
| Constant | 0.118* | 0.122** | 0.145** | 0.120** | 0.149** | 0.073 | 0.075 | 0.102* | 0.078 | 0.116** |
| | (1.98) | (2.04) | (2.42) | (2.10) | (2.60) | (1.39) | (1.46) | (1.98) | (1.47) | (2.34) |

## Table X
## Replacing Asset Growth With Its Subcomponents

This table presents alphas (left) and corresponding t-statistics (right) of spread portfolios (high minus low) of 35 anomalies. The sample period is 1972-2016. In Panels A1 and A2, the alphas are calculated using a version of the Hou, Xue, and Zhang (2015) four factor model (HXZ), where the asset growth factor has been replaced with an analogous factor based on a subcomponent of asset growth. In Panels B1 and B2, we make the same adjustment to the Fama and French (2015) five factor model (FF5F). Panels A1 and B1 use subcomponents of asset growth from the left hand side of the balance sheet: cash, noncash current assets (NCCA), PPE and other. In panels A2 and B2 we use subcomponents of asset growth from the right hand side of the balance sheet: operating liabilities (OLIAB), long-term debt (DBT), common equity (EQ), and retained earnings (RE). Please see Appendix A for details on how the anomalies are constructed. For comparison purposes, the table also reports results using the original HXZ and FF5F models (columns titled "AG") and versions of these models without an investment factor (columns titled "none"). "Mean $|\alpha|$: spread" is the mean absolute values of the 35 spread-portfolio alphas. "Mean $|\alpha|$: all" is the mean absolute value of all the decile-portfolio alphas of all anomalies. "N($|t| > 2$)" counts how many of the 35 anomalies have spread-portfolio alphas with t-statistics greater than 2 in absolute value. "N($p < 5\%$)" counts for how many of the 35 anomalies the model employed are rejected by the Gibbons, Ross, and Shanken (1989) test at the 5% level.

Panel A1: Decomposition of total assets. Alphas obtained using HXZ-like models

| | Alphas of spread portfolios | | | | | | T-statistics of spread portfolios | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anomaly | AG | None | CASH | NCCA | PPE | Other | AG | None | CASH | NCCA | PPE | Other |
| SUE | 0.13 | 0.19 | 0.18 | 0.12 | 0.18 | 0.23 | 1.02 | 1.64 | 1.53 | 0.97 | 1.56 | 1.58 |
| SUE6 | 0.00 | 0.00 | 0.00 | -0.02 | -0.01 | 0.04 | -0.01 | -0.04 | 0.01 | -0.13 | -0.10 | 0.35 |
| Abr | 0.74 | 0.70 | 0.72 | 0.69 | 0.77 | 0.74 | 4.90 | 5.12 | 5.28 | 4.79 | 5.33 | 4.81 |
| Abr6 | 0.31 | 0.27 | 0.28 | 0.29 | 0.30 | 0.32 | 2.84 | 2.74 | 2.90 | 2.66 | 2.85 | 2.83 |
| RE | -0.13 | -0.01 | 0.01 | -0.13 | 0.06 | -0.10 | -0.62 | -0.03 | 0.06 | -0.61 | 0.31 | -0.46 |
| RE6 | -0.17 | -0.12 | -0.10 | -0.17 | -0.08 | -0.14 | -0.79 | -0.63 | -0.52 | -0.81 | -0.42 | -0.61 |
| R6_6 | 0.22 | 0.32 | 0.32 | 0.14 | 0.31 | 0.31 | 0.71 | 1.10 | 1.14 | 0.47 | 1.02 | 1.04 |
| R11_1 | 0.24 | 0.41 | 0.42 | 0.16 | 0.36 | 0.38 | 0.62 | 1.18 | 1.25 | 0.44 | 0.99 | 0.97 |
| Imom | 0.12 | 0.24 | 0.22 | 0.03 | 0.25 | 0.17 | 0.42 | 0.92 | 0.87 | 0.11 | 0.95 | 0.60 |
| BM | 0.21 | 0.88 | 0.80 | 0.32 | 0.68 | 0.37 | 1.26 | 4.20 | 4.20 | 1.79 | 3.46 | 1.94 |
| EP | 0.15 | 0.61 | 0.52 | 0.28 | 0.54 | 0.25 | 0.69 | 2.86 | 2.61 | 1.28 | 2.52 | 1.11 |
| CFP | 0.20 | 0.67 | 0.58 | 0.28 | 0.61 | 0.26 | 1.02 | 3.24 | 3.01 | 1.42 | 2.91 | 1.30 |
| NOP | 0.20 | 0.69 | 0.62 | 0.31 | 0.58 | 0.44 | 1.30 | 3.68 | 3.55 | 1.93 | 3.28 | 2.39 |
| Dur | -0.21 | -0.61 | -0.54 | -0.29 | -0.53 | -0.35 | -1.10 | -2.95 | -2.79 | -1.47 | -2.60 | -1.73 |
| AG | 0.06 | -0.57 | -0.50 | -0.09 | -0.34 | -0.10 | 0.47 | -3.49 | -3.07 | -0.57 | -2.32 | -0.61 |
| NOA | -0.43 | -0.43 | -0.46 | -0.54 | -0.34 | -0.46 | -2.25 | -2.70 | -2.88 | -2.98 | -2.00 | -2.50 |
| dPIA | -0.23 | -0.64 | -0.62 | -0.35 | -0.36 | -0.44 | -1.71 | -4.35 | -4.13 | -2.46 | -2.88 | -3.03 |
| IG | -0.07 | -0.44 | -0.41 | -0.15 | -0.24 | -0.23 | -0.57 | -3.56 | -3.39 | -1.25 | -2.06 | -1.86 |
| NSI | -0.27 | -0.60 | -0.57 | -0.42 | -0.49 | -0.42 | -1.98 | -4.17 | -4.11 | -2.90 | -3.51 | -2.71 |
| CEI | -0.26 | -0.76 | -0.70 | -0.40 | -0.61 | -0.50 | -1.92 | -4.83 | -4.62 | -2.80 | -3.97 | -3.29 |
| IvG | 0.00 | -0.45 | -0.44 | -0.03 | -0.31 | -0.13 | -0.02 | -3.19 | -3.05 | -0.25 | -2.27 | -0.98 |
| IvC | -0.27 | -0.61 | -0.61 | -0.24 | -0.48 | -0.37 | -1.84 | -4.04 | -4.00 | -1.70 | -3.13 | -2.46 |
| OA | -0.46 | -0.45 | -0.49 | -0.37 | -0.48 | -0.46 | -3.44 | -3.80 | -4.23 | -2.73 | -3.82 | -3.52 |
| POA | -0.19 | -0.56 | -0.56 | -0.21 | -0.48 | -0.25 | -1.42 | -4.03 | -4.03 | -1.50 | -3.59 | -1.64 |
| PTA | -0.13 | -0.50 | -0.49 | -0.27 | -0.36 | -0.29 | -0.85 | -3.27 | -3.16 | -1.60 | -2.51 | -1.60 |
| ROE | 0.00 | 0.12 | 0.12 | 0.00 | 0.19 | 0.05 | -0.03 | 1.10 | 0.95 | -0.02 | 1.40 | 0.43 |
| ROA | 0.05 | 0.04 | 0.06 | 0.03 | 0.13 | 0.09 | 0.53 | 0.44 | 0.57 | 0.26 | 1.15 | 0.87 |
| GPA | 0.04 | -0.04 | -0.01 | 0.15 | -0.01 | 0.05 | 0.32 | -0.29 | -0.10 | 1.12 | -0.05 | 0.38 |
| NEI | 0.10 | 0.00 | 0.04 | 0.11 | 0.04 | 0.13 | 0.99 | 0.02 | 0.44 | 1.04 | 0.42 | 1.21 |
| FP6 | -0.11 | -0.01 | -0.06 | -0.08 | -0.10 | -0.21 | -0.80 | -0.04 | -0.41 | -0.52 | -0.73 | -1.49 |
| OCA | 0.08 | 0.30 | 0.26 | 0.14 | 0.21 | 0.16 | 0.66 | 2.74 | 2.42 | 1.27 | 1.97 | 1.32 |
| AdM | -0.04 | 0.59 | 0.48 | 0.14 | 0.44 | 0.20 | -0.14 | 2.06 | 1.88 | 0.50 | 1.52 | 0.67 |
| RDM | 0.63 | 0.69 | 0.68 | 0.74 | 0.58 | 0.75 | 2.79 | 3.37 | 3.20 | 3.33 | 2.80 | 3.38 |
| OL | -0.04 | 0.06 | 0.04 | 0.15 | 0.00 | 0.13 | -0.25 | 0.38 | 0.20 | 0.84 | 0.00 | 0.68 |
| Svol | -0.14 | -0.16 | -0.20 | -0.12 | -0.22 | -0.14 | -0.67 | -0.84 | -1.03 | -0.58 | -1.10 | -0.70 |
| Mean $\lvert\alpha\rvert$: spread | 0.19 | 0.39 | 0.37 | 0.23 | 0.33 | 0.28 | | | | | | |
| Mean $\lvert\alpha\rvert$: all | 0.10 | 0.12 | 0.12 | 0.10 | 0.11 | 0.10 | | | | | | |
| N($\lvert t\rvert > 2$) | 5 | 21 | 20 | 8 | 18 | 10 | | | | | | |
| N($p < 5\%$) | 18 | 23 | 22 | 16 | 21 | 16 | | | | | | |

## Table X
## Replacing Asset Growth With Its Subcomponents (continued)

Panel A2: Decomposition of liabilities & shareholders' equity. Alphas obtained using HXZ-like models

| | Alphas of spread portfolios | | | | | | T-statistics of spread portfolios | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anomaly | AG | None | OLIAB | DBT | EQ | RE | AG | None | OLIAB | DBT | EQ | RE |
| SUE | 0.13 | 0.19 | 0.14 | 0.16 | 0.22 | 0.06 | 1.02 | 1.64 | 1.14 | 1.36 | 1.81 | 0.51 |
| SUE6 | 0.00 | 0.00 | 0.01 | -0.07 | 0.05 | -0.12 | -0.01 | -0.04 | 0.08 | -0.66 | 0.43 | -1.00 |
| Abr | 0.74 | 0.70 | 0.71 | 0.66 | 0.80 | 0.57 | 4.90 | 5.12 | 5.03 | 4.65 | 5.57 | 4.08 |
| Abr6 | 0.31 | 0.27 | 0.29 | 0.22 | 0.34 | 0.20 | 2.84 | 2.74 | 2.83 | 2.25 | 3.35 | 1.95 |
| RE | -0.13 | -0.01 | -0.02 | -0.21 | 0.03 | -0.25 | -0.62 | -0.03 | -0.09 | -1.10 | 0.15 | -1.15 |
| RE6 | -0.17 | -0.12 | -0.07 | -0.31 | -0.07 | -0.33 | -0.79 | -0.63 | -0.34 | -1.65 | -0.38 | -1.56 |
| R6_6 | 0.22 | 0.32 | 0.34 | 0.06 | 0.41 | -0.01 | 0.71 | 1.10 | 1.12 | 0.22 | 1.36 | -0.04 |
| R11_1 | 0.24 | 0.41 | 0.40 | 0.13 | 0.49 | -0.06 | 0.62 | 1.18 | 1.08 | 0.38 | 1.35 | -0.16 |
| Imom | 0.12 | 0.24 | 0.24 | 0.03 | 0.28 | -0.02 | 0.42 | 0.92 | 0.89 | 0.10 | 0.96 | -0.07 |
| BM | 0.21 | 0.88 | 0.55 | 0.87 | 0.46 | 0.57 | 1.26 | 4.20 | 2.92 | 4.20 | 2.82 | 3.15 |
| EP | 0.15 | 0.61 | 0.39 | 0.69 | 0.16 | 0.52 | 0.69 | 2.86 | 1.79 | 3.14 | 0.87 | 2.46 |
| CFP | 0.20 | 0.67 | 0.46 | 0.69 | 0.26 | 0.57 | 1.02 | 3.24 | 2.24 | 3.26 | 1.46 | 2.85 |
| NOP | 0.20 | 0.69 | 0.41 | 0.77 | 0.35 | 0.61 | 1.30 | 3.68 | 2.52 | 3.94 | 2.71 | 3.27 |
| Dur | -0.21 | -0.61 | -0.43 | -0.67 | -0.22 | -0.56 | -1.10 | -2.95 | -2.11 | -3.19 | -1.33 | -2.91 |
| AG | 0.06 | -0.57 | -0.24 | -0.49 | -0.26 | -0.25 | 0.47 | -3.49 | -1.69 | -2.91 | -1.62 | -1.74 |
| NOA | -0.43 | -0.43 | -0.47 | -0.31 | -0.55 | -0.41 | -2.25 | -2.70 | -2.70 | -1.97 | -3.14 | -2.61 |
| dPIA | -0.23 | -0.64 | -0.43 | -0.51 | -0.47 | -0.39 | -1.71 | -4.35 | -3.10 | -3.51 | -3.22 | -2.98 |
| IG | -0.07 | -0.44 | -0.24 | -0.40 | -0.26 | -0.24 | -0.57 | -3.56 | -2.19 | -3.27 | -2.25 | -1.94 |
| NSI | -0.27 | -0.60 | -0.46 | -0.63 | -0.29 | -0.60 | -1.98 | -4.17 | -3.30 | -4.18 | -2.29 | -4.06 |
| CEI | -0.26 | -0.76 | -0.55 | -0.75 | -0.41 | -0.58 | -1.92 | -4.83 | -3.73 | -4.74 | -3.14 | -3.82 |
| IvG | 0.00 | -0.45 | -0.25 | -0.39 | -0.25 | -0.20 | -0.02 | -3.19 | -1.87 | -2.67 | -1.76 | -1.53 |
| IvC | -0.27 | -0.61 | -0.45 | -0.52 | -0.50 | -0.35 | -1.84 | -4.04 | -3.12 | -3.43 | -3.22 | -2.52 |
| OA | -0.46 | -0.45 | -0.51 | -0.43 | -0.56 | -0.38 | -3.44 | -3.80 | -4.13 | -3.60 | -4.68 | -2.92 |
| POA | -0.19 | -0.56 | -0.40 | -0.54 | -0.40 | -0.34 | -1.42 | -4.03 | -2.97 | -3.81 | -2.83 | -2.29 |
| PTA | -0.13 | -0.50 | -0.30 | -0.62 | -0.21 | -0.36 | -0.85 | -3.27 | -2.03 | -4.16 | -1.44 | -2.43 |
| ROE | 0.00 | 0.12 | 0.03 | 0.18 | -0.06 | 0.11 | -0.03 | 1.10 | 0.27 | 1.43 | -0.52 | 0.78 |
| ROA | 0.05 | 0.04 | 0.04 | 0.09 | -0.02 | 0.10 | 0.53 | 0.44 | 0.35 | 0.81 | -0.21 | 0.79 |
| GPA | 0.04 | -0.04 | -0.01 | -0.04 | -0.05 | 0.19 | 0.32 | -0.29 | -0.06 | -0.29 | -0.37 | 1.45 |
| NEI | 0.10 | 0.00 | 0.06 | 0.00 | 0.09 | 0.06 | 0.99 | 0.02 | 0.58 | 0.03 | 1.02 | 0.51 |
| FP6 | -0.11 | -0.01 | -0.09 | 0.01 | -0.07 | -0.01 | -0.80 | -0.04 | -0.60 | 0.05 | -0.51 | -0.06 |
| OCA | 0.08 | 0.30 | 0.18 | 0.25 | 0.15 | 0.23 | 0.66 | 2.74 | 1.56 | 2.38 | 1.27 | 2.04 |
| AdM | -0.04 | 0.59 | 0.25 | 0.69 | 0.17 | 0.55 | -0.14 | 2.06 | 0.91 | 2.40 | 0.74 | 1.72 |
| RDM | 0.63 | 0.69 | 0.65 | 0.69 | 0.73 | 0.69 | 2.79 | 3.37 | 2.88 | 3.36 | 3.32 | 3.19 |
| OL | -0.04 | 0.06 | -0.02 | 0.13 | -0.08 | 0.12 | -0.25 | 0.38 | -0.14 | 0.70 | -0.46 | 0.73 |
| Svol | -0.14 | -0.16 | -0.18 | -0.33 | -0.12 | -0.19 | -0.67 | -0.84 | -0.88 | -1.59 | -0.60 | -0.96 |
| Mean $\lvert\alpha\rvert$: spread | 0.19 | 0.39 | 0.29 | 0.39 | 0.28 | 0.31 | | | | | | |
| Mean $\lvert\alpha\rvert$: all | 0.10 | 0.12 | 0.10 | 0.13 | 0.10 | 0.11 | | | | | | |
| N($\lvert t\rvert > 2$) | 5 | 21 | 16 | 20 | 13 | 16 | | | | | | |
| N($p < 5\%$) | 18 | 23 | 18 | 22 | 20 | 20 | | | | | | |

**Table X**
**Replacing Asset Growth With Its Subcomponents (continued)**

Panel B1: Decomposition of total assets. Alphas obtained using FF5F-like models

| | Alphas of spread portfolios | | | | | | T-statistics of spread portfolios | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anomaly | AG | None | CASH | NCCA | PPE | Other | AG | None | CASH | NCCA | PPE | Other |
| SUE | 0.48 | 0.49 | 0.49 | 0.47 | 0.48 | 0.49 | 4.15 | 4.14 | 4.12 | 4.00 | 3.98 | 3.93 |
| SUE6 | 0.31 | 0.33 | 0.33 | 0.30 | 0.31 | 0.29 | 2.79 | 3.02 | 2.93 | 2.62 | 2.59 | 2.60 |
| Abr | 0.98 | 0.97 | 0.96 | 0.95 | 1.01 | 0.96 | 7.09 | 6.83 | 6.62 | 6.89 | 7.01 | 6.84 |
| Abr6 | 0.49 | 0.47 | 0.45 | 0.49 | 0.49 | 0.49 | 5.13 | 5.00 | 4.69 | 4.98 | 5.02 | 4.74 |
| RE | 0.66 | 0.66 | 0.60 | 0.62 | 0.67 | 0.49 | 2.77 | 2.90 | 2.67 | 2.72 | 2.84 | 1.97 |
| RE6 | 0.52 | 0.51 | 0.47 | 0.49 | 0.51 | 0.37 | 2.40 | 2.53 | 2.29 | 2.31 | 2.40 | 1.57 |
| R6_6 | 1.04 | 1.06 | 0.97 | 0.96 | 1.05 | 0.96 | 3.55 | 3.65 | 3.23 | 3.34 | 3.46 | 3.17 |
| R11_1 | 1.31 | 1.37 | 1.27 | 1.22 | 1.33 | 1.22 | 3.68 | 3.99 | 3.51 | 3.48 | 3.68 | 3.18 |
| Imom | 0.75 | 0.77 | 0.72 | 0.65 | 0.78 | 0.68 | 2.63 | 2.72 | 2.42 | 2.34 | 2.65 | 2.33 |
| BM | 0.02 | 0.03 | 0.06 | 0.02 | 0.03 | 0.03 | 0.15 | 0.30 | 0.54 | 0.19 | 0.29 | 0.26 |
| EP | -0.04 | -0.11 | -0.10 | -0.02 | -0.06 | -0.06 | -0.33 | -0.85 | -0.75 | -0.20 | -0.46 | -0.47 |
| CFP | -0.05 | -0.11 | -0.09 | -0.06 | -0.04 | -0.08 | -0.40 | -0.88 | -0.74 | -0.50 | -0.33 | -0.57 |
| NOP | 0.13 | 0.25 | 0.28 | 0.14 | 0.19 | 0.25 | 1.09 | 2.07 | 2.31 | 1.20 | 1.55 | 2.06 |
| Dur | -0.01 | 0.06 | 0.05 | -0.01 | 0.03 | -0.05 | -0.05 | 0.47 | 0.41 | -0.04 | 0.22 | -0.38 |
| AG | 0.02 | -0.21 | -0.30 | -0.03 | -0.11 | 0.00 | 0.17 | -1.46 | -2.07 | -0.18 | -0.78 | 0.03 |
| NOA | -0.53 | -0.62 | -0.63 | -0.58 | -0.54 | -0.55 | -3.11 | -3.71 | -3.77 | -3.30 | -3.08 | -3.05 |
| dPIA | -0.34 | -0.52 | -0.54 | -0.39 | -0.36 | -0.45 | -2.88 | -3.68 | -3.85 | -2.89 | -3.09 | -3.15 |
| IG | -0.17 | -0.31 | -0.34 | -0.16 | -0.19 | -0.20 | -1.50 | -2.64 | -2.84 | -1.40 | -1.71 | -1.62 |
| NSI | -0.31 | -0.41 | -0.46 | -0.34 | -0.35 | -0.36 | -2.47 | -3.17 | -3.54 | -2.64 | -2.73 | -2.63 |
| CEI | -0.29 | -0.40 | -0.42 | -0.29 | -0.35 | -0.36 | -2.67 | -3.40 | -3.41 | -2.61 | -3.01 | -3.06 |
| IvG | -0.09 | -0.23 | -0.22 | -0.04 | -0.16 | -0.06 | -0.74 | -1.68 | -1.59 | -0.32 | -1.22 | -0.46 |
| IvC | -0.34 | -0.46 | -0.44 | -0.27 | -0.39 | -0.35 | -2.62 | -3.39 | -3.33 | -2.06 | -2.90 | -2.51 |
| OA | -0.41 | -0.38 | -0.30 | -0.32 | -0.41 | -0.43 | -3.41 | -3.30 | -2.55 | -2.61 | -3.47 | -3.47 |
| POA | -0.17 | -0.27 | -0.25 | -0.13 | -0.24 | -0.14 | -1.36 | -2.10 | -1.92 | -1.04 | -1.90 | -1.09 |
| PTA | -0.05 | -0.17 | -0.18 | -0.07 | -0.10 | -0.12 | -0.32 | -1.15 | -1.18 | -0.50 | -0.68 | -0.77 |
| ROE | 0.57 | 0.58 | 0.52 | 0.51 | 0.57 | 0.49 | 4.23 | 4.36 | 4.02 | 3.94 | 4.15 | 3.78 |
| ROA | 0.58 | 0.55 | 0.48 | 0.52 | 0.55 | 0.53 | 4.59 | 4.49 | 3.76 | 4.29 | 4.22 | 4.30 |
| GPA | 0.15 | 0.21 | 0.21 | 0.18 | 0.18 | 0.19 | 1.22 | 1.65 | 1.64 | 1.45 | 1.37 | 1.49 |
| NEI | 0.40 | 0.39 | 0.32 | 0.38 | 0.37 | 0.41 | 4.25 | 4.21 | 3.66 | 4.10 | 3.85 | 4.23 |
| FP6 | -0.60 | -0.63 | -0.59 | -0.57 | -0.57 | -0.60 | -3.74 | -3.89 | -3.61 | -3.46 | -3.37 | -3.64 |
| OCA | 0.28 | 0.37 | 0.39 | 0.27 | 0.31 | 0.27 | 2.52 | 3.21 | 3.25 | 2.44 | 2.76 | 2.28 |
| AdM | -0.27 | -0.15 | -0.12 | -0.22 | -0.18 | -0.13 | -1.51 | -0.86 | -0.66 | -1.19 | -0.99 | -0.72 |
| RDM | 0.50 | 0.56 | 0.60 | 0.60 | 0.53 | 0.64 | 2.33 | 2.62 | 2.88 | 2.70 | 2.42 | 2.88 |
| OL | 0.08 | 0.12 | 0.15 | 0.17 | 0.08 | 0.17 | 0.50 | 0.76 | 0.95 | 1.03 | 0.52 | 1.00 |
| Svol | -0.20 | -0.23 | -0.22 | -0.18 | -0.23 | -0.17 | -1.00 | -1.15 | -1.13 | -0.91 | -1.12 | -0.84 |
| Mean $\|\alpha\|$: spread | 0.38 | 0.43 | 0.41 | 0.36 | 0.39 | 0.37 | | | | | | |
| Mean $\|\alpha\|$: all | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | | | | | | |
| N($\|t\| > 2$) | 21 | 24 | 24 | 21 | 21 | 20 | | | | | | |
| N($p < 5\%$) | 23 | 24 | 26 | 23 | 24 | 24 | | | | | | |

**Table X**
**Replacing Asset Growth With Its Subcomponents (continued)**

Panel B2: Decomposition of liabilities & shareholders' equity. Alphas obtained using FF5F-like models

| | Alphas of spread portfolios | | | | | | T-statistics of spread portfolios | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anomaly | AG | None | OLIAB | DBT | EQ | RE | AG | None | OLIAB | DBT | EQ | RE |
| SUE | 0.48 | 0.49 | 0.49 | 0.50 | 0.49 | 0.49 | 4.15 | 4.14 | 4.11 | 3.82 | 4.15 | 4.18 |
| SUE6 | 0.31 | 0.33 | 0.33 | 0.26 | 0.33 | 0.33 | 2.79 | 3.02 | 3.01 | 2.34 | 2.90 | 2.98 |
| Abr | 0.98 | 0.97 | 0.97 | 0.94 | 0.98 | 0.98 | 7.09 | 6.83 | 6.79 | 6.43 | 6.90 | 7.05 |
| Abr6 | 0.49 | 0.47 | 0.47 | 0.45 | 0.48 | 0.49 | 5.13 | 5.00 | 4.99 | 4.47 | 5.09 | 5.34 |
| RE | 0.66 | 0.66 | 0.66 | 0.40 | 0.66 | 0.69 | 2.77 | 2.90 | 2.90 | 1.81 | 2.95 | 3.19 |
| RE6 | 0.52 | 0.51 | 0.51 | 0.31 | 0.52 | 0.54 | 2.40 | 2.53 | 2.51 | 1.47 | 2.55 | 2.67 |
| R6_6 | 1.04 | 1.06 | 1.05 | 0.85 | 1.07 | 1.09 | 3.55 | 3.65 | 3.66 | 2.94 | 3.64 | 3.83 |
| R11_1 | 1.31 | 1.37 | 1.37 | 1.18 | 1.37 | 1.39 | 3.68 | 3.99 | 4.03 | 3.48 | 3.90 | 4.07 |
| Imom | 0.75 | 0.77 | 0.77 | 0.62 | 0.78 | 0.80 | 2.63 | 2.72 | 2.71 | 2.22 | 2.69 | 2.87 |
| BM | 0.02 | 0.03 | 0.04 | -0.02 | 0.03 | 0.04 | 0.15 | 0.30 | 0.31 | -0.20 | 0.24 | 0.32 |
| EP | -0.04 | -0.11 | -0.12 | -0.09 | -0.11 | -0.09 | -0.33 | -0.85 | -0.96 | -0.72 | -0.85 | -0.72 |
| CFP | -0.05 | -0.11 | -0.13 | -0.15 | -0.10 | -0.10 | -0.40 | -0.88 | -1.03 | -1.18 | -0.81 | -0.78 |
| NOP | 0.13 | 0.25 | 0.26 | 0.28 | 0.22 | 0.20 | 1.09 | 2.07 | 2.23 | 2.15 | 1.92 | 1.66 |
| Dur | -0.01 | 0.06 | 0.07 | 0.07 | 0.07 | 0.03 | -0.05 | 0.47 | 0.61 | 0.57 | 0.53 | 0.25 |
| AG | 0.02 | -0.21 | -0.25 | -0.08 | -0.15 | -0.16 | 0.17 | -1.46 | -1.92 | -0.53 | -1.14 | -1.23 |
| NOA | -0.53 | -0.62 | -0.63 | -0.50 | -0.63 | -0.60 | -3.11 | -3.71 | -3.82 | -2.99 | -3.76 | -3.55 |
| dPIA | -0.34 | -0.52 | -0.54 | -0.35 | -0.46 | -0.48 | -2.88 | -3.68 | -4.08 | -2.49 | -3.71 | -3.75 |
| IG | -0.17 | -0.31 | -0.33 | -0.26 | -0.26 | -0.28 | -1.50 | -2.64 | -3.04 | -2.17 | -2.37 | -2.54 |
| NSI | -0.31 | -0.41 | -0.42 | -0.40 | -0.37 | -0.39 | -2.47 | -3.17 | -3.34 | -3.04 | -2.96 | -3.06 |
| CEI | -0.29 | -0.40 | -0.41 | -0.33 | -0.36 | -0.36 | -2.67 | -3.40 | -3.52 | -2.85 | -3.22 | -3.24 |
| IvG | -0.09 | -0.23 | -0.24 | -0.12 | -0.19 | -0.19 | -0.74 | -1.68 | -1.86 | -0.89 | -1.46 | -1.52 |
| IvC | -0.34 | -0.46 | -0.47 | -0.35 | -0.43 | -0.43 | -2.62 | -3.39 | -3.56 | -2.38 | -3.17 | -3.26 |
| OA | -0.41 | -0.38 | -0.37 | -0.38 | -0.42 | -0.36 | -3.41 | -3.30 | -3.22 | -3.19 | -3.70 | -3.12 |
| POA | -0.17 | -0.27 | -0.28 | -0.19 | -0.25 | -0.23 | -1.36 | -2.10 | -2.21 | -1.43 | -1.97 | -1.89 |
| PTA | -0.05 | -0.17 | -0.19 | -0.28 | -0.12 | -0.13 | -0.32 | -1.15 | -1.39 | -1.79 | -0.82 | -0.96 |
| ROE | 0.57 | 0.58 | 0.58 | 0.56 | 0.56 | 0.60 | 4.23 | 4.36 | 4.33 | 4.16 | 4.25 | 4.60 |
| ROA | 0.58 | 0.55 | 0.55 | 0.52 | 0.56 | 0.58 | 4.59 | 4.49 | 4.42 | 4.07 | 4.58 | 4.83 |
| GPA | 0.15 | 0.21 | 0.22 | 0.16 | 0.21 | 0.22 | 1.22 | 1.65 | 1.78 | 1.27 | 1.67 | 1.75 |
| NEI | 0.40 | 0.39 | 0.38 | 0.38 | 0.40 | 0.40 | 4.25 | 4.21 | 4.16 | 3.74 | 4.39 | 4.40 |
| FP6 | -0.60 | -0.63 | -0.62 | -0.51 | -0.62 | -0.63 | -3.74 | -3.89 | -3.82 | -3.14 | -3.86 | -3.91 |
| OCA | 0.28 | 0.37 | 0.38 | 0.31 | 0.34 | 0.37 | 2.52 | 3.21 | 3.50 | 2.98 | 2.88 | 3.28 |
| AdM | -0.27 | -0.15 | -0.15 | -0.07 | -0.17 | -0.18 | -1.51 | -0.86 | -0.84 | -0.37 | -0.95 | -1.01 |
| RDM | 0.50 | 0.56 | 0.57 | 0.69 | 0.58 | 0.55 | 2.33 | 2.62 | 2.70 | 3.24 | 2.67 | 2.57 |
| OL | 0.08 | 0.12 | 0.14 | 0.19 | 0.12 | 0.13 | 0.50 | 0.76 | 0.85 | 1.11 | 0.71 | 0.79 |
| Svol | -0.20 | -0.23 | -0.23 | -0.35 | -0.22 | -0.20 | -1.00 | -1.15 | -1.14 | -1.72 | -1.08 | -1.02 |
| Mean $\|\alpha\|$: spread | 0.38 | 0.43 | 0.43 | 0.37 | 0.42 | 0.42 | | | | | | |
| Mean $\|\alpha\|$: all | 0.12 | 0.12 | 0.12 | 0.11 | 0.12 | 0.12 | | | | | | |
| N($\|t\| > 2$) | 21 | 24 | 24 | 21 | 22 | 22 | | | | | | |
| N($p < 5\%$) | 23 | 24 | 25 | 20 | 25 | 24 | | | | | | |

## Table XI
## Replacing Asset Growth With Its Subcomponents: Performance Using Various Test Assets

This table summarizes the ability of various factor models to explain monthly excess returns on several sets of test assets (the same ones used in Table IV). The sample period is 1972-2016. In Panel A and B, we use factor models which are variations of the Hou, Xue, and Zhang (2015) four factor model (HXZ), where the asset growth factor has been replaced with an analogous factor based on a subcomponent of asset growth. In Panels C and D, we make the same adjustment to the Fama and French (2015) five factor model (FF5F). Panels A and C use subcomponents of asset growth from the left hand side of the balance sheet: cash, noncash current assets (NCCA), PPE and other. In panels B and D we use subcomponents of asset growth from the right hand side of the balance sheet: operating liabilities (OLIAB), long-term debt (DBT), common equity (EQ) and retained earnings (RE). For comparison purposes, the table also reports results using the original HXZ and FF5F models (columns titled "AG") and versions of these models without an investment factor (columns titled "none"). "Mean $|\alpha|$" is the average of the absolute alphas corresponding to each set of portfolios. "N($|t| > 2$) " is the number of alpha t-statistics with absolute value greater than 2. "GRS test statistic" is the Gibbons, Ross, and Shanken (1989) statistic that tests whether the alpha estimates corresponding to each set of portfolios are jointly 0.

Panel A: Decomposing total assets. Performance of HXZ-like models

| | AG | None | CASH | NCCA | PPE | Other |
|---|---|---|---|---|---|---|
| *Panel A1: All 171 portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.098 | 0.221 | 0.193 | 0.12 | 0.165 | 0.128 |
| N($\|t\| > 2$) | 21 | 88 | 75 | 31 | 54 | 32 |
| GRS test statistic | 1.887 | 2.18 | 2.182 | 1.956 | 2.063 | 1.929 |
| *Panel A2: 25 Size-BM portoflios* | | | | | | |
| Mean $\|\alpha\|$ | 0.104 | 0.25 | 0.218 | 0.134 | 0.187 | 0.141 |
| N($\|t\| > 2$) | 4 | 14 | 12 | 5 | 10 | 5 |
| GRS test statistic | 3.191 | 4.28 | 4.121 | 3.588 | 3.531 | 3.622 |
| *Panel A3: 25 Size-AG Portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.087 | 0.232 | 0.202 | 0.11 | 0.159 | 0.112 |
| N($\|t\| > 2$) | 5 | 20 | 16 | 7 | 9 | 7 |
| GRS test statistic | 3.256 | 4.846 | 4.818 | 3.493 | 4.181 | 3.495 |
| *Panel A4: 25 Size-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.051 | 0.085 | 0.067 | 0.057 | 0.067 | 0.063 |
| N($\|t\| > 2$) | 0 | 4 | 2 | 1 | 2 | 1 |
| GRS test statistic | 1.497 | 2.129 | 1.962 | 1.592 | 1.723 | 1.757 |
| *Panel A5: 32 Size-BM-AG portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.097 | 0.229 | 0.197 | 0.12 | 0.166 | 0.136 |
| N($\|t\| > 2$) | 4 | 16 | 14 | 6 | 10 | 5 |
| GRS test statistic | 2.185 | 3.261 | 3.368 | 2.442 | 2.829 | 2.583 |
| *Panel A6: 32 Size-BM-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.13 | 0.269 | 0.239 | 0.154 | 0.212 | 0.156 |
| N($\|t\| > 2$) | 3 | 16 | 14 | 4 | 11 | 5 |
| GRS test statistic | 1.968 | 2.568 | 2.597 | 2.088 | 2.3 | 2.032 |
| *Panel A7: 32 Size-AG-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.108 | 0.239 | 0.215 | 0.133 | 0.18 | 0.147 |
| N($\|t\| > 2$) | 5 | 18 | 17 | 8 | 12 | 9 |
| GRS test statistic | 2.411 | 3.825 | 4.144 | 2.794 | 3.329 | 2.889 |

**Table XI**
**Replacing Asset Growth With Its Subcomponents: Performance Using Various Test Assets (continued)**

Panel B: Decomposing liabilities and shareholders' equity. Performance of HXZ-like models

| | AG | None | OLIAB | DBT | EQ | RE |
|---|---|---|---|---|---|---|
| *Panel B1: All 171 portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.098 | 0.221 | 0.135 | 0.224 | 0.128 | 0.175 |
| N($\|t\| > 2$) | 21 | 88 | 38 | 86 | 41 | 62 |
| GRS test statistic | 1.887 | 2.18 | 2.025 | 2.018 | 2.016 | 2.002 |
| *Panel B2: 25 Size-BM portoflios* | | | | | | |
| Mean $\|\alpha\|$ | 0.104 | 0.25 | 0.146 | 0.271 | 0.131 | 0.192 |
| N($\|t\| > 2$) | 4 | 14 | 7 | 15 | 6 | 11 |
| GRS test statistic | 3.191 | 4.28 | 3.594 | 3.811 | 3.532 | 3.838 |
| *Panel B3: 25 Size-AG Portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.087 | 0.232 | 0.129 | 0.212 | 0.133 | 0.158 |
| N($\|t\| > 2$) | 5 | 20 | 7 | 16 | 9 | 12 |
| GRS test statistic | 3.256 | 4.846 | 4.171 | 4.025 | 4.026 | 3.786 |
| *Panel B4: 25 Size-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.051 | 0.085 | 0.048 | 0.099 | 0.065 | 0.095 |
| N($\|t\| > 2$) | 0 | 4 | 1 | 5 | 3 | 4 |
| GRS test statistic | 1.497 | 2.129 | 1.596 | 1.895 | 1.751 | 1.851 |
| *Panel B5: 32 Size-BM-AG portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.097 | 0.229 | 0.135 | 0.229 | 0.131 | 0.173 |
| N($\|t\| > 2$) | 4 | 16 | 6 | 17 | 8 | 12 |
| GRS test statistic | 2.185 | 3.261 | 2.765 | 2.876 | 2.891 | 2.911 |
| *Panel B6: 32 Size-BM-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.13 | 0.269 | 0.174 | 0.294 | 0.143 | 0.235 |
| N($\|t\| > 2$) | 3 | 16 | 7 | 17 | 6 | 9 |
| GRS test statistic | 1.968 | 2.568 | 2.13 | 2.371 | 2.114 | 2.69 |
| *Panel B7: 32 Size-AG-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.108 | 0.239 | 0.158 | 0.218 | 0.154 | 0.179 |
| N($\|t\| > 2$) | 5 | 18 | 10 | 16 | 9 | 14 |
| GRS test statistic | 2.411 | 3.825 | 3.367 | 3.315 | 3.249 | 3.117 |

## Table XI
## Replacing Asset Growth With Its Subcomponents: Performance Using Various Test Assets (continued)

| Panel C: Decomposing total assets. Performance of FF5F-like models | | | | | | |
|---|---|---|---|---|---|---|
| | AG | None | CASH | NCCA | PPE | Other |
| *Panel C1: All 171 portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.099 | 0.107 | 0.116 | 0.102 | 0.101 | 0.111 |
| N($\|t\| > 2$) | 36 | 37 | 39 | 37 | 35 | 37 |
| GRS test statistic | 1.901 | 1.969 | 2.088 | 1.898 | 1.98 | 1.885 |
| *Panel C2: 25 Size-BM portoflios* | | | | | | |
| Mean $\|\alpha\|$ | 0.105 | 0.102 | 0.107 | 0.109 | 0.101 | 0.12 |
| N($\|t\| > 2$) | 6 | 5 | 5 | 6 | 6 | 7 |
| GRS test statistic | 3.369 | 3.323 | 3.429 | 3.49 | 3.175 | 3.736 |
| *Panel C3: 25 Size-AG Portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.095 | 0.111 | 0.129 | 0.102 | 0.101 | 0.1 |
| N($\|t\| > 2$) | 5 | 7 | 8 | 6 | 6 | 5 |
| GRS test statistic | 3.674 | 4.04 | 4.521 | 3.73 | 3.794 | 3.754 |
| *Panel C4: 25 Size-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.051 | 0.047 | 0.048 | 0.054 | 0.048 | 0.058 |
| N($\|t\| > 2$) | 1 | 2 | 3 | 1 | 1 | 2 |
| GRS test statistic | 1.669 | 1.713 | 1.684 | 1.735 | 1.568 | 1.755 |
| *Panel C5: 32 Size-BM-AG portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.108 | 0.129 | 0.139 | 0.112 | 0.115 | 0.127 |
| N($\|t\| > 2$) | 9 | 10 | 9 | 10 | 10 | 10 |
| GRS test statistic | 2.597 | 2.812 | 3.027 | 2.685 | 2.665 | 2.811 |
| *Panel C6: 32 Size-BM-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.11 | 0.103 | 0.104 | 0.107 | 0.108 | 0.121 |
| N($\|t\| > 2$) | 5 | 3 | 3 | 5 | 4 | 4 |
| GRS test statistic | 2.138 | 1.943 | 1.952 | 2.03 | 2.06 | 2.15 |
| *Panel C7: 32 Size-AG-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.113 | 0.137 | 0.153 | 0.119 | 0.12 | 0.127 |
| N($\|t\| > 2$) | 10 | 10 | 11 | 9 | 8 | 9 |
| GRS test statistic | 3.357 | 3.678 | 4.142 | 3.36 | 3.451 | 3.345 |

**Table XI**
**Replacing Asset Growth With Its Subcomponents: Performance Using Various Test Assets (continued)**

Panel D: Decomposing liabilities and shareholders' equity. Performance of FF5F-like models

| | AG | None | OLIAB | DBT | EQ | RE |
|---|---|---|---|---|---|---|
| *Panel D1: All 171 portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.099 | 0.107 | 0.111 | 0.093 | 0.107 | 0.108 |
| N($\|t\| > 2$) | 36 | 37 | 38 | 32 | 37 | 38 |
| GRS test statistic | 1.901 | 1.969 | 2.041 | 1.795 | 1.962 | 1.961 |
| *Panel D2: 25 Size-BM portoflios* | | | | | | |
| Mean $\|\alpha\|$ | 0.105 | 0.102 | 0.103 | 0.097 | 0.107 | 0.108 |
| N($\|t\| > 2$) | 6 | 5 | 5 | 5 | 5 | 5 |
| GRS test statistic | 3.369 | 3.323 | 3.313 | 2.849 | 3.381 | 3.355 |
| *Panel D3: 25 Size-AG Portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.095 | 0.111 | 0.117 | 0.093 | 0.109 | 0.112 |
| N($\|t\| > 2$) | 5 | 7 | 8 | 6 | 7 | 8 |
| GRS test statistic | 3.674 | 4.04 | 4.496 | 3.119 | 4.026 | 4.053 |
| *Panel D4: 25 Size-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.051 | 0.047 | 0.048 | 0.045 | 0.047 | 0.05 |
| N($\|t\| > 2$) | 1 | 2 | 2 | 0 | 2 | 2 |
| GRS test statistic | 1.669 | 1.713 | 1.708 | 1.317 | 1.667 | 1.711 |
| *Panel D5: 32 Size-BM-AG portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.108 | 0.129 | 0.135 | 0.104 | 0.128 | 0.129 |
| N($\|t\| > 2$) | 9 | 10 | 9 | 9 | 10 | 10 |
| GRS test statistic | 2.597 | 2.812 | 3.097 | 2.363 | 2.848 | 2.853 |
| *Panel D6: 32 Size-BM-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.11 | 0.103 | 0.103 | 0.098 | 0.107 | 0.106 |
| N($\|t\| > 2$) | 5 | 3 | 3 | 4 | 4 | 4 |
| GRS test statistic | 2.138 | 1.943 | 1.931 | 1.705 | 1.969 | 2.005 |
| *Panel D7: 32 Size-AG-Profitability portfolios* | | | | | | |
| Mean $\|\alpha\|$ | 0.113 | 0.137 | 0.143 | 0.114 | 0.133 | 0.132 |
| N($\|t\| > 2$) | 10 | 10 | 11 | 8 | 9 | 9 |
| GRS test statistic | 3.357 | 3.678 | 4.105 | 2.962 | 3.641 | 3.672 |

## Appendix A: List of Anomalies

We have utilized NYSE breakpoints for the purposes of portfolio formation for the vast majority of the below listed anomalies. In instances where NYSE breakpoints have not be utilized, we have marked these anomalies with a star (*).

**B1 SUE, SUE6** – Standardized unexpected earnings (SUE) is calculated based on Foster, Olsen, and Shevlin (1984). SUE is the difference between the most recent announced quarterly earnings per share (Compustat quarterly item EPSPXQ) and the quarterly earnings per share from 4 quarters ago divided by the standard deviation of the change in quarterly earnings over the prior 8 quarters. A minimum of 6 quarterly earnings observations are required to be available to complete the calculation.

For portfolio formation, the most recently announced earnings must be associated with a fiscal quarter end within the 6 months preceding the portfolio formation date. In addition, the report date (Compustat quarterly item RDQ) must be after the fiscal quarter end. These restrictions help ensure that incorrect or dated information is excluded from the portfolios.

At the start of each month t, all NYSE, Amex, and NASDAQ stocks are separated into deciles based on the most recent SUE value. Value-weighted portfolio returns are calculated for each month over the current month, t, for SUE and over months, t to t+5, for SUE6. Deciles are rebalanced each month. For SUE6, there are six separate deciles associated with each month. Each of these separate deciles is from the start of one of the prior six months. The SUE6 decile return is the average return of these six separate deciles in a given month.

**B2 Abr, Abr6** – Our calculation of cumulative abnormal stock return (Abr) follows Chan, Jegadeesh, and Lakonishok (1996). Specifically, this anomaly focuses on returns around earnings announcement dates and is calculated as:

$$Abr_i = \sum_{d=-2}^{+1} r_{id} - r_{md} \tag{B1}$$

where $r_{id}$ is firm $i$'s return on day $d$, and $r_{md}$ is the value weighted return on the market index. Earnings announcements coincide with day 0 in the above equation. One day after the earnings announcement is included to help ensure any delayed reaction is a part of the cumulative abnormal return calculation. For portfolio formation, the most recently announced earnings must be associated with a fiscal quarter end within the 6 months preceding portfolio formation.

Deciles are formed each month t based on the most recent Abr. Value-weighted portfolio returns are calculated for each month over the current month, *t*, for Abr and over months, *t* to *t+5*, for Abr6. Deciles are rebalanced each month. For Abr6, there are six separate deciles associated with each month. Each of these separate deciles is from the start of one of the prior six months. The Abr6 decile return is the average return of these six separate deciles in a given month.

**B3 RE, RE6** – Chan, Jegadeesh, and Lakonishok (1996) also outline a measure of earnings surprise represented by the changes in analysts' forecasts of earnings. Institutional Brokers' Estimate System (IBES) is our source for the earnings forecast data. The formula to calculate the 6-month moving average of the past changes in analyst forecasts is below:

$$RE_{it} = \sum_{j=1}^{6} \frac{f_{i,t-j} - f_{i,t-j-1}}{p_{i,t-j-1}} \tag{B2}$$

$f_{i,t-j}$ is the consensus mean forecast (IBES item MEANEST) issued in month *t-j* for firm *i*'s current fiscal year earnings where fiscal period indicator is equal to 1, and $p_{i,t-j-1}$ is the share price one month prior (IBES item PRICE). Prices are adjusted for stock splits with a minimum of 4 monthly forecast changes required.

**B4 R6_6** – Each month *t* stocks are placed into deciles based on the returns over months *t-7* to *t-2*. For the purposes of the value weighted return calculation and portfolio formation, we skip month *t-1*. Value weighted returns are calculated starting in month *t*. These returns are calculated from month *t* to *t+5* for this anomaly. Portfolios are rebalanced each month. For R6_6, there are six separate deciles associated with each month. Each of these separate deciles is from the start of one of the prior six months. The R6_6 decile return is the average return of these six separate deciles in a given month.

**B4a R11_1** – Adopting the methodology outlined in Fama and French (1996), R11_1 portfolios are formed each month based on returns over the 11 month period from *t-12* to *t-2*. We skip month *t-1* and form portfolios in month *t*. Each month, value weighted returns are calculated for each portfolio. These portfolios are rebalanced each month.

**B5 Imom*** – Industry momentum, originally identified by Moskowitz and Grinblatt (1999), is a strategy based on purchasing stocks in "winner" industries and selling stocks in loser industries. Each month *t* we sort industries into winners and losers based on their previous value-weighted returns from *t-6* to *t-1*. We utilize Fama-Frenchs 49-industry classification and omit financial firms from our testing. The omission of financial firms leaves 45 industries, which are divided into 9 separate portfolios. Each portfolio containing five distinct industries. Returns for these portfolios are obtained by taking the average of the equal-weighted return for each of the five industries in the portfolio. These portfolios are held for 6 months from *t* to *t+5*, and are rebalanced at the start of *t+1*. For Imom, there are six separate deciles associated with each month. Each of these separate deciles is from the start of one of the prior six months. The Imom decile return is the average return of these six separate deciles for a given month.

**B6 BM** – Each year *t*, we sort stocks into deciles based on their book-to-market ratio or BM. BM is the ratio of the book equity for the fiscal year ending in calendar year *t-1* divided by the market equity at the end of December of *t-1*. Value-weighted returns are calculated for the period from July of year *t* to June of year *t+1*. These deciles are rebalanced annually at the end of June of year *t+1*.

**B7 EP** – Following Basu (1983), we form deciles based on the earnings-to-price (EP) ratio at the end of June of year *t*. EP is the ratio of earnings as measured by Compustat item IB for the fiscal year ending in calendar year *t-1* divided by the market equity (from CRSP or Compustat) as of December *t-1*. We exclude firms with negative earnings. Value-weighted returns are calculated each month based on portfolios formed in July of year *t* and held until June of year *t+1*. The deciles are rebalanced at the end of June of year *t+1*.

**B8 CFP** – Cash flow to market equity (CFP) is measured as the ratio of cash flow at the end of the fiscal year ended in calendar year *t-1* divided by market equity measured as of December of year *t-1*. Cash flows are defined as income before extraordinary items (Compustat item IB) plus depreciation (Compustat item DP) attributable to equity, plus deferred taxes (Compustat item

TXDI). To obtain the component of deprecation attributable to equity, we multiply depreciation by market equity divided by total assets (Compustat item AT) less book equity plus market equity.

We form portfolios at the end of June of year $t$ based on the CFP value. Negative cash flow firms are not included in portfolios. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B9 NOP** – NOP stands for net payouts over market equity at the end of calendar year *t-1*. Total payouts less equity issuances represents net payouts. To obtain total payouts, we add dividends (Compustat item DVC) plus repurchases. We calculate repurchases as the total spent on purchases of common and preferred stock (Compustat item PRSTKC) plus any negative change from the prior year in the value of preferred stock outstanding (Compustat item PSTKRV). We calculate equity issuances as the sale of common and preferred stock (Compustat item SSTK) less any positive change from the prior year in the value of preferred stock.

We form decile portfolios at the end of June of year $t$ based on the NOP for the fiscal year ending in calendar year *t-1*. We exclude firms with zero net payouts. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*. Data related to the sale of common and preferred stock is first available in 1971. Accordingly, our NOP deciles start in July of 1972.

**B10 Dur** – Our equity duration calculation follows that of Dechow, Sloan, and Soliman (2004). We adopt the following equation for our calculation of equity duration:

$$Dur = \frac{\sum_{t=1}^{T} t \times CD_t/(1+r)^t}{ME} + \left(T + \frac{1+r}{r}\right)\frac{P - \sum_{t=1}^{T} CD_t/(1+r)^t}{ME} \tag{B3a}$$

where $D_t$ is net cash distributions in year $t$, ME is market equity, T represents the length of the forecast period, and $r$ is the cost of equity. Market equity, ME, is the price per share at the fiscal year-end (Compustat item PRCC_F) multiplied by the shares outstanding (Compustat item CSHO). Net cash distribution equals:

$$CD_t = BE_{t-1}(ROE_t - g_t) \tag{B3b}$$

where $BE_{t-1}$ represents book equity at the end of year *t-1*, $ROE_t$ represents return on equity in year $t$and $g_t$ is the growth in book equity in year $t$. $ROE_t$ follows a first-order autoregressive process with an autocorrelation of 0.57 and mean of 0.12. Growth in book equity, on the other hand, follows a similar process with autocorrelation of 0.24 and a mean of 0.06. To obtain a $ROE_t$ for year 0, we calculate ROE as income before extraordinary items (Compustat item IB) over the lagged book equity from one year prior as measured by (Compustat item CEQ). The book equity growth rate is the annual change sales (Compustat item SALE). We allow for a forecasting period of 10 years (T=10) and cost of equity is assumed to equal 0.12 (r=0.12).

We form decile portfolios at the end of June of year $t$ based on the Dur for the fiscal year ending in calendar year *t-1*. Each month, value weighted returns are calculated for portfolios formed in July of year t and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B11 AG** – We follow Cooper, Gulen, and Schill (2008) for our calculation of asset growth (AG). AG is defined as:

$$AG_{i,t} = \frac{AT_{i,t} - AT_{i,t-1}}{AT_{i,t-1}} \tag{B4}$$

where $AT$ is total assets and corresponds to the same Compustat data item. We form decile portfolios at the end of June of year $t$ based on the AG for the fiscal year ending in calendar year *t-1*. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B12 NOA** – Net Operating Assets, or NOA, is operating assets less operating liabilities divided by total assets at fiscal year ending in t-2 as defined by Hirshleifer, Hou, Teoh, and Zhang (2004). We calculate operating assets as total assets (Compustat item AT) less cash and short-term investments (Compustat item CHE). Operating liabilities are total assets (Compstat item AT) less the current portion of debt (Compustat item DLC), long-term debt (Compustat item DLTT), minority interest (Compustat item MIB), preferred stock (Compustat item PSTK), and common equity (Compustat item CEQ). Missing values of the current portion of debt, long-term debt, minority interest, and preferred stock are set equal to zero.

We form decile portfolios at the end of June of year $t$ based on the NOA for the fiscal year ending in calendar year *t-1*. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B13 dPIA** – dPIA is the sum of the change in gross property plant and equipment (Compustat item PPEGT) and change in inventory (Compustat item INVT) divided by lagged total assets. This calculation follows Lyandres, Sun, and Zhang (2008). We form decile portfolios at the end of June of year $t$ based on the dPIA for the fiscal year ending in calendar year *t-1*. Each month value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B14 IG** – Investment growth (IG), as in Xing (2008), is the growth in capital expenditure (Compustat item CAPX) from fiscal year *t-2* to year *t-1*. We form decile portfolios at the end of June of year $t$ based on the IG for the fiscal year ending in calendar year *t-1*. Each month value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B15 NSI** – Net stock Issuance (NSI), as defined by Fama and French (2008), is the natural log of the ratio of split-adjusted shares outstanding at the fiscal year ending in calendar year *t-1* to split-adjusted shares outstanding at the fiscal year ending *t-2*. Split-adjusted shares outstanding are common shares outstanding (Compustat item CSHO) multiplied by the adjustment factor (Compustat item AJEX). We form decile portfolios at the end of June of year $t$ based on the NSI for the fiscal year ending in calendar year *t-1*. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*. We require firms to have a non-zero value of NSI.

**B16 CEI** – The growth in market equity that is not attributable to returns is our measure of composite equity issuance (CEI). We adopt the following method for the purposes of this paper:

$$CEI = log\left(\frac{ME_t}{ME_{t-1}}\right) - r(t-5, t) \tag{B5}$$

For the purposes of portfolio formation, which occurs at the end of June of year $t$, we use the cumulative log return on the stock from the last trading day of June of year *t-5* to the last day of trading in June of year $t$ for the variable *r(t-5,t)*. $ME_t$ is the market equity from the last trading day of June in year $t$. ME is based on the price and shares outstanding, both of which are obtained from CRSP.

We form decile portfolios at the end of June of year $t$ based on the CEI for the fiscal year ending in calendar year *t-1*. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B17 IvG** – Inventory growth (IvG) is the growth rate in inventory (Compustat item INVT) from fiscal year ending in calendar year *t-2* to fiscal year ending in calendar year *t-1* divided by the average of total assets (Compustat item AT) for the fiscal years ending in calendar year *t-2* and *t-1*. We form decile portfolios at the end of June of year $t$ based on the IvG for the fiscal year ending in calendar year *t-1*. We require firms to have a non-zero value of IvC for inclusion in portfolio formation. Each month value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B18 IvC** – Inventory change (IvG) is the change in inventory (Compustat item INVT) from fiscal year ending in calendar year *t-2* to fiscal year ending in calendar year *t-1* divided by the average of total assets (Compustat item AT) for the fiscal years ending in calendar year *t-2* and *t-1*. This is calculation is based on Thomas and Zhang (2002). We form decile portfolios at the end of June of year t based on the IvC for the fiscal year ending in calendar year *t-1*. We require firms to have a non-zero value of IvC for inclusion in portfolio formation. Each month value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B19 OA** Operating accruals (OA) fall into two distinct periods: pre-1988 and post-1988. Prior to 1988, we utilize the balance sheet approach proposed by Sloan (1996) to calculate OA. In line with this approach, we define OA as:

$$OA = (\Delta ACT - \Delta CHE) - (\Delta LCT - \Delta DLC - \Delta TXP) - DP \tag{B6}$$

where each of the above variables corresponds to the annual change in the same Compustat data item. *DLC*, *TXP*, and *DP* are replaced with zero if missing.

For the post-1988 period, we adopt the Hribar and Collins (2002) methodology to calculate OA. Using this approach, OA is equal to net income (Compustat item NI) less the cash flow from operations (Compustat item OANCF). Data from the statement of cash flows become available from Compustat in 1988. We form decile portfolios at the end of June of year $t$ based on the OA divided by total assets (Compustat item AT) for the fiscal year ending in calendar year *t-1*. Each month value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B20 POA** – As an alternative to the traditional measures of accruals scaled by assets, Hafzalla, Lundholm, and VanWinkle (2011) suggest that scaling by sales may be more appropriate for differentiating between the firms with more extreme differences among highly sophisticated forecasts and naïve forecasts of earnings. Percent Operating Assets (POA) is OA as defined in **B19** divided by net income (Compustat item NI) for the fiscal year ending in calendar year *t-1*. We form decile portfolios at the end of June of year $t$ based on the POA for the fiscal year ending in calendar year *t-1*. Each month value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B21 PTA** – Percent total accruals (PTA) is total accruals divided by the absolute value of net income (Compustat item NI) from the fiscal year ending in calendar year *t-1*. Our measure of total accruals is from Richardson, Sloan, Soliman, and Tuna (2005) for period prior to 1988. Total accruals is the sum of the change in net non-cash working capital, the change in net non-current operating assets, and the change in net financial assets. We define net non-cash working capital as current operating assets less current operating liabilities obtained from the following equation:

$$WC = (ACT - CHE) - (LCT - DLC) \tag{B7a}$$

The variables on the left hand side of the above equation correspond to the related Compustat data item. We replace DLC with zero if the variable is missing. We define net non-current operating assets as non-current operating assets less non-current operating liabilities obtained from the following equation:

$$NCOA = (AT - ACT - IVAO) - (LT - LCT - DLTT) \tag{B7b}$$

The variables on the left hand side of the above equation correspond to the related Compustat data item. IVAO and DLTT are assumed zero if missing. We define net financial assets as financial assets less financial liabilities obtained from the following equation:

$$FINA = (IVST + IVAO) - (DLTT + DLC + PSTK) \tag{B7c}$$

The variables on the left hand side of the above equation correspond to the related Compustat data item. All items above are assumed zero if missing.

Post 1988, we utilize the statement of cash flow to estimate total accruals. We use the following equation to estimate total accruals:

$$TotalAccruals = NI - OANCF - IVNCF - FINCF + SSTK - PRSTKC - DV \tag{B7d}$$

The variables on the left hand side of the above equation correspond to the related Compustat data item. Items SSTK, PRSTKC and DV are assumed zero if missing. We form decile portfolios at the end of June of year $t$ based on the PTA for the fiscal year ending in calendar year *t-1.* Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1.* Portfolios are rebalanced at the end of June of year *t+1.*

**B22 ROE** – We calculate return on equity (ROE) as income before extraordinary items (Compustat item IBQ) scaled by book equity from 1 quarter prior. Book equity is shareholders' equity plus balance sheet deferred taxes and investment tax credit (Compustat item TXDITCQ) less the book value of preferred stock. TXDITCQ is assumed zero if missing. There are three alternative ways of obtaining shareholder equity. We obtain shareholders' equity using the following methods in the order presented *i)* as stockholders' equity (Compustat item SEQQ), or *ii)* common equity (Compustat item CEQQ) plus preferred stock at redemption value (Compustat item PSTKRQ), or *iii)* total assets (Compustat item ATQ) less total liabilities (Compustat item LTQ). If preferred stock at redemption value is unavailable, we use preferred stock at carrying value (Compustat item PSTKQ).

We form decile portfolios each month based on the ROE from the most recent quarterly filing. Each month, value weighted returns are calculated for each portfolio. Portfolios are rebalanced at the end of each month. For portfolio formation, the most recently announced earnings must be associated with a fiscal quarter end within the 6 months preceding the portfolio formation date. In addition, the report date (Compustat quarterly item RDQ) must be after the fiscal quarter end. These restrictions ensure that incorrect or dated information is excluded from the portfolios.

**B23 ROA** – Return on Assets (ROA) is income before extraordinary items (Compustat item IBQ) divided by total assets (Compustat item ATQ) from the preceding quarter. We form decile portfolios each month based on the ROA from the most recent quarterly filing. Each month, value weighted returns are calculated for each portfolio. Portfolios are rebalanced at the end of each month. For portfolio formation, the most recently announced earnings must be associated with a fiscal quarter end within the 6 months preceding the portfolio formation date. These restrictions help ensure that dated information is excluded from the portfolios.

**B24 GPA** – Gross profits to assets (GPA) is total revenue (Compustat item REVT) less cost of goods sold (Compustat item COGS) over concurrent total assets. We form decile portfolios at the end of June of year $t$ based on the GPA for the fiscal year ending in calendar year *t-1*. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B25 NEI*** – We define NEI as the number of consecutive quarters with an increase in quarterly earnings over the same period in the preceding year as measured by Compustat item IBQ. Our measure of NEI uses up to 8 quarters; thus the measure ranges from 0 to 8. We form 9 portfolios based on NEI based on the most recently reported quarter announcement date (Compustat item RDQ). For portfolio formation, the most recently announced earnings must be associated with a fiscal quarter end within the 6 months preceding the portfolio formation date. These restrictions help ensure that dated information is excluded from the portfolios. Value-weighted portfolio returns are calculated each month $t$. We rebalance portfolios each month.

**B26 FP6** – We follow Campbell, Hilscher, and Szilagyi (2008) in the construction of our failure probability (FP) measure. Specifically, we use the parameter estimates obtained using a lag of 6 as reported in Campbell, Hilscher, and Szilagyi (2008) Table IV column 3. FP has the following formula:

$$\begin{aligned} FP_t = &-9.146 - 20.264 NIMTAAVG_t + 1.416 TLMTA_t - 7.129 EXRETAVG_t \\ &+ 1.411 SIGMA_t - 0.045 RSIZE_t - 2.132 CASHMTA_t + 0.075 MB_t - 0.058 PRICE_t \end{aligned} \quad \text{(B8a)}$$

where NIMTAAVGt and EXRETAVGt are defined as:

$$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t-1,t-3} + ... + \phi^9 NIMTA_{t-10,t-12}) \quad \text{(B8b)}$$

$$EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}(EXRET_{t-1} + ... + \phi^{11} NIMTA_{t-12}) \quad \text{(B8c)}$$

NIMTA is quarterly net income (Compustat item NIQ) over the sum of market equity (CRSP shares outstanding multiplied by market price) and total liabilities (Compustat item LTQ). EXRET is calculated using the following equation:

$$EXRET = log(1 + R_{i,t}) - log(1 + R_{SP500,t}) \quad \text{(B8d)}$$

or the log excess return on firm equity relative to the SP 500 index. $\phi$ is equal to $2^{-1/3}$.

SIGMA is the annualized rolling 3-month sample standard deviation calculated as follows:

$$SIGMA = \sqrt{\frac{252}{N-1}\sum\nolimits_{k\in\{t-1,t-2,t-3\}} r_k^2} \quad \text{(B8e)}$$

where $k$ represents the number of trading days in the associated month 1, 2 or 3 months prior, N is the total number of trading days over the 3 months, and $r_k$ is the daily return for a given firm. We consider SIGMA to be missing if there are fewer than five non-zero observations over the three-month period. TLMTA is the ratio of total liabilities (Compustat item LTQ) over the sum of market equity (CRSP shares outstanding multiplied by market price) and total liabilities (Compustat item LTQ). RSIZE is the relative size of each firm to that of the SP 500 index. Size is the log of market equity for both the firm and index.

CASHMTA is the ratio of cash and short-term investments (Compustat item CHEQ) over the sum of market equity (CRSP shares outstanding multiplied by market price) and total liabilities (Compustat item LTQ). MB is the market-to-book equity. We use the definition of book equity from B22 ROE. To modulate the effect of measurement errors for small firms, we add 10% of the difference between market equity and book equity to our calculation of book equity. Negative values of book equity that persist in the presence of these adjustments are set equal to \$1. Finally, we define PRICE as the log of price truncated above at \$15. We require prices to be above \$1 at the date of portfolio formation. All variables in our calculation of FP are winsorized at the $5^{th}$ and $95_{th}$ percentile across all observations.

Each month, we form decile portfolios based on our FP calculation. This value of FP is from accounting data from the fiscal quarter ending at least 4 months ago. This 4-month gap is to ensure that all variables used in the estimation of FP are publicly available at the time of inclusion into a portfolio. Decile returns are from the 6 months following portfolio formation (month $t$ to $t+5$). Portfolios are rebalanced each month. There are six separate deciles associated with each month. Each of these separate deciles is from the start of one of the prior six months. The FP decile return is the average return of these six separate deciles in a given month.

**B27 OCA** – This is a measure of organizational capital (OC) scaled by total assets from the same fiscal year. Organizational capital is a function of selling, general, and administrative expense (Compustat item XSGA) as in the following equation:

$$OC_{it} = (1-\delta)OC_{i,t-1} + \frac{XSGA_t}{CPI_t} \tag{B9a}$$

where $CPI_t$ is the consumer price index from year $t$ and $\delta$ is the annual depreciation rate for

OC. To obtain a starting point for OC, we use the calculation:

$$OC_{i,0} = \frac{XSGA_{i,0}}{(g + \delta)} \tag{B9b}$$

where $XSGA_{i,0}$ is the first observation of XSGA that is positive or zero. $g$ is the long-term growth rate of XSGA and assumed to be 10% as in Eisfeldt and Papanikolaou (2013). We use a depreciation rate of 15% also following Eisfeldt and Papanikolaou (2013). After the initial observation of XSGA is obtained, XSGA is assumed zero if missing. To be included in portfolio formation, a firm must have a non-missing value of XSGA for the fiscal year ending in calendar year *t-1*. We also omit firms with zero OC.

We standardize our measure of OCA by demeaning using the industry mean and scaling this demeaned value by the industry standard deviation. We use the Fama and French (1997) 17 industry classification. To obtain the industry mean and standard deviation, we winsorize at the $1^{st}$ and $99^{th}$ percentile of each year. We form decile portfolios at the end of June of year $t$ based on the OCA for the fiscal year ending in calendar year *t-1*. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B28 AdM** – We measure advertising expense to market equity (AdM) as the ratio of advertising expense (Compustat item XAD) for fiscal year ending in calendar year *t-1* to market equity (from CRSP or Compustat) as of December of year *t-1*. We require firms to have a positive value of advertising expense. Otherwise, we exclude the firm from portfolio formation. We form decile portfolios at the end of June of year $t$ based on the AdM for the fiscal year ending in calendar year *t-1*. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*. Given limitations on the availability of XAD, we begin portfolio formation in July 1973.

**B29 RDM** – We measure R&D to market equity (RDM) as the ratio of R&D expense (Compustat item XRD) for fiscal year ending in calendar year *t-1* to market equity (from CRSP or Compustat) as of December of year *t-1*. We require firms to have a positive value of R&D expense. Otherwise, we exclude the firm from portfolio formation. We form decile portfolios at the end of

June of year $t$ based on the RDM for the fiscal year ending in calendar year *t-1*. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*. RDM portfolios start in July of 1976. This is to account for the 1975 codification of rules related to the recognition of R&D on a firm's financial statements.

**B30 OL** – For operating leverage (OL), we adopt the Novy-Marx (2011) approach where operating costs are scaled by current total assets (Compustat item AT). We define operating costs as cost of goods sold (Compustat item COGS) plus selling, general, and administrative expense (Compustat item XSGA). We form decile portfolios at the end of June of year $t$ based on the OL for the fiscal year ending in calendar year *t-1*. Each month, value weighted returns are calculated for portfolios formed in July of year $t$ and held until June of year *t+1*. Portfolios are rebalanced at the end of June of year *t+1*.

**B31 Svol** – Systematic volatility (Svol) is from the following equation:

$$r_d^i = \beta_0^i + \beta_{MKT}^i MKT_d + \beta_{dVXO}^i dVXO_d + \epsilon_d^i \tag{B10}$$

where $\beta_{dVXO}^i$ represents our measure of *Svol*. $r_{di}$ is the daily return to stock $i$ in excess of the one-month Treasury bill rate. $MKT_d$ is the market factor, and $dVXO_d$ is the aggregate volatility shock measured as the daily change in the SP100 volatility index from the Chicago Board Options Exchange. We form decile portfolios at the end of each month $t$ based on the $\beta_{dVXO}^i$ obtained using the daily returns for firm $i$ in month *t-1*. Value-weighted returns are calculated each month. Rebalancing takes place each month. January 1986 is the first date when volatility index is available; thus our Svol portfolios start in February of 1986.

## Appendix B: Sample of papers using CAPX and PPE to measure investment

| No. | Authors | Year | Journal |
|---|---|---|---|
| 1 | Fazzari, Hubbard, Petersen | 1988 | Brookings Papers on Economic Activity |
| 2 | Mork, Shleifer, Vishny | 1990 | Brookings Papers on Economic Activity |
| 3 | Whited | 1992 | Journal of Finance |
| 4 | Bond, Meghir | 1994 | Review of Economic Studies |
| 5 | Kaplan, Zingales | 1997 | Quarterly Journal of Economics |
| 6 | Hadlock | 1998 | RAND Journal of Economics |
| 7 | Cleary | 1999 | Journal of Finance |
| 8 | Rajan, Servaes, Zingales | 2000 | Journal of Finance |
| 9 | Whited | 2001 | Journal of Finance |
| 10 | Malmendier, Tate | 2005 | Journal of Finance |
| 11 | Rauh | 2006 | Journal of Finance |
| 12 | Almeida, Campello | 2007 | Review of Financial Studies |
| 13 | Hennessy, Levy, Whited | 2007 | Journal of Financial Economics |
| 14 | Chava, Roberts | 2008 | Journal of Finance |
| 15 | Lyandres, Sun, Zhang | 2008 | Review of Financial Studies |
| 16 | Polk, Sapienza | 2009 | Review of Financial Studies |
| 17 | Liu, Whited, Zhang | 2009 | Journal of Political Economy |
| 18 | Almeida, Campello, Galvao | 2010 | Review of Financial Studies |
| 19 | Denis, Sibilkov | 2010 | Review of Financial Studies |
| 20 | Cooper, Priestley | 2011 | Journal of Financial Economics |
| 21 | Erickson, Whited | 2012 | Review of Financial Studies |
| 22 | Chen, Chen | 2012 | Journal of Financial Economics |
| 23 | Bolton, Chen, Wang | 2013 | Journal of Financial Economics |
| 24 | Kahle, Stulz | 2013 | Journal of Financial Economics |
| 25 | Kogan, Papanikolaou | 2013 | Review of Financial Studies |
| 26 | Foucault, Fresard | 2014 | Journal of Financial Economics |
| 27 | Bustamante | 2015 | Review of Financial Studies |
| 28 | Kruger, Landier, Thesmar | 2015 | Journal of Finance |
| 29 | Asker, Farre-Mensa, Ljungqvist | 2015 | Review of Financial Studies |
| 30 | Warusawitharana, Whited | 2016 | Review of Financial Studies |
| 31 | Almeida, Cunha, Ferreira, Restrepo | 2017 | Journal of Finance |