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One of the most important challenges in the field of asset pricing is understanding anomalies: empirical patterns that seem to defy explanation by standard asset pricing theories. The traditional approach to explaining these patterns focuses on the behavior of investors. Empirical evidence on anomalies has been cited widely in the academic literature on “behavioral finance” which challenges the efficient market hypothesis and admits the possibility of investor irrationality. I pursue a different approach in my work. Instead of focusing on the behavior of investors, I focus on the behavior of firms. In particular, I investigate whether recognizing the richness of firm investment decisions can help to explain some of the empirical patterns that are often labeled as anomalies.

My research explores the theoretical relation between firm attributes, investment decisions, and stock returns, and examines various empirical patterns that are often labeled as anomalies. A key insight that emerges in this setting is that evidence that firm characteristics forecast stock returns does not necessarily imply that stocks are mispriced.2

The WACC equation predicts that, all else equal, stocks of firms that are investing heavily should earn lower average returns than stocks with low investment, and that stocks with high return-on-equity (ROE) should earn higher average returns than stocks with low ROE. When expected returns are time-varying (and, more importantly, vary in the cross section), then stock prices vary and they will be related to investment and ROE according to the WACC equation. In particular, stock prices will not adjust in a way that gives rise to a cross-sectionally constant discount rate, which is only true if all firms are equally risky and stock prices follow a random walk.

Building on an early contribution by John Cochrane,1 I recognize that expressing the expected stock return, which equals the levered WACC, as a function of firm characteristics provides a framework for interpreting anomalies in the data. I label this relation “the WACC equation.” This framework does not depend on investor attributes. A key


Exploring Asset Pricing Anomalies
Lu Zhang*

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Building on an early contribution by John Cochrane,1 I recognize that expressing the expected stock return, which equals the levered WACC, as a function of firm characteristics provides a framework for interpreting anomalies in the data. I label this relation “the WACC equation.” This framework does not depend on investor attributes. A key insight that emerges in this setting is that evidence that firm characteristics forecast stock returns does not necessarily imply that stocks are mispriced.2
In addition, high ROE relative to low investment must imply high costs of capital, which are necessary to offset the high ROE to induce low NPVs for new capital and therefore low investment. Conversely, low ROE relative to high investment must imply low costs of capital, which are necessary to offset the low ROE to induce high NPVs for new capital and therefore high investment.

My co-authors and I evaluate the empirical power of the WACC equation using factor regressions, a standard technique in empirical finance that relates the return on a security to the contemporaneous returns on a number of “factors.” In one of the most widely cited applications of such factor models, Eugene Fama and Kenneth French specify three factors: the excess return on the overall stock market (the market factor), the return spread between small and large stocks, and the return spread (the value factor, denoted HML) between value stocks (with high book value of equity relative to the market value of equity) and growth stocks (with low book value of equity relative to the market value of equity). Mark Carhart subsequently forms a four-factor model by adding to the Fama-French model the return spread (the momentum factor, denoted UMD) between winners (stocks with high prior six-to-twelve-month returns) and losers (stocks with low prior six-to-twelve-month returns). The Carhart four-factor model is the current empirical benchmark for estimating expected returns in academic research and in investment management practice.

Motivated by the WACC equation, my co-authors and I propose a new four-factor model which we label the "q-model" that includes the market factor, a size factor, an investment factor, and an ROE factor. With a few exceptions, the q-model's performance is at least comparable to, and often better than, that of the Carhart model in explaining a comprehensive list of anomalies in factor regressions. A comparative advantage of the q-model is its economic motivation.

We construct the size, the investment, and the ROE factors from two-by-three-by-three sorts of stocks based on size (market equity), investment-to-assets, and ROE. The investment factor is the difference (low-minus-high) between the simple average of the returns on the six low investment portfolios and the simple average of the returns of the six high investment portfolios. The ROE factor is the difference (high-minus-low) between the simple average of the returns on the six high ROE portfolios and the simple average of the returns of the six low ROE portfolios.

From January 1972 to December 2012, the investment factor earned an average return of 0.45 percent per month, and the ROE factor earned an average 0.58 percent. Both average returns are statistically distinguishable from zero. The investment factor has a high correlation of 0.69 with the value factor, HML, and the ROE factor has a high correlation of 0.50 with the momentum factor, UMD. The Carhart four-factor model has difficulty explaining our factor returns, but the q-model can explain the Carhart factor returns. The evidence suggests that HML and UMD might be noisy versions of our new factors.

More importantly, using a set of 33 anomalies that are significant in the broad cross section, we show that the q-model performs well relative to the Carhart model. Across the 33 high-minus-low decile portfolios, the average magnitude of the unexplained average returns is 0.21 percent per month in the q-model, which is lower than 0.34 percent in the Carhart model and 0.55 percent in the Fama-French model. The number of anomalies still associated with unexplained average returns is also much lower: 4 for the q-model, 18 for the Carhart model, and 25 for the Fama-French model. The q-model's performance, combined with its economic motivation, suggests that it might be able to serve as a new empirical workhorse for estimating expected returns.

Fama and French (2013) have recently incorporated variables that resemble our new factors into their three-factor model to form a five-factor asset pricing model. My co-authors and I also explore a dynamic model with corporate income taxes and debt, and design a novel asset pricing test by matching average levered WACCs to average stock returns across different sets of testing portfolios. The results provide some support for our investment approach, and suggest that the WACC equation can explain a substantial portion of the spreads in average stock returns of portfolios sorted on unexpected earnings, book-to-market equity, and capital investment. The average magnitude of the model errors across ten unexpected earnings deciles is 0.7 percent per annum, which is lower than 4 percent from the Fama-French model. The high-minus-low decile has an error of –0.4 percent in our model, in contrast to 14.1 percent from the Fama-French model. Across ten book-to-market deciles, the average absolute error is 2.3 percent, which is comparable with 2.8 percent in the Fama-French model. However, the high-minus-low error is only 1.2 percent in our model relative to 7.3 percent in the Fama-French model. As such, portfolios of firms seem to do a good job of aligning investment with costs of capital. One weakness is that our estimates of capital's share and the adjustment cost parameter vary across different sets of the testing portfolios.

We also apply our dynamic WACC model to price momentum and earnings momentum, two important anomalies in the cross section. To this end, we refine our empirical procedure by measuring monthly levered WACCs using annual accounting data. Because the stock composition of momentum portfolios changes monthly, portfolio fundamentals such as investment also vary monthly even though firm-level fundamentals are constant within a fiscal year. Since winners (stocks with high unexpected earnings or high short-term prior returns) have higher expected investment growth than losers (stocks with low unexpected earnings or low short-term prior returns) the dynamic WACC model succeeds in accounting for average momentum profits. In addition, as the expected investment growth spread between winners and losers converges within 12 months after the portfolio formation in the data, momentum profits predicted in the model also converge within 12 months as in the data.
To understand the value premium, I also develop a dynamic, quantitative investment model in which asymmetric adjustment costs of capital and the countercyclical price of risk combine to cause assets in place to be harder to adjust downward (and therefore riskier) than growth options, especially in bad times when the price of risk is high.9 This model’s key prediction that value stocks are riskier than growth stocks in bad times seems to contradict conventional wisdom. My co-author and I address this seeming contradiction by defining the state of the economy based on the expected equity risk premium.10 Peaks are identified as periods with the 10 percent lowest market risk premiums, and troughs as periods with the 10 percent highest risk premiums. As the model predicts, the market beta of HML is positive (0.40) in troughs but negative (–0.33) in peaks, suggesting that at least part of the value premium is attributable to risk.

Why do firm characteristics often seem to have more explanatory power than risk measures in explaining returns? My co-author and I offer suggestive evidence by showing that measurement errors in estimated betas can explain this pattern. For example, beta estimates from 36-month rolling-window regressions are average betas in the past three-year period, whereas the true beta is time-varying.11

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11 Lin and Zhang, 2013, op. cit.