

The 52-week high, q theory and the cross-section of stock returns^{*}

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Abstract

Hou, Xue and Zhang's (2015) q-factor model outperforms other factor models in capturing the PTH (the ratio of current price to 52-week high price) anomaly: High-PTH stocks earn high future returns. PTH's relations with future profitability and future investment growth are both significantly positive, and they mirror PTH's relation with future returns in the cross-section and by time horizons. Incorporating the information about future investment growth contained in price level variables (e.g., PTH) helps the q factors to capture better those anomalies rooted in future investment growth. Together, these results suggest that the PTH anomaly is consistent with the investment CAPM.

JEL Classifications: G12, G14

Keywords: 52-week high, q-factor model, anomalies, profitability, investment growth

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1. Introduction

George and Hwang (2004) document a price-to-high (PTH) anomaly: firms with stock prices nearest to their 52-week highs (high-PTH firms) earn higher factor-adjusted returns on average than firms whose stock prices are farthest from their 52-week highs (low-PTH firms). They interpret this finding as underreaction to information because investors use the 52-week high as a reference point when evaluating the impact of information on prices.¹ Their interpretation focuses on the implications for investors' behavior. In this paper, we consider the PTH anomaly using the framework of investment-based asset pricing (the investment CAPM).² Our findings suggest that the PTH anomaly is consistent with the joint hypothesis that (a) PTH is positively related to expected profitability and expected investment growth; and (b) firms with higher expected profitability and higher expected investment growth have higher expected stock returns, as predicted by the investment CAPM.

The investment CAPM is built on the q-theory of investment, which was first applied to asset pricing by Cochrane (1991). Under q-theory, optimal investment equates the marginal return on the firm's investment to its cost of capital. This relation can be written as an "investment CAPM" wherein expected stock returns are written as a function of variables that describe the firm's investment opportunities. In a two-period model, expected stock returns are a function of current investment and expected

¹ See Huddart, Lang, and Yetman (2009), Liu, Liu, and Ma (2011), Baker, Pan, and Wurgler (2012), Li and Yu (2012), Bhootra and Hur (2013), Driessen, Lin, and VanHemert (2013) for similar interpretations of PTH.

² We follow Zhang (2015) in using the term "investment CAPM" to refer to the equation for expected stock return derived from investment-based asset pricing.

profitability. In a multiperiod model, expected stock returns depend on current investment, expected profitability, and also expected investment growth (Liu, Whited, and Zhang, 2009; Liu and Zhang, 2014).

Hou, Xue, and Zhang (HXZ) (2015) test the investment CAPM using the Black, Jensen, and Scholes (1972) portfolio approach. They build a q-factor model, which includes a market factor, a size factor, an investment factor and a profitability factor. In their construction, asset growth measures current investment; and ROE, which measures current profitability, is therefore a proxy for expected profitability *and* expected investment growth. They show that the q-factor model outperforms the Fama-French (1993) three-factor and Carhart (1997) models in capturing a wide range of anomalies, including momentum. They further show that the q-factor model captures momentum through the ROE factor, suggesting that past stock prices contain information about expected profitability and/or expected investment growth. Although PTH and momentum are conceptually different in capturing the information contained in past stock prices, it is possible that PTH is also positively related to expected profitability and/or expected investment growth.³ If so, and if cross-sectional variation in expected stock returns follows the prediction of the investment CAPM, then stocks with high PTH should earn high future returns. We conduct four sets of tests of this joint hypothesis.

First, we examine whether the q-factor model outperforms other factor models in capturing the PTH anomaly. We find that among the factor models we examine—i.e., the

³ Momentum captures how stock prices have changed over a fixed period of time, while PTH captures how prices have changed from their recent peaks. Perhaps due to this conceptual difference, PTH is different from momentum in how it predicts stock returns. George and Hwang (2004) find that PTH has independent power in predicting future stock returns even after controlling momentum.

single-factor market model (market), the Fama-French three-factor (FF3) and five-factor (FF5) models, the Carhart model (Carhart), and the q-factor model—the q-factor model delivers the best performance, whether the PTH anomaly is formed based on the entire sample using value weighted returns (ALL&VW) or based on the all-but-micro capitalization sample and equal weighted returns (ABM&EW). In particular, the q-factor model is the only model that results in an insignificant high-minus-low PTH decile alpha, which is also the smallest in magnitude across all the models. The average magnitude of alpha across all the deciles is the smallest for the q-factor model as well. The q-factor model is the only model that is not rejected by the test of Gibbons, Ross, and Shanken (GRS) (1989) in ALL&VW, but it is rejected in ABM&EW. Moreover, the loading on the profitability factor increases across the low to high PTH deciles, and it is large and positive for the high-minus-low PTH decile, suggesting that the q-factor model captures the PTH anomaly through the profitability factor.

Second, consistent with the prediction of the joint hypothesis above, we find that stocks with low current investment and high PTH earn very high returns and stocks with high current investment and low PTH earn very low returns, and that the q-factor model outperforms the other models in capturing these extreme returns.

Third, we find that PTH is positive and significant as a predictor of both future profitability (FROE) and future investment growth (FGROW). Furthermore, we find that among firms with smaller size, younger age, lower book-to-market ratio, lower credit rating, higher share turnover, and higher return volatility, PTH has a stronger relation with both FROE and FGROW, and accordingly, the relation between PTH and future stock returns (FRET) is stronger among such firms as well. In addition, we find that the

relation between PTH and FROE is persistently positive, but the relation between PTH and FGROW changes from positive at short horizons to negative at long horizons. The relation between PTH and FRET also changes from positive to negative, suggesting that the relation between PTH and FGROW is important to the relation between PTH and FRET.

Fourth, we examine whether price level variables (including PTH and PTL—i.e., the ratio of the current price to the lowest price during the past year) contain additional information about FROE and FGROW beyond what is already contained in ROE, and if so, whether a factor that combines the information in ROE and price levels outperforms the ROE factor in capturing the operating accrual (OA) and R&D-to-market (RD/M) anomalies. As explained above, ROE serves as a proxy for expected profitability and expected investment growth in constructing the q factors. Indeed, we find that ROE has a significantly positive relation with both FROE and FGROW. However, ROE's predictive power for FROE is much stronger than for FGROW, suggesting that ROE is a better proxy for expected profitability than it is for expected investment growth. This, in turn, suggests the ROE factor might be weak in capturing *certain* anomalies that are formed on variables strongly related to FGROW.

HXZ (2015) find that the q-factor model underperforms the FF3 and Carhart models in capturing the OA and RD/M anomalies, which could occur if OA and RD/M are strongly related to FGROW. We find that the relation between OA (RD/M) and FGROW is significantly negative (positive). We also find that OA (RD/M) is positively (negatively) related to FROE. Thus, both anomaly variables are related to FGROW and FROE with opposite signs. Although the ROE factor in the q model captures well the

return variation associated with FROE, it leaves the return variation associated with FGROW uncaptured. This could explain why the q-factor model results in a greater negative alpha for the OA anomaly and a greater positive alpha for the RD/M anomaly, relative to the FF3 and Carhart models, which capture neither source of variation.

When we examine PTH and PTL, we find that although they do not add much to the prediction of FROE, they do contain a significant amount of additional information about FGROW beyond what is contained in ROE. Hence, a factor constructed by combining the information in ROE, PTH and PTL should better capture the return variation associated with both FROE and FGROW than a factor based on ROE alone. If the investment CAPM is well specified, this alternative profitability factor should outperform the ROE factor in capturing the OA and RD/M anomalies.

This is what we find. However, it is important to note that our result do *not* suggest that this alternative factor would outperform the ROE factor in capturing all anomalies. The ROE factor is likely to do better at capturing anomalies formed on variables mainly containing information about expected profitability. Instead, our results imply that when the q-factor model cannot capture a certain anomaly, the reason might lie in the fact that the anomaly is strongly related to expected investment growth for which ROE serves as an imperfect proxy, rather than in the misspecification of the investment CAPM.

The rest of the paper is organized as follows. Section 2, provides background on the investment CAPM and specifies the predictions that we test. The data are described in Section 3, and results of the tests are reported in Section 4. Section 5 concludes.

2. The investment CAPM

The investment CAPM is built on the q-theory of investment. Under q-theory, firms invest to the point where the expected return on investment is equal to the cost of capital. In a simple two-period model, this can be written as follows (see HXZ, 2016, p. 31-33 for a development of Equations (1) and (2))

$$E_t[r_{it+1}^S] = \frac{E_t[\Pi_{it+1}/A_{it+1}] + 1}{1 + a(I_{it}/A_{it})}, \quad (1)$$

where A_{it} is the book value of assets for firm i at date t , I_{it} is the investment level, and $a > 0$ is a constant parameter in the asset adjustment cost function. With quadratic adjustment costs, the marginal cost to the firm of adding an extra unit of assets at t is $1 + a(I_{it}/A_{it})$, which is the sum of the unit marginal cost of the assets and the marginal adjustment cost. The numerator, $E_t[\Pi_{it+1}/A_{it+1}] + 1$, is the expected payoff to this extra investment at $t+1$, which consists of the expected return and the terminal value of the unit of assets. Thus, $(E_t[\Pi_{it+1}] + 1)/[1 + a(I_{it}/A_{it})]$ is the expected investment return on a marginal unit of assets. Without leverage, the cost of capital is equal to the expected stock return, $E_t[r_{t+1}^S]$, and firms optimize by choosing investment such that the expected investment return is equal to the expected stock return for the marginal unit of investment.⁴ This is the equation that Zhang (2015) refers to as the investment CAPM.

In a multiperiod model, there are additional terms in the numerator

$$E_t[r_{it+1}^S] = \frac{E_t[\Pi_{it+1}/A_{it+1}] + (a/2)E_t[(I_{it+1}/A_{it+1})^2] + (1 + aE_t[I_{it+1}/A_{it+1}])}{1 + a(I_{it}/A_{it})}. \quad (2)$$

The term $(a/2)E_t[(I_{it+1}/A_{it+1})^2]$ is the expected savings in adjustment costs at date $t+1$

⁴ Liu, Whited, and Zhang (2009) show that with debt and taxes the investment return equals the weighted average cost of capital, or equivalently, that the expected stock return equals the levered investment return.

resulting from an additional unit of investment at date t , and $1 + aE_t[I_{it+1}/A_{it+1}]$ is the continuation value of a unit investment at date t . Note that $(1 + aE_t[I_{it+1}/A_{it+1}]) / [(1 + a(I_{it}/A_{it}))]$ is approximately equal to $E_t[I_{it+1}/I_{it}]$, which is the expected investment growth rate.⁵ The intuition is that pairing lower investment at date t with higher investment at date $t+1$ (i.e., high expected investment growth) leverages cost savings and continuation value to enable a firm's investment return to meet the market's required return. This component of investment return is absent from the two-period model.

The comparative statics of the investment CAPM in Eq. (2) are that expected stock returns should be higher for firms with: lower current investment, higher expected profitability, or higher expected investment growth, all else equal. Thus, according to the investment CAPM, expected stock returns will be related to firm characteristics that are, in turn, associated with current investment, expected profitability, and/or expected investment growth (see Lin and Zhang, 2013).⁶

The stock price levels of high-PTH firms are close to their highest levels over the past year, which indicates that these firms have not experienced recent negative shocks to productivity. On the other hand, low-PTH firms, with current stock prices far below their

⁵ Because the cost function is convex, the cost level (the squared term) is monotonically related to the marginal cost (linear term) in the cross-section. Focusing on expected investment growth as we do below corresponds to approximating cross-sectional variation in $(x_t^2 + x_t)/x_{t-1}$ with variation in x_t/x_{t-1} .

⁶ Many of the cross-sectional relations between firm characteristics and stock returns documented in the literature have an interpretation that is consistent with the investment CAPM (e.g., Lyandres, Sun, and Zhang, 2008; Liu, Whited, and Zhang, 2009; Wu, Zhang, and Zhang, 2010; Liu and Zhang, 2014).

previous highs, are likely to have suffered negative productivity shocks. Thus, high-PTH firms should have higher expected profitability than low-PTH firms.

If positive productivity shocks affect growth rates in the systematic component of firms' value (see Johnson, 2002; Sagi and Seasholes, 2007), then high PTH will be associated with higher risk and higher expected returns than low PTH. Alternatively, high PTH may be associated with the arrival of good news to which investors have underreacted, implying higher expected returns for high PTH than low PTH. In either case, high expected returns could lead high-PTH firms to have lower current investment relative to future investment, resulting in an association between high PTH and high investment growth. If this reasoning is correct, and if the investment CAPM is well specified, then high-PTH firms will have higher expected stock returns, higher profitability and/or higher investment growth than low-PTH firms. In other words, the PTH anomaly could be consistent with the joint hypothesis that the investment CAPM is well specified and that PTH is related to expected profitability and/or expected investment growth.

Our tests of this joint hypothesis are based on the following observations. The investment CAPM predicts that firms with low investment and high expected profitability and/or high expected investment growth should have very high expected stock returns, while firms with high investment and low expected profitability and/or low expected investment growth should have very low expected stock returns. Therefore, if PTH is positively related to expected profitability and/or expected investment growth, then according to the investment CAPM, firms with low investment and high PTH should earn

very high future stock returns, and firms with high investment and low PTH should earn very low future stock returns.

HXZ (2015) test the investment CAPM by formulating a linear factor model, which they call the q-factor model. It includes four factors: a market factor (MKT), which is the market excess return; a size factor (ME), which is the difference between the return on a portfolio of stocks with small market equity capitalization (i.e., small-cap) and the return on a portfolio of large-cap stocks; an investment factor (I_A), which is the difference between the return on a portfolio of stocks with low asset growth and the return on a portfolio of stocks with high asset growth; and a profitability factor (ROE), which is the difference between the return on a portfolio of high ROE stocks and the return on a portfolio of low ROE stocks. In this model, asset growth is used to measure *observable* investment, and ROE is used as a proxy for *unobservable* expected profitability and expected investment growth. HXZ (2015) find that among the 35 anomalies that have significant high-minus-low decile returns, the q-factor model outperforms the FF3 and Carhart models in capturing most of these anomalies, with the exceptions being the operating accrual (OA) anomaly and the R&D-to-market (RD/M) anomaly.

Therefore, if the joint hypothesis is true, we expect the following. First, the q-factor model should capture the PTH anomaly better than other factor models. Second, the intersection of high (low) PTH and low (high) asset growth should earn very high (low) stock returns; and the q-factor model should capture these extreme returns better than other factor models. Third, PTH should be positively associated with future profitability and/or future investment growth; and when such associations become stronger (weaker), whether in the cross-section or by time horizons, the association between PTH and future

stock returns should also be stronger (weaker). Fourth, to the extent that PTH and other measures of price level (such as PTL) contain information about expected profitability and/or expected investment growth beyond what is contained in ROE, a profitability factor that combines the information in ROE and price level should outperform the ROE factor in capturing *certain* anomalies. Likely candidates are anomalies formed on variables (such as OA and RD/M) that contain information about expected profitability and/or expected investment growth beyond what is contained in ROE. These are the four questions we examine in Section 4.

3. Data

Stock return and price data are obtained from CRSP, and accounting data are obtained from the Compustat annual and quarterly industrial files. Our sample includes common stocks (CRSP share codes 10 and 11) that are traded on the NYSE, AMEX and NASDAQ. Following Fama and French (2006) and HXZ (2015), we exclude financial firms (SIC codes from 6000 to 6999). Our main variable of interest is PTH, which is calculated as the ratio of the month-end price to the highest daily closing price (adjusted by stock splits and stock dividends) during the past 12 months. We exclude firms with less than 12 months' price history. The sample period (in terms of portfolio returns) starts from January 1972 due to the availability of data to calculate ROE, and it ends in December 2014.

4. Results

This section reports the four sets of results testing the joint hypothesis that PTH is positively related to expected profitability and/or expected investment growth, and that the investment CAPM is well specified.

4.1. PTH anomaly and the q-factor model

Our first set of tests examines the performance of the HXZ (2015) q-factor model in capturing the PTH anomaly relative to other factor models. If the joint hypothesis above is true, we expect the q-factor model to outperform other factor models in capturing the PTH anomaly.

Panel A of Table 1 (ALL&VW) constructs the PTH anomaly based on the entire sample of stocks and value weighted returns within the PTH decile portfolios, while Panel B of Table 1 (ABM&EW) constructs the PTH anomaly based on the all-but-micro capitalization sample and equal weighted returns. The all-but-micro sample omits stocks whose market capitalization is below the 20th percentile of NYSE market capitalizations as of the portfolio formation month. For Panel A, at the end of each month t , stocks are sorted into deciles by PTH on the last trading day of month $t-1$ using NYSE breakpoints. We follow HXZ (2016) to use PTH smaller than 1 to form the portfolio breakpoints. This is because in some months there is a disproportionately large number of stocks with prices reaching their 52-week highs, which would result in missing observations in some deciles in these months if the entire cross-section of PTH is used to form portfolio breakpoints. The decile portfolios are held for the next 6 months (i.e., from month $t+1$ to month $t+6$). To mitigate the effects of bid-ask bounce on stock returns, we follow HXZ (2015) and many others in skipping month t before calculating portfolio returns. Hence, the monthly return of each decile is the simple average of the value weighted returns to the six portfolios formed during the past six months. The PTH anomaly in Panel B is constructed in the same way as in Panel A except that all-but-micro breakpoints are used to form PTH deciles and returns are equally weighted within each of the six portfolios.

The factor models we consider in this section include: the single-factor market model (market), the Fama-French (1993) three-factor model (FF3), FF3 augmented by Carhart (1997)'s momentum factor (Carhart), the Fama-French (2015) five-factor model (FF5) and the HXZ (2015) q-factor model (q). In addition to the market, size and value factors in FF3, FF5 includes two additional factors: the robust-minus-weak (RMW) factor, which is the difference between the returns to portfolios of stocks with robust and weak expected operating profitability as proxied by current gross profitability (Novy-Marx, 2013), and the conservative-minus-aggressive (CMA) factor which is the difference between the returns to portfolios of stocks with low and high expected investment as proxied by current asset growth (Cooper, Gulen, and Schill, 2008). RMW and CMA are similar to the profitability and investment factors in the q-factor model. HXZ (2016) show that FF5 cannot explain the investment and profitability q-factor returns, while the q factors can explain the value, RMW and CMA returns. They conclude that FF5 is a noisy version of the q-factor model.⁷

We compare the performance of the factor models on three dimensions, which we refer to as H-L, Ave. | α | and $P(\text{GRS})$. H-L is the high-minus-low decile alpha, that is, the alpha of the zero-investment portfolio that is long stocks in the highest PTH decile and short stocks in the lowest PTH decile. Ave. | α | is the average magnitude of alphas across the decile portfolios. $P(\text{GRS})$ is the p -value of the Gibbons, Ross, and Shanken (1989) (GRS) test, whose null hypothesis is that the alphas are jointly zero across the decile portfolios.

⁷ Except the q factors, which are provided by Lu Zhang, all the other factors are obtained from Kenneth French's website.

The tops of Panels A and B report the factor-adjusted returns (i.e., alphas) to the decile portfolios ranked by PTH for each factor model. q is the only model with insignificant H-L at the 5% significance level in both ALL&VW and ABM&EW. H-L is significant for the FF5 model in both ALL&VW and ABM&EW, and it is significant for the Carhart model in ALL&VW. Furthermore, the q-factor model has the smallest Ave. $|a|$ among all factor models at 0.05% per month in ALL&VW. The Ave. $|a|$ for the FF5 and Carhart models are 0.17% and 0.10% per month in ALL&VW. However, in ABM&EW, the Ave. $|a|$ are similar with 0.14 for the q-factor model, and 0.17 and 0.13 for FF5 and Carhart models, respectively. The q-factor model is not rejected by the GRS test in ALL&VW (p -value = 0.169), but it is rejected in ABM&EW (p -value = 0.044). All the other factor models are rejected by the GRS test in both ALL&VW and ABM&EW. These results suggest that the q-factor model captures the PTH anomaly better than all the other factor models that we consider.

The bottoms of Panels A and B report the loadings on the q model's factors. In both panels, the loading on the ROE factor increases from the low to high PTH deciles. Furthermore, the loading of the high-minus-low PTH decile return on the ROE factor is significantly positive and has the highest magnitude among the loadings on all four q factors. This result, combined with the fact that the ROE factor earns the highest average return among the four q factors as shown in HXZ (2015), suggests that the q-factor model captures the PTH anomaly through the ROE factor, which is consistent with the joint hypothesis.

Panel C of Table 1 repeats the analyses in Panels A and B by constructing the PTH anomaly using the alternative holding periods of one month and 12 months. The results

still suggest that the q-factor model is the best factor model in capturing the PTH anomaly. Across the four combinations (two choices of holding periods and two choices of return weighting schemes), the q-factor model always delivers an insignificant H-L. In contrast, H-L is significant for all four combinations of the FF5 model, and for two combinations of the Carhart model: the 1-month holding period in ALL&VW and the 12-month holding period in ABM&EW. The q model has the smallest Ave. $|a|$ in three combinations; though in ABM&EW, the 12-month holding period Ave. $|a|$ are similar for the Carhart, FF5 and q models at 0.13%, 0.14% and 0.15% per month, respectively. The GRS test rejects the q-factor model in three out of the four combinations, and it rejects all the other factor models in all four combinations.⁸

4.2. Portfolios sorted by PTH and asset growth (AG)

⁸ HXZ (2016) report that the high-minus-low decile return of the PTH anomaly is insignificant under the Carhart model when the holding period is one month in both ALL&VW and ABM&EW. On the other hand, our results show that in both cases, the high-minus-low return of the PTH anomaly is significant. This difference is due to our skipping one month before calculating the portfolio returns. Consistent with HXZ (2016), we also find (not tabulated) that the high-minus-low decile return in month t following portfolio formation based on PTH at the end of month $t-1$ (i.e., no skipping one month before calculating portfolio returns) is insignificant in both ALL&VW and ABM&EW. Furthermore, HXZ (2016) find that the Carhart model captures the PTH anomaly in all three cases that they examine: 6-month holding period in ALL&VW, 6-month holding period in ABM&EW, and 12-month holding period in ABM&EW. Our results in Table 1 show that the Carhart model captures the PTH anomaly in the latter two cases, but cannot capture the PTH anomaly in the first case. This difference is also due to skipping a month. Importantly, regardless of skipping a month (where the anomaly is stronger) or not, the q-factor model captures the PTH anomaly for all holding periods and return weighting schemes better than the other models.

In this section we test the predictions, which follow from the joint hypothesis, that stocks with high (low) PTH *and* low (high) asset growth earn very high (low) future returns, and that these extreme returns are better captured by the q-factor model than by the other models.

In Table 2, we form 25 portfolios double sorted by PTH and AG. The left side of the table (ALL&VW) is based on the entire sample and value weighted returns, and the right side of the table (ABM&EW) is based on the all-but-micro sample and equal weighted returns. For ALL&VW, at the end of month t , we sort all stocks independently into five groups based on PTH at the end of month $t-1$ using 20%, 40%, 60% and 80% NYSE breakpoints, and into five groups based on AG using 20%, 40%, 60% and 80% NYSE breakpoints. AG is calculated as the percentage change in total assets (Compustat annual item AT)—i.e., the difference in AT between the current and previous fiscal years divided by AT of the previous fiscal year. Following prior studies, if month t falls in June to December of calendar year y or in January to May of year $y+1$, then AG with fiscal year ending in calendar year $y-1$ is used for the ranking in month t (i.e., AG with fiscal year ending in calendar year $y-1$ is matched with stock returns from July of y to June of $y+1$). This creates 25 portfolios and the value weighted return in month $t+1$ is calculated for each of the 25 portfolios. For ABM&EW, the procedures for forming the 25 portfolios are the same as in ALL&VW, except that all-but-micro breakpoints are used to separate PTH and AG groups, and equal weighted returns are calculated for each portfolio.

The top of Table 2 reports the average returns (in percent) in excess of the risk-free rate to the 25 portfolios. In both ALL&VW and ABM&EW, stocks in the group of

PTH1&AG5 earn extremely low returns while stocks in the group of PTH5&AG1 earn high returns.

The middle of Table 2 reports the alphas for various factor models to the zero-investment portfolio (PTH5&AG1–PTH1&AG5), which is long the stocks in PTH5&AG1 and short the stocks in PTH1&AG5. The q-factor model outperforms the other models in capturing the return to this zero-investment portfolio. In ALL&VW, the FF5 and Carhart models have alphas of 0.88 (*t-statistic* = 3.78) and 0.61 (*t-statistic* = 3.61), compared to 0.34 (*t-statistic* = 1.45) for the q model. In ABM&EW, the alphas are larger for all models at 1.10 (*t-statistic* = 4.09), 0.75 (*t-statistic* = 4.83) and 0.56 (*t-statistic* = 2.06) for the FF5, Carhart and q models, respectively. Nevertheless, in both ALL&VW and ABM&EW, q's alpha is the smallest and least significant across all the models.

The bottom of Table 2 reports the loadings of the zero-investment portfolio (PTH5&AG1–PTH1&AG5) on the q factors. Not surprisingly, it loads heavily on both the profitability factor and the investment factor, suggesting that both factors make significant contributions in capturing the return to PTH5&AG1–PTH1&AG5. Overall, the results in Table 2 are consistent with the predictions, hence supporting the joint hypothesis.

4.3. Forecasting FROE, FGROW, and FRET with PTH

In this section, we test directly whether PTH is positively related to future profitability (FROE) and/or future investment growth (FGROW), which are the variables that the investment CAPM predicts should be positively related to expected stock returns. In addition, we examine whether the relation between PTH and future stock returns (the

PTH-FRET relation) is consistent with the relation between PTH and FROE (the PTH-FROE relation) and/or the relation between PTH and FGROW (the PTH-FGROW relation), both in the cross-section and across holding horizons.

We measure FROE using the forthcoming annual ROE, which is calculated as income before extraordinary items (Compustat annual item IB) divided by 1-year-lagged book equity.⁹ Following Liu and Zhang (2014), we measure FGROW as growth in the annual investment-to-capital ratio (I/K), where investment (I) is capital expenditures (annual item CAPX) minus sales of property, plant and equipment (annual item SPPE, set to zero if missing); and capital (K) is net property, plant and equipment (annual item PPENT). It is important to note that I can be negative if firms downsize. Consequently, the simple ratio of the current year's I/K to the previous year's I/K can be negative even if investment is higher in the current year than in the previous year. To avoid this, we calculate the investment growth for fiscal year $FY+1$ ($FGROW_{FY+1}$) as $[1 + \left(\frac{I_{FY+1}}{K_{FY+1}}\right)] / [(1 + \left(\frac{I_{FY}}{K_{FY}}\right))]$. Because I/K must be greater than -1, both the numerator and the denominator are always positive, and the ratio is larger when future I/K is greater than current I/K . We use the natural logarithm of FGROW, which varies from negative to

⁹ Following Davis, Fama, and French (2000), we define book equity as stockholder's equity (Compustat annual item SEQ), minus preferred stock, plus balance sheet deferred taxes and investment tax credit (annual item TXDITC) if available, minus post-retirement benefit asset (annual item PRBA) if available. If stockholder's equity is missing, we use common equity (annual item CEQ) plus the preferred stock par value (annual item PSTK). We measure preferred stock as the preferred stock liquidating value (annual item PSTKL) or the preferred stock redemption value (annual item PSTKRV) or the preferred stock par value (annual item PSTK) in that order of availability. If these variables are missing, we use book assets (annual item AT) minus liabilities (annual item LT).

positive, as a dependent variable in the regressions. The timing of FROE and FGROW is described in detail below.

We need to align FROE, FGROW and FRET in time, where the former two variables are observed at an annual frequency, and stock returns are observed at a monthly frequency.¹⁰ We follow the matching technique that Liu and Zhang (2014) use in their structural estimation of a q model. Their technique assigns an annual observation to each month. The general principle is that FROE and FGROW correspond to changes between two annual periods that are “centered” at mid-year. Thus, the observation of FROE (and FGROW) corresponding to a fiscal year that ends in month t is matched with the twelve FRETs of months $t-17$ to $t-6$. For example, for firms with a fiscal year ending in December of 2000, the FROE and FGROW of fiscal year 2000 are matched with monthly stock returns from July of 1999 through June of 2000; while for firms with a fiscal year ending in June of 2000, FROE and FGROW of fiscal year 2000 are matched with monthly stock returns from January of 1999 to December of 1999.

As above, we include only common stocks (share code 10 and 11) traded on NYSE/AMEX/NASDAQ and we exclude financial firms (SIC code from 6000 to 6999). We require firms to have non-missing PTH, ROE, FROE, FGROW and FRET.¹¹ ROE, FROE and FGROW are winsorized at the first and 99th percentiles each month.

¹⁰ We also tried measuring FROE and FGROW using quarterly data, and the results are qualitatively similar to those using annual data. However, the results using quarterly data are generally weaker than those using annual data, perhaps because of the seasonality in quarterly data (see Liu and Zhang, 2014) and the lower quality of investment data at the quarterly versus annual frequency.

¹¹ In the next section, we compare PTH with ROE as predictors of FROE, FGROW and FRET. Hence, we require firms to have non-missing ROE here in order to maintain the same sample.

4.3.1. The PTH-FROE, PTH-FGROW and PTH-FRET relations

We estimate Fama-MacBeth (1973) regressions to test the PTH-FROE, PTH-FGROW and PTH-FRET relations. The specifications are

$$Depvar_{i,t+1} = \beta_0 + \beta_1 PTH_{i,t-1} + \varepsilon_{i,t+1}, \quad (3)$$

where the dependent variable is either FROE, or FGROW, or FRET at month $t+1$. The independent variable is standardized PTH at the end of month $t-1$. Standardized PTH is calculated as the difference between PTH and its cross-sectional mean, divided by the cross-sectional standard deviation. We use standardized PTH to facilitate comparison with other predictors in Section 4.4.1. As in Table 1, we skip one month between PTH and the dependent variables to avoid the effects of bid-ask bounce on stock returns.

We conduct two types of regressions: ALL&WLS and ABM&OLS. The former refers to weighted least squares applied to the entire sample, where the weights are stocks' market capitalizations at the end of month t . WLS gives greater weight to large stocks and is analogous to value weighting in forming portfolios as in ALL&VW in Table 1. The latter is ordinary least squares applied to the all-but-micro sample. OLS gives equal weight to each stock and is analogous to equal weighting in forming portfolios as in ABM&EW in Table 1.¹²

The results of estimating Eq. (3) are reported in Panel A of Table 3. The relation between PTH and FROE is significantly positive (7.85 with t -statistic = 10.77 in ALL&WLS, and 5.14 with t -statistic = 10.02 in ABM&OLS), as is the relation between

¹² The corresponding results based on OLS regressions applied to the entire sample (ALL&OLS) can be found in online appendix A.1. Furthermore, we also use the portfolio method as in Table 2 to compute the average FROE, FGROW and FRET in the 25 portfolios doubled sorted by PTH and ROE. These results are available in online appendix A.2 (see <https://sites.google.com/site/ylemcam>).

PTH and FGROW (2.99 with t -statistic = 9.57 in ALL&WLS, and 2.63 with t -statistic = 8.35 in ABM&OLS).¹³ These results indicate that PTH is significantly positively related to both future profitability *and* future investment growth. The relation between PTH and future stock returns is significantly positive as well (0.26 with t -statistic = 2.24 in ALL&WLS, and 0.23 with t -statistic = 2.46 in ABM&OLS). These findings are consistent with the joint hypothesis.

4.3.2. PTH-FROE, PTH-FGROW and PTH-FRET relations in the cross-section

In this subsection, we test whether the PTH-FRET relation is stronger among firms with stronger PTH-FROE and/or PTH-FGROW relations. In particular, we examine the cross-sectional differences in these relations between firms with high and low values of several characteristics including firm size, firm age, share turnover, return volatility, credit rating and book-to-market ratio (the definitions of these variables are provided in Table 3). These are the firm characteristics examined by Liu and Zhang (2014) in their investigation of momentum.

We estimate Fama-MacBeth (1973) regressions of this form:

$$\begin{aligned} Depvar_{i,t+1} = & \beta_0 + \beta_1 PTH_{i,t-1} + \beta_2 CDUM_{i,t-1} \\ & + \beta_3 PTH_{i,t-1} \times CDUM_{i,t-1} + \varepsilon_{i,t+1}, \end{aligned} \quad (4)$$

¹³ The t -statistics are calculated using the Newey–West (1994) heteroskedasticity and autocorrelation consistent estimates of standard errors. Following the suggestion of Newey and West (1994), we use the integer portion of $12(T/100)^{2/9}$, where T is the number of observations, as the lag length (L). As a robustness check, we also conduct annual Fama-MacBeth regression by including only July of each year in the sample. The dependent and independent variables in the annual regressions are less auto-correlated than those in the monthly regressions. The results (available in online appendix A.3) are similar to those using monthly regressions.

where $CDUM_{i,t-1}$ is a dummy variable that indicates whether the characteristic of firm i at the end of month $t-1$ is above or below the cross-sectional median. If $CDUM_{i,t-1}$ is below the cross-sectional median, then it is set to 1; otherwise, it is set to 0. Our focus of interest is on the coefficient of the interaction term $PTH_{i,t-1} \times CDUM_{i,t-1}$. In order to simplify the table, we report only the coefficients on the interaction terms (i.e., we omit the coefficients on PTH and CDUM).

The results, which are reported in Panel B of Table 3, are easy to summarize. Across all the characteristics we examine, the coefficients on $PTH \times CDUM$ in predicting FRET have the same signs as those predicting FROE and FGROW, and almost all of these coefficients (i.e., 34 out of 36 coefficients) are significant. In particular, the PTH-FROE and PTH-FGROW relations are stronger among firms with smaller size, younger age, lower credit rating, and lower book-to-market ratios, and there is also a stronger PTH-FRET relation among these firms. On the other hand, the PTH-FROE and PTH-FGROW relations are weaker among firms with lower share turnover and lower return volatility, and there is likewise a weaker PTH-FRET relation among these firms. These results suggest that the cross-sectional variation in the PTH-FRET relation follows the pattern of the cross-sectional variation in the strength of the PTH-FROE and PTH-FGROW relations, which provides further support for the joint hypothesis.¹⁴

4.3.3. PTH-FROE, PTH-FGROW and PTH-FRET relations by time horizons

¹⁴ We are not aware of any theory that predicts the cross-sectional variation in the PTH-FROE and PTH-FGROW relations. This is an interesting question for future research.

In this subsection, we investigate whether the dynamics of the PTH-FRET relation mirror the dynamics of the PTH-FROE and/or PTH-FGROW relations. We estimate the following monthly Fama-MacBeth (1973) regressions:

$$Depvar_{i,t+n} = \beta_{0,n} + \beta_{1,n}PTH_{i,t-1} + \varepsilon_{i,t+n} \quad (for\ 1 \leq n \leq 36). \quad (5)$$

This is the same as Eq. (3), except that the dependent variable is at month $t + n$. Estimating the profile of coefficients across various horizons enables us to examine the persistence of PTH at month $t-1$ as a predictor for FROE, FGROW and FRET from two months to three years ahead.

Fig. 1 plots the t -statistics of the coefficients on PTH as a function of n , for regressions with FROE, FGROW and FRET as dependent variables, respectively. For example, FROE_T denotes the t -statistic on PTH when the dependent variable is FROE. As in Table 3, we estimate the regressions in two different ways: ALL&WLS and ABM&OLS.

The general trends are clear in Fig. 1. A significant positive PTH-FROE relation is persistent across horizons. However, the PTH-FGROW relation changes from significantly positive at short horizons to significantly negative at long horizons. Interestingly, the PTH-FRET relation also changes from significantly positive to significantly negative at horizons when the negative PTH-FGROW relation is most negative. It becomes insignificant after month 28. These general patterns are consistent with the idea that while PTH is a stable predictor of future ROE over various horizons, the PTH-FGROW relation is as important as (if not more important than) the PTH-FROE relation to whether and how PTH predicts future stock returns. High PTH coincides

initially with high future investment growth and high future stock returns, then later with low future investment growth and low future stock returns.

Liu and Zhang (2014) use a structural estimation approach that allows for separate variation in expected profitability and investment growth to examine whether momentum returns can be explained by the q-theory of investment. The estimates from the structural model suggest that momentum returns are more strongly related to future investment growth than to future ROE, and also that the dynamics of momentum returns mirror the dynamics of future investment growth. The similarity of their findings and ours, in spite of using different methods and anomaly variables, suggests that expected investment growth can be more important than expected profitability in explaining why some anomaly variables predict returns.

The PTH-ROE and PTH-FGROW relations are smoother across months than is the PTH-FRET relation. Also, the PTH-FRET relation becomes insignificant earlier than the PTH-FGROW relation. This is likely due to FRET being measured monthly while, as explained above, the same annual FROE and FGROW are used for a sequence of 12 months. Because of this, the PTH-FRET relation is not likely to follow the PTH-FGROW relation exactly on a month-by-month basis. Therefore, it makes more sense to look at the general trend in these relations (as we did above) rather than comparing them month-by-month.

4.4. Comparing and combining ROE, PTH and PTL

We observe in Table 1 that the ROE factor is key to the ability of the q-factor model to explain the PTH anomaly. In Fig. 1, the predictive power of PTH for future returns follows a pattern that mirrors the relation between PTH and FGROW. This

suggests that PTH predicts returns because it is related to both expected profitability and expected investment growth.

In this section, we examine the degree to which PTH contains information relevant to forecasting future returns that is not already captured by ROE.¹⁵ If this is significant, and if the investment CAPM is well specified, then a factor based on both PTH and ROE should outperform the ROE factor in capturing *certain* anomalies formed on variables whose information content is more similar to that of PTH than ROE. Furthermore, since different measures of price level might contain different types of information, we include PTL (the ratio of current price to the *lowest* price in the past one year) in our analysis as well.

4.4.1. Forecasting FROE, FGROW and FRET with ROE, PTH and PTL

We first use Eq. (3) to examine separately how ROE and PTL are related to FROE, FGROW and FRET in univariate regressions. Following HXZ (2015), quarterly ROE is calculated as income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged book equity.¹⁶ The earnings data used to calculate ROE are based

¹⁵ Although results in Table 1 show that the ROE factor fully captures the high-minus-low PTH decile returns, there is also evidence in Table 1 suggesting that across other deciles, PTH might still contain information relevant to forecasting future returns that is not already captured by ROE. In particular, Panel B of Table 1 shows that q's alphas are significant from the sixth to the ninth PTH deciles in ABM&EW, and that the GRS test rejects the q-factor model in ABM&EW. Furthermore, Table 2 shows that the q-factor model cannot capture the extreme returns to the zero-investment portfolio double sorted by PTH and AG in ABM&EW.

¹⁶ Following HXZ (2015), book equity is the quarterly version of the annual book equity measure in Davis, Fama, and French (2000). In particular, book equity is shareholders' equity, plus balance-sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock.

on the most recent public quarterly earnings announcement prior to the end of month t , such that the fiscal quarter end corresponding to this quarterly earnings announcement must be within six months prior the end of month t . Similar to PTH, PTL is measured as the stock price at the end of month $t-1$ divided by the lowest daily closing price in the past 12 months (adjusted for stock splits and stock dividends).

We report in Panel A of Table 4 two sets of results of forecasting FRET: including January returns (i.e., all months' returns) and excluding January returns. George and Hwang (2004) document that the PTH anomaly is much stronger when January returns are excluded. In particular, the average return to the strategy of buying high-PTH stocks and selling low-PTH stocks is 0.45% for all months, and it increases to 1.23% when January returns are excluded.¹⁷ Since the January effect is more pronounced among small stocks, the ALL&WLS and ABM&OLS regression methods we adopt mitigate (but do not eliminate) the impact of the January effect on the PTH-FRET relation, and hence January does not influence the results reported so far. However, as will be clear shortly,

Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity. We use redemption value (item PSTKRQ) if available, or carrying value for the book value of preferred stock.

¹⁷ The reason for this striking difference is because this strategy earns an average return of -8.27% in January. The reason for the negative January return is due to tax loss selling near the year end (Roll, 1983; Griffiths and White, 1993; D'Mello, Ferris, and Hwang, 2001). Investors sell loser stocks to realize tax loss benefits near year end, which depresses stock prices. However, stock prices rebound after the year end when the selling pressure disappears. Stocks with low PTH have accumulated large capital losses, making them candidates for tax-loss selling at the end year.

the January effect has, in some cases, a significant impact that obscures a clear understanding of the results when its influence is not accounted for.

The univariate regression results are reported at the top of Panel A in Table 4. To facilitate comparison, we include in this table the results for PTH as well. As in Panel A of Table 3, all the explanatory variables are standardized, so we can compare the magnitudes of the coefficients to see which variable has the strongest association with FROE and FGROW in univariate regressions. Similarly, we can compare the adjusted R^2 to see which variable has the greatest power in explaining FROE and FGROW in univariate regressions.

Not surprisingly, among the three variables, ROE is the best predictor of FROE. The magnitude of the coefficient and the adjusted- R^2 for ROE are both much higher than those for PTH and PTL. PTH also is significantly positively related to FROE, but PTL is not. The results are different when predicting FGROW. ROE is the weakest predictor of FGROW—the magnitude of the coefficient is the lowest (though still significant) and the adjusted R^2 is the smallest for ROE—among the three predictors. PTH is the strongest predictor of FGROW and PTL is also a significant predictor.

We then estimate multivariate regressions. We start with regressions that include both PTH and ROE as explanatory variables. ROE continues to be a much better predictor for FROE than PTH. The magnitude of the coefficient on ROE decreases only slightly from its counterpart in the univariate regression (from 19.44 to 18.45 in ALL&WLS, and from 10.97 to 10.28 in ABM&OLS). PTH also continues to be significantly related to FROE. However, the magnitude of its coefficient decreases to almost half of its counterpart in the univariate regression (from 7.85 to 4.31 in

ALL&WLS, and from 5.14 to 2.99 in ABM&OLS), suggesting that a significant portion of information contained in PTH about FROE is also contained in ROE. The story is opposite when predicting FGROW. ROE is not significantly related to FGROW, yet PTH continues to be significantly positively related to FGROW, and the magnitude of its coefficient barely changes (from 2.99 to 2.93 in ALL&WLS, and from 2.63 to 2.60 in ABM&OLS). These results suggest that PTH subsumes the information contained in ROE about FGROW.

In the regression with FRET as the dependent variable (and when January returns are included) PTH is not significant anymore (t -statistic = 1.90) in ALL&WLS, though still significant (t -statistic = 2.15) in ABM&OLS. After excluding January returns, the PTH-FRET relation remains positive and significant (t -statistic = 3.02 in ALL&WLS, t -statistic = 3.22 in ABM&OLS), and its strength is close to that in the univariate regression with PTH as the only explanatory variable, thus confirming the important role played by FGROW in generating the PTH-FRET relation. In the regressions including ROE and PTL as explanatory variables, the coefficients on ROE and PTL in predicting FROE and FGROW are similar to their counterparts in the univariate regressions, suggesting that ROE and PTL contain largely different information for predicting each of the three dependent variables.

Next, we estimate multivariate regressions that include ROE, PTH and PTL as explanatory variables. The coefficients continue to suggest that ROE is the best predictor for FROE and the worst predictor for FGROW among the three predictors. The adjusted R^2 's also suggest that PTH and PTL provide at best a moderate amount of additional information about FROE beyond what is already contained in ROE. However, they do

contain significant predictive information for FGROW that is *not* contained in ROE. Specifically, in ALL&WLS (ABM&OLS), the adjusted R^2 for the regression of predicting FROE by ROE is 36.31% (31.82%), and it increases slightly to 39.46% (35.21%) when adding PTH and PTL to the regression. On the other hand, there is a large increase in adjusted R^2 when adding PTH and PTL to ROE in predicting FGROW (from 0.64% to 4.49% in ALL&WLS, and from 0.46% to 4.08% in ABM&OLS).

Finally, we add to the multivariate regressions two control variables: The most recent annual asset growth (AG) and June firm size (MV). The results remain largely unchanged from the previous set, except in two aspects: the coefficient on ROE in predicting FGROW becomes significant again; and the magnitude of the coefficient on PTL in predicting FGROW almost doubles.

Overall, the results in Panel A of Table 4 suggest that although PTH and PTL do not provide much additional information about FROE beyond what is already in ROE, they do contain a significant amount of information about FGROW beyond what is contained in ROE.

4.4.2. Combining PTH, PTL and ROE to capture the OA and RD/M anomalies

HXZ (2015) find that the q-factor model outperforms FF3 and Carhart models in capturing a wide range of anomalies, but underperforms them in capturing these two anomalies: the operating accrual (OA) anomaly and the R&D-to-market (RD/M) anomaly. It is possible that these two anomalies are consistent with the investment CAPM, and the reason the q-factor model fails in capturing them is because OA and RD/M contain information about expected investment growth, which is not captured well by the ROE factor in the q model.

Panel B of Table 4 reports the relations between OA and RD/M with FROE, FGROW and FRET.¹⁸ The results are consistent with the possibility described above. In both ALL&WLS and ABM&OLS, the relation between OA and FROE is positive while the relation between OA and FGROW is negative. The positive relation between OA and FROE reflects the fact that accruals are part of earnings in accrual accounting. However, accruals are also investment in working capital (see Stickney, Brown, and Wahlen, 2003; Zhang, 2007; Wu, Zhang, and Zhang, 2010), and investment tends to be lumpy at the firm level. As such, high accruals might forecast low investment growth, giving rise to a negative OA-FGROW relation. The relation between RD/M and FROE is negative because R&D is expensed under GAAP, thereby reducing current earnings. However,

¹⁸ Prior to 1988, OA is calculated using the balance-sheet approach of Sloan (1996). In particular, $OA = (\Delta CA - \Delta CASH) - (\Delta CL - \Delta STD - \Delta TP) - DP$. ΔCA is the change in current assets (Compustat annual item ACT), $\Delta CASH$ is the change in cash or cash equivalents (item CHE), ΔCL is the change in current liabilities (item LCT), ΔSTD is the change in debt included in current liabilities (item DLC, zero if missing), ΔTP is the change in income taxes payable (item TXP, zero if missing), and DP is depreciation and amortization (item DP, zero if missing). Starting from 1988, OA is calculated using the statement of cash flows as in Hribar and Collins (2002). In particular, OA is equal to net income (item NI) minus net cash flow from operations (item OANCF). OA is scaled by total assets (item AT) of the previous fiscal year. RD/M is calculated as R&D expenses (Compustat annual item XRD) divided by the market equity (from CRSP) at the end of December of the year in which the fiscal year ended, as in Chan, Lakonishok, and Sougiannis (2001). Only firms with positive R&D expenses are included. If month t is either from June to December in year y or from January to May in year $y+1$, it is matched with OA and RD/M with fiscal year ending in calendar year $y-1$ (i.e., OA and RD/M with fiscal year ending in year $y-1$ are matched with FROE, FGROW and FRET from July of year y to June of year $y+1$). Due to data availability, the sample period for RD/M starts from June 1976.

high RD/M creates growth opportunities, which likely gives rise to a positive relation between RD/M and FGROW.

Notably, these two particular anomaly variables each has opposite relations with FROE and FGROW, and the signs of the relations are flipped between the two anomalies.¹⁹ This suggests that the reason they are not captured by the q-factor model is because they are strongly associated with FGROW in a direction that is opposite to their association with FROE. Unlike the PTH anomaly, where PTH's associations with both FROE and FRGOW are positive, the ROE factor in the q-factor model is unlikely to capture the OA and RD/M anomalies because OA's (and RD/M's) relations with FROE and FGROW are opposite in sign.

We find in Section 4.4.1 that ROE is a powerful predictor of FROE, but it is *not* a good predictor of FGROW. Hence, the ROE factor can capture well the information about FROE contained in OA and RD/M, but leaves the information about FGROW in

¹⁹ Fama and French (2006) show that there is a significantly negative relation between positive operating accruals and future profitability, and an insignificant relation between negative operating accruals and future profitability (see their Table 1). This evidence seems inconsistent with our results showing a significantly positive relation between operating accruals and future profitability. The reasons for this difference are: (1) they control for current profitability in their regression while we do not, and (2) they separate operating accruals into positive and negative operating accruals while we do not. We can replicate their results using their methods. However, our methods are more appropriate for investigating the question we are interested in, namely, how operating accruals are related to future profitability in the cross-section. Fama and French (2006) also show that neither positive nor negative operating accruals are related to future asset growth. Except the two differences in methodology mentioned previously, the dependent variable we are interested in is the growth rate of future investment (i.e., future investment divided by current investment) instead of future investment (asset growth) itself.

these two anomaly variables largely uncaptured. As a result, the q-factor model yields a more negative alpha in the OA anomaly and a more positive alpha in the RD/M anomaly (alphas that match the sign of their respective relations with FGROW), relative to other factor models (such as FF3 and Carhart) that do not include ROE as a factor. The q model filters out the relation with FROE, while leaving the FGROW relation intact. This could explain why the q-factor model underperforms FF3 and Carhart models in capturing the OA and RD/M anomalies.

We also find in Section 4.4.1 that PTH and PTL contain a significant amount of information about FGROW beyond what is contained in ROE. We would therefore expect a factor that combines the information in ROE, PTH and PTL to outperform the ROE factor in capturing the OA and RD/M anomalies. Such a finding would be consistent with the investment CAPM.

To examine this, we construct an alternative q-factor model that exploits information in the ranking by ROE *and* by the price level variables PTH and PTL, which we denote as the q:RP factor model. The construction of q:RP is the same as HXZ (2015)'s baseline q-factor model, except that the ROE factor is replaced by a factor constructed from the combined rankings of ROE, PTH and PTL. At the end of each month t , stocks are ranked independently, in ascending order, by ROE, PTH and PTL. Observations with the same value of ROE (PTH or PTL) are assigned the same rank. The timeline of these three variables is the same as in Section 4.4.1. For each stock, we calculate the ROE-and-price rank (RP) as the average of these three rankings. Next, stocks are sorted independently into three RP groups using 30% and 70% NYSE breakpoints, into three asset growth groups using 30% and 70% NYSE breakpoints, and

into two size groups using the 50% NYSE breakpoint. This results in 18 portfolios. Value weighted returns are calculated for each portfolio. The RP factor is the difference between the average return to the six high RP portfolios and the average return to the six low RP portfolios. The investment factor is the difference between the average return to the six low asset growth portfolios and the average return to the six high asset growth portfolios. The size factor is the difference between the average return to the nine small size portfolios and the average return to the nine large size portfolios.

The average factor returns are reported in Panel C of Table 4. We also include the returns to the q factors and the FF5 factors for comparison. On average, the RP factor in q:RP earns a lower return than the ROE factor in q (0.50% vs. 0.55%). As the RP factor blends FROE and FGROW while the ROE factor emphasizes FROE, the higher return earned by the ROE factor could exist because FROE is more strongly associated with FRET than is FGROW. Our purpose, however, is to see whether a factor that incorporates information about FGROW better captures the OA and RD/M anomalies. The results are reported in Pane D of Table 4.

We construct the OA and RD/M anomalies in two ways: the first is based on the entire sample and value weighted returns (ALL&VW) and the second is based on the all-but-micro sample and equal weighted returns (ABM&EW). Consistent with HXZ (2015), we find that the q-factor model can capture neither the OA nor the RD/M anomalies. The high-minus-low alpha (H-L) for q is significantly negative in capturing the OA anomaly, and significantly positive in capturing the RD/M anomaly. We also find that FF5 cannot capture these two anomalies either.

Importantly, q:RP outperforms q in capturing these two anomalies. Specifically, in capturing the OA anomaly, the H-L for q:RP is insignificant and has a smaller magnitude than the H-L for q (-0.26 with *t-statistic* = -1.62 vs. -0.48 with *t-statistic* = -2.90 in ALL&VW; and -0.24 with *t-statistic* = -1.95 vs. -0.47 with *t-statistic* = -3.92 in ABM&EW). In capturing the RD/M anomaly, the H-L for q:RP is still positive and significant but it has a smaller magnitude and a lower *t-statistic* than the H-L for q (0.54 with *t-statistic* = 2.49 vs. 0.76 with *t-statistic* = 3.78 in ALL&VW; and 0.74 with *t-statistic* = 3.69 vs. 0.90 with *t-statistic* = 4.15 in ABM&EW). The average magnitude of alpha across the anomaly deciles (Ave. |a|) is also lower for q:RP than for q in three out of the four cases, resulting in a lower average Ave. |a| for q:PR than for q (0.22 vs. 0.25). However, all models are rejected by the GRS test.

Overall, the results in Table 4 are consistent with the joint hypothesis. They further suggest that capturing information about both expected profitability and expected investment growth is necessary to explain some anomalies that are consistent with the investment CAPM. In particular, the failure of the q-factor model in capturing the OA and RD/M anomalies appears not to be evidence contrary to the investment CAPM but rather evidence that the q-factor model is too parsimonious a representation to capture implications of the investment CAPM that are important for explaining these two anomalies.

5. Conclusions

We consider the PTH anomaly using the framework of the investment CAPM. We find strong evidence supporting the joint hypothesis that (a) PTH is positively related to expected profitability and expected investment growth; and (b) firms with high expected

profitability and high expected investment growth have high expected stock returns, as predicted by the investment CAPM. Although our results are silent about whether investors misprice stocks, our results do indicate that firms align their investment policies properly with their cost of capital and that the PTH anomaly is consistent with this alignment.

Our results also suggest that expected investment growth can be important to explaining the cross-sectional relation between firm characteristics and expected stock returns. Hence, incorporating expected investment growth into the construction of investment-based factor models can potentially improve their performance in capturing a wide range of anomalies, especially those formed on variables that are strongly associated with expected investment growth.

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Table 1 The PTH anomaly

The top of panel A reports the factor-adjusted returns (i.e., alphas) of the decile portfolios ranked by PTH, which is calculated as the closing price at the end of each month divided by the highest price (adjusted by stock splits and stock dividends) during the last 12 months. At the end of each month t , all stocks are sorted into deciles by PTH of month $t-1$ using NYSE breakpoints. PTH smaller than 1 is used to form the portfolio breakpoints. The decile portfolios are held for the next 6 months (i.e., from month $t+1$ to month $t+6$), and the monthly value weighted (VW) return is calculated for each portfolio. Hence, the monthly return in each decile (D1 to D10) is the average return of six portfolios formed during the past six months. H-L is the return to the zero-investment portfolio which longs stocks in the highest PTH decile (D10) and shorts stocks in the lowest PTH decile (D1). Ave. $|\alpha|$ is the average magnitude of the alphas across the decile portfolios. $P(\text{GRS})$ reports the p -value of the GRS test whose null hypothesis is that the alphas are jointly zero across the deciles. Except the raw return in excess of risk free rate (denoted as “ret - rf”), we consider the following factor models. “market” denotes the market model which includes the value weighted market return as the only factor. “FF3” denotes the Fama-French (1993) three factor model. “Carhart” denotes the FF3 factors plus Carhart (1997)'s momentum factor. “FF5” denotes the Fama-French (2015) five factor model, whose factor returns are obtained from Kenneth French's website. “q” denotes Hou, Xue, and Zhang (2015)'s q-factor model, whose factor returns are provided by Lu Zhang. The bottom of panel A reports the loadings on the q factors, which include the ROE factor (ROE), the investment factor (I_A), the market factor (MKT) and the size factor (ME) (Denotations in the parentheses are those used in Hou et al. (2015)). Panel B repeats the analyses in panel A with all-but-micro capitalization (ABM) stocks and equal weighted (EW) returns. The breakpoints for forming PTH deciles are based on all-but-microcap stocks. Panel C repeats the analyses in panels A and B by holding the portfolios for 1 month or 12 months after portfolio formation. The sample is from January 1972 to December 2014. t -statistics adjusted for heteroscedasticity and autocorrelations are in parentheses.

Table 1 Continued

Panel A: ALL&VW													
	D1 (L)	D2	D3	D4	D5	D6	D7	D8	D9	D10 (H)	H-L	Ave. α	P (GRS)
<i>Factor-adjusted returns (i.e., alphas)</i>													
ret - rf	0.02 (0.04)	0.30 (1.04)	0.45 (1.78)	0.54 (2.37)	0.55 (2.57)	0.60 (2.93)	0.59 (3.03)	0.64 (3.48)	0.65 (3.56)	0.69 (3.75)	0.67 (2.47)	0.50	
market	-0.80 (-4.27)	-0.39 (-3.19)	-0.17 (-1.70)	-0.04 (-0.49)	0.00 (0.03)	0.07 (1.39)	0.08 (1.97)	0.16 (3.62)	0.19 (3.32)	0.24 (3.42)	1.04 (4.48)	0.21	0.001
FF3	-0.90 (-5.41)	-0.46 (-3.85)	-0.22 (-2.17)	-0.10 (-1.41)	-0.04 (-0.61)	0.04 (0.88)	0.09 (2.04)	0.20 (4.24)	0.22 (3.91)	0.29 (4.08)	1.19 (5.46)	0.26	0.000
Carhart	-0.26 (-2.35)	-0.03 (-0.40)	0.15 (2.10)	0.12 (1.92)	0.11 (1.99)	0.10 (1.94)	0.07 (1.59)	0.08 (1.98)	0.04 (0.87)	0.02 (0.39)	0.28 (2.26)	0.10	0.044
FF5	-0.61 (-3.44)	-0.31 (-2.36)	-0.11 (-0.94)	-0.11 (-1.47)	-0.06 (-0.97)	-0.02 (-0.47)	0.05 (1.12)	0.11 (2.25)	0.14 (2.22)	0.21 (2.64)	0.82 (3.43)	0.17	0.022
q	-0.08 (-0.44)	0.02 (0.14)	0.17 (1.46)	0.02 (0.19)	0.05 (0.63)	0.02 (0.33)	0.04 (0.85)	0.04 (0.91)	0.03 (0.54)	0.07 (0.85)	0.15 (0.63)	0.05	0.169
<i>Loadings on q factors</i>													
ROE	-0.96 (-6.36)	-0.56 (-6.14)	-0.42 (-5.99)	-0.15 (-2.02)	-0.08 (-1.92)	0.06 (1.30)	0.09 (2.92)	0.18 (5.22)	0.24 (6.93)	0.27 (4.79)	1.23 (6.06)		
I_A	-0.43 (-2.91)	-0.21 (-2.05)	-0.19 (-2.08)	0.06 (0.61)	0.00 (0.03)	0.04 (0.61)	-0.01 (-0.39)	0.02 (0.43)	0.01 (0.20)	-0.03 (-0.30)	0.40 (1.77)		
ME	0.41 (3.19)	0.19 (2.04)	0.08 (1.04)	0.04 (0.66)	0.02 (0.27)	-0.01 (-0.26)	-0.01 (-0.22)	0.00 (-0.16)	0.01 (0.22)	0.07 (1.22)	-0.34 (-1.84)		
MKT	1.29 (33.61)	1.17 (32.64)	1.07 (31.71)	1.06 (41.30)	1.01 (53.04)	1.00 (53.73)	0.96 (64.35)	0.92 (58.50)	0.90 (51.81)	0.87 (34.13)	-0.42 (-7.16)		

Table 1 Continued

Panel B: ABM&EW													
	D1 (L)	D2	D3	D4	D5	D6	D7	D8	D9	D10 (H)	H-L	Ave. α	P (GRS)
<i>Factor-adjusted returns (i.e., alphas)</i>													
ret - rf	0.11 (0.28)	0.41 (1.31)	0.66 (2.35)	0.72 (2.80)	0.78 (3.23)	0.86 (3.73)	0.85 (3.83)	0.89 (4.18)	0.90 (4.28)	0.92 (4.30)	0.81 (2.80)	0.71	
market	-0.77 (-3.38)	-0.33 (-2.24)	-0.02 (-0.18)	0.08 (0.88)	0.18 (2.10)	0.28 (3.60)	0.29 (3.79)	0.36 (4.68)	0.38 (4.65)	0.40 (4.27)	1.17 (4.70)	0.31	0.000
FF3	-0.83 (-4.17)	-0.44 (-3.55)	-0.15 (-1.64)	-0.05 (-0.70)	0.05 (0.89)	0.16 (3.34)	0.19 (4.06)	0.26 (5.37)	0.30 (5.19)	0.36 (5.02)	1.19 (4.85)	0.28	0.000
Carhart	-0.07 (-0.42)	0.02 (0.27)	0.15 (2.31)	0.14 (2.60)	0.16 (3.23)	0.18 (3.66)	0.14 (2.93)	0.17 (3.43)	0.14 (2.63)	0.11 (2.02)	0.18 (1.03)	0.13	0.009
FF5	-0.40 (-1.65)	-0.21 (-1.46)	-0.04 (-0.34)	-0.01 (-0.17)	0.04 (0.69)	0.12 (2.64)	0.14 (3.13)	0.21 (4.07)	0.24 (3.82)	0.29 (3.72)	0.69 (2.33)	0.17	0.004
q	0.21 (0.77)	0.12 (0.76)	0.16 (1.45)	0.11 (1.27)	0.11 (1.53)	0.14 (2.48)	0.10 (2.20)	0.14 (2.79)	0.13 (2.23)	0.14 (1.88)	-0.07 (-0.21)	0.14	0.044
<i>Loadings on q factors</i>													
ROE	-1.24 (-5.77)	-0.65 (-5.30)	-0.38 (-4.43)	-0.20 (-3.09)	-0.08 (-1.64)	0.02 (0.60)	0.08 (3.01)	0.13 (5.51)	0.19 (6.80)	0.25 (6.16)	1.49 (6.15)		
I_A	-0.62 (-2.57)	-0.29 (-1.80)	-0.10 (-0.81)	0.00 (-0.01)	0.04 (0.53)	0.07 (1.18)	0.08 (1.72)	0.08 (2.01)	0.07 (1.33)	0.01 (0.19)	0.63 (2.11)		
ME	0.53 (3.32)	0.50 (4.18)	0.49 (5.21)	0.49 (6.07)	0.48 (6.97)	0.48 (10.64)	0.50 (19.93)	0.47 (21.02)	0.47 (12.66)	0.51 (9.53)	-0.02 (-0.10)		
MKT	1.32 (25.35)	1.19 (31.54)	1.13 (34.27)	1.09 (44.50)	1.05 (50.66)	1.02 (60.45)	0.98 (63.57)	0.94 (68.52)	0.92 (55.13)	0.91 (41.74)	-0.41 (-6.27)		

Table 1 Continued

Panel C: Alternative portfolio holding periods												
	ALL&VW						ABM&EW					
	Holding 1 month			Holding 12 months			Holding 1 month			Holding 12 months		
	H-L	Ave. a	P(GRS)	H-L	Ave. a	P(GRS)	H-L	Ave. a	P(GRS)	H-L	Ave. a	P(GRS)
ret - rf	0.70	0.54		0.42	0.53		0.96	0.72		0.57	0.71	
	(2.16)			(1.75)			(3.07)			(2.23)		
market	1.11	0.24	0.000	0.73	0.16	0.010	1.38	0.35	0.000	0.88	0.24	0.000
	(4.08)			(3.61)			(5.18)			(4.10)		
FF3	1.25	0.25	0.000	0.92	0.21	0.000	1.39	0.31	0.000	0.96	0.23	0.000
	(4.78)			(5.12)			(5.37)			(4.49)		
Carhart	0.18	0.15	0.003	0.25	0.08	0.019	0.38	0.14	0.002	0.13	0.13	0.013
	(1.10)			(2.03)			(2.21)			(0.80)		
FF5	0.83	0.16	0.016	0.65	0.15	0.001	0.87	0.21	0.001	0.57	0.14	0.001
	(2.73)			(3.53)			(2.92)			(2.29)		
q	0.10	0.10	0.203	0.08	0.05	0.001	0.19	0.12	0.014	-0.12	0.15	0.012
	(0.32)			(0.46)			(0.64)			(-0.50)		

Table 2 Stock returns in the portfolios double sorted by PTH and asset growth (AG)

For the value weighted (VW) returns in the left panel, at the end of each month t , all stocks are sorted independently into five groups based on PTH of month $t-1$ using 20%, 40%, 60% and 80% NYSE breakpoints, and into five groups based on asset growth (AG) using 20%, 40%, 60% and 80% NYSE breakpoints. AG is calculated as the percentage change in total assets (Compustat annual item AT), that is, the difference in AT between the current and previous fiscal years divided by AT of the previous fiscal year. If month t is either from June to December in year y or from January to May in year $y+1$, then the current AG is that of the fiscal year ending in calendar year $y-1$. For the equal weighted (EW) returns in the right panel, all-but-micro (ABM) stocks are sorted independently into five PTH groups and five AG groups using all-but-micro breakpoints. The top of the table shows the average excess returns (i.e., raw return in excess of risk-free rate of return: $ret - rf$) to the 25 portfolios in the month following portfolio formation (i.e., month $t+1$). The middle of the table reports the factor-adjusted returns (i.e., alphas) to the zero-investment portfolio (AG1&PTH5 – AG5&PTH1) which is long stocks of AG1&PTH5 and short stocks of AG5&PTH1 for different factor models. The bottom of the table reports the loadings of this zero-investment portfolio on the q factors. t -statistics adjusted for heteroscedasticity and autocorrelation are in parentheses.

Table 2 Continued

	ALL&VW					ABM&EW				
<i>Average excess returns (ret – rf) to 25 PTH×AG portfolios</i>										
	AG1	AG2	AG3	AG4	AG5	AG1	AG2	AG3	AG4	AG5
PTH1	0.52 (1.34)	0.73 (2.17)	0.80 (2.36)	0.62 (1.93)	-0.35 (-0.96)	0.56 (1.41)	0.78 (2.22)	0.80 (2.40)	0.37 (1.03)	-0.39 (-0.99)
PTH2	1.11 (3.86)	1.06 (3.98)	0.78 (3.05)	0.61 (2.37)	0.27 (0.87)	1.04 (3.56)	1.01 (4.02)	0.87 (3.37)	0.65 (2.28)	0.21 (0.62)
PTH3	0.94 (3.87)	0.74 (3.39)	0.65 (2.92)	0.68 (3.05)	0.58 (2.13)	1.05 (4.15)	0.94 (4.25)	0.89 (3.93)	0.86 (3.41)	0.62 (2.05)
PTH4	0.93 (4.29)	0.67 (3.37)	0.80 (4.03)	0.68 (3.19)	0.52 (1.91)	1.00 (4.35)	0.86 (4.37)	0.87 (4.18)	0.79 (3.31)	0.77 (2.73)
PTH5	0.81 (3.91)	0.59 (3.37)	0.53 (2.91)	0.67 (3.24)	0.89 (3.64)	0.98 (4.35)	0.84 (4.5)	0.81 (4.12)	0.93 (4.11)	1.01 (3.72)
<i>Factor-adjusted returns (i.e., alphas) to (AG1&PTH5 – AG5&PTH1)</i>										
	estimate	t-statistic				estimate	t-statistic			
market	1.53	(6.48)				1.78	(7.31)			
FF3	1.41	(6.25)				1.59	(6.69)			
Carhart	0.61	(3.61)				0.75	(4.83)			
FF5	0.88	(3.78)				1.10	(4.09)			
q	0.34	(1.45)				0.56	(2.06)			
<i>Loadings of (AG1&PTH5 – AG5&PTH1) on q factors</i>										
	estimate	t-statistic				estimate	t-statistic			
ROE	0.95	(4.89)				0.94	(4.25)			
I_A	1.23	(6.08)				1.22	(3.88)			
ME	-0.10	(-0.59)				0.10	(0.37)			
MKT	-0.39	(-5.75)				-0.49	(-6.47)			

Table 3 Forecasting future profitability, future investment growth and future stock return

Panel A reports the results of the following monthly Fama-MacBeth (1973) regressions: $Depvar_{i,t+1} = \beta_0 + \beta_1 PTH_{i,t-1} + \varepsilon_{i,t+1}$. The independent variable is standardized PTH at the end of month $t-1$. Standardized PTH is calculated as the difference between PTH and its cross-sectional mean, divided by its cross-sectional standard deviation. The dependent variable (Depvar) is future profitability (FROE), future investment growth (FGROW) and future stock return (FRET) in month $t+1$, respectively. FROE is measured using the forthcoming annual ROE, which is calculated as income before extraordinary items (Compustat annual item IB) divided by 1-year-lagged book equity (see footnote 9 for the definition of annual book equity). FGROW is calculated as the growth rate of annual investment-to-capital ratio using the formula $[1 + (\frac{I_{FY+1}}{K_{FY+1}})] / [1 + (\frac{I_{FY}}{K_{FY}})]$ (the subscript indicates fiscal year), in which investment I is measured by capital expenditure (annual item CAPX) minus sales of property, plant and equipment (annual item SPPE, set to zero if missing), and capital K is measured by net property, plant and equipment (annual item PPENT). We further transform FGROW to its logarithmic form. FROE and FGROW with fiscal year ending at month fy is matched with the monthly stock returns from month $fy-18$ to month $fy-6$. All three dependent variables are multiplied by 100. For each dependent variable, we conduct two types of regressions: ALL&WLS and ABM&OLS. The former is a weighted least squares (WLS) regression on the entire sample and the latter is an ordinary least squares (OLS) regression on the all-but-micro sample.

Panel B reports the results of the following monthly Fama-MacBeth (1973) regressions: $Depvar_{i,t+1} = \beta_0 + \beta_1 PTH_{i,t-1} + \beta_2 CDUM_{i,t-1} + \beta_3 PTH_{i,t-1} \times CDUM_{i,t-1} + \varepsilon_{i,t+1}$. $CDUM_{i,t-1}$ is a dummy variable, indicating whether a characteristic (including firm size, firm age, turnover, stock return volatility, credit rating and book-to-market ratios) of firm i at the end of month $t-1$ is above or below the cross-sectional median. If $CDUM_{i,t-1}$ is below the cross-sectional median, then it is set to 1; otherwise, it is set to 0. We use NYSE breakpoints for “ALL&WLS” and ABM breakpoints for “ABM&OLS”. Firm size is the market capitalization at the end of month $t-1$. Firm age is the number of months from the firm’s first appearance in CRSP to month $t-1$. Turnover is the monthly average ratio of trading volume to shares outstanding during the past 12 months until the end of month $t-1$. Stock return volatility is the standard deviation of weekly excess returns during the past 12 months until the end of month $t-1$. Credit rating is the most recent Compustat annual item SPLTICRM. The monthly regression starts in January 1986 for credit ratings due to availability of the data. Book-to-market is calculated as the most recent annual book value of at least six months prior to month $t-1$ divided by the market capitalization at the end of month $t-1$. To save space, we only report the estimates of the coefficients on the interaction term $PTH \times CDUM$ (i.e., we omit reporting the estimates of the coefficient on PTH and CDUM). t -statistics adjusted for heteroscedasticity and autocorrelations are in parentheses.

Panel A: Univariate regressions						
PTH	ALL&WLS			ABM&OLS		
	FROE	FGROW	FRET	FROE	FGROW	FRET
	7.85	2.99	0.26	5.14	2.63	0.23
	(10.77)	(9.57)	(2.24)	(10.02)	(8.35)	(2.46)

Table 3 Continued

Panel B: Interactions between PTH and firm characteristic dummies						
	ALL&WLS			ABM&OLS		
	FROE	FGROW	FRET	FROE	FGROW	FRET
PTH× Low Size	3.33 (8.28)	0.73 (6.09)	0.16 (2.06)	0.66 (2.89)	0.33 (2.43)	0.10 (2.24)
PTH× Low Age	2.23 (4.82)	1.91 (6.78)	0.44 (5.66)	0.55 (1.75)	1.39 (5.13)	0.36 (7.23)
PTH× Low Turnover	-0.79 (-1.30)	-1.56 (-5.14)	-0.40 (-4.64)	-0.96 (-3.99)	-1.13 (-5.99)	-0.21 (-3.68)
PTH× Low Volatility	-3.95 (-6.27)	-1.78 (-5.03)	-0.42 (-4.39)	-1.77 (-6.56)	-1.57 (-5.62)	-0.27 (-4.02)
PTH× Low Credit Rating	4.41 (4.69)	0.68 (3.07)	0.26 (2.24)	3.39 (7.33)	0.87 (4.09)	0.24 (3.10)
PTH× Low B/M	1.33 (3.08)	1.44 (5.85)	0.30 (3.39)	1.10 (3.25)	1.29 (6.96)	0.31 (5.33)

Table 4 Comparing and combining ROE, PTH and PTL

Panel A reports the results of regressing FROE, FGROW and FRET in month $t+1$ on standardized ROE, PTH and PTL using the Fama-MacBeth (1973) regression as described in Panel A of Table 3. All months' returns are included for FRET-Jan Inc., and non-January months' returns are included for FRET-Jan Exc. ROE is the most recently announced quarterly earnings prior to month t , which is calculated as income before extraordinary items (Compustat quarterly item IBQ) divided by 1-quarter-lagged book equity (see footnote 16 for the definition of quarterly book equity). PTL is the stock price at the end of month $t-1$ divided by the lowest price during the past one year. The independent variables are standardized by subtracting the cross-sectional mean and dividing by the cross-sectional standard deviation. Asset growth (AG) and firm size (MV, in logarithmic form) are control variables. If month $t+1$ is from July of year y to June of year $y+1$, then it is matched with AG of fiscal year ending in year $y-1$ and with MV at the end of June in year $y+1$. Adj_R^2 is the average adjusted R^2 of the monthly regressions.

Panel B reports the results of the monthly Fama-MacBeth (1973) regression in which FROE, FGROW and FRET in month $t+1$ are regressed on operating accruals (OA) and R&D-to-market (RD/M) at month t (see footnote 18 for the definitions of OA and RD/M at month t). All three dependent variables are multiplied by 100. Except FRET, all variables in the regressions are winsorized at the first and 99th percentiles each month.

Panel C reports the time-series average returns to factors in q, q:RP and FF5 models. Factors in q:RP are constructed in the same way as those in q, except that ROE in q is replaced by RP. At the end of each month t , all stocks are ranked in ascending order by ROE, PTH and PTL independently (the timeline is the same as in Panel A). RP for each stock is the simple average of these three rankings.

Panel D reports the results of fitting the OA and RD/M anomaly returns to the factor models. Under 'ALL&VW', all stocks are sorted into deciles based on OA (RD/M) using NYSE breakpoints and value weighted returns are calculated for each decile portfolio. Under "ABM&EW", all-but-micro stocks are sorted into deciles based on OA (RD/M) using all-but-micro breakings and equal weighted returns are calculated for each decile portfolio. H-L is the average return of the hedge portfolio which is long the highest decile and short the lowest decile in each anomaly. $t(H-L)$ is the associated t -statistic. Ave. | α | is the average magnitude of the alphas across the decile portfolios for each anomaly. $P(GRS)$ reports the p -value of the GRS test whose null hypothesis is that alphas are jointly zero across the deciles.

Table 4 Continued

Panel A: Forecasting FROE, FGROW and FRET with ROE, PTH and PTL								
	ALL&WLS				ABM&OLS			
	FROE	FGROW	FRET- Inc. Jan	FRET- Exc. Jan	FROE	FGROW	FRET- Inc. Jan	FRET- Exc. Jan
<i>Univariate Regressions</i>								
ROE	19.44 (10.99)	0.99 (3.38)	0.22 (3.00)	0.31 (4.21)	10.97 (10.87)	0.72 (3.58)	0.20 (3.49)	0.26 (4.43)
<i>Adj_R²</i>	<i>36.31%</i>	<i>0.64%</i>	<i>1.17%</i>	<i>1.18%</i>	<i>31.82%</i>	<i>0.46%</i>	<i>0.90%</i>	<i>0.89%</i>
PTH	7.85 (10.77)	2.99 (9.57)	0.26 (2.24)	0.40 (3.40)	5.14 (10.02)	2.63 (8.35)	0.23 (2.46)	0.33 (3.53)
<i>Adj_R²</i>	<i>7.53%</i>	<i>3.26%</i>	<i>3.43%</i>	<i>3.28%</i>	<i>8.10%</i>	<i>3.34%</i>	<i>2.60%</i>	<i>2.52%</i>
PTL	0.51 (0.66)	1.09 (6.52)	0.24 (2.27)	0.25 (2.34)	0.95 (2.02)	1.08 (7.05)	0.18 (2.03)	0.20 (2.22)
<i>Adj_R²</i>	<i>3.16%</i>	<i>1.26%</i>	<i>3.41%</i>	<i>3.29%</i>	<i>3.41%</i>	<i>1.00%</i>	<i>2.38%</i>	<i>2.33%</i>
<i>Multi-variate Regressions</i>								
ROE	18.45 (10.79)	0.27 (1.28)	0.19 (2.95)	0.24 (3.59)	10.28 (10.83)	0.10 (0.86)	0.15 (3.28)	0.19 (3.96)
PTH	4.31 (10.19)	2.93 (10.30)	0.22 (1.90)	0.35 (3.02)	2.99 (10.66)	2.60 (8.96)	0.20 (2.15)	0.30 (3.22)
<i>Adj_R²</i>	<i>38.77%</i>	<i>3.63%</i>	<i>4.34%</i>	<i>4.20%</i>	<i>34.65%</i>	<i>3.50%</i>	<i>3.24%</i>	<i>3.14%</i>
ROE	19.12 (10.93)	0.92 (3.16)	0.21 (3.18)	0.30 (4.52)	10.78 (10.67)	0.65 (3.05)	0.19 (3.85)	0.25 (4.82)
PTL	0.06 (0.13)	1.10 (6.38)	0.21 (2.10)	0.21 (2.06)	0.43 (1.82)	1.09 (6.64)	0.15 (1.74)	0.16 (1.87)
<i>Adj_R²</i>	<i>37.22%</i>	<i>1.85%</i>	<i>4.35%</i>	<i>4.23%</i>	<i>32.74%</i>	<i>1.43%</i>	<i>3.07%</i>	<i>3.02%</i>
ROE	18.18 (10.98)	0.30 (1.49)	0.19 (3.54)	0.24 (4.38)	10.15 (10.95)	0.13 (1.06)	0.16 (4.21)	0.19 (5.08)
PTH	4.52 (8.95)	2.84 (9.46)	0.16 (1.33)	0.30 (2.45)	3.07 (9.40)	2.51 (8.61)	0.17 (1.82)	0.27 (2.82)
PTL	-0.81 (-1.66)	0.47 (2.36)	0.18 (1.73)	0.15 (1.37)	-0.32 (-1.17)	0.43 (2.60)	0.10 (1.13)	0.08 (0.92)
<i>Adj_R²</i>	<i>39.46%</i>	<i>4.49%</i>	<i>7.52%</i>	<i>7.29%</i>	<i>35.21%</i>	<i>4.08%</i>	<i>5.56%</i>	<i>5.46%</i>
ROE	17.40 (11.15)	0.48 (3.12)	0.22 (4.56)	0.27 (5.35)	9.91 (11.00)	0.24 (3.33)	0.18 (5.20)	0.21 (6.11)
PTH	3.44 (7.94)	2.30 (9.13)	0.10 (0.89)	0.24 (2.03)	2.70 (9.40)	1.94 (9.05)	0.13 (1.40)	0.23 (2.41)
PTL	0.45 (1.10)	0.87 (4.84)	0.16 (1.57)	0.14 (1.33)	0.21 (0.86)	0.81 (5.51)	0.10 (1.18)	0.09 (1.04)
AG	-1.16 (-1.80)	-2.73 (-9.94)	-0.22 (-5.07)	-0.21 (-4.71)	-0.79 (-2.90)	-2.51 (-9.16)	-0.20 (-5.77)	-0.20 (-5.60)
MV	2.51 (9.60)	-0.20 (-1.95)	-0.13 (-1.94)	-0.10 (-1.48)	1.36 (10.09)	-0.19 (-2.88)	-0.10 (-2.14)	-0.08 (-1.69)
<i>Adj_R²</i>	<i>41.10%</i>	<i>7.47%</i>	<i>9.40%</i>	<i>9.11%</i>	<i>36.07%</i>	<i>6.83%</i>	<i>6.70%</i>	<i>6.54%</i>

Table 4 Continued

Panel B: Predicting FROE, FGROW and FRET with OA or RD/M								
	ALL&WLS			ABM&OLS				
	FROE	FGROW	FRET	FROE	FGROW	FRET		
OA	14.34 (5.36)	-5.64 (-2.60)	-1.11 (-2.10)	13.70 (5.68)	-8.69 (-4.22)	-1.26 (-3.23)		
RD/M	-92.63 (-3.97)	12.64 (4.23)	2.69 (1.93)	-54.98 (-1.45)	25.21 (3.96)	2.84 (2.64)		
Panel C: Factor returns								
	q: RP	q		FF5				
Profitability	0.50 (3.18)	0.55 (4.87)	RMW	0.28 (2.81)				
Investment	0.45 (5.11)	0.43 (5.29)	CMA	0.36 (4.10)				
Size	0.22 (1.53)	0.29 (2.10)	SMB	0.22 (1.59)				
			HML	0.38 (2.88)				
Panel D: Capturing OA and RD/M anomalies								
	OA-ALL&VW				OA-ABM&EW			
	H-L	t(H-L)	Ave. a	P(GRS)	H-L	t(H-L)	Ave. a	P(GRS)
q:RP	-0.26	(-1.62)	0.11	0.018	-0.24	(-1.95)	0.21	0.000
q	-0.48	(-2.90)	0.17	0.000	-0.47	(-3.92)	0.18	0.000
FF5	-0.51	(-3.42)	0.15	0.002	-0.48	(-4.59)	0.14	0.000
	RD/M-ALL&VW				RD/M-ABM&EW			
	H-L	t(H-L)	Ave. a	P(GRS)	H-L	t(H-L)	Ave. a	P(GRS)
q:RP	0.54	(2.49)	0.20	0.034	0.76	(3.78)	0.35	0.000
q	0.76	(3.27)	0.28	0.001	0.90	(4.15)	0.38	0.000
FF5	0.56	(2.45)	0.21	0.016	0.76	(3.85)	0.24	0.005

Figure 1 Dynamics of the PTH-FROE, PTH-GROW and PTH-FRET relations

This figure depicts the t -statistics of the estimates of the coefficient on PTH when regressing FROE, FGROW and FRET in month $t + n$ (n is from 1 to 36) on PTH in month $t-1$ using the regression method described in Panel A of Table 3. The top figure is based on the WLS regressions on the entire sample (ALL&WLS), and the bottom figure is based on the OLS regression on the ABM sample (ABM&OLS).

