Investment-Based Asset Pricing and Its Applications

by

Chen Xue

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Doctoral Committee:

Professor Tyler G. Shumway, Co-Chair
Professor Lu Zhang, Ohio State University, Co-Chair
Associate Professor Feng Li
Associate Professor Paolo Pasquariello
Assistant Professor Yusuf Can Masatlioglu

To my parents and my wife for their unconditional support and love

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ABSTRACT

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Co-Chairs: Tyler G. Shumway and Lu Zhang

Investment-based asset pricing (Cochrane (1991, 1996)) is a useful approach to understanding the cross-section of asset prices and returns. The first chapter incorporates its insights into mutual fund performance evaluation. Motivated by the investment model, I show that investment and profitability convey useful information about future fund returns. However, such information is not taken into account by the standard benchmarks that build exclusively on the size, value, and momentum effects. As a result, funds favoring low investment or high profitability stocks tend to outperform, while funds favoring high investment or low profitability stocks tend to underperform. Accounting for investment and profitability changes performance estimates significantly and helps explain the good performance of growth-oriented funds, high activeness funds, or small funds. I propose new performance benchmarks that incorporate investment and profitability. The results show that a new comprehensive benchmark accounts for the cross-section of stock returns better and tracks mutual fund returns much more closely.

The second chapter shows that the investment model matches cross-sectional asset prices both in first differences and in *levels*. With ten book-to-market deciles as the testing portfolios, the investment model largely matches the Tobin's Q spread, while maintaining a good fit for the average return spread across the extreme deciles. The model's fit results from three aspects of our econometric strategy: (i) We test the model at the portfolio level to alleviate the impact of measurement errors; (ii) we match the first moment to mitigate the impact of temporal misalignment between asset prices and investment; and (iii) we allow for nonlinear marginal costs of investment. The model also does a good job in matching asset price levels within each industry, allowing technological heterogeneity across industries. Our evidence suggests that any differences between the intrinsic value and the market value of equity tend to dissipate in the long run.

CHAPTER I

Cross-Sectional Stock Returns and Mutual Fund Performance Evaluation: An Investment-Based Investigation[†]

Abstract

Standard benchmarks that build exclusively on the size, value, and momentum effects can be problematic for evaluating mutual funds. Motivated by investment-based asset pricing, I show that investment and profitability convey useful information about future fund returns. However, such information is not taken into account by the standard benchmarks. As a result, funds favoring low investment or high profitability stocks tend to outperform, while funds favoring high investment or low profitability stocks tend to underperform. Accounting for investment and profitability changes performance estimates significantly and helps explain the good performance of growth-oriented funds, high activeness funds, or small funds. I propose new performance benchmarks that incorporate investment and profitability. The results show that a new comprehensive benchmark accounts for the cross-section of stock returns better and tracks mutual fund returns much more closely.

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1.1 Introduction

Active equity mutual fund management has grown into a multi-trillion dollar industry. According to the *2011 Investment Company Fact Book*, the industry managed almost 5 trillion dollars at the end of 2010. A conservative 1% estimate in additional expenses for active management implies that managed funds cost investors nearly 50 billion dollars more than index funds. Proponents of managed funds often justify the additional expenses with the popular belief that active management can create value. In particular, the proponents believe that skillful managers can "beat the market" by picking undervalued securities. The existence and identification of skillful managers are therefore of great interest to both investors and researchers.

Because fund managers can implement a wide range of investment strategies, selecting a proper benchmark is essential to performance evaluation. Ideally, a benchmark should properly adjust for any systematic exposures so that a manager is not rewarded for taking more risk. More generally, additional expenses are not warranted if the same returns can be achieved more cheaply by passive strategies. In all, mutual fund performance evaluation calls for an asset pricing model that describes the cross-section of stock returns well.

Academic research has provided a useful model based on the size and value effects popularized by Fama and French (1992, 1993). This model has been widely adopted by both researchers and practitioners (Chan, Dimmock, and Lakonishok (2009)). For example, the famous Morningstar style box categorizes mutual funds into nine groups along those two attributes. More recently, benchmark models also include the momentum effect of Jegadeesh and Titman (1993) (e.g., Carhart (1997), and Daniel, Grinblatt, Titman, and Wermers (1997)). Despite their widespread applications, the asset pricing literature has identified a long list of stock return anomalies that cannot be explained by those standard benchmark models.[1] In other words, the cross-section of stock returns has gone far beyond the size, value, and momentum effects. This fact raises a serious question whether the standard benchmarks that build exclusively on those effects are sufficient for evaluating mutual fund performance.

To answer this question, I apply the investment-based asset pricing theory to mutual fund performance evaluation. The investment-based theory suggests that two firm fundamentals, investment and profitability, provide a parsimonious description of the cross-section of stock returns (e.g., Cochrane (1991), and Zhang (2005a)). The theoretical intuition is supported by good empirical performance (e.g, Liu, Whited, and Zhang (2009), and Chen, Novy-Marx, and Zhang (2011)). In particular, empirical evidences show that investment and profitability can capture additional information about future stock returns, and hence the investment-based model often outperforms standard models in pricing a wide range of stock return anomalies. The findings have two implications for mutual fund performance evaluation. First, investment and profitability might convey additional information about mutual fund returns that is not taken into account by the standard benchmarks. Second, alternative benchmarks built on the investment-based theory can be useful for performance evaluation.

I show that the standard benchmarks can be problematic for evaluating mutual funds. The standard benchmarks can not account for the average stock returns associated with investment and profitability. However, mutual funds show distinct preferences for investment and profitability when forming their portfolios. As a result, funds favoring low investment or high profitability stocks tend to outperform the standard benchmarks, while funds favoring high investment or low profitability stocks tend to underperform. For example, when funds are sorted into deciles based on their invest-

[1]For example, the standard benchmark models cannot account for the average stock returns associated with earnings momentum (Bernard and Thomas (1984)), accruals (Sloan (1996)), profitability (Haugen and Baker (1996)), idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006)), financial distress (Campbell, Hilscher, and Szilagyi (2008)), asset growth (Cooper, Gulen, and Schill (2008)), or net stock issues (Pontiff and Woodgate (2008)).

ing preferences for profitability, the spread in benchmark-adjusted returns is 5.03% per year for the Fama-French three-factor model, 2.63% for the Carhart four-factor model, and 2.56% for the characteristic-based benchmark of Daniel et al. (DGTW, 1997). The predictive power of investment and profitability becomes even stronger for funds favoring small and growth stocks, and can be fairly persistent over time.

Consistently, adjusting for the investment and profitability effects changes performance estimates significantly. Between July 1980 and June 2010, average fund performance drops by 0.24% per year, while on average 28% of funds experience an adjustment of more than 2% in their annual performance estimates. Given the size and competitiveness of the mutual fund industry, such changes have serious economic implications for both investors and managers. The findings can also be linked to previous research on mutua fund performance. As examples, I show that accounting for investment and profitability helps explain the good performance of growth-oriented funds (Daniel et al. (1997)), high activeness funds (Cremers and Petajisto (2009)), and small funds (Chen, Hong, Huang, and Kubik (2004)).

I propose new characteristic-based benchmarks using investment-based asset pricing. I show that an investment-based benchmark formed on size, investment, and profitability does well when evaluating mutual fund performance, compared with the standard benchmark formed on size, book-to-market (B/M), and momentum. However, each benchmark has its own merit. The investment-based benchmark does better in capturing the cross-section of average returns, while the DGTW benchmark produces less volatile tracking errors. Therefore, I also propose a comprehensive benchmark that merges both sets of characteristics. The comprehensive benchmark performs well to justify its complexity. It provides a better control for the cross-section of stock returns. Across nine sets of stock portfolios, the average magnitude of unmatched return spreads is 0.77% per year for the comprehensive benchmark, compared with 2.03% for the DGTW benchmark and 1.54% for the investment-based benchmark. The comprehensive benchmark also tracks mutual fund returns much more closely. For example, the average tracking error volatility for aggressive-growth funds is 8.03% per year for the comprehensive benchmark, compared with 9.08% for the DGTW benchmark and 9.67% for the investment-based benchmark. The results suggest that the comprehensive benchmark can be a useful tool for mutual fund performance evaluation in the future.

My study contributes to the debate about the value of active fund management. Since Jensen (1968), many studies find that mutual funds on average underperform their benchmarks by a significant margin on a net return basis (e.g., Brown and Goetzmann (1995), Gruber (1996), and Carhart (1997)). Meanwhile, other studies find evidences of stock-picking skill based on mutual fund stock holdings (e.g., Grinblatt and Titman (1993), Daniel et al. (1997), and Wermers (2000)). For example, Wermers (2000) shows that between 1975 and 1994 mutual funds hold stocks that outperform the market by 1.3% per year, but their net returns underperform by 1%. With a better control for the cross-section of stock returns, I show that an average fund produces no superior performance even before costs and expenses. The finding suggests that active management on average does not create value for fund investors.

Past studies find more positive results for subgroups of mutual funds. For example, there are evidences of good performance for funds with growth-orientation (Daniel et al. (1997)), small size (Chen et al. (2004)), high industry concentration (Kacperczyk, Sialm, and Zheng (2005)), high return gap (Kacperczyk, Sialm, and Zheng (2008)), or high activeness (Cremers and Petajisto (2009)). I show that some of the findings can be affected by the standard benchmarks' insufficient control for average stock returns.

My study is also related to the research on mutual fund investing styles. Existing studies mostly focus on size, value/growth, and momentum (e.g., Brown and Goetzmann (1997), Davis (2001), and Chan et al. (2002)). However, my results show that mutual fund investing strategies can be more diverse. Moreover, past findings of mutual fund performance are often concentrated in small-sized funds or small-cap funds. Those funds tend to show even more complex styles in their stock holdings. A more comprehensive study of mutual fund styles can be valuable for understanding their investing approaches and performance.

Finally, I contribute to the investment-based asset pricing literature by bridging it with mutual fund research. Based on the real portfolios of mutual funds, my findings provide direct evidence that the investment-based theory can be useful in practice. Thus, my study complements the existing literature that largely focuses on theory (e.g., Berk, Green, and Naik (1999), Carlson, Fisher, and Giammarino (2004), and Zhang (2005b)) and standard asset pricing tests (e.g., Liu et al. (2009), and Chen et al. (2011)).

The rest of the paper is organized as follows. In Section 2.3, I describe the data, variable measurements, and benchmarking methods. In Section 1.3, I show that investment and profitability have predictive power for mutual fund returns, but such predictability is not taken into account by the standard benchmarks. In Section 1.4, I show that adjusting for investment and profitability can have significant effects on performance evaluation. In Section 1.5, I propose new benchmarks motivated from the investment-based theory and evaluate their performance. Section 2.5 concludes.

1.2 Data and Methodology

1.2.1 Data

For all NYSE, AMEX, and NASDAQ common stocks between July 1975 and June 2010, I obtain their monthly returns and prices from the Center for Research in Security Prices (CRSP) and annual and quarterly accounting information from the Compustat database. Mutual fund data come from three sources. First, data on quarterly equity holdings and investment objectives are from the Thomson-Reuters

(TR) mutual fund database, which provides the primary fund sample for my analysis. Second, data on monthly fund net returns and annual expense ratios are obtained from the CRSP mutual fund database. Multiple share classes in the CRSP database are aggregated to eliminate duplicates. Finally, the MFLINKs product of Wharton Research Data Services (WRDS) provides a unique fund identifier, which is used to consistently match funds over time and to merge data between the TR database and the CRSP database. The mutual fund sample is from July 1980 to June 2010.[2]

Because my focus is on domestic equity mutual funds, I limit the sample to mutual funds having an investment objective of aggressive-growth, growth, or growth-and-income, following Daniel et al. (1997).[3] I use the investment objectives from the TR database since they have more complete and consistent coverage than those from the CRSP database (see footnote 14 of Kosowski, Timmerman, Wermers, and White (2006)). When a fund's objective is missing for the current quarter, I use its most recent objective from the past. Following Cremers and Petajisto (2009), I exclude funds with fewer than ten stocks or less than ten million dollars in their matched common stock holdings. This restriction helps reduce the biases and noises associated with small funds.

Table 1.1 provides a summary of the cleaned mutual fund sample. The number of funds in the sample increases substantially from around 200 to well over 1,000 in recent years. Accordingly, aggregate fund assets increase dramatically to over two trillion dollars. As expected, most fund investments are held in domestic common stocks, accounting for about three quarters of total fund assets. Between July 1980 and June 2010, a strategy that buys and holds quarterly fund stock portfolios would generate a gross return about 1.05% per month across all funds. In contrast, directly

[2]More technical details of the mutual fund data are included in Appendix A.

[3]Daniel et al. (1997) also include funds with an investment objective of "balance" or "income". However, those fund types are no longer included in the latest investment objective classifications in the TR database.

investing in the mutual funds would yield an equal-weighted return about 0.92% per month after costs and expenses.

1.2.2 Variable Definitions

The definitions for size, B/M, and momentum follow the conventions. Size is share price times the number of shares outstanding from the CRSP at the end of June. At the beginning of July in year t, a stock's B/M is its book equity for the fiscal year ending in $t-1$ divided by its market equity at the end of December in year $t-1$. Book equity is shareholders equity, plus balance sheet deferred taxes and investment tax credit (Compustat item TXDITC) if available, minus the book value of preferred stock. Depending on availability, I use stockholders equity (item SEQ), or common equity (item CEQ) plus the carrying value of preferred stock (item PSTK), or total assets (item AT) minus total liabilities (item LT) as shareholders equity. Depending on availability, I use redemption (item PSKTRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock. Market equity is market capitalization from the Compustat (items PRCC_F times CSHO) or CRSP. Momentum is the average monthly return for the past 12 months lagging by one month. Following Daniel et al. (1997), I require at least six monthly returns when calculating momentum.

I measure investment as the annual growth rate in total assets (Compustat item AT) following Cooper, Gulen, and Schill (2008). I choose asset growth because it is the most comprehensive measure of capital investment. As comparisons, previous studies often focus more narrowly on investments in fixed assets (e.g, Xing (2008)) or fixed assets and inventories (e.g., Chen et al. (2011)).

Following Chen et al. (2011), I measure profitability as return-on-equity (ROE) from the latest available quarterly reports. The economic rationale is that current profitability is the strongest predictor of future profitability (Fama and French (2006)). ROE is defined as income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged book equity. 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. Depending on availability, I 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. I use redemption value (item PSTKRQ) if available, or carrying value (item PSTKQ) for the book value of preferred stock. A quarterly report is deemed available right after the public earnings announcement date (item RDQ) or four months after the fiscal quarter end.

1.2.3 Benchmarking Methodology

I employ two types of benchmarks that are the most widely used in the literature: factor-based and characteristic-based.[4] The factor-based benchmark adjusts the returns of managed portfolios by controlling for their exposures to common factors in the cross-section of stock returns. To evaluate manager performance, portfolio returns in excess of the risk-free rate are regressed on the factor returns:

$$r_t - r_{f,t} = \alpha + \sum_k \beta_k F_{k,t} + u_t, \tag{1.1}$$

in which r_t is the portfolio return in time t, $r_{f,t}$ is the risk-free rate, α is the intercept, β_k is the return sensitivity to the kth factor, $F_{k,t}$ is the kth factor return, and u_t is the residual. The estimated intercept can be interpreted as the abnormal return generated by manager skills, while the sensitivity terms represent a manager's factor exposures or investment styles.

[4]Alternative methods include the effective asset mix regression of Sharpe (1992), the cross-sectional regression of Fama and MacBeth (1973), and nonlinear payoff robust benchmarks (Goerzmann, Ingersoll, Spiegel, and Welch (2007)). I ignore those alternatives for simplicity.

The construction of a factor-based benchmark boils down to the choice of the factors. Not surprisingly, it follows the development in asset pricing research. Early studies such as Jensen (1968) adopt the capital asset pricing model (CAPM) and use only a single market factor. Recent studies mostly use the Fama-French three-factor model (Fama and French (1993)) and the Carhart four-factor model (Carhart (1997)), which add more factors to control for the size, value, and momentum effects. More complex features can also be built into the factor-based benchmark. For example, a conditional factor model can be used to capture the time variations in risk and expected returns as well as managers' style drifts and timing attempts (e.g., Henriksson and Merton (1981), and Ferson and Schadt (1996)).

The characteristic-based benchmark uses the predictability of firm characteristics for the cross-section of stock returns. Accordingly, it adjusts returns of stocks by subtracting the average returns associated with their characteristics. Given a set of characteristics, stocks are normally classified into benchmark portfolios with similar characteristics. For example, the widely used benchmark of Daniel et al. (1997) classifies stocks into 125 benchmark portfolios based on size, B/M, and momentum. The benchmark portfolio returns can be interpreted as the returns to passive strategies that invest in diversified portfolios of stocks with similar characteristics. An active manager's stock selection skill, if any, is reflected by any additional returns generated beyond the benchmark portfolio returns. For a managed portfolio, the benchmark-adjusted return, called characteristic selectivity (CS), is formally defined as in Daniel et al. (1997):

$$\alpha_{CS,t} = \sum_{j=1}^{N} \omega_{j,t-1}(r_{j,t} - r_t^{b_{j,t-1}}), \tag{1.2}$$

where $\alpha_{CS,t}$ is the abnormal return generated by a manager's stock selection during time t, $\omega_{j,t-1}$ is the investment weight on stock j, $r_{j,t}$ is the return of stock j in t, $b_{j,t-1}$ is the benchmark assignment for stock j, and $r_t^{b_{j,t-1}}$ is the benchmark return for stock j in t.

Similar to a factor-based benchmark, the economic content of a characteristic-based benchmark is reflected by the choice of benchmark characteristics. Since the seminal work of Daniel et al. (1997), most recent studies use size, B/M, and often momentum as well, parallel to the Fama-French three-factor model and the Carhart four-factor model.

Because covariances and characteristics are equivalent from a general equilibrium perspective (Lin and Zhang (2011)), the two benchmarking methods are fundamentally similar. However, there are important empirical differences. The characteristic-based method has several advantages over the factor-based method. First, characteristics provide better empirical forecasts of cross-sectional stock returns than factor exposures (e.g., Daniel and Titman (1997), and Lin and Zhang (2011)). Characteristics are directly observable, and the benchmark can be updated timely to control for portfolio style drifts. In contrast, the factor-based method generally requires a long history of returns, and becomes even more noisy in conditional forms. Second, Cremers, Petajisto, and Zitzewitz (2010) show that the popular Fama-French and Carhart models can produce significant abnormal returns even for passive indices such as the S&P 500 and Russell 2000. The characteristic-based method generally has no such issues.

The characteristic-based method also has some drawbacks. Most importantly, it requires detailed data on portfolio holdings, which can be difficult to obtain timely.[5] In contrast, the factor-based method only requires portfolio return data, which are more readily available. In addition, the formation of benchmark portfolios is more subject to ad hoc choices such as the number of portfolios and sorting frequency. Small variations in those choices can have significant impact on performance eval-

[5]Prior to 1985, mutual funds were legally required to report their holdings quarterly. The reporting requirement was changed to semi-annually between 1985 and 2004. However, mutual funds often voluntarily reported their holdings to major data providers on a quarterly basis. The reporting requirement was changed back to quarterly after 2004. For my fund sample, the average reporting lag is about 3.84 months between 1981 and 2010.

uation (e.g., Chan et al. (2009)). Finally, because holding data are not available continuously, the characteristic-based method generally focuses on hypothetical holding returns that differ from actual portfolio returns. As a result, agency problems such as window dressing can create biases for performance evaluation (e.g., Meier and Schaumburg (2006)).

For my analysis, I employ three widely used benchmarks: the Fama-French three-factor model, the Carhart four-factor model, and the DGTW characteristic-based benchmark.[6]

1.3 Investment-Based Return Predictability and Mutual Fund Performance

The investment-based theory suggests that two firm characteristics, investment and profitability, are associated with future average stock returns. The economics is intuitive: Firms will invest more when profitability is high and discount rates (expected returns) are low. Controlling for profitability, high investment is associated with low expected returns; while controlling for investment, high profitability signals high expected returns. I show that the average returns associated with investment and profitability are not taken into account by the standard performance benchmarks. However, mutual funds show distinct preferences for investment and profitability when forming their portfolios. As a result, the performance of mutual funds can be predicted by the investment and profitability characteristics of their stock holdings.

[6] The factor data are obtained from Ken French's website and the DGTW benchmark assignments and returns are obtained from Russ Wermers's website. The technical details for the benchmarks including the modified DGTW benchmark are documented in Appendix B.

1.3.1 Investment-Based Return Predictability

I first form stock portfolios based on investment and profitability, and show that their future returns cannot be captured by the standard benchmarks. To the extent that those portfolios can be passively held by any fund manager regardless of his true investment skill, the results suggest that the standard benchmarks can be problematic for evaluating mutual fund performance.

At the beginning of July in each year t, I sort stocks into quintiles based on their asset growth for the fiscal year ending in $t-1$. At the beginning of each month, I also sort stocks into quintiles based on their latest available ROE. Value-weighted portfolio returns are calculated from July 1975 to June 2010. To ensure that the portfolios are not concentrated in small illiquid stocks, the portfolios are constructed to have equal total market value rather than equal number of firms. This construction makes the results easier to interpret for mutual funds, which typically hold large diversified portfolios.

Table 1.2 shows that standard performance benchmarks cannot capture the average returns associated with investment and profitability. In Panel A, investment negatively predicts future average returns, consistent with Cooper et al. (2008). The high-minus-low return spread is -4.58% per year in raw terms, and remains at -1.89% to -2.74% after benchmark adjustments. For example, the low asset growth quintile beats the high quintile by 2.37% per year according to the DGTW benchmark.

In Panel B, profitability has a strong positive predictive power for benchmark-adjusted returns. The high-minus-low spread is 8.92% per year for the Fama-French model, 5.55% for the Carhart model, and 5.19% for the DGTW benchmark. Moreover, the standard benchmarks cannot capture the returns associated with either low or high profitability. For example, the top ROE quintile beats the Carhart model by 2.64% per year, while the low quintile lags the benchmark by 2.90%.

Because mutual fund managers sometimes focus on a subset of stocks, I also repeat the analysis for six stock subsamples defined by size and B/M. At the beginning of July, I split all stocks into three groups based on their size using the 30% and 70% NYSE breakpoints. Then within each size group, I further split the stocks into two groups based on their B/M. The sequential sorts produce six subsamples: small-growth, small-value, mid-growth, mid-value, large-growth and large-value. The classifications are roughly in line with those used by mutual funds. For brevity, only results for the DGTW benchmark are presented.

Panel A of Table 1.3 shows that the predictive power of investment is stronger for small stocks and growth stocks. For example, the low asset growth quintile beats the high quintile by 7.35% per year in the small-growth subsample. The spread in benchmark-adjusted return is also significant for mid-growth stocks, at −5.10% per year, but becomes moderate in other subsamples. In Panel B, the predictive power of profitability is pervasive across the subsamples and is also stronger for small stocks and growth stocks. For example, the spread in benchmark-adjusted returns is on average 17.65% per year for small stocks, 9.01% for mid-cap stocks, and 3.51% for large stocks.

The findings suggest that the standard benchmarks can be problematic for evaluating mutual fund performance, if mutual funds have distinct preferences for investment and profitability when forming their portfolios. Intuitively, investment and profitability are observable firm fundamentals that are widely used by practitioners. Hence, it would not be surprising if fund managers use them to guide their investment decisions. For example, managers might simply prefer highly profitable firms.[7]

[7] The legendary investor Warren Buffett uses investing criteria that greatly emphasize the profitability effect.His five criteria include: (1) Free cash flow of at least $250 million, (2) Net profit margin of 15% or more, (3) Return on equity of at least 15% for each of the past three years and the most recent quarter, (4) A dollar's worth of retained earnings creating at least a dollar's worth of shareholder value over the past five years, (5) Market capitalization of at least $500 million. Beating the market consistently over the years, Buffett has been credited with superior investment skills. However, his performance might become less impressive once the profitability effect is taken into account.

Those managers are likely to be deemed skillful by the standard benchmarks, even though similar returns are achievable by passive strategies. In the following section, I directly examine the stock holdings of mutual funds, and show that they exhibit distinct investing styles for investment and profitability.

1.3.2 Characteristics of Mutual Fund Stock Holdings

I follow Chan, Chen, and Lakonishok (2002) in measuring the characteristics of mutual fund stock holdings. To be specific, I rank stocks into percentiles (between 0 and 1) based on a given characteristic, and then calculate the value-weighted rankings of fund stock holdings. The fund-level characteristic rankings reflect how the average stock held by the fund would be ranked among all stocks. In other words, they reflect the investing preferences or styles of mutual funds for the characteristic. Hence, I call them style indices for simplicity. For each mutual fund, I calculate the style indices for both the conventional and new characteristics using its latest stock holdings. The stock-level percentile rankings are assigned annually for size, B/M, and asset growth at the beginning of each July, and assigned monthly for momentum and ROE.

Panel A of Table 1.4 summarizes the distributional statistics for each style index. Mutual fund portfolios vary substantially in the new characteristics, as in the conventional ones. For example, the standard deviation of the style index is 0.09 for both investment and profitability, which is similar to those for size and momentum. Across the funds, the asset growth index ranges from 0.31 to 0.86. That is, some funds appear to prefer firms with moderate asset expansion, while others prefer firms that invest very aggressively. Overall, mutual funds tend to tilt their investments towards high asset growth stocks. The asset growth index has a mean of 0.58, and is above 0.50 for more than three quarters of the funds. The ROE index also varies widely across the funds, from 0.33 to 0.88. In addition, mutual funds shows a strong preference for high profitability. The ROE index is above 0.50 even for funds ranked at the bottom 5%. In other words, even the least profitability-oriented funds generally don't concentrate their holdings in low profitability firms.

Since the new characteristics can be correlated with the conventional ones at the fund level, I also construct adjusted style indices for investment and profitability. Specifically, I adjust the percentile rankings of a stock by subtracting the value-weighted rankings of its DGTW benchmark portfolio. The DGTW benchmark portfolios can be interpreted as diversified style portfolios formed on size, B/M, and momentum. Hence, the adjusted indices represent fund preferences that are more orthogonal to the conventional styles. The variations in investment and profitability remain significant after the adjustment. For example, the range of the adjusted index drops only moderately from 0.54 to 0.44 for asset growth, and from 0.55 to 0.46 for ROE. The mean indices are around 0.01 for both asset growth and ROE. Thus, controlling for the styles in size, B/M, and momentum, an average fund show some preferences for firms with high investment and profitability.

A characteristic is more relevant for evaluating mutual fund performance if it captures persistent differences in mutual fund holdings. Otherwise, any temporary deviations can be averaged out over time and the characteristic may not matter much over the long term. Following Chan et al. (2002), I compute the cross-sectional correlations between the current and one-year lagged values of a style index. A high correlation implies that relative to its peers a fund with a given preference for a characteristic tends to have similar preference in the future. In Panel B of Table 1.4, mutual funds show fairly high consistency in their preferences for investment and profitability. The mean correlation is 0.75 for asset growth and 0.79 for ROE. For comparison, the consistency is somewhat higher for size and B/M but much lower for momentum. Controlling for the conventional styles only reduce the consistency in new characteristics moderately. The mean correlation remains at around 0.60 for both asset growth and ROE. Therefore, investment and profitability seem to capture new information about the investing preferences of mutual funds.

1.3.3 Mutual Fund Performance

1.3.3.1 Predicting Mutual Fund Performance

Mutual funds show distinct investing preferences for investment and profitability. However, the standard performance benchmarks cannot account for the average returns associated with investment and profitability. This suggests that the investing preferences of mutual funds can have predictive power for their future performance. Thus, I sort mutual funds into portfolios based on the investment and profitability characteristics of their holdings, and see if this generates dispersions in future performance. Specifically, I sort mutual funds into deciles based on their style indices for asset growth or ROE at the beginning of each quarter. Equal-weighted portfolio returns are calculated each month from July 1980 to June 2010, and the portfolios are rebalanced quarterly.

Because I try to predict mutual fund performance using stock characteristics, my analysis focuses on gross holding returns. Gross holding returns are defined as the buy-and-hold returns constructed from quarterly fund stock holdings. Although they may differ from actual fund returns, holding returns are suited for evaluating the stock selection or asset allocation skills of mutual fund managers.[8]

Panel A of Table 1.5 shows that the preference for investment negatively predicts future fund returns. As mutual funds tilts towards high asset growth stocks, their excess returns decrease almost monotonically from 8.47% to 5.80% per year. However, the spread is largely captured by the standard benchmarks. The spread in adjusted returns are moderate, ranging from −0.22% per year for the DGTW benchmark to −0.74% for the Carhart model. The moderate spread is consistent with the disper-

[8]See Wermers(2006) for a comprehensive review of the holding-based performance evaluation research.

sion in fund preferences. The average asset growth index ranges from 0.43 to 0.74 (untabulated), neither too extreme. The standard benchmarks have more troubles evaluating stocks with extremely low or high asset growth.

In Panel B, profitability has a positive predictive power for mutual fund returns. High ROE funds beat their low ROE peers by almost 2% per year in raw returns. After benchmark adjustment, the return spread becomes more monotonic and further increases to as much as 5.03% per year. For example, the high ROE decile outperforms the low decile by more than 2.50% according to both the Carhart model and the DGTW benchmark. Moreover, the spread is more attributed to the positive performance of high ROE funds. The high ROE decile beats the benchmarks by 1.90% to 3.51% per year, while even low ROE funds generally do not show very negative performance. The finding is consistent with the strong preference for high profitability stocks of an average fund.

1.3.3.2 Fund Performance in Subsamples

Earlier analysis shows that the predictive power of investment and profitability varies across stock subsamples. Thus, I also examine if such variations exist for mutual funds. At the beginning of each quarter, I classify all funds into three subsamples based on the size characteristic of their stock holdings (small-cap, mid-cap, and large-cap), and separately into three value/growth subsamples based on their investment objectives (aggressive-growth, growth, and growth-and-income).[9]

Panel A of Table 1.6 shows that the investment effect is relatively stronger among small-cap funds and especially growth-oriented funds. For example, the spread in benchmark-adjusted returns increases in magnitude to -1.27% per year for growth funds, but reverses to 0.11% for growth-and-income funds. The findings are con-

[9]For subsample and subsequent analyses, I only present the results for the DGTW benchmark, which generally produce the least noisy estimates. Results for other benchmarks are largely similar and hence are omitted for brevity.

sistent with the fact that the preference for investment varies more widely among growth-oriented funds.

In Panel B, profitability also exhibits stronger predictive power for small-cap funds and growth-oriented funds. For example, the high ROE decile beats the low decile by 4.20% per year for small-cap funds and by 4.43% for aggressive-growth funds. This finding suggests that the profitability effect is especially important to control for when evaluating those funds. For other subsamples, the results are more moderate but remain economically meaningful. For example, the spread in benchmark-adjusted returns is still close to 2% per year even among large-cap funds.

1.3.3.3 Persistence in Mutual Fund Performance

Since mutual fund holdings are fairly consistent over time, I also examine the predictive power of investment and profitability for fund performance over the long term. Figure 1 plots the average style indices of the fund portfolios sorted by their preferences for investment or profitability. The figure shows that although fund holdings tend to converge somewhat over time, the differences largely remain. Even after 5 years, the spreads in the style indices are still more than 50% of the spreads at the portfolio formation date. Moreover, the relative order in holding preferences across the fund deciles always stays the same. However, the preferences for investment and profitability evolve somewhat differently over time. In Panel A, both high and low asset growth deciles converge similarly towards more moderate values between 0.51 and 0.67. In contrast, the convergence in preference for profitability comes disproportionately from low ROE funds in Panel B. the average ROE index of the high ROE decile drops slowly from 0.80 to 0.75, while that of the low decile increases more quickly from 0.51 to 0.60. The convergence also shows that most funds tilt their holdings towards high profitability stocks over the long term.

In Panel A of Table 1.7, the investment effect is well captured by the standard benchmarks, as the preferences for investment generally becomes less extreme over time. The spread in benchmark-adjusted returns is generally close to zero and even turns positive after the first year. In contrast, profitability has a much more persistent predictive power over time. In Panel B, high ROE funds beat the low ROE funds significantly by 2.17% in the first year and 1.55% in the second. The spread decreases to 1.15% in the third year, but remains positive for the next two years. In addition, the spread largely comes from the persistent good performance of high ROE funds. The high ROE decile beats the DGTW benchmark by 1.74%, 1.35% and 1.11% per year during the first three years.

1.3.3.4 Performance Based on Fund Net Returns

Gross holding returns ignore portfolio changes between quarterly reports, trading costs, and fees and expenses, which can affect the net returns realized by fund investors. As a robustness check, I test if the predictability of fund performance also applies to realized fund net returns. To focus on fund managers' investing skills, I add fund expenses back to the net returns. Since the characteristic-based benchmarks no longer apply, the results are based on the Fama-French three-factor model and the Carhart four-factor model.

Panel A of Table 1.8 shows that investment has a weaker predictive power for fund net returns. Although high asset growth funds earn lower average returns than low asset growth funds, the benchmark-adjusted returns are mostly flat across the portfolios. For example, the spread is only -0.08% per year based on the Carhart model. The weaker results are not surprising because the characteristics of fund holdings are based on only part of fund assets.

In contrast, the predictive power of profitability holds up relatively well for fund net returns. In Panel B of Table 1.8, the spread in benchmark-adjusted returns is 4.24% per year for the Fama-French model and 2.05% for the Carhart model. Both spreads are only slightly narrower than those based on holding returns. Moreover, the management fees charged by high ROE funds seem justified according to the standard benchmarks. For example, the high ROE decile beats the Carhart model by 1.61% per year, while charges their investors an annual expense of 1.18%.

1.3.4 Discussion

Investment and profitability seem to capture useful information about future mutual fund returns. However, such information is not sufficiently taken into account by the standard performance benchmarks, which can lead to predictability in mutual fund performance. The finding raises the question whether the investment-based return predictability should be controlled for when evaluating mutual funds. In other words, whether the performance associated with investment and profitability reflects real investing skills, and hence should be rewarded or penalized for.

There are reasons to believe that the average returns associated with investment and profitability should be controlled for. First, the investment-based theory suggests that the differences in average returns can be attributed to differences in risk, which is supported by evidences from several recent studies (e.g. Liu et al. (2009)). Because managers should be evaluated on a risk-adjusted basis, the average returns associated with investment and profitability should not be attributed to performance. The observed mutual fund preferences also provide evidences consistent with the risk-based explanation. For example, given the strong returns associated with high profitability stocks, most funds do not take extreme positions. High turnovers can be one concern, but another possibility is that a high profitability strategy can also be risky.

More generally, the observed fund performance could have been generated by diversified passive strategies based on investment and profitability. Investment and profitability are firm fundamentals that have been widely used by practitioners for a long time. For example, profitability has long been emphasized by value investors such

Warren Buffett. Given that such strategies do not require any private information or knowledge, the associated returns are unlikely to reflect real investing skills.

However, caution is also needed when interpreting the historical performance of mutual funds. The return predictability of investment and profitability is observed *ex post*. If such predictability is not entirely attributed to risk and *ex ante* was expected by only a few managers, then part of the associated returns might still represent performance. If this is the case, accounting for the investment-based return predictability helps better identify the sources of mutual fund performance.

Finally, the answer is clearer for performance evaluation in the future. The average returns associated with investment and profitability should be controlled for. Otherwise, existing benchmarks can be exploited by passive strategies based on investment and profitability. Table 1.9 provides examples of potential strategies: holding favorable stocks (low asset growth or high ROE quintile) or avoiding unfavorable stocks (high asset growth or low ROE quintile).[10] To evaluate the impact of additional trading costs, I also calculate the implied annual portfolio turnovers over that of the passive index of holding all stocks. The results are presented only for the DGTW benchmark and are similar for other benchmarks.

Panel A of Table 1.9 shows that avoiding high investment stocks can improve fund performance with little increase in turnovers. For managers who target the whole market, the strategy produces a significant performance of 41 basis points per year with only 14% in additional turnovers. Consistent with earlier results, the strategy is more effective for growth managers. In particular, a small-growth manager can enhance his performance by 1.74% per year while adding almost no additional turnovers.

[10] The stock quintiles for asset growth are formed at the beginning of each July, and the ROE quintiles are formed at the beginning of the second month of each quarter. Because most firms announce their earnings during the first month of each quarter, the timing for profitability helps utilizes more updated information. Monthly rebalanced ROE portfolios produce stronger results but with somewhat higher turnovers. A caveat for interpreting the results is that the strategies are back-tested on historical data and can be risky in the short run.

In Panel B of Table 1.9, both profitability strategies produce significant performance. For all stocks, concentrating in high ROE stocks generates a benchmark-adjusted return of 1.86% per year, though with 133% in additional turnovers. Avoiding low ROE stocks generates a more moderate performance of 0.75%, but with a much lower 39% increase in turnovers. The strategies are effective for most fund styles, especially for funds favoring smaller stocks and growth stocks. For example, by focusing on high ROE stocks, a small-growth manager can beat the small-growth index by 8.56% per year at the cost of 132% in additional turnovers. Assuming a round trip transaction cost of 1% to 2%, the strategy can generate an impressive performance of 5.92% to 7.24% per year in net terms.

1.4 Adjusting for Investment-Based Return Predictability

I show that fund performance estimates can change significantly once we control for the average returns associated with investment and profitability. This finding has practical implications for investors and also can be linked to previous research on mutual fund performance.

1.4.1 Changes in Fund Performance Estimates

I use the DGTW benchmark as the baseline model for performance evaluation. To adjust for the average returns associated with investment and profitability, I form 125 "control portfolios" using size, asset growth and ROE. At the beginning of July in each year t, stocks are sorted into five portfolios based on their size at the end of June in t using the NYSE breakpoints, and then sequentially into five portfolios based on their asset growth for the fiscal year ending in $t-1$. Within each of the 25 portfolios, stocks are further sorted into five portfolios based on their latest available ROE at the beginning of each month. The three-way sort produces a total of 125 control portfolios for which the value-weighted monthly characteristic selectivity (CS) measures are calculated based on the DGTW benchmark. For each stock, I adjust its CS measure by subtracting the CS measure of its control portfolio. When asset growth or ROE is missing for a stock, its CS measure is not adjusted. The idea is that the adjustment on average will remove any predictable abnormal returns associated with investment and profitability. I use size as an additional conditioning variable because investment and profitability tend to work differently across size subsamples.

Panel A of Table 1.10 shows the average fund performance before and after the adjustment. Controlling for investment and profitability tends to make fund performance estimates closer to zero. Between July 1980 and June 2010, an average fund beats the DGTW benchmark by 46 basis points per year, but by only 22 basis points after the adjustment. The performance change of 24 basis points per year is statistically significant at the 1% level, and is also economically significant given the size of the mutual fund industry. The results are consistent with the strong preference for profitability of an average fund. Across subsamples, the adjustment seems to have a stronger effect on growth funds. For example, the reduction in full sample performance estimate is 36 basis points per year for aggressive-growth funds, compared with 11 basis points for growth-and-income funds. The adjustment effect is fairly consistent over time though somewhat stronger in early period.

The finding can be related to those of Daniel et al. (1997). The authors evaluate mutual fund performance from 1975 to 1994 using a similar sample and conclude that mutual funds, particularly aggressive-growth funds, show some stock selection skills. For the overlapped sample period, my analysis suggests that a substantial part of the performance might be attributed to the average returns associated with investment and profitability. For example, Daniel et al. (1997) find an average performance of 108 basis points per year between January 1980 and December 1994 for aggressive-growth funds. Using their same sample screen, my estimate is about 112 basis points per year between July 1980 and December 1994. But after the adjustment, the performance of aggressive-growth funds drops by more than half to only 55 basis points per year. The stronger adjustment effect for aggressive-growth funds is consistent with their investing preferences. On average, aggressive-growth funds have a preference for small-growth stocks with high profitability.

Performance estimates can change quite significantly for individual funds. In Panel B of Table 1.10, I report the time-series mean fractions of funds whose annual performance estimates change more than a certain percentage or change signs. In an average year, 28% of the funds experience an adjustment more than 2%, while 8% of the funds experience an adjustment more than 4%. In addition, annual performance estimates change signs for 11% of the funds. The adjustment is even stronger for aggressive-growth funds and in more recent years. For example, after 1995 37% of aggressive-growth funds experience an adjustment more than 2%, and 15% of them experience an adjustment more than 4%. Given the competitiveness of the mutual fund industry, similar adjustments can dramatically change the fortune of a fund manager.

Not surprisingly, the adjustment effect is directly related to fund preferences for investment and profitability. Panel A of Table 1.11 shows that the adjustment reduces the performance of low asset growth funds but increases that of high asset growth funds. As a result, the spread in performance shrinks to almost zero after the adjustment. Similarly in Panel B, the performance of high ROE funds drops from 1.90% to 0.60% per year, while the performance of low ROE funds reverses from -0.66% to 0.28%. The changes can have important implications for investors. For example, the 1.30% reduction for high ROE funds suggests that their annual expense ratio of 1.18% may no longer be justified.

1.4.2 Potential Links to Previous Findings

The results can be linked to past research on mutual fund performance. As examples, I show that accounting for investment and profitability helps explain: the positive relation between fund activeness and performance, and the negative relation between fund size and performance.

1.4.2.1 Mutual Fund Activeness

Conceptually, a mutual fund manager can beat his benchmark only by deviating from it. Hence, a skillful manager tends to have both high activeness and good performance. Based on this intuition, Cremers and Petajisto (2009) shows that mutual fund managers who deviate more from their benchmark on average perform better than those who deviate less. However, if the benchmark model does not sufficiently account for the cross-section of average returns, the good performance of active funds might be attributed to uncontrolled exposures or investing styles.

Following Cremers and Petajisto (2009), I sort mutual funds into deciles at the beginning of each month based on their active share and examine their future performance. The portfolios are equal-weighted, and the results are based on gross holding returns between April 1990 and December 2006.[11]

Panel A of Table 1.12 shows that adjusting for investment and profitability reduces the performance of both high and low activeness funds. However, the reduction is much stronger for high activeness funds. The performance of the high active share decile drops by 0.79% per year, compared with 0.23% for the low decile. The difference of 0.56% per year is both economically and statistically significant. After the adjustment, the performance spread across the fund deciles drops from 0.71% to only 0.14% per year. The results are consistent with the characteristics of mutual fund

[11] The active share measure, defined as the fraction of fund portfolio holding that differs from its benchmark index holding, is developed by Cremers and Petajisto (2009) and Petajisto (2010). The data are from Antti Petajisto's website. Note that the moderate performance spread between high and low active share funds here is due to the use of the DGTW benchmark, consistent with the results in Table 9 of Cremers and Petajisto (2009). Their main analysis uses the practical indices (e.g., S&P 500) as the benchmarks, which produces stronger results. Using the practical indices, my analysis produces a quintile performance spread of 2.17% per year between April 1990 and December 2003, close to the estimate of 2.29% in their study.

holdings. On average, high active share funds are more concentrated in small stocks with high profitability. This helps boost their returns given the strong profitability effect among stock stocks. My finding suggests that the good performance of high active share funds documented by Cremers and Petajisto (2009) might be overestimated.

1.4.2.2 Mutual Fund Size

A recent study by Chen et al. (2004) shows that future fund performance tends to deteriorate with fund size. Since the results tend to be especially pronounced for funds favoring small and illiquid stocks, the authors conclude that their results are mostly driven by the liquidity of fund stock holdings. However, my analysis shows that the negative relation between fund size and performance largely disappear once we control for the average returns associated with investment and profitability. Therefore, an alternative explanation of their findings is the standard benchmarks' insufficient control for cross-sectional stock returns.

At the beginning of each quarter, I sort funds into deciles based on their total net assets. The portfolios are equal-weighted, and the results are based on gross holding returns between July 1980 and June 2010. To be consistent with Chen et al. (2004), I relax my sample restriction on the size of fund common equity holdings to 1 million dollars.

Panel B of Table 1.12 shows that before the adjustment fund size negatively predicts future performance, consistent with the findings of Chen et al. For example, the small fund decile beats the DGTW benchmark by 0.72% per year, while the large decile by only 0.22% per year. The spread of 0.51% per year is statistically significant at the 10% level. However, investing preferences also differ between small and large funds. In particular, small funds have a preference for small stocks with high profitability. Once we adjust for the average returns associated with investment and profitability, the performance of the small size decile drops by 0.53% per year.

In contrast, the performance of large fund decile barely changes. As a result, the performance gap related to fund size shrinks to almost zero.

1.5 New Performance Benchmarks

The results show that the standard benchmarks cannot account for the average returns associated with investment and profitability. This drawback can have serious effects on performance evaluation. A solution to this problem is to draw upon a different asset pricing model that performs well in explaining the cross-section of stock returns. The investment-based asset pricing model is a good candidate. It is motivated by economic theory and also has good empirical performance. In this section, I construct new benchmarks motivated from the investment-based asset pricing, and compare them with the standard benchmarks.

1.5.1 Construction of New Benchmarks

The investment-based asset pricing theory states that expected stock returns are directly linked to two firm characteristics, investment and profitability (e.g., Zhang (2005a)). The intuition is straightforward: Firms tend to invest more when profitability is high and discount rates (expected return) are low. Fixing profitability, high investment is associated with low expected returns; while controlling for investment, high profitability implies high expected returns.

Building on the economic intuition, I construct a new characteristic-based benchmark using size, investment, and profitability. I include size because both empirical evidence (e.g., Fama and French (2008)) and theory (e.g., Li, Livdan, and Zhang (2009)) suggest that investment and profitability work differently across size subsamples. Moreover, this triple-characteristic benchmark facilitates a direct comparison with the widely used DGTW benchmark, which includes size, value, and momentum.

To compare the benchmarks more directly, I construct both the DGTW benchmark and the investment-based benchmark using the same procedure and a common sample of stocks with non-missing information on size, B/M, momentum, asset growth and ROE. In terms of market value, the sample on average covers 93% of all NYSE, AMEX, and NASDAQ common stocks between July 1975 and June 2010. At the beginning of July in each year t, stocks are sorted into five portfolios based on their size at the end of June in t using the NYSE breakpoints. Within each size quintile, stocks are further sorted into five portfolios based on their B/M or asset growth for the fiscal year ending in $t-1$. I follow Daniel et al. (1997) and adjust B/M by subtracting the long-term industry average B/M. The industry definitions follow the 48 Fama-French industry classifications. Finally, within each of the 25 size-B/M or size-investment portfolios, stocks are sorted into five portfolios based on their momentum or ROE at the beginning of each month. The three-way sequential sort on size, B/M, and momentum forms the 125 benchmark portfolios for the DGTW benchmark, while the three-way sequential sort on size, asset growth, and ROE forms the 125 benchmark portfolios for the investment-based benchmark. Value-weighted monthly returns are calculated for each set of portfolios and then used as the benchmark returns for their member stocks.

The DGTW benchmark and the investment-based benchmark both have their own merits. The DGTW benchmark has strong practical motivations. Size and valuation define the most popular investing styles of mutual funds (e.g., Chan et al. (2009)). Moreover, there are also substantial evidences of momentum investing by mutual funds (e.g., Grinblatt, Titman, Wermers (1995)). Hence, the size, value, and momentum effects are natural benchmarking choices from a practical perspective. Meanwhile, the investment-based benchmark has a more solid economic foundation, which is supported by good empirical performance. To combine their strengths, I also construct a comprehensive benchmark that includes both sets of characteristics.

Because a simple multiple sort is limited by the number of stocks available, I use an iterative procedure to construct the comprehensive benchmark. For a given stock, its comprehensive benchmark return is calculated as the sum of its DGTW benchmark return and the DGTW CS measure of its investment-based benchmark portfolio:

$$r_t^b = r_t^{DGTW_{i,t-1}} + \sum_{j \in INV_{i,t-1}} \omega_{j,t-1} CS_t^{DGTW_{j,t-1}}, \tag{1.3}$$

where r_t^b is the benchmark return for stock i during time t, $DGTW_{i,t-1}$ is the DGTW benchmark portfolio assignment for stock i, $r_t^{DGTW_{i,t-1}}$ is the DGTW benchmark return of stock i in t, $INV_{i,t-1}$ is the investment-based benchmark portfolio assignment for stock i, $\omega_{j,t-1}$ is the weight of stock j in portfolio $INV_{i,t-1}$, and $CS_t^{DGTW_{j,t-1}}$ is the DGTW CS measure of stock j in t.[12]

1.5.2 Evaluating Passive Stock Portfolios

I first examine the ability of the new benchmarks in accounting for the cross-section of average stock returns. At the beginning of each July, I sort stocks into quintiles based on their B/M, asset growth, net stock issues, or total accruals. At the beginning of each month, I also sort stocks into quintiles based on their momentum, ROE, standardized earnings surprise (SUE), failure probability, or idiosyncratic volatility.[13] As earlier, the portfolios are constructed to have equal total market value. The portfolios are value-weighted and the sample period is from July 1975 to June 2010.

Table 1.13 shows that the investment-based benchmark performs well compared with the DGTW benchmark. As expected, the investment-based benchmark almost perfectly matches the return spreads generated by asset growth and ROE. In contrast, the DGTW benchmark leaves large parts of the spreads unmatched. The investment-

[12]The results for the comprehensive benchmark are not materially affected by the order of the iterative procedure.

[13]The technical details of anomaly variable definitions are included in Appendix C.

based benchmark also performs better in matching the portfolios formed on SUE, failure probability, idiosyncratic volatility, and net stock issues, consistent with the findings of Chen et al. (2011). For example, the benchmark-adjusted return spread across the failure probability portfolios is only -0.02% per year for the investment-based benchmark, compared with -1.33% for the DGTW benchmark.

Despite its good overall performance, the investment-based benchmark cannot match the returns associated with B/M and momentum. The benchmark-adjusted return spreads are both more than 3% per year. The shortcoming might be explained by two reasons. First, the characteristic-based benchmark employs a simple sort, which might not adequately capture the nonlinear feature of the investment-based model. In contrast, Liu et al. (2009) and Liu and Zhang (2011) show that B/M and momentum portfolios can be better matched by a nonlinear structure estimation. Second, investment and profitability are likely to be measured with errors by asset growth and ROE. For example, as a comprehensive measure of investment, asset growth does not distinguish different types of investments (e.g. fixed assets investment and working capital investment) that convey different information about expected returns.

Not surprisingly, the comprehensive benchmark performs the best. In Table 1.13, the comprehensive benchmark closely matches the return spreads generated by its underlying characteristics, and generally performs the best in matching other return anomalies. Across all sets of portfolios, the average unmatched return spread is only 0.77% per year for the comprehensive benchmark, compared with 2.03% for the DGTW benchmark and 1.54% for the investment-based benchmark. The comprehensive benchmark has some troubles explaining the returns associated with net stock issues and total accruals. However, a substantial part of the unmatched return spreads is due to the negative performance of stocks with high equity issuances or accruals. This is less problematic for mutual funds, given that they are prohibited from short-selling.

The comprehensive benchmark also tracks stock returns more closely. Measured by the standard errors of benchmark-adjusted returns (untabulated), the comprehensive benchmark is on average 31% less noisy than the DGTW benchmark and 33% less noisy than the investment-based benchmark. In all, the comprehensive benchmark seems to provide enough benefits to justify its complexity.

1.5.3 The Cross-Section of Mutual Fund Returns

I also evaluate how well the new benchmarks can capture the cross-section of mutual fund returns. At the beginning of each quarter, I sort mutual funds into deciles based on the characteristics of their stock holdings. The portfolios are equal-weighted, and the results are based on gross holding returns between July 1980 and June 2010.

Table 1.14 shows that the investment-based benchmark performs somewhat better than the DGTW benchmark. Across all sets of portfolios, the average magnitude of unmatched return spreads is 0.95% per year for the investment-based benchmark, compared with 1.26% for the DGTW benchmark. In addition, the investment-based benchmark matches the return spreads generated by both its own characteristics and those of the DGTW benchmark. For example, the benchmark-adjusted return spread across the momentum deciles is 1.31% for the investment-based benchmark, only slight larger than the 1.06% for the DGTW benchmark.

The comprehensive benchmark performs very well in matching the cross-section of fund returns. In Table 1.14, the unmatched return spreads are mostly close to zero and statistically insignificant. Across all sets of portfolios, the average magnitude of unmatched return spreads drops to only 0.49% per year for the comprehensive benchmark. In contrast, both the DGTW benchmark and the investment-based benchmark have problem matching fund returns associated with SUE and failure probability. For example, the benchmark-adjusted return spread across the SUE deciles is 0.38% per year for the comprehensive benchmark, substantially lower than the 1.65% for the

DGTW benchmark and the 1.57% for the investment-based benchmark.

1.5.4 Mutual Fund Performance

Given the good performance of the new benchmarks, I apply them to evaluate mutual funds and see if they lead to different conclusions about mutual fund performance.

Following Daniel et al. (1997), I use each of the benchmarks to decompose mutual fund holding returns into three attributes of average style (AS), characteristic selectivity (CS), and characteristic timing (CT). The CS measure is defined by equation (1.2). For month t, the AS measure and the CT measure are constructed as:

$$AS_t = \sum_{j=1}^{N} \omega_{j,t-13} r_t^{b_{j,t-13}}, \tag{1.4}$$

$$CT_t = \sum_{j=1}^{N} (\omega_{j,t-1} r_t^{b_{j,t}} - \omega_{j,t-13} r_t^{b_{j,t-13}}), \tag{1.5}$$

where $\omega_{j,t-1}$ ($\omega_{j,t-13}$) is the investment weight on stock j at the beginning of month t ($t-12$), $b_{j,t-1}$ ($b_{j,t-13}$) is the benchmark assignment for stock j at the beginning of month t ($t-12$), and $r_t^{b_{j,t-1}}$ ($r_t^{b_{j,t-13}}$) is the return of benchmark portfolio $b_{j,t-1}$ ($b_{j,t-13}$) in t.

The three attributes convey detailed information about a fund manager's performance. The AS attribute measures the return component associated with his preferences for certain stock characteristics. The CS attribute measures his ability in selecting the best performing stocks among those with similar characteristics. The CT attribute measures the manager's timing ability in tilting towards the best performing styles. For each fund, I also calculate the tracking error volatility of each benchmark, defined as the time-series standard error of the fund's monthly CS measures. The tracking error volatility of a benchmark is lower, if it tracks fund returns more closely over time. For accuracy, I require a minimum of 36 monthly observations for the calculation.

Table 1.15 shows that the investment-based benchmark decomposes fund returns similarly as the DGTW benchmark. The average style measure across all funds is 11.50% per year for the investment-based benchmark and 11.67% for the DGTW benchmark. The investment-based benchmark attributes a slightly lower value to managers' stock selection skills than the DGTW benchmark, 0.28% versus 0.33% per year.[14] But neither of them is statistically different from zero, and a t-test fails to reject the equality between the two estimates. Moreover, both benchmarks agree that fund managers have little timing ability, consistent with past studies (e.g, Daniel et al. (1997)). Across the fund subsamples, both benchmarks suggest that growth-oriented funds are more likely to have skills in stock selection and style timing. For example, aggressive-growth funds on average outperform growth-and-income funds by around 0.50% per year in stock selection according to either benchmark.

In terms of tracking error volatility, the DGTW benchmark performs somewhat better than the investment-based benchmark, especially for more growth-oriented funds. For example, the average tracking error volatility across aggressive-growth funds is 9.08% per year for the DGTW benchmark, compared with 9.67% for the investment-based benchmark. Therefore, size, B/M and momentum appear to match fund returns more closely than size, investment and profitability. The finding is not surprising. Size and valuation define the two most widely used investing styles of mutual funds, which gives a natural edge to the DGTW benchmark.

Combining the two benchmarks provides a closer match for fund returns. For all funds, the comprehensive benchmark assigns the highest estimate of 11.71% per year to fund average styles but merely 0.08% to stock selection skills. In other words, an average fund generates almost no value, even before costs. The comprehensive

[14]The performance estimates in Table 1.15 differ slightly from those in Table 1.10, because the analysis here is limited to stocks with non-missing information on size, B/M, momentum, asset growth, and ROE.

benchmark also suggests that an average fund does not possess significant style timing skills. The characteristic timing measure is only 0.27% per year across all funds and not distinguishable from zero. Across the fund subsamples, only aggressive-growth funds show some moderate skills: 0.38% per year in stock selection and 0.62% in style timing.

The advantage of the comprehensive benchmark is also reflected by the improved efficiency in tracking fund returns. Across all funds, the comprehensive benchmark has the lowest tracking error volatility at 6.10% per year, which is lower than the 6.88% for the DGTW benchmark and the 7.52% for the investment-based benchmark. t-tests of zero reductions in tracking error volatility are strongly rejected at the 1% significance level. The reduction is also significant in economic terms given that alternative models often cluster in their tracking error volatilities (e.g., Chan et al. (2009)). The improvement becomes even more apparent for the most volatile aggressive-growth funds. The comprehensive benchmark reduces the average tracking error volatility of aggressive-growth funds by more than 1% per year, relative to the DGTW benchmark. In practice, this seemingly moderate reduction in tracking error volatility can translate to substantial efficiency gain in identifying manager skills. For example, to identify an aggressive-growth manager with a "true" alpha of 4% per year at the 10% significance level, the DGTW benchmark would require a sample size of about 14 years, compared with just 11 years for the comprehensive benchmark. In other words, the DGTW benchmark suffers an efficiency loss of roughly 27% relative to the comprehensive benchmark.[15]

[15] The simple illusion is adapted from the example in footnote 10 of Chan et al. (2009). For an benchmark-adjusted return of 4% per year to be declared statistically nonzero at just the 10% significance level, the minimum number of years required is about $(\frac{1.64\sigma_{TE}}{4})^2$. For aggressive-growth funds in my analysis, σ_{TE} is 9.08% for the DGTW benchmark and 8.03% for the comprehensive benchmark. These translate to a require sample size of 14 years and 11 years, or an efficiency loss of 3 years for the DGTW benchmark. The efficiency loss is even more dramatic for smaller abnormal returns and higher statistical significance.

1.6 Conclusion

Motivated by investment-based asset pricing, I show that investment and profitability contain useful information about future fund returns that is not taken into account by the standard performance benchmarks. Accounting for investment and profitability changes performance estimates significantly, and the changes can be related to previous findings of manager skills. I propose new benchmarks for performance evaluation. The results show that incorporating investment and profitability helps better control for the cross-section of stock returns and reduce the noisiness in performance estimates. In the future, further research is warranted to investigate how previous findings of mutual fund performance are affected by the standard benchmarks' insufficient control for stock returns. In addition, a more comprehensive study of mutual fund investing styles can provide useful insights about their investment approaches and performance.

Table 1.1 Summary Statistics for Mutual Fund Sample

For each year between July 1980 and June 2010, I report the simple averages of total net assets, stock holdings, gross holding returns, and realized net returns across all funds. Gross holding returns are the buy-and-hold returns implied by fund stock holdings. Asset values are in million dollars and returns are in percent. I also report the number of unique funds in the sample and separately for each fund type. The mutual fund sample includes all US equity funds with a self-declared investment objective of aggressive-growth (A-G), growth, or growth-and-income (G&I). Funds with fewer than ten stocks or less than ten million dollars in their common stock holdings are excluded.

	Numbers of Funds				Assets		Monthly Returns	
Year	All	A-G	Growth	G&I	Total	Stock	Holding	Net
1981	217	62	97	58	177	137	2.53	2.39
1982	219	71	125	77	180	132	−1.20	−0.95
1983	235	63	118	82	199	154	5.26	4.72
1984	262	75	127	89	262	187	−1.29	−1.11
1985	275	82	142	97	267	200	2.28	1.94
1986	326	85	168	107	312	232	2.69	2.38
1987	374	86	209	114	375	272	1.52	1.33
1988	403	97	236	120	461	274	−0.07	−0.16
1989	428	105	246	111	357	261	1.44	1.25
1990	460	119	264	121	437	282	1.30	1.15
1991	532	136	314	141	387	279	0.67	0.57
1992	612	150	321	143	439	326	1.24	1.17
1993	759	163	438	173	513	372	1.67	1.45
1994	971	175	619	206	565	395	0.14	0.15
1995	1,137	185	749	228	586	412	1.98	1.66
1996	1,253	178	838	369	802	570	2.04	1.80
1997	1,442	159	927	356	946	667	1.97	1.75
1998	1,575	165	1,045	366	1,109	856	2.03	1.80
1999	1,579	163	1,061	355	1,350	1,057	1.45	1.35
2000	1,577	162	1,069	346	1,653	1,362	1.78	1.60
2001	1,540	154	1,051	335	1,810	1,422	−0.60	−0.67
2002	1,448	151	984	313	1,627	1,280	−1.31	−1.35
2003	1,383	150	937	296	1,335	1,081	0.24	0.16
2004	1,343	143	913	287	1,689	1,367	1.88	1.69
2005	1,288	141	869	278	2,075	1,590	0.80	0.70
2006	1,237	137	831	269	2,427	1,842	0.94	0.88
2007	1,172	127	785	260	2,791	2,073	1.56	1.48
2008	1,106	122	739	245	3,322	2,216	−1.01	−0.90
2009	1,070	121	710	239	2,316	1,578	−2.06	−2.08
2010	928	102	619	207	2,584	1,966	1.51	1.38
Mean	905	128	585	213	1,112	828	1.05	0.92

Table 1.2 Performance of Passive Stock Portfolios

At the beginning of July in each year t, I sort stocks into five portfolios based on their asset growth for the fiscal year ending in $t-1$. At the beginning of each month, stocks are also sorted into five portfolios based on their return-on-equity (ROE). The portfolios are constructed to have equal total market value, and value-weighted portfolio returns are calculated from July 1975 to June 2010. For each set of portfolios, I report the mean returns in excess of the one-month T-bill rate ($r-rf$), the estimated intercepts from the Fama-French three-factor regression (α_{FF}) and the Carhart four-factor regression (α_{Caht}), and the mean characteristic selectivity measure based on the DGTW benchmark (α_{DGTW}). All estimates are in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations.

	Panel A: Asset Growth				Panel B: ROE			
	$r-rf$	α_{FF}	α_{Caht}	α_{DGTW}	$r-rf$	α_{FF}	α_{Caht}	α_{DGTW}
Low	8.40	1.31	1.26	0.74	2.81	−5.14	−2.90	−3.16
	(3.17)	(1.80)	(1.64)	(1.51)	(0.85)	(−4.79)	(−2.93)	(−4.27)
2	6.36	0.50	0.29	−0.10	6.13	−0.48	−0.09	−0.06
	(2.66)	(0.74)	(0.41)	(−0.18)	(2.34)	(−0.73)	(−0.12)	(−0.13)
3	6.55	1.18	0.71	0.73	6.32	0.74	0.53	−0.04
	(2.63)	(1.63)	(0.95)	(1.53)	(2.42)	(1.07)	(0.81)	(−0.09)
4	5.08	−0.18	0.40	0.15	6.77	2.13	1.11	0.95
	(1.68)	(−0.21)	(0.43)	(0.29)	(2.43)	(2.78)	(1.32)	(1.88)
High	3.82	−1.42	−0.63	−1.62	7.85	3.78	2.64	2.03
	(1.08)	(−1.90)	(−0.81)	(−2.16)	(2.78)	(3.46)	(2.55)	(3.07)
H−L	−4.58	−2.74	−1.89	−2.37	5.04	8.92	5.55	5.19
	(−2.46)	(−2.35)	(−1.48)	(−2.25)	(2.45)	(4.69)	(3.10)	(4.21)

Table 1.3 Performance of Passive Stock Portfolios in Subsamples

At the beginning of July in each year t, stocks in a subsample are sorted into five portfolios based on their asset growth for the fiscal year ending in $t-1$. At the beginning of each month, stocks in the subsample are also sorted into five portfolios based on their return-on-equity (ROE). The portfolios are constructed to have equal total market value, and value-weighted portfolio returns are calculated from July 1975 to June 2010. The stock subsamples are formed at the beginning of each July by first splitting stocks into three size groups (small, mid, large) and then sequentially into two groups based on their B/M (growth, value). The breakpoints for size are the 30% and 70% breakpoints of NYSE stocks. I report the mean characteristic selectivity measure based on the DGTW benchmark (α_{DGTW}). All estimates are in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations.

	Small Growth	Small Value	Mid Growth	Mid Value	Large Growth	Large Value
			Panel A: Asset Growth			
Low	0.52	1.73	0.54	−0.58	0.88	0.82
	(0.39)	(1.54)	(0.62)	(−0.70)	(1.06)	(0.90)
3	1.51	1.71	2.11	1.39	0.38	−0.64
	(2.31)	(2.04)	(2.87)	(1.91)	(0.50)	(−0.73)
High	−6.83	−0.82	−4.65	0.76	−1.06	−0.46
	(−5.60)	(−0.89)	(−3.36)	(0.92)	(−1.03)	(−0.51)
H−L	−7.35	−2.55	−5.19	1.34	−1.94	−1.29
	(−4.44)	(−1.54)	(−3.01)	(1.08)	(−1.27)	(−0.97)
			Panel B: ROE			
Low	−9.62	−6.28	−5.17	−3.34	−1.54	−1.67
	(−4.09)	(−4.43)	(−2.84)	(−2.83)	(−1.49)	(−1.56)
3	0.05	0.06	0.22	0.81	0.81	0.34
	(0.07)	(0.06)	(0.29)	(0.95)	(1.00)	(0.48)
High	9.74	9.67	5.05	4.46	1.55	2.25
	(8.93)	(9.19)	(5.05)	(4.79)	(1.68)	(2.27)
H−L	19.35	15.95	10.22	7.80	3.09	3.92
	(6.38)	(7.61)	(4.45)	(4.40)	(1.95)	(2.49)

Table 1.4 Characteristics of Mutual Fund Stock Holdings

At the beginning of each July, I rank stocks into percentiles (between 0 and 1) based on their size (ME), book-to-market (B/M), or asset growth (AG). At the beginning of each month, I also sort stocks into percentiles based on their momentum (MOM) or return-on-equity (ROE). For each fund, its style indices are calculated as the value-weighted characteristic rankings of its latest stock holdings. I also construct the adjusted rankings for asset growth (AG*) and return-on-equity (ROE*). The adjusted rankings for a given stock are its original rankings subtracted by the value-weighted rankings of the stock's DGTW benchmark portfolio. In Panel A, I report the time-series averages of the cross-sectional statistics for the style indices. In Panel B, I report the correlations between its current value and one-year lagged value, averaged across all funds and then over time. The sample period covers July 1980 to June 2010.

	Panel A: Distributions						
	ME	B/M	MOM	AG	ROE	AG*	ROE*
mean	0.89	0.36	0.58	0.58	0.68	0.02	0.01
std	0.10	0.13	0.09	0.09	0.09	0.06	0.05
min	0.41	0.09	0.29	0.31	0.33	−0.21	−0.26
p5	0.69	0.17	0.44	0.44	0.52	−0.08	−0.09
p25	0.85	0.27	0.51	0.52	0.63	−0.02	−0.02
median	0.92	0.35	0.57	0.57	0.69	0.01	0.01
p75	0.96	0.44	0.64	0.63	0.74	0.06	0.04
p95	0.98	0.58	0.75	0.73	0.80	0.12	0.09
max	0.99	0.80	0.89	0.86	0.88	0.23	0.20
p75−p25	0.11	0.17	0.12	0.11	0.11	0.08	0.06
p95−p5	0.29	0.41	0.31	0.29	0.28	0.21	0.18
max-min	0.58	0.71	0.61	0.54	0.55	0.44	0.46
	Panel B: Correlations Between Current and One-Year Lagged Styles						
	ME	B/M	MOM	AG	ROE	AG*	ROE*
Pearson	0.96	0.90	0.52	0.75	0.79	0.62	0.64
Spearman	0.94	0.90	0.49	0.75	0.79	0.62	0.59

Table 1.5 Performance of Mutual Funds

At the beginning of each July, I rank stocks into percentiles (between 0 and 1) based on their asset growth (AG). At the beginning of each month, I also sort stocks into percentiles based on their return-on-equity (ROE). For each fund, its style indices are calculated as the value-weighted characteristic rankings of its latest stock holdings. In Panel A, funds are sorted into deciles at the beginning of each quarter based on the style index for asset growth. For each portfolio, equal-weighted fund holding returns are calculated from July 1980 to June 2010. In Panel B, fund portfolios are constructed similarly using the style index for ROE. For each set of portfolios, I report the mean returns in excess of the one-month T-bill rate ($r-rf$), the estimated intercepts from the Fama-French three-factor regression (α_{FF}) and the Carhart four-factor regression (α_{Caht}), and the mean characteristic selectivity measure based on the DGTW benchmark (α_{DGTW}). All estimates are in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations.

	Panel A: Asset Growth				Panel B: ROE			
	$r-rf$	α_{FF}	α_{Caht}	α_{DGTW}	$r-rf$	α_{FF}	α_{Caht}	α_{DGTW}
Low	8.47	0.65	0.84	0.45	6.75	−1.52	−0.31	−0.66
	(2.78)	(0.73)	(0.94)	(0.78)	(1.81)	(−1.61)	(−0.34)	(−1.00)
2	8.12	0.57	0.68	0.69	7.28	−0.56	−0.30	0.00
	(2.67)	(0.81)	(0.92)	(1.89)	(2.08)	(−0.85)	(−0.42)	(0.01)
3	8.01	0.83	0.65	0.52	7.01	−0.43	−0.40	0.05
	(2.56)	(1.35)	(1.02)	(1.64)	(2.04)	(−0.71)	(−0.61)	(0.14)
4	8.01	1.26	1.02	0.64	7.33	0.17	−0.13	0.36
	(2.60)	(2.45)	(1.83)	(2.32)	(2.14)	(0.30)	(−0.20)	(0.96)
5	7.40	0.81	0.62	0.53	7.25	0.53	0.24	0.49
	(2.31)	(1.65)	(1.15)	(1.89)	(2.18)	(0.92)	(0.38)	(1.38)
6	7.12	0.56	0.23	0.31	7.43	0.92	0.72	0.55
	(2.13)	(1.13)	(0.40)	(1.00)	(2.22)	(1.51)	(1.09)	(1.46)
7	7.37	1.10	0.58	0.51	7.08	1.03	0.58	0.51
	(2.11)	(2.10)	(0.99)	(1.23)	(2.15)	(1.83)	(0.93)	(1.45)
8	6.76	0.68	0.23	0.29	7.50	1.53	1.11	0.74
	(1.83)	(1.14)	(0.33)	(0.50)	(2.26)	(2.43)	(1.66)	(1.98)
9	6.49	0.30	−0.11	0.45	7.18	1.57	1.00	0.64
	(1.60)	(0.39)	(−0.12)	(0.62)	(2.11)	(2.07)	(1.28)	(1.31)
High	5.80	0.03	0.10	0.23	8.71	3.51	2.32	1.90
	(1.24)	(0.02)	(0.08)	(0.20)	(2.39)	(3.32)	(2.15)	(2.87)
H−L	−2.67	−0.62	−0.74	−0.22	1.96	5.03	2.63	2.56
	(−0.89)	(−0.39)	(−0.45)	(−0.15)	(1.02)	(3.00)	(1.67)	(2.51)

Table 1.6 Performance of Mutual Funds in Subsamples

At the beginning of each quarter, I sort funds into three groups based on the style index for size: small-cap, mid-cap, and big-cap. Separately, I also split funds into three value/growth subsamples using their investment objectives: aggressive-growth, growth, and growth-and-income. In Panel A, funds in a subsample are sorted into deciles at the beginning of each quarter based on their style index for asset growth. For each portfolio, equal-weighted fund holding returns are calculated from July 1980 to June 2010. In Panel B, fund portfolios are constructed similarly using the style index for ROE. I report the mean characteristic selectivity measures based on the DGTW benchmark. All estimates are shown in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations.

	Small Cap	Mid Cap	Large Cap	Aggressive Growth	Growth	Growth Income
			Panel A: Asset Growth			
Low	0.72	0.61	0.20	1.17	0.84	0.05
	(1.07)	(0.70)	(0.45)	(1.42)	(1.50)	(0.07)
3	1.25	0.59	0.27	1.57	0.85	−0.02
	(2.37)	(1.40)	(1.03)	(2.58)	(2.38)	(−0.04)
8	0.82	0.10	0.10	0.60	0.14	0.13
	(1.05)	(0.15)	(0.26)	(0.55)	(0.25)	(0.53)
High	0.51	0.53	0.23	0.64	−0.43	0.16
	(0.37)	(0.41)	(0.31)	(0.38)	(−0.40)	(0.28)
H−L	−0.21	−0.08	0.03	−0.52	−1.27	0.11
	(−0.13)	(−0.04)	(0.03)	(−0.27)	(−0.90)	(0.09)
			Panel B: ROE			
Low	−1.05	−0.44	−0.63	−1.38	−0.65	−0.35
	(−1.17)	(−0.44)	(−1.20)	(−1.29)	(−0.90)	(−0.40)
3	0.45	−0.31	−0.02	−0.21	−0.28	−0.52
	(1.04)	(−0.62)	(−0.07)	(−0.24)	(−0.72)	(−1.15)
8	1.58	0.58	0.09	1.66	0.65	0.10
	(2.37)	(1.26)	(0.28)	(1.87)	(1.72)	(0.37)
High	3.15	2.04	1.19	3.05	1.55	0.82
	(3.25)	(2.68)	(2.15)	(2.76)	(2.58)	(2.00)
H−L	4.20	2.49	1.82	4.43	2.20	1.17
	(2.96)	(1.73)	(2.00)	(2.87)	(2.16)	(1.13)

Table 1.7 Persistence in Mutual Fund Performance

At the beginning of each July, I rank stocks into percentiles (between 0 and 1) based on their asset growth (AG). At the beginning of each month, I also sort stocks into percentiles based on their return-on-equity (ROE). For each fund, its style indices are calculated as the value-weighted characteristic rankings of its latest stock holdings. In Panel A, funds are sorted into deciles at the beginning of each quarter based on the style index for asset growth. For each portfolio, equal-weighted fund holding returns are calculated from July 1980 to June 2010. In Panel B, fund portfolios are constructed similarly using the style index for ROE. For each set of fund portfolios, I report the mean characteristic selectivity measure based on the DGTW benchmark (α_{DGTW}) during the first quarter and each of the first five years after portfolio formation. All estimates are in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations.

	Qtr 1	Year 1	Year 2	Year 3	Year 4	Year 5
			Panel A: Asset Growth			
Low	0.45	0.55	0.41	0.22	0.01	0.14
	(0.78)	(1.50)	(1.15)	(0.38)	(0.02)	(0.26)
3	0.52	0.48	0.38	0.29	0.35	0.38
	(1.64)	(1.20)	(0.99)	(1.09)	(1.18)	(1.32)
8	0.29	0.43	0.55	0.49	0.17	0.36
	(0.50)	(0.60)	(0.77)	(0.95)	(0.34)	(0.73)
High	0.23	0.40	1.14	1.02	0.46	0.58
	(0.20)	(0.35)	(0.98)	(0.91)	(0.41)	(0.55)
H−L	−0.22	−0.08	1.01	0.80	0.45	0.44
	(−0.15)	(−0.05)	(0.68)	(0.55)	(0.31)	(0.33)
			Panel B: ROE			
Low	−0.66	−0.44	−0.20	−0.04	0.01	0.31
	(−1.00)	(−0.74)	(−0.38)	(−0.09)	(0.03)	(0.59)
3	0.05	0.16	0.28	0.41	0.33	0.39
	(0.14)	(0.51)	(0.86)	(1.29)	(0.97)	(1.07)
8	0.74	0.49	0.25	0.28	0.10	0.35
	(1.98)	(1.31)	(0.68)	(0.70)	(0.26)	(0.86)
High	1.90	1.74	1.35	1.11	0.62	0.74
	(2.87)	(2.74)	(2.21)	(1.75)	(0.96)	(1.13)
H−L	2.56	2.17	1.55	1.15	0.60	0.43
	(2.51)	(2.40)	(1.92)	(1.40)	(0.70)	(0.48)

Table 1.8 Performance of Mutual Funds, Net Returns Before Expenses

At the beginning of each July, I rank stocks into percentiles (between 0 and 1) based on their asset growth (AG). At the beginning of each month, I also sort stocks into percentiles based on their return-on-equity (ROE). For each fund, its style indices are calculated as the value-weighted characteristic rankings of its latest stock holdings. In Panel A, funds are sorted into deciles at the beginning of each quarter based on the style index for asset growth. For each portfolio, equal-weighted fund net returns before expenses are calculated from July 1980 to June 2010. In Panel B, fund portfolios are constructed similarly using the style index for ROE. For each set of fund portfolios, I report the mean fund net returns in excess of the one-month T-bill rate (mean) and the estimated intercepts from the Fama-French three-factor regression (α_{FF}) and the Carhart four-factor regression (α_{Caht}), as well as the mean expense ratios. All estimates are in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations.

	Panel A: Asset Growth				Panel B: ROE			
	$r-rf$	α_{FF}	α_{Caht}	Exp	$r-rf$	α_{FF}	α_{Caht}	Exp
Low	7.44	0.30	0.58	1.14	5.86	−1.49	−0.44	1.23
	(2.69)	(0.38)	(0.72)		(1.73)	(−1.68)	(−0.51)	
3	7.23	0.73	0.63	1.05	6.97	0.15	0.21	1.13
	(2.57)	(1.55)	(1.27)		(2.19)	(0.28)	(0.38)	
8	6.01	0.44	−0.10	1.19	6.92	1.29	0.87	1.04
	(1.74)	(0.84)	(−0.17)		(2.22)	(2.59)	(1.66)	
High	6.14	0.73	0.50	1.28	7.67	2.75	1.61	1.18
	(1.38)	(0.69)	(0.45)		(2.29)	(3.08)	(1.77)	
H−L	−1.31	0.42	−0.08	0.14	1.81	4.24	2.05	−0.05
	(−0.45)	(0.29)	(−0.05)	(11.64)	(1.04)	(2.76)	(1.39)	(−3.88)

Table 1.9 Investment-Based Trading Strategies

The trading strategies are based on quintile stock portfolios with equal total market value. In Panel A, I rank stocks based on their asset growth at the beginning of each July. In Panel B, I rank stocks on their return-on-equity (ROE) at the beginning of the second month in each quarter. For each set of portfolios, value-weighted monthly returns are calculated for two trading strategies: holding the low asset growth or high ROE quintile ("Best 20%") and holding all but the high asset growth or low ROE ("Best 80%") quintiles. For each strategy, I report the mean characteristic selectivity measures (α) based on the DGTW benchmark and the mean annual turnover above that of the value-weighted index of all stocks (ΔTO) between July 1976 and June 2010. The exercise is repeated for the all stocks as well as six annually rebalanced size-B/M subsamples. The CS measures are in annualized percent, turnovers in decimals, and t-statistics are adjusted for heteroscedasticity and autocorrelations.

	All Stocks			Small-Growth			Small-Value			Mid-Growth			Mid-Value			Large-Growth			Large-Value		
	α	t_α	ΔTO	α	t_α	ΔTO	α	t_α	ΔTO	α	t_α	ΔTO	α	t_α	ΔTO	α	t_α	ΔTO	α	t_α	ΔTO
	Panel A: Asset Growth																				
Best 20%	0.78	1.58	0.61	0.90	0.79	0.37	0.99	0.85	0.39	0.62	0.72	0.44	−1.01	−1.37	0.44	0.81	1.00	0.57	1.00	1.31	0.50
Best 80%	0.41	2.25	0.14	1.74	6.97	0.05	0.47	2.20	0.06	1.15	3.78	0.07	−0.05	−0.22	0.07	0.32	1.38	0.10	0.07	0.35	0.11
	Panel B: ROE																				
Best 20%	1.86	2.94	1.33	8.56	7.40	1.32	7.13	8.79	1.70	4.61	4.85	1.29	3.86	4.84	1.67	1.13	1.28	1.44	2.64	3.00	1.76
Best 80%	0.75	4.17	0.39	2.23	4.09	0.23	1.34	3.34	0.35	1.45	3.47	0.30	0.81	2.85	0.38	0.45	1.81	0.36	0.61	2.36	0.43

Table 1.10 Changes in Mutual Fund Performance After Adjusting for Investment and Profitability

At the beginning of each July, I sort stocks into five portfolios based on size using the NYSE breakpoints, and then sequentially into five portfolios based on asset growth. Within each of the 25 portfolios, stocks are further sorted into five portfolios based on return-on-equity (ROE) at the beginning of each month. The three-way sort produces a total of 125 control portfolios for which the value-weighted monthly characteristic selectivity (CS) measures are calculated based on the DGTW benchmark. For each stock, I adjust its CS measure by subtracting the CS measure of its control portfolio. In Panel A, I report the cross-sectional means of the unadjusted CS measures (α), the adjusted CS measures ($\hat{\alpha}$), and the changes in CS measures ($\Delta\alpha$), averaged between July 1980 and June 2010. The CS measures are in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations. In Panel B, I report the time-series average fractions of funds whose annual performance estimates change more than a certain percentage or change signs after the adjustment.

	All Funds			Aggressive Growth			Growth			Growth and Income		
Panel A: Average Fund Performance												
	α	$\hat{\alpha}$	$\Delta\alpha$	α	$\hat{\alpha}$	$\Delta\alpha$	α	$\hat{\alpha}$	$\Delta\alpha$	α	$\hat{\alpha}$	$\Delta\alpha$
Full Sample	0.46	0.22	−0.24	1.17	0.81	−0.36	0.43	0.18	−0.25	0.11	0.00	−0.11
	(1.52)	(0.88)	(−3.04)	(1.53)	(1.33)	(−1.69)	(1.40)	(0.71)	(−2.89)	(0.47)	(0.01)	(−1.20)
First Half	0.53	0.26	−0.28	1.32	0.71	−0.60	0.45	0.19	−0.25	0.16	0.11	−0.06
	(1.09)	(0.65)	(−2.20)	(1.14)	(0.79)	(−1.94)	(0.95)	(0.50)	(−2.00)	(0.62)	(0.49)	(−0.50)
Second Half	0.39	0.18	−0.21	1.03	0.91	−0.12	0.41	0.17	−0.24	0.06	−0.10	−0.16
	(1.09)	(0.60)	(−2.11)	(1.02)	(1.09)	(−0.41)	(1.05)	(0.50)	(−2.09)	(0.14)	(−0.35)	(−1.13)
Panel B: Individual Fund Performance												
	> 2%	> 4%	sign	> 2%	> 4%	sign	> 2%	> 4%	sign	> 2%	> 4%	sign
Full Sample	0.28	0.08	0.11	0.39	0.14	0.09	0.27	0.07	0.11	0.22	0.05	0.12
First Half	0.27	0.06	0.11	0.41	0.13	0.09	0.24	0.04	0.12	0.22	0.04	0.11
Second Half	0.28	0.10	0.11	0.37	0.15	0.09	0.29	0.10	0.11	0.22	0.06	0.12

Table 1.11 Changes in Mutual Fund Performance Related to Investment and Profitability

In Panel A, I rank mutual funds into deciles based on the style index for asset growth at the beginning of each quarter. Equal-weighted holding returns of the fund portfolios are calculated from January 1981 to December 2010. In Panel B, profitability portfolios are constructed similarly using the style index for ROE. For each set of portfolios, I report the unadjusted CS measures (α), the adjusted CS measures ($\hat{\alpha}$), and the changes in CS measures ($\Delta\alpha$). The CS measures are in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations.

	Panel A: Asset Growth			Panel B: ROE		
	α	$\hat{\alpha}$	$\Delta\alpha$	α	$\hat{\alpha}$	$\Delta\alpha$
Low	0.45	0.32	−0.13	−0.66	0.28	0.94
	(0.78)	(0.82)	(−0.50)	(−1.00)	(0.60)	(3.01)
3	0.52	0.25	−0.27	0.05	0.21	0.16
	(1.64)	(1.02)	(−2.24)	(0.14)	(0.68)	(1.56)
8	0.29	−0.04	−0.33	0.74	0.15	−0.59
	(0.50)	(−0.10)	(−1.70)	(1.98)	(0.54)	(−4.19)
High	0.23	0.33	0.10	1.90	0.60	−1.30
	(0.20)	(0.39)	(0.21)	(2.87)	(1.38)	(−4.20)
H−L	−0.22	0.01	0.23	2.56	0.32	−2.24
	(−0.15)	(0.01)	(0.33)	(2.51)	(0.54)	(−3.99)

Table 1.12 Changes in Mutual Fund Performance Related to Fund Activeness and Fund Size

In Panel A, I rank mutual funds into deciles based on active share at the beginning of each month. Equal-weighted holding returns of the fund portfolios are calculated from April 1981 to December 2006. In Panel C, I sort funds into deciles based on total net assets at the beginning of each quarter. Equal-weighted holding returns of the fund portfolios are calculated from July 1980 to June 2010. For each set of portfolios, I report the time-series averages of the unadjusted CS measures (α), the adjusted CS measures ($\hat{\alpha}$), and the changes in CS measures ($\Delta\alpha$). I also report the average style indices for size (ME), book-to-market (B/M), and momentum (MOM), as well as the adjusted indices for asset growth (AG*) and return-on-equity (ROE*). The CS measures are in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations.

	Panel A: Active Share							
	α	$\hat{\alpha}$	$\Delta\alpha$	ME	B/M	MOM	AG*	ROE*
Low	0.16	−0.07	−0.23	0.95	0.30	0.54	0.00	0.01
	(0.88)	(−0.52)	(−2.36)					
3	0.38	0.03	−0.35	0.96	0.30	0.56	0.01	0.01
	(1.01)	(0.11)	(−2.87)					
8	0.21	−0.10	−0.31	0.83	0.34	0.60	0.04	0.01
	(0.30)	(−0.18)	(−1.38)					
High	0.87	0.08	−0.79	0.72	0.40	0.58	0.03	0.03
	(1.01)	(0.12)	(−2.86)					
H−L	0.71	0.14	−0.56					
	(0.86)	(0.23)	(−2.08)					
	Panel B: Fund Size							
	α	$\hat{\alpha}$	$\Delta\alpha$	ME	B/M	MOM	AG*	ROE*
Small	0.72	0.20	−0.53	0.86	0.37	0.57	0.02	0.02
	(2.14)	(0.70)	(−5.01)					
3	0.64	0.30	−0.34	0.87	0.36	0.58	0.02	0.01
	(1.92)	(1.04)	(−3.62)					
8	0.63	0.37	−0.26	0.89	0.35	0.59	0.02	0.01
	(1.56)	(1.10)	(−2.44)					
Large	0.22	0.24	0.03	0.93	0.37	0.56	0.01	−0.01
	(0.68)	(0.91)	(0.31)					
L−S	−0.51	0.05	0.55					
	(−1.82)	(0.21)	(4.84)					

Table 1.13 Characteristic-Based Benchmarks, Passive Stock Portfolios

At the beginning of each July, I sort stocks into quintiles with equal total market value based on asset growth, book-to-market (B/M), net stock issues, or total accruals. At the beginning of each month, stocks are also sorted into quintiles based on their momentum, return-on-equity (ROE), standardized earnings surprise (SUE), failure probability, or idiosyncratic volatility (IVOL). For each set of portfolios, value-weighted portfolio returns are calculated from July 1975 to June 2010. I report the average benchmark-adjusted returns for the DGTW benchmark (DGTW), the investment-based benchmark (INV), and the comprehensive benchmark (ALL). The estimates are in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations.

	α_{DGTW}	α_{INV}	α_{ALL}	α_{DGTW}	α_{INV}	α_{ALL}	α_{DGTW}	α_{INV}	α_{ALL}
	B/M			Momentum			Asset Growth		
Low	−0.49	−1.33	−0.57	−0.16	−1.30	0.51	0.86	−0.10	−0.07
	(−0.61)	(−1.74)	(−1.18)	(−0.83)	(−1.09)	(2.12)	(1.72)	(−0.72)	(−0.68)
High	−0.21	1.67	0.40	0.43	2.57	−0.05	−1.88	−0.12	−0.07
	(−0.41)	(2.25)	(0.97)	(1.51)	(1.90)	(−0.18)	(−2.29)	(−0.79)	(−0.51)
H−L	0.28	3.00	0.97	0.59	3.87	−0.57	−2.74	−0.02	0.00
	(0.23)	(2.18)	(1.26)	(1.68)	(1.64)	(−1.30)	(−2.35)	(−0.09)	(−0.01)
	ROE			SUE			Failure Probability		
Low	−3.21	−0.35	−0.30	−1.66	−0.99	−0.54	0.42	−0.32	−0.61
	(−4.52)	(−1.95)	(−2.07)	(−2.92)	(−2.17)	(−1.51)	(0.67)	(−0.4)	(−1.28)
High	2.08	0.26	0.02	1.59	1.45	0.69	−0.91	−0.30	0.24
	(3.47)	(0.85)	(0.11)	(3.21)	(3.01)	(1.77)	(−0.96)	(−0.28)	(0.34)
H−L	5.29	0.61	0.32	3.25	2.44	1.23	−1.33	0.02	0.85
	(4.85)	(1.63)	(1.27)	(3.54)	(3.13)	(1.99)	(−0.97)	(0.01)	(0.84)
	IVOL			Net Stock Issues			Total Accruals		
Low	0.28	−0.19	−0.15	1.36	1.15	0.85	0.51	1.22	0.50
	(0.43)	(−0.26)	(−0.32)	(2.53)	(2.49)	(2.28)	(0.71)	(1.56)	(0.96)
High	−1.14	−0.67	−0.64	−2.27	−0.65	−0.74	−1.28	−1.95	−1.14
	(−1.18)	(−0.64)	(−0.92)	(−3.51)	(−1.24)	(−1.96)	(−2.00)	(−3.21)	(−2.37)
H−L	−1.41	−0.48	−0.49	−3.63	−1.80	−1.59	−1.80	−3.17	−1.64
	(−0.95)	(−0.29)	(−0.47)	(−3.50)	(−2.37)	(−2.66)	(−1.80)	(−3.23)	(−2.21)

Table 1.14 Characteristic-Based Benchmarks, Mutual Fund Portfolios

At the beginning of each July, I rank stocks into percentiles based on book-to-market (B/M), asset growth, net stock issues, or total accruals. At the beginning of each month, stocks are also ranked into percentiles based on momentum, return-on-equity (ROE), standardized earnings surprise (SUE), failure probability, or idiosyncratic volatility (IVOL). For each fund, its style indices are calculated as the value-weighted characteristic rankings of its latest stock holdings. At the beginning of each quarter, I sort funds into deciles based on their style indices. The fund portfolios are equal-weighted, and the results are based on gross holding returns between July 1980 and June 2010. I report the average benchmark-adjusted returns for the DGTW benchmark (DGTW), the investment-based benchmark (INV), and the comprehensive benchmark (ALL). The estimates are in annualized percent and the t-statistics in the parentheses are adjusted for heteroscedasticity and autocorrelations.

	α_{DGTW}	α_{INV}	α_{ALL}	α_{DGTW}	α_{INV}	α_{ALL}	α_{DGTW}	α_{INV}	α_{ALL}
	B/M			Momentum			Asset Growth		
Low	0.34	0.11	0.13	−0.08	−0.09	0.05	0.50	0.49	0.22
	(0.33)	(0.09)	(0.18)	(−0.14)	(−0.09)	(0.11)	(0.85)	(0.81)	(0.55)
High	0.20	0.84	0.19	0.98	1.22	0.38	−0.69	−0.24	−0.34
	(0.33)	(1.15)	(0.39)	(0.99)	(0.72)	(0.49)	(−0.57)	(−0.19)	(−0.42)
H−L	−0.13	0.73	0.06	1.06	1.31	0.34	−1.19	−0.74	−0.56
	(−0.09)	(0.42)	(0.06)	(0.82)	(0.54)	(0.34)	(−0.74)	(−0.44)	(−0.56)
	ROE			SUE			Failure Probability		
Low	−0.95	0.31	0.07	−0.56	−0.42	−0.16	1.75	1.83	0.93
	(−1.52)	(0.55)	(0.16)	(−1.13)	(−0.74)	(−0.42)	(2.20)	(1.58)	(1.52)
High	1.42	0.69	0.19	1.10	1.15	0.22	−1.02	−0.64	−0.48
	(2.21)	(1.05)	(0.46)	(1.68)	(1.63)	(0.44)	(−1.44)	(−0.76)	(−0.87)
H−L	2.36	0.38	0.12	1.65	1.57	0.38	−2.77	−2.47	−1.41
	(2.40)	(0.45)	(0.21)	(1.91)	(1.72)	(0.59)	(−2.26)	(−1.40)	(−1.50)
	IVOL			Net Stock Issues			Total Accruals		
Low	0.57	0.28	0.20	0.92	0.53	0.37	0.45	0.59	0.31
	(1.05)	(0.42)	(0.50)	(1.86)	(0.93)	(1.11)	(0.87)	(1.03)	(0.78)
High	−0.81	−0.49	−0.74	−0.90	−0.14	−0.25	0.19	−0.24	−0.13
	(−0.71)	(−0.32)	(−0.84)	(−0.75)	(−0.10)	(−0.29)	(0.24)	(−0.29)	(−0.22)
H−L	−1.38	−0.77	−0.94	−1.82	−0.66	−0.62	−0.26	−0.83	−0.45
	(−0.91)	(−0.38)	(−0.84)	(−1.20)	(−0.37)	(−0.61)	(−0.26)	(−0.86)	(−0.63)

Table 1.15 Characteristic-Matched Benchmarks, Mutual Fund Performance

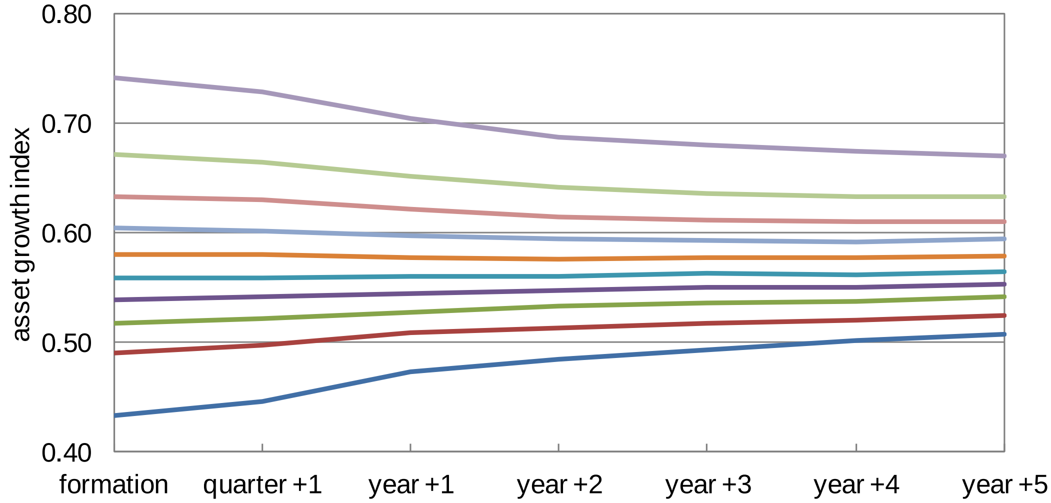
Monthly mutual fund gross holding returns are decomposed into three attributes of average style (AS), characteristic selectivity (CS), and characteristic timing (CT) using the DGTW benchmark, the investment-based benchmark (INV) or the comprehensive benchmark (ALL). The monthly return attributes are then averaged equally across all funds existing during the month, and the time-series averages across all months are presented along with the t-statistics. For each fund, the tracking error volatility (σ_{TE}) is computed as the time-series standard error of the fund's monthly CS measures. The cross-section average of tracking error volatilities is then calculated across all funds with at least 36 monthly returns. The attribute measures and tracking error volatilities are in annualized percent. The sample period is from July 1980 to June 2010 except for the AS and CT attributes, where it starts from July 1981.

	All Funds						Aggressive Growth					
	AS	CS	t_{CS}	CT	t_{CT}	σ_{TE}	AS	CS	t_{CS}	CT	t_{CT}	σ_{TE}
DGTW	11.50	0.33	1.09	0.22	1.03	6.88	11.35	0.68	0.90	0.49	1.62	9.08
INV	11.67	0.28	0.85	0.12	0.82	7.52	11.61	0.77	0.89	0.19	1.02	9.67
ALL	11.71	0.08	0.32	0.27	1.03	6.10	11.51	0.38	0.64	0.62	1.87	8.03
	Growth						Growth and Income					
	AS	CS	t_{CS}	CT	t_{CT}	σ_{TE}	AS	CS	t_{CS}	CT	t_{CT}	σ_{TE}
DGTW	11.52	0.32	1.05	0.29	1.27	6.88	11.46	0.20	0.79	−0.04	−0.15	5.01
INV	11.76	0.25	0.74	0.14	0.89	7.55	11.48	0.12	0.42	0.03	0.18	5.43
ALL	11.70	0.09	0.34	0.33	1.26	6.11	11.72	−0.02	−0.12	−0.06	−0.19	4.44

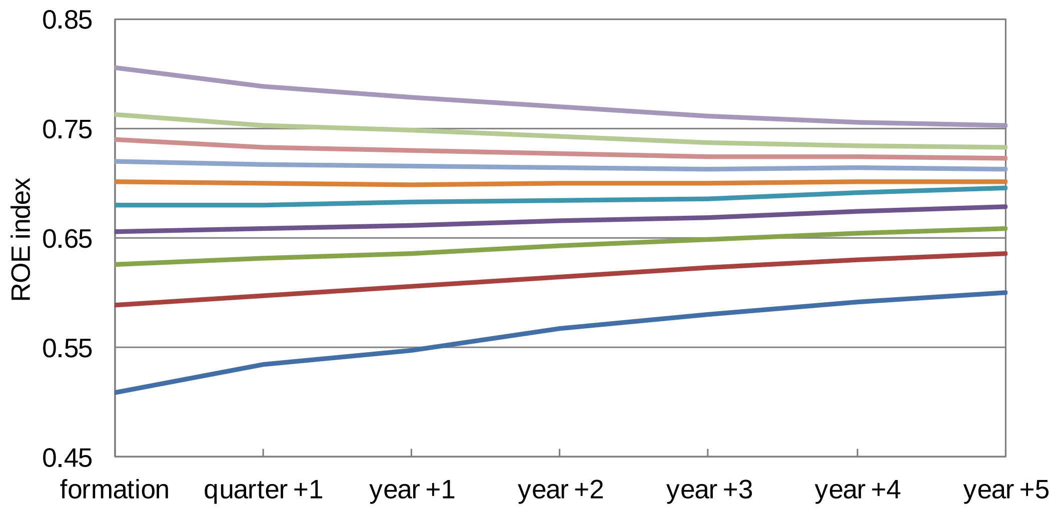
Figure 1.1 Persistence in Characteristics of Mutual Fund Stock Holdings

In Panel A, mutual funds are sorted into deciles at the beginning of each quarter based on the style index for asset growth. Similarly in Panel B, fund deciles are formed quarterly using the style index return-on-equity (ROE). The figures show the average style indices for the fund portfolios at the formation date and their future average style indices for up to five years.

Panel A: Asset Growth



Panel B: ROE



Appendices

A Mutual Fund Data

Mutual fund data come from three sources. First, the Thomson-Reuters (TR) mutual fund database provides the data on quarterly equity holdings (items CUSIP and SHARES), quarterly report date (item RDATE), quarterly total net assets (item ASSETS) and investment objective codes (item IOC). Second, the CRSP mutual fund database provides data on monthly net fund returns (item MRET), monthly total net assets (item MTNA), annual turnovers (item TURN_RATIO) and annual expense ratios (item EXP_RATIO). Multiple share classes in the CRSP database are aggregated to eliminate duplicates. Finally, the MFLINKs product of Wharton Research Data Services (WRDS) provides an unique fund identifier (item WFICN) which is matched with fund identifiers from the TR database (item FUNDNO) and the CRSP database (item CRSP_FUNDNO). I use the WRDS fund identifier because it provides consistent fund identification over time and also helps merge data from the TR database and the CRSP database. See the appendices in Wermers (1999, 2000) for detailed introductions to the databases and data manuals from WRDS for more technical details.

B Mutual Fund Benchmarks

B.1 The Characteristic-Based Benchmark of Daniel, Grinblatt, Titman, and Wermers (1997)

At the beginning of July in each year t, all common stocks from NYSE, AMEX, and NASDAQ are sorted into quintiles based on their size at the end of June using the NYSE breakpoints. Within each size quintile, stocks are further sorted into quintiles based on their (industry-adjusted) B/M for the fiscal year ending in $t-1$. Finally, within each of the 25 size-B/M portfolios, stocks are sorted into quintiles based on their momentum. Momentum is measured as the average return between June of $t-1$ to May of t. In total, 125 benchmark portfolios are formed and their value-weighted returns are used as the benchmark returns for their member stocks.

Annual benchmark assignments and monthly benchmark returns are obtained from Russ Wermers' website for the period from July 1975 to June 2010.[16]

B.2 Factor-Based Benchmarks

I employ two conventional factor models that are standard in the literature: the Fama-French three-factor model (Fama and French (1993)) and the Carhart four-factor model (Carhart (1997)):

$$r_t - r_{f,t} = \alpha_{FF} + \beta_{MKT}MKT_t + \beta_{SMB}SMB_T + \beta_{HML}HML_t + u_t,$$
$$r_t - r_{f,t} = \alpha_{Caht} + \beta_{MKT}MKT_t + \beta_{SMB}SMB_T + \beta_{HML}HML_t + \beta_{MOM}MOM_t + v_t,$$

in which r_t is the portfolio/fund return during month t, $r_{f,t}$ is the risk-free rate in t, α_{FF} is the abnormal return relative to the Fama-French model, α_{Caht} is the abnormal return relative to the Carhart model, MKT_t, SMB_t, HML_t, and MOM_t are respectively the market, size, book-to-market, and momentum factors, the βs represent the corresponding factor exposures of the fund return, and u_t and v_t are the residual terms. Monthly risk-free rates (one-month T-Bill rate) and factor returns are obtained from Ken French's website.

C Variable Definitions

- *Size* – Size, or market equity, is share price times the number of shares outstanding from the CRSP.

- *Book-to-Market* (B/M) – At the beginning of July in year t, a stock's book-to-market is its book equity for the fiscal year ending in $t-1$ divided by its market equity at the end of December in year $t-1$. Book equity is shareholders equity, plus balance sheet deferred taxes and investment tax credit (Compustat annual

[16] The DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/. This version is slightly different from the original DGTW benchmark and is adapted from Wermers (2004).

item TXDITC) if available, minus the book value of preferred stock. Depending on availability, I use stockholders equity (item SEQ), or common equity (item CEQ) plus the carrying value of preferred stock (item PSTK), or total assets (item AT) minus total liabilities (item LT) as shareholders equity. Depending on availability, I use redemption (item PSKTRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock. Market equity is market capitalization from the Compustat (items PRCC_F times CSHO) or CRSP.

- *Momentum* – For month t, a stock's momentum is the twelve-month average return from month $t - 13$ to $t - 2$. Following Daniel, Grinblatt, Titman, and Wermers (1997), I require at least six monthly returns for the calculation.

- *Asset Growth* – Following Cooper, Gulen, and Schill (2008), I measure asset growth as the annual growth rate in total assets (Compustat annual item AT).

- *Return-on-Equity* (ROE) – Following Chen, Novy-Marx, and Zhang (2011), I measure return-on-equity as quarterly income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged book equity from the latest available quarterly reports. 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. Depending on availability, I 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. I use redemption value (item PSTKRQ) if available, or carrying value (item PSTKQ) for the book value of preferred stock. Quarterly reports are deemed available right after its public earnings announcement date (item RDQ) or four months after the fiscal quarter end (in that order).

- *Earnings Surprise* – Following Foster, Olsen, and Shevlin (1984), I measure earnings surprises as Standardized Unexpected Earnings (SUE). SUE is the change in the most recently announced quarterly earnings per share (Compustat quarterly item EPSPXQ) from its value four quarters ago divided by the standard deviation of quarterly earnings changes over the prior eight quarters. For accuracy, I require a minimum of six quarterly observations.

- *Failure Probability* – Following Campbell, Hilscher, and Szilagyi (2008, the third column in Table 4), I measure failure probability as:

$$
\begin{aligned}
P_t \equiv & -9.164 - 20.264 NIMTAAVG_t + 1.416 TLMTA_t \\
& -7.129 EXRETAVG_t + 1.411 SIGMA_t - 0.045 RSIZE_t \\
& -2.132 CASHMTA_t + 0.075 MB_t - 0.058 PRICE_t \qquad (1.6) \\
NIMTAAVG_{t-1,t-12} \equiv & \tfrac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t-1,t-3} + \cdots + \phi^9 NIMTA_{t-10,t-12}) \\
EXRETAVG_{t-1,t-12} \equiv & \tfrac{1-\phi}{1-\phi^{12}}(EXRET_{t-1} + \cdots + \phi^{11} EXRET_{t-12})
\end{aligned}
$$

in which $\phi = 2^{-1/3}$. NIMTA is net income (Compustat quarterly item NIQ) divided by the sum of market equity and total liabilities (item LTQ). $EXRET \equiv \log(1 + R_{it}) - \log(1 + R_{S\&P500,t})$ is the monthly log stock return in excess of the S&P 500 log return. TLMTA is the ratio of total liabilities (item LTQ) divided by the sum of market equity and total liabilities. SIGMA is the annualized three-month rolling sample standard deviation: $\sqrt{\frac{252}{N-1}\sum_{k\in t-1,t-1,t-3} r_k^2}$, in which k is the index of trading days in months $t-1$, $t-2$, and $t-3$, r_k is the daily stock return, and N is the total number of trading days in the three-month period. SIGMA is treated as missing if there are less than five nonzero observations. RSIZE, the relative size, is measured as the log ratio of market equity to that of the S&P 500 index. CASHMTA is the ratio of cash and short-term investments (item CHEQ) divided by the sum of market equity and total liabilities. MB is the market-to-book equity, in which book equity is measured in the same way as the denominator of ROE. Following Campbell et al., I add 10% of the difference between market and book equity to the book equity to alleviate measurement issues for extremely small book equity values. For firm-month observations that still have negative book equity after this adjustment, I replace these negative values with $1 to ensure that the market-to-book ratios for these firms are in the right tail of the distribution. PRICE is log price per share, truncated above at $15. I further eliminate stocks with a price less than $1. Following Campbell et al., I winsorize each of the variables in the right-hand side of equation (1.6) at the 5th and 95th percentiles of all firm-month observations.

- *Idiosyncratic Volatility* – Following Ang, Hodrick, Xing, and Zhang (2006), I measure a stock's idiosyncratic volatility as the standard deviation of the residuals from the Fama-French three-factor regression using daily returns over the previous month. For accuracy, I require a minimum of 15 daily stock returns.

- *Net Stock Issues* – Following Fama and French (2008), I measure net stock issues as the natural log of the ratio of the split-adjusted shares outstanding to the one-year-lagged split-adjusted shares outstanding. The split-adjusted shares outstanding is shares outstanding (Compustat annual item CSHO) times the adjustment factor (item ADJEX_C).

- *Total Accruals* – Following Sloan (1996), I measure total accruals as changes in non-cash working capital minus depreciation expense scaled by the average total assets in the latest two years. The non-cash working capital is the change in non-cash current assets minus the change in current liabilities less short-term debt and taxes payable:

$$TAC \equiv (\Delta CA - \Delta CASH) - (\Delta CL - \Delta STD - \Delta TP) - DP, \tag{1.7}$$

in which 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 short-term debt (item DLC), ΔTP is the change in income taxes payable (item TXP), and DP is depreciation and amortization expense (item DP).

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CHAPTER II

Cross-Sectional Tobin's Q[‡]

Abstract

The neoclassical investment model matches cross-sectional asset prices both in first differences and in *levels*. With ten book-to-market deciles as the testing portfolios, the investment model largely matches the Tobin's Q spread, while maintaining a good fit for the average return spread across the extreme deciles. The model's fit results from three aspects of our econometric strategy: (i) We test the model at the portfolio level to alleviate the impact of measurement errors; (ii) we match the first moment to mitigate the impact of temporal misalignment between asset prices and investment; and (iii) we allow for nonlinear marginal costs of investment. The model also does a good job in matching asset price levels within each industry, allowing technological heterogeneity across industries. Our evidence suggests that any differences between the intrinsic value and the market value of equity tend to dissipate in the long run.

[‡] This chapter is coauthored with Frederico Belo (University of Minnesota; email: fbelo@umn.edu) and Lu Zhang (Ohio State University and NBER; e-mail: zhanglu@fisher.osu.edu). For helpful comments, we thank Andrew Abel, Kerry Back, Gurdip Bakshi, Jonathan Berk, Mark Flannery, Vito Gala, Eric Ghysels, Bob Goldstein, Rick Green, Burton Hollifield, Kewei Hou, Pete Kyle, Mark Loewenstein, Jay Ritter, Paulo Rodrigues, Neng Wang, Toni Whited, René Stulz, and seminar participants at the 2010 CEPR/Studienzentrum Gerzensee European Summer Symposium in Financial Markets, Duke University, the 2010 European Finance Association Annual Meetings, Federal Reserve Bank of New York, Michigan State University, Shanghai University of Finance and Economics, Tsinghua University, the 2010 University of British Columbia Phillips, Hager and North Centre for Financial Research Summer Finance Conference, The Ohio State University, University of Florida, University of Maryland, and University of Minnesota.

2.1 Introduction

What determines equity valuation? This economic question is immensely important in practice. A vast literature has built on present value models such as the dividend discounting and the residual income models for valuation purposes (e.g., Ohlson (1995), Dechow, Hutton, and Sloan (1999), and Frankel and Lee (1998)). Widely practiced in financial services industry, valuation is at the core of standard business school curriculum around the world, with many textbook treatments (e.g., Palepu and Healy (2008), Koller, Goedhart, and Wessles (2010), and Penman (2010)). Working from the perspective of investors' demand of risky securities, the traditional valuation approach aims to calculate the present value of future dividends. Although conceptually sound, its implementation often involves ad hoc assumptions that seem to leave at least some room for an alternative approach.

In asset pricing, the cross section of valuation is virtually a virgin territory. Reflecting on the surprising lack of valuation research in asset pricing, Cochrane (2011, p. 1063) writes:

> [W]e have to answer the central question, what is the source of *price* variation? When did our field stop being 'asset pricing' and become 'asset expected returning'? Why are betas exogenous? A lot of price variation comes from discount-factor news. What sense does it make to 'explain' expected returns by the covariation of expected return shocks with market market return shocks? Market-to-book ratios should be our *left-hand* variable, the thing we are trying to *explain*, not a sorting characteristic for expected returns. Focusing on expected returns and betas rather than prices and discounted cashflows makes sense in a two-period or i.i.d. world, since in that case betas are all cashflow betas. It makes much less sense in a world with time-varying discount rates (original emphasis).

We take a first stab at the valuation question from the perspective of managers' *supply* of risky securities. The basic idea is simple: Managers, if behaving optimally, will adjust the supply of capital assets to respond to their market price movements.

As such, we can back out a given asset's market value from managers' cost of supplying such an asset. Technically, we develop the neoclassical investment model as a valuation tool to pin down the levels (Tobin's Q) of cross-sectional asset prices, while maintaining a good fit for the first differences (stock returns). We incorporate corporate taxes, leverage, and nonlinear marginal costs of investment into the baseline investment model. The key valuation equation emerges under constant returns to scale (i.e. the Hayashi (1982) conditions): Tobin's Q equals marginal q, which can be inferred from the investment data via a specified adjustment costs function. We use generalized methods of moments (GMM) to evaluate the model's fit in matching average Tobin's Q across the book-to-market deciles. We use these deciles because of their large spread in Tobin's Q (the value spread) as well as in average returns (the value premium).

In general equilibrium, the demand approach and the supply approach to valuation are equivalent: One can read the price from either the demand or the supply curve of an asset. However, we see three practical advantages of the supply approach over the present value-based demand approach. First, the only input that the supply approach requires is the current-period's investment-to-capital. Through the functional form of the marginal costs of investment, investment-to-capital gives the shadow price of physical capital, and allows us to value a firm's installed capital stock. As such, the supply approach relieves us of the burden of forecasting earnings or cash flows many years into the future, a task that is challenging but necessary to implement the demand approach.

Second, by equating Tobin's Q directly to the marginal costs of investment, the supply approach does not need to take a stand on the discount rate. It is well known that the valuation estimates from the standard present value models are extremely sensitive to the assumed discount rate.[1] Third, at least in principle, the parameter

[1] For example, Lundholm and Sloan (2007, p. 193) lament: "None of the standard finance models

estimates from the supply approach are technology-driven "deep" parameters, which should be invariant to changes in optimizing behavior and economic policy per Lucas (1976). As such, the parameters via structural estimation should be more stable than the non-structural parameters such as the discount rate in the standard present value models.

Our key finding is that the neoclassical investment model matches cross-sectional asset prices both in first differences and in levels. When we use the investment model to match the Tobin's Q moments only, the model predicts a Tobin's Q spread of 2.83, which is about 94% of the spread observed in the data, 3.01. Across the book-to-market deciles, the average magnitude of the model errors is 0.17, which is less than 11% of the average Tobin's Q across the deciles, 1.58. A scatter plot of average predicted average Tobin's Q in the model against average realized Tobin's Q in the data across the testing portfolios is largely aligned with the 45-degree line. Also, the model fits the valuation levels with low adjustment costs that amount to 1.61% of sales.

Adding expected return moments in the GMM does not affect the model's fit on the Q moments. The fit on the levels is achieved without sacrificing a good fit on expected returns. The alpha of the high-minus-low decile is only -1.08% per annum, which is substantially smaller than the alphas from the CAPM (14.61%), the Fama-French (1993) three-factor model (6.71%), and the Carhart (1997) four-factor model (6.82%). However, the average magnitude of the alphas across the book-to-market deciles in the investment model is 1.96%, which is smaller than that from the CAPM (4.53%), but larger than those from the Fama-French model (1.46%) and from the

provide estimates that describe the actual data very well. The discount rate that you use in your valuation has a large impact on the result, yet you will rarely feel very confident that the rate you have assumed in the right one. The best we can hope for is a good understanding of what the cost of capital represents and some ballpark range for what a reasonable estimate might be." Penman (2010, p. 666) write: "Compound the error in beta and the error in the risk premium and you have a considerable problem. The CAPM, even if true, is quite imprecise when applied. Let's be honest with ourselves: No one knows what the market risk premium is. And adopting multifactor pricing models adds more risk premiums and betas to estimate. These models contain a strong element of smoke and mirrors."

Carhart model (1.50%).

The investment model also does a good job in matching the Q levels at the industry level. With the book-to-market quintiles within each industry as the testing portfolios, the average magnitude of the Q errors is 0.20, which is less than 11% of the Tobin's Q averaged across the industries, 1.85. The model predicts a Tobin's Q spread of 1.69, which is about 85% of the spread of 1.99 averaged across the industries. Because average Q is estimated more precisely than average returns, using the Q moments facilitates greatly the identification of the model's parameters, and increases the power of the tests. These benefits are especially important at the more disaggregated industry level, in which expected returns are noisy. As such, we argue that cross-sectional valuation should be taken seriously as a new dimension of the data to discipline structural financial models.

The neoclassical investment framework is originally developed to understand investment behavior, both at the aggregate level and at the firm level. The failure of this framework in matching levels is well known in the literature on standard investment regressions, which in effect test the model in levels (e.g., Chirinko (1993)). Our key finding that the model matches the cross section of Tobin's Q (as well as the cross section of returns) might be surprising. The crux lies in three aspects of our econometric approach. First, we conduct the estimation at the portfolio level, which mitigates the impact of measurement errors in Tobin's Q and other characteristics, errors that are likely responsible for the empirical failure of investment regressions (e.g., Erickson and Whited (2000)).

Second, we explore whether investment is a sufficient statistic for average Tobin's Q. Focusing on the first moment alleviates the impact of any temporal misalignment between asset prices and investment that can arise from, for example, investment lags. Third, while investment regressions are derived under the standard assumption of quadratic adjustment costs, we allow the marginal cost of investment to be nonlinear. We show that this nonlinearity is crucial for the model's fit. With standard quadratic adjustment costs, the model implied Tobin's Q spread is only 0.57, which is less than 19% of the spread in the data. Intuitively, Tobin's Q is only proportional to investment-to-capital in the quadratic model. With the nonlinearity, Tobin's Q is convex in investment-to-capital. As such, for a given magnitude of spread in investment-to-capital, the convexity magnifies the investment spread so as to produce a larger spread in Tobin's Q.

Our key finding has important implications. Shiller (1989, 2000) argues that measurement errors in Tobin's Q that are likely responsible for the failure of investment regressions can arise from the differences between the intrinsic value and the market value of equity (see also Bond and Cummins (2000)). Our evidence that the neoclassical investment model matches cross-sectional Tobin's Q suggests that the market value of equity and investment data are well aligned on average, and that, at the minimum, the differences between the intrinsic value of equity and the market value of equity are short-lived and tend to dissipate in the long run.

Our work contributes to the literature that studies the interaction between investment and asset prices. Cochrane (1991, 1996) is the first to use the investment model to study asset prices. Cooper and Priestley (2009) show that the output gap is a strong predictor of stock returns. Liu, Whited, and Zhang (2009) study how stock returns related to earnings surprises, book-to-market, and investment. Jermann (2010, 2011) studies the equity premium and the term structure of interest rates derived from firms' optimality conditions. Cooper and Priestley (2011) show that the negative relation between investment and average stock returns is likely due to risk. Gourio (2011) examines the effect of putty-clay technology on stock return volatility. Imrohoroglu and Tuzel (2011) examine the link between firm-level total factor productivity and expected returns. Jones and Tuzel (2012) study the link between inventory investment and the cost of capital. However, none of the aforementioned studies tackle the valuation issue. Pástor and Veronesi (2003, 2006) examine aggregate stock market valuation. We differ by focusing on the large cross-sectional differences in Tobin's Q.

The rest of the paper unfolds as follows. We present the investment model and derive its implications for cross-sectional Tobin's Q and stock returns in Section 2.2. We discuss econometric and data issues in Section 2.3, present the estimation results in Section 2.4, and conclude in Section 2.5.

2.2 The Model of the Firms

We specify a neoclassical model of investment to derive a valuation equation. Time is discrete and the horizon infinite. Firms choose costlessly adjustable inputs each period, taking their prices as given, to maximize operating profits (revenues minus expenditures on these inputs). Taking the operating profits as given, firms optimally choose investment and debt to maximize the market equity.

The operating profits function for firm i at time t is $\Pi(K_{it}, X_{it})$, in which K_{it} is capital and X_{it} is a vector of exogenous aggregate and firm-specific shocks. We assume that the firm has a Cobb-Douglas production function with constant returns to scale. This assumption implies that $\Pi(K_{it}, X_{it}) = K_{it}\partial\Pi(K_{it}, X_{it})/\partial K_{it}$, and that the marginal product of capital, $\partial\Pi(K_{it}, X_{it})/\partial K_{it} = \kappa Y_{it}/K_{it}$, in which κ is the capital's share and Y_{it} is sales.

Capital depreciates at an exogenous rate of δ_{it}. We allow δ_{it} to be firm-specific and time-varying:

$$K_{it+1} = I_{it} + (1 - \delta_{it})K_{it}, \tag{2.1}$$

in which I_{it} is investment. Firms incur adjustment costs when investing. The adjustment costs function, denoted $\Phi(I_{it}, K_{it})$, is increasing and convex in I_{it}, is decreasing in K_{it}, and has constant returns to scale in I_{it} and K_{it}. We allow the marginal costs of investment to be nonlinear:

$$\Phi_{it} \equiv \Phi(I_{it}, K_{it}) = \frac{1}{\nu}\left(\eta \frac{I_{it}}{K_{it}}\right)^{\nu} K_{it}, \tag{2.2}$$

in which $\eta > 0$ is the slope adjustment cost parameter and $\nu > 1$ is the curvature adjustment cost parameter. The case with $\nu = 2$ reduces to the standard quadratic functional form.[2]

We allow firms to finance investment with one-period debt. At the beginning of time t, firm i issues an amount of debt, denoted B_{it+1}, which must be repaid at the beginning of time $t+1$. Let r^B_{it} denote the gross corporate bond return on B_{it}. We can write taxable corporate profits as operating profits minus depreciation, adjustment costs, and interest expense: $\Pi(K_{it}, X_{it}) - \delta_{it}K_{it} - \Phi(I_{it}, K_{it}) - (r^B_{it} - 1)B_{it}$. Let τ_t be the corporate tax rate. We define the payout of firm i as:

$$\begin{aligned} D_{it} \;\; \equiv \;\; & (1-\tau_t)[\Pi(K_{it}, X_{it}) - \Phi(K_{it}, K_{it})] - I_{it} \\ & + B_{it+1} - r^B_{it}B_{it} + \tau\delta_{it}K_{it} + \tau_t(r^B_{it} - 1)B_{it}, \end{aligned} \tag{2.3}$$

in which $\tau_t\delta_{it}K_{it}$ is the depreciation tax shield and $\tau_t(r^B_{it} - 1)B_{it}$ is the interest tax shield.

Let M_{t+1} be the stochastic discount factor from t to $t+1$, which is correlated with the aggregate component of the productivity shock X_{it}. The firm chooses optimal

[2] We place the slope adjustment cost parameter η inside the parentheses of equation (2.2) to make the unit of η independent of the curvature parameter. With a free curvature parameter, the mean of $(I_{it}/K_{it})^{\nu}$ varies substantially with the curvature. The mean is very small when the curvature is high, and large when ν is low. As such, when η is placed outside the parentheses as in Merz and Yashiv (2007), the point estimate of η is affected by the large change in mean of $(I_{it}/K_{it})^{\nu}$. In particular, its point estimate can vary substantially between zero and, when the curvature parameter is high, values greater than 10,000, causing stability problems in the estimation.

capital investment and debt to maximize the cum-dividend market value of equity:

$$V_{it} \equiv \max_{\{I_{it+\triangle t}, K_{it+\triangle t+1}, B_{it+\triangle t+1}\}_{\triangle t=0}^{\infty}} E_t \left[\sum_{\triangle t=0}^{\infty} M_{t+\triangle t} D_{it+\triangle t} \right], \tag{2.4}$$

subject to a transversality condition given by $\lim_{T\to\infty} E_t[M_{t+T} B_{it+T+1}] = 0$.

To express firm i's equilibrium market value of equity and stock return as a function of observable firm characteristics, we let $P_{it} \equiv V_{it} - D_{it}$ be the ex-dividend equity value and the firm's valuation ratio or Tobin's Q as $Q_{it} \equiv (P_{it} + B_{it+1})/K_{it+1}$. The first-order condition of maximizing equation (2.4) with respect to I_{it} implies that:

$$Q_{it} = 1 + (1-\tau_t)\eta^{\nu} \left(\frac{I_{it}}{K_{it}} \right)^{\nu-1}. \tag{2.5}$$

As such, Tobin's Q is a nonlinear function of investment-to-capital, I_{it}/K_{it}.[3]

In addition, combining the first-order conditions of maximizing equation (2.4) with respect to I_{it} and $K_{it+\triangle t+1}$ implies that $E_t[M_{t+1} r^I_{it+1}] = 1$, in which r^I_{it+1} is the investment return, defined as:

$$\begin{aligned} r^I_{it+1} \quad \equiv \quad & \left((1-\tau_{t+1}) \left[\kappa \frac{Y_{it+1}}{K_{it+1}} + \frac{\nu-1}{\nu} \left(\eta \frac{I_{it+1}}{K_{it+1}} \right)^{\nu} \right] + \delta_{it+1}\tau_{t+1} + (1-\delta_{it+1}) \right. \\ & \left. \left[1 + (1-\tau_{t+1})\eta^{\nu} \left(\frac{I_{it+1}}{K_{it+1}} \right)^{\nu-1} \right] \right) \Big/ \left(1 + (1-\tau_t)\eta^{\nu} \left(\frac{I_{it}}{K_{it}} \right)^{\nu-1} \right). \end{aligned} \tag{2.6}$$

The first-order condition of maximizing equation (2.4) with respect to $B_{it+\triangle t+1}$ implies that $E_t[M_{t+1} r^{Ba}_{it+1}] = 1$, in which $r^{Ba}_{it+1} \equiv r^B_{it+1} - (r^B_{it+1} - 1)\tau_{t+1}$ is the after-tax corporate bond return. Let $r^S_{it+1} \equiv (P_{it+1} + D_{it+1})/P_{it}$ be the stock return and $w_{it} \equiv B_{it+1}/(P_{it} + B_{it+1})$ be the market leverage. Under constant returns to scale, the investment return is the weighted average of the stock return and the after-tax

[3] We estimate the investment model at the portfolio level (see Section 2.3.2). The portfolio-level investment is always positive, meaning that the marginal adjustment cost of investment, $(1-\tau_t)\eta^{\nu} (I_{it}/K_{it})^{\nu-1}$, is always well defined.

corporate bond return (see Liu, Whited, and Zhang (2009)):

$$r^I_{it+1} = w_{it} r^{Ba}_{it+1} + (1 - w_{it}) r^S_{it+1}. \tag{2.7}$$

Equivalently, the stock return equals the levered investment return:

$$r^S_{it+1} = \frac{r^I_{it+1} - w_{it} r^{Ba}_{it+1}}{1 - w_{it}}. \tag{2.8}$$

Equations (2.5) and (2.8) express firm i's Tobin's Q and stock return as functions of firm characteristics, providing the key predictions that we test empirically. To a first approximation, stock returns can be viewed as the first differences of equity value. Examining equations (2.5) and (2.8) simultaneously allows us to evaluate the fit of the model in both the levels and the first differences of asset prices, providing a new cross-sectional test for the neoclassical investment model.

2.3 Econometric Methodology and Sample Construction

Section 2.3.1 presents the econometric methodology, and Section 2.3.2 describe the data.

2.3.1 Econometric Methodology

2.3.1.1 Moment Conditions

We test if the average Tobin's Q observed in the data equals the average Q predicted in the model:

$$E\left[Q_{it} - \left(1 + (1 - \tau_t)\eta^\nu \left(\frac{I_{it}}{K_{it}}\right)^{\nu - 1}\right)\right] = 0. \tag{2.9}$$

In addition, we test whether the average stock return equals the average levered investment return:

$$E\left[r^S_{it+1} - \frac{r^I_{it+1} - w_{it} r^{Ba}_{it+1}}{1 - w_{it}}\right] = 0. \tag{2.10}$$

To construct a formal test, define the model errors from their empirical moments as:

$$e^Q_i \equiv E_T\left[Q_{it} - \left(1 + (1-\tau_t)\eta^{\nu}\left(\frac{I_{it}}{K_{it}}\right)^{\nu-1}\right)\right], \tag{2.11}$$

$$e^R_i \equiv E_T\left[r^S_{it+1} - \frac{r^I_{it+1} - w_{it} r^{Ba}_{it+1}}{1 - w_{it}}\right], \tag{2.12}$$

in which $E_T[\cdot]$ is the sample mean of the series in brackets. We call e^Q_i the average Q error and e^R_i the average return error. The key identification assumption for estimation and testing is that both model errors have a mean of zero, an assumption standard in most Euler equation tests.

To see where the model errors come from, we note that although equations (2.5) and (2.8) are exact relations, measurement errors in variables are likely to invalidate them in practice. For equation (2.5), measurement errors can arise from mismeasured components of Q that are better observed by firms than by econometricians, such as the market value of debt and the replacement value of the capital stock. In addition, the intrinsic value of equity can diverge from the market value of equity. For equation (2.8), the model errors can arise because of measurement or specification errors: Marginal product of capital might not be proportional to sales-to-capital, and adjustment costs might not be given by equation (2.2).

2.3.1.2 Estimation Method

We estimate the model parameters, κ, η and ν using one-stage GMM to minimize a weighted average of e^Q_i, a weighted average of e^R_i, or a weighted average of both e^Q_i and e^R_i. When the stock return and Tobin's Q moments are estimated separately, we use the identity weighting matrix in one-stage GMM to preserve the economic structure of the testing portfolios, following Cochrane (1996). However, e_i^Q can often be larger than e_i^R by an order of magnitude. As such, when we estimate the expected return and Tobin's Q moments simultaneously, we adjust the weighting matrix such that the weights for different sets of moments make their errors comparable in magnitude. Specifically, we multiply the Q moments by a factor of $\sum_i \left|\widehat{e_i^R}\right| / \sum_i \left|\widehat{e_i^Q}\right|$, in which $\widehat{e_i^Q}$ is portfolio i's Q error from estimating only the Q moments, and $\widehat{e_i^R}$ is portfolio i's expected return error from estimating only the expected return moments. In most of our applications, $\sum_i \left|\widehat{e_i^R}\right| / \sum_i \left|\widehat{e_i^Q}\right|$ is about 0.10.

Following the standard GMM procedure, we estimate the parameters, $\mathbf{b} \equiv (\kappa, \eta, \nu)$, by minimizing a weighted combination of the sample moments, denoted by $\mathbf{g}_T$. The GMM objective function is a weighted sum of squares of the model errors, $\mathbf{g}_T'\mathbf{W}\mathbf{g}_T$, in which $\mathbf{W}$ is the adjusted identity matrix. Let $\mathbf{D} = \partial \mathbf{g}_T / \partial \mathbf{b}$. We estimate $\mathbf{S}$, a consistent estimate of the variance-covariance matrix of the sample errors $\mathbf{g}_T$, with a Bartlett kernel with a window length of three. The estimate of $\mathbf{b}$, denoted $\hat{\mathbf{b}}$, is asymptotically normal with variance-covariance matrix: $\mathrm{var}(\hat{\mathbf{b}}) = (\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\mathbf{S}\mathbf{W}\mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}/T$. To construct standard errors for individual model errors, we use $\mathrm{var}(\mathbf{g}_T) = \frac{1}{T}\left[\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\right]\mathbf{S}\left[\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\right]'$, which is the variance-covariance matrix for $\mathbf{g}_T$. We follow Hansen (1982, lemma 4.1) to form a χ^2 test that all or a subset of the model errors are jointly zero: $\mathbf{g}_T'\left[\mathrm{var}(\mathbf{g}_T)\right]^+\mathbf{g}_T \sim \chi^2(\#\,\text{moments} - \#\,\text{parameters})$, in which χ^2 denotes the chi-square distribution, and the superscript $+$ denotes pseudo-inversion.

We conduct the estimation at the portfolio level, for several reasons. First, the use of portfolio level data significantly reduces the impact of the measurement errors in firm-level data that have plagued the empirical performance of the investment model in investment regressions. By aggregating the firm-level data to the portfolio level, the impact of measurement errors, such as those related to unobserved firm-level fixed effects, is reduced. Second, because forming portfolios helps diversify residual variances, the expected return and Tobin's Q spreads are more reliable statistically across portfolios than across individual stocks. Finally, investment data at the portfolio level are smoother than firm-level data, consistent with the smooth adjustment costs function in equation (2.2).

2.3.1.3 Discussion

Cross-sectional Tobin's Q is a new dimension of the data not explored in the prior literature. Although the Tobin's Q moments in equation (2.9) are related to the investment Euler equation tested in, for example, Whited (1992) and Hall (2004), our test design exploits the information contained in stock valuation data. In contrast, investment Euler equation tests use investment and cash flows data only, but ignore stock prices. Liu, Whited, and Zhang (2009) explore the expected return moments in equation (2.10). We focus on Tobin's Q. As noted, cross-sectional valuation is an important economic question. The Q moments also help identify the adjustment cost parameters that are otherwise hard to pin down from noisy expected return moments (see Section 2.4).

Our valuation test differs from the Merz-Yashiv (2007) test. Merz and Yashiv derive and test a valuation equation from combining the first-order conditions of equity value-maximizing with respect to I_{it} and K_{it+1} (see also Israelsen (2010)). With our notations, their valuation equation is:

$$\begin{aligned} Q_{it} \;&=\; E_t\left[M_{t+1}\left((1-\tau_{t+1})\left[\frac{\partial \Pi_{it+1}}{\partial K_{it+1}} - \frac{\partial \Phi_{it+1}}{\partial K_{it+1}}\right]\right.\right. \\ &\qquad \left.\left. + \, \delta_{it+1}\tau_{t+1} + (1-\delta_{it+1})\left[1 + (1-\tau_{t+1})\frac{\partial \Phi_{it+1}}{\partial I_{it+1}}\right]\right)\right]. \quad (2.13) \end{aligned}$$

To implement this valuation equation, Merz and Yashiv parameterize the marginal product of capital and the stochastic discount factor, M_{t+1} (as the inverse of the firm's weighted average cost of capital). In contrast, we implement directly the Tobin's Q equation (2.5), which is immune to the specification errors in the marginal product of capital and as well as those in M_{t+1}.

The investment regression literature tests whether Tobin's Q is a sufficient statistic of investment. The investment regressions are often performed on Tobin's Q with cash flow or lagged investment as controls (e.g., Fazzari, Hubbard, and Petersen (1988)). As surveyed by Chirinko (1993), the neoclassical investment model is typically rejected because the investment regressions produce very low goodness-of-fit coefficients. In addition, cash flow and lagged investment are often significant, even when Tobin's Q is controlled for, whereas Tobin's Q is insignificant, even when it is used alone.

Our econometric approach differs from the standard investment regressions in three aspects. First, as noted, we conduct the estimation at the portfolio level, which mitigates the impact of measurement errors in both Tobin's Q and other characteristics. Second, we test whether investment is a sufficient statistic for *average* Tobin's Q. Focusing on the first moment only alleviates greatly the impact of year-fixed effects as well as the impact of any temporal misalignment between asset prices and investment. The temporal misalignment can arise because investment lags prevent high and medium frequency movements in asset prices to be reflected immediately in the investment data (e.g., Lettau and Ludvigson (2002)). Also, Tobin's Q depends on both existing capital and available technologies yet to be installed, but investment depends only on currently installed technology. As such, Tobin's Q is too forward-looking relative to investment, causing investment to be more responsive to Q at long horizons than at short horizons (e.g., Abel and Eberly (2002)). Third, we allow the marginal cost of investment to be nonlinear in the estimation, while the standard investment regressions can be derived only under the assumption that the marginal cost of investment is linear.

2.3.2 Data

Our sample consists of all common stocks on NYSE, Amex, and Nasdaq from 1965 to 2008. The firm-level data are from the Center for Research in Security Prices (CRSP) monthly stock file and the annual Standard and Poor's Compustat files. We delete firm-year observations with missing data or for which total assets, gross capital stock, or sales are either zero or negative. We include only firms with fiscal year ending in the second half of the calendar year. We also exclude firms with primary standard industrial classifications between 4900 and 4949 and between 6000 and 6999 because the neoclassical investment theory is unlikely to apply to regulated or financial firms.

2.3.2.1 Portfolio Definitions

We use ten book-to-market deciles from Fama and French (1993) as the main testing portfolios. We use these portfolios because sorting on book-to-market generates simultaneously a large cross-sectional spread in Tobin's Q and a large cross-sectional spread in average returns, thereby increasing the power of the statistical tests. Following Fama and French, we sort all stocks on book-to-market equity at the end of June of year t into ten deciles based on the NYSE breakpoints for the fiscal year ending in the calendar year $t-1$. Book-to-market equity is book equity for the fiscal year ending in $t-1$ divided by the market equity for December of year $t-1$.[4] Firm-year observations with negative book equity are excluded. We calculate equal-weighted annual returns from July of year t to June of year $t+1$ for the portfolios, which are rebalanced at the end of each June. We use equal-weighted portfolio returns because these returns

[4]Following Fama and French (1993), we measure book equity as stockholder equity plus balance sheet deferred taxes (Compustat annual item TXDB if available) and investment tax credit (item ITCB if available) plus post-retirement benefit liabilities (item PRBA ifavailable) minus the book value of preferred stock. Depending on data availability, we use redemption (item PSTKRV), liquidation (item PSTKL), or par value (item PSTK), to represent the book value of preferred stock. Stockholder equity is equal to Moody's book equity (from Kenneth French's Web site), the book value of common equity (item CEQ) plus the par value of preferred stock, or the book value of assets (item AT) minus total liabilities (item LT). The market value of common equity is the closing price per share (item PRCC_F) times the number of common shares outstanding (item CSHO).

present a higher hurdle for asset pricing models to pass than value-weighted returns.

The construction of the book-to-market deciles includes firms from different sectors of the economy. As such, the construction ignores the fact that technologies (in particular, the capital's share κ and the adjustment cost parameters η and ν) might vary across industries. To alleviate this concern, we also perform an industry-level analysis by constructing five book-to-market quintiles within each industry. We examine quintiles instead of deciles in each industry to guarantee that each portfolio contains a sufficient number of firms to alleviate the impact of measurement errors in firm-level data. We construct the book-to-market quintiles within each industry following the Fama-French (1993) procedure. The only difference is that we use all firms within a given industry (not just NYSE firms) to construct the breakpoints because the number of NYSE firms in some industries is too small.

2.3.2.2 Variable Measurement and Timing Alignment

We largely follow Liu, Whited, and Zhang (2009) in measuring accounting variables and in aligning their timing with the timing of stock returns at the portfolio level. We make two changes. First, we equal-weight (as opposed to value-weight) corporate bond returns for the testing portfolios to make the weighting of bond returns consistent with that of stock returns. Second, we include all the firms with fiscal year ending in the second half of the calendar year. In contrast, Liu et al. only include firms with fiscal year ending in December. Our procedure enlarges the sample substantially.

The capital stock, K_{it}, is gross property, plant, and equipment (Compustat annual item PPEGT), and investment, I_{it}, is capital expenditures (item CAPX) minus sales of property, plant, and equipment (item SPPE if available). The capital depreciation rate, δ_{it}, is the amount of depreciation (item DP) divided by the capital stock. Output, Y_{it}, is sales (item SALE). Total debt, B_{it+1}, is long-term debt (item DLTT) plus short term debt (item DLC). Market leverage, w_{it}, is the ratio of total debt to the sum of total debt and the market value of equity. We measure the tax rate, τ_t, as the statutory corporate income tax (from the Commerce Clearing House, annual publications).

The after-tax corporate bond returns, r^{Ba}_{it+1}, are computed from r^{B}_{it+1} using the average of tax rates in year t and $t+1$. For the pre-tax corporate bond returns, r^{B}_{it+1}, we follow Blume, Lim, and Mackinlay (1998) to impute the credit ratings for firms with no rating data from Compustat (item SPLTICRM), and then assign the corporate bond returns for a given credit rating (from Ibbotson Associates) to all the firms with the same credit ratings.[5]

We aggregate firm-level characteristics to portfolio-level characteristics as in Fama and French (1995). For example, Y_{it+1}/K_{it+1} is the sum of sales in year $t+1$ for all the firms in portfolio i formed in June of year t divided by the sum of capital stocks at the beginning of year $t+1$ for the same set of firms. I_{it+1}/K_{it+1} in the numerator of r^{I}_{it+1} is the sum of investment in year $t+1$ for all the firms in portfolio i formed in June of year t divided by the sum of capital stocks at the beginning of year $t+1$ for the same set of firms. I_{it}/K_{it} in the denominator of r^{I}_{it+1} is the sum of investment in year t for all the firms in portfolio i formed in June of year t divided by the sum of capital stocks at the beginning of year t for the same set of firms. Because the firm composition of portfolio i changes from year to year due to annual rebalancing,

[5]Specifically, we first estimate an ordered probit model that relates credit ratings to observed explanatory variables using all the firms that have credit ratings data. We then use the fitted value to calculate the cutoff value for each credit rating. For firms without credit ratings we estimate their credit scores using the coefficients estimated from the ordered probit model and impute credit ratings by applying the cutoff values of different credit ratings. Finally, we assign the corporate bond returns for a given credit rating from Ibbotson Associates to all the firms with the same credit rating. The ordered probit model contains the following explanatory variables: interest coverage, the ratio of operating income after depreciation (Compustat annual item OIADP) plus interest expense (item XINT) to interest expense; the operating margin, the ratio of operating income before depreciation (item OIBDP) to sales (item SALE), long-term leverage, the ratio of long-term debt (item DLTT) to assets (item AT); total leverage, the ratio of long-term debt plus debt in current liabilities (DLC) plus short-term borrowing (item BAST) to assets; the natural logarithm of the market value of equity (item PRCC_C times item CSHO) deflated to 1973 by the consumer price index; and the market beta and residual volatility from the market regression. We estimate the beta and residual volatility for each firm in each calendar year with at least 200 daily returns from CRSP. We adjust for nonsynchronous trading with one leading and one lagged values of the market return.

I_{it+1}/K_{it+1} in the numerator of r^I_{it+1} is different from I_{it+1}/K_{it+1} in the denominator of r^I_{it+2}. Other characteristics are aggregated analogously.

2.4 Estimation Results

We report the estimation results from the sample including all publicly traded firms in Section 2.4.1 and from industry-specific samples in Section 2.4.2.

2.4.1 Matching Average Tobin's Q and Stock Returns in the Cross Section

2.4.1.1 Descriptive Tests

Table 1 reports the averages and standard deviations of stock returns, Tobin's Q, and other accounting characteristics for each book-to-market decile as well as for the high-minus-low decile. We define the value spread as the Tobin's Q of the low book-to-market (growth) decile minus the Tobin's Q of the high book-to-market (value) decile.[6] From the first row of the table, sorting on book-to-market equity produces a large value spread of 3.01 with a standard error of 1.13. We also observe a large spread of 14.84% per annum in the average equal-weighted return, which is more than 4.5 standard errors from zero. This large spread is a well established fact known as the value premium (e.g., Rosenberg, Reid, and Lanstein (1985)).

The volatility of Tobin's Q is, in relative terms, smaller than the volatility of stock returns. The annualized return volatility averaged across the deciles is 25.16%, which is more than 1.5 times the average return of 16.23% across the deciles. In contrast, the volatility of Tobin's Q averaged across the deciles is 0.59, which is less than 40%

[6] Albeit related, our definition of the value spread differs from Cohen, Polk, and Vuolteenaho's (2003). Cohen et al. define the value spread as the log book-to-market equity of the value decile minus the log book-to-market equity of the growth decile. We adopt our definition based on the spread in Tobin's Q because Q arises more naturally from the neoclassical investment model (see equation (2.5)).

of the average Tobin's Q of 1.58. This evidence means that valuation moments are more precisely estimated in the data than expected return moments. As such, using the Q moments in testing the investment model increases the power of the tests.

Equation (2.5) shows that Tobin's Q is an increasing function of the current investment-to-capital, I_{it}/K_{it}. Table 1 shows that consistent with the cross-sectional variation in Tobin's Q, value firms have lower current-period's investment-to-capital on average than growth firms: 0.07 versus 0.17 per annum. Equations (2.6) and (2.8) provide a list of expected return components. The predicted stock return in the model is increasing in the growth rate of investment-to-capital, $(I_{it+1}/K_{it+1})/(I_{it}/K_{it})$, market leverage, w_{it}, and the next-period's marginal product of capital, Y_{it+1}/K_{it+1}, as well as decreasing in the current-period's investment-to-capital, I_{it}/K_{it}. Table 1 also shows that value firms have higher growth rates of investment-to-capital and higher market leverage than growth firms. These cross-sectional variations go in the right direction in accounting for the cross-sectional variation in expected stock returns. Going in the wrong direction, however, value firms also have lower next-period's marginal product of capital than growth firms.

2.4.1.2 Point Estimates

Table 2 reports the point estimates and overall performance of the investment model using three sets of moments. In the Q column, we match average Tobin's Q using moment condition (2.9). In the r column, we match average stock returns using moment condition (2.10). Finally, in the $Q + r$ column, we estimate the two sets of moment conditions jointly.

There are only three parameters in the model, the slope adjustment cost parameter, η, the curvature adjustment cost parameter, ν, and the capital's share parameter, κ. Table 2 shows that the parameter estimates seem stable across the three sets of moments. The η estimate ranges from 4.58 to 5.15, and is always significant. The

ν estimate ranges from 4.17 to 5.65, and are significantly positive. In addition, the ν estimates are significantly above two when the Q moments are used in the estimation. The evidence suggests that the adjustment costs function in the Tobin's Q data exhibits more curvature than the standard quadratic functional form. The point estimates of η and ν also imply that the adjustment costs function is increasing and convex in investment-to-capital. The capital's share parameter is estimated to be 0.24 when matching the expected return moments and 0.23 when matching both expected return and Tobin's Q moments.

To interpret the magnitude of the adjustment costs, Table 2 reports the implied adjustment costs relative to annual sales, computed as $\Phi_{it}/Y_{it} = \left(\eta I_{it}/K_{ij}\right)^{\nu} / (\nu Y_{it})$. We calculate this proportion by first computing the portfolio-level time series of realized adjustment costs-to-sales ratio and then averaging this ratio over time and across portfolios. The estimated magnitude of the adjustment costs is small across all sets of moments. The adjustment costs range from 1.61% (estimating Tobin's Q moments only) to 1.67% (estimating expected return moments only). These ratios are at the lower end of the empirical estimates surveyed in, for example, Hamermesh and Pfann (1996).

2.4.1.3 Overall Model Performance

Table 2 also reports three overall performance measures: the mean absolute Q errors (m.a.q.e.), the mean absolute return errors (m.a.r.e.), and the χ^2 test. The m.a.q.e. and the m.a.r.e. are the means of the absolute errors across portfolios given by equations (2.11) and (2.12), respectively.

According to all three metrics, the investment model performs well in matching average returns and Tobin's Q simultaneously across the testing portfolios. The m.a.q.e. is 0.17 both when we estimate the Tobin's Q moments only and when we estimate the expected return and Q moments jointly. These errors are small, representing less than 11% of the average Tobin's Q of these portfolios (1.58, see Table

1). For expected returns, the m.a.r.e. ranges from 1.81% (matching expected return moments only) to 1.96% (matching expected return and Q moments jointly). These errors are also small, representing less than 12.5% of the average return of these portfolios (16.23%, see Table 1). The model is not rejected by the χ^2 test across any set of moments, with p-values all above 20%.

2.4.1.4 Individual Model Errors

The mean absolute errors and the χ^2 test reported in Table 2 only indicate overall model performance. To provide a more complete picture of the fit, Table 3 reports the average Q errors from equation (2.11) and the expected return errors from equation (2.12) for all the individual portfolios, as well as their corresponding t-statistics. To put these expected return errors into perspective, we also report traditional asset pricing tests such as the CAPM, the Fama-French (1993) three-factor model, and the Carhart (1997) four-factor model on the ten book-to-market deciles. The data for the factor returns and the risk-free rate are from Kenneth French's Web site. We also report the mean absolute error for each model, computed as the mean of the absolute alphas across portfolios.

Panel A in Table 3 reports the Q errors when we use the model to match the average Q moments only. Even though the errors are economically small, with the average magnitude being less than 11% of the average Tobin's Q across the deciles, most Q errors are more than two standard errors from zero. The significance of the model errors results from the fact that the Q moments are estimated precisely in the data. All the parameters and the moment conditions are estimated precisely. As such, even economically small errors lead to formal statistical rejections.

Panel B in Table 3 reports the expected return errors when the model is estimated to match average stock returns only. The model generates low model errors, and compares well with the performance from standard asset pricing models. Nine out of ten individual expected return errors are insignificant. The high-minus-low decile has an error of -1.21% per annum, which is substantially lower in magnitude than the errors from the traditional models: 14.61% from the CAPM, 6.71% from the Fama-French model, and 6.82% from the Carhart model. The mean absolute error is 1.81% in the investment model, which is somewhat higher than 1.46% in the Fama-French model and 1.50% in the Carhart model, but lower than 4.53% in the CAPM.

Panel C in Table 3 reports the Tobin's Q errors and the expected return errors when we use the model to match both sets of moments simultaneously. Overall, the model does a good job in matching the moments. Because of the lower precision of the stock return moments, all the moment conditions are less precisely estimated. As such, most of the individual Tobin's Q errors are not significant. The Q error for the high-minus-low decile increases in magnitude slightly from -0.18 from Panel A to -0.22. However, the expected return error for the high-minus-low decile even decreases somewhat in magnitude from -1.21% per annum in Panel B to -1.08%. The average magnitude of the Q errors across all ten deciles remains at 0.17 with and without estimating the Q moments jointly with the expected return moments. The average magnitude of the expected return errors increases slightly from 1.81% when we estimate the expected return moments only to 1.96% when we estimate the expected return moments and the average Q moments jointly.

Figure 1 illustrates the investment model's fit across different sets of moment conditions. We plot the average predicted Tobin's Q against the average realized Tobin's Q (Panels A and C), as well as the average levered investment returns against the average realized stock returns (Panels B and D) for the ten book-to-market deciles. If the model's fit is perfect, all the scattered points should lie exactly on the 45-degree line. The figure shows that the scattered observations are largely aligned with the 45-degree line. In addition, comparing Panels A and C shows that the model's fit on the average Q moments is robust to the addition of the expected return moments into the GMM estimation. Similarly, comparing Panels B and D shows that the model's fit on the expected return moments is robust to the addition of the average Q moments into the GMM estimation. The bottomline is that the neoclassical investment model matches the data on cross-sectional asset prices not only in first-differences (stock returns), but also in levels (Tobin's Q).

2.4.1.5 Parameter Stability

The model's parameters are in principle "deep" structural parameters, describing the nature of production and capital adjustment technologies, which should be invariant to changes in optimizing behavior and economic policy per Lucas (1976). As such, any evidence of parameter instability would indicate specification and measurement errors in the model. We study the stability of the parameter estimates in two ways, subsample analysis and recursive estimation. The main finding is that adding the Q moments in the estimation makes the parameter estimates more stable over time.

Table 4 reports the GMM estimation and tests over two 25-year subsamples, with the testing portfolios formed annually in June based on book-to-market equity at the end of fiscal year ending in calendar year from 1965 to 1989 and from 1983 to 2007. The table shows that the Tobin's Q moments seem important for identifying the structural parameters. The parameter estimates when we use the Tobin's Q moments are more stable across subperiods. In particular, when only expected return moments are used, the capital's share parameter, κ, is estimated to be 0.21 ($t = 4.12$) in the first subsample, but 0.57 ($t = 0.45$) in the second subsample. As such, the second estimate is less precise. In contrast, when we add the Tobin's Q moments jointly with expected return moments, the κ estimate varies from 0.20 to 0.22 across the two subsamples, with t-statistics both above five.

Another indication of the parameter stability provided by the Q moments is the implied adjustment costs-to-sales ratio, Φ/Y. With only expected return moments, this implied ratio is 0.91% in the first subsample, but is 13.6% in the second subsample. Once we add the average Q moments into the GMM estimation, the implied ratio varies only from 0.51% to 1.85% across the two subsamples. The increased stability reflects the fact that the Tobin's Q moments are more precisely estimated than the expected return moments. In turn, this precision gives rise to the higher precision of the point estimates when we include the average Q moments.[7]

Table 5 provides further evidence on parameter stability by estimating the model recursively using a series of expanding windows. The expanding windows start from 1965. At year $T = 1989, \ldots, 2007$, we use all the accounting variables up to year T and stock returns up to year $T + 1$ to estimate the model's parameters. Table 5 reports the time series of the point estimates. From Panel A, the point estimates from matching average Q moments are stable. The slope adjustment cost parameter, η, is on average 4.79 with a coefficient of variation (C.V., calculated as standard deviation divided by mean) of 4.35%. The curvature parameter, ν, is on average 6.26 with a C.V. of 6.12. From Panel B, estimating expected return moments only shows more time variation in the parameter estimates. In particular, the C.V. for the η parameter is 9.93%, and the C.V. for the ν parameter is 20.63%. Panel C shows that adding the Q moments more than halves the C.V.s of the estimates: The C.V. for the η estimate drops from 9.93% to 4.77%, and the C.V. for the ν estimate from 20.63% to 10.24%. Finally, with the terminal year of expanding windows starts from 1989, the κ estimates are stable with and without the Q moments in the GMM.

[7] In untabulated results, we have experimented with halving the full sample by using the 1965–1987 and 1986–2008 subsamples. The average Q moments play an even more important role in stabilizing the parameter estimates. With only expected return moments, the κ estimate is 0.22 in the first subsample, but it hits the upper bound of one in the second subsample. Adding the Q moments brings the κ estimate back to 0.24 in the second subsample.

2.4.1.6 The Role of Nonlinearity in the Marginal Cost of Investment

To quantify the importance of the ν parameter for matching Tobin's Q, we estimate the restricted version of the model with quadratic adjustment costs. In particular, we set $\nu = 2$ before choosing freely the η and κ parameters to minimize the GMM objective function. From Panel A of Table 6, the adjustment costs implied from the quadratic model are higher than those from the baseline model. In particular, the adjustment costs-to-sales ratio is 11.21% when estimating expected return moments only. The ratio is between 4–6% when the Q moments are included. The average Q error is 0.62 when estimating the Q moments only and 0.66 when estimating the Q moments and the expected return moments jointly. In contrast, the average Q error is only 0.17 in the baseline model.

Panel B of Table 6 reports large errors for individual portfolios from the quadratic model. In particular, when estimating the Q moments only, the model underpredicts the Tobin's Q of the growth decile by 1.77, and overpredicts that of the value decile by 0.67. As such, the model underpredicts the value spread by 2.44, which is more than 80% of the value spread (3.01) in the data! Panel A of Figure 2 confirms that the quadratic model fails miserably to match the value spread: The scatter plot is only slightly upward-sloping, deviating substantially from the 45-degree line. The fit on the Q moments from matching the Q moments and the expected return moments is largely similar (see Panel C of Figure 2). Finally, consistent with Liu, Whited, and Zhang (2009), the quadratic model matches well the expected return moments. The m.a.r.e. is only 2.36% per annum, and the error for the high-minus-low decile is 0.33%. Comparing Panels B and D in Figure 2 shows that including the Q moments into the estimation only deteriorates slightly the fit for the expected returns.

Why does the curvature parameter help the model to match the Tobin's Q levels? Intuitively, with quadratic adjustment costs, investment-to-capital is proportional to

Tobin's Q because the marginal cost of investment is linear in investment. With curvature, Q is a nonlinear function of investment. For a given magnitude of spread in investment-to-capital, the nonlinearity magnifies the investment-to-capital spread to produce a larger spread in Tobin's Q.[8]

2.4.2 Matching Expected Returns and Average Tobin's Q Within Each Industry

We also ask whether the investment model can capture the value spread and the value premium at the more disaggregated industry level. Because the magnitudes of the value spread and the value premium vary across industries, this extension provides an additional set of moments for the model to match. These within-industry tests allow explicitly technological heterogeneity across industries.

2.4.2.1 Descriptive Tests

Using the Fama and French (1997) 17-industry classification, we test the investment model across the following industries: food, mines, oil, clothes, durables, chemicals, consumer, construction, steel, fabricated paper, machinery, cars, transportation, and retail. Out of the 17 industries, we exclude financials and utilities because these firms are not included in the main sample. In addition, we exclude the "other" industry because of its insufficient number of firms to form portfolios.

Table 7 reports the time series averages of selected characteristics of the book-to-market quintiles within each industry. We report the value premium, $\bar{r}^S_{H-L}$, the value spread, $\bar{Q}_L - \bar{Q}_H$, as well as the m.a.r.e. and the high-minus-low alphas, α_{H-L}, for the CAPM, Fama-French model and the Carhart model for each industry. The value premium is positive across all the industries, but its magnitude shows some

[8] Prior studies have shown that the nonlinearity in the marginal cost of investment is important for understanding quantity data and stock market data (e.g., Abel and Eberly (2001), Israelsen (2010), and Jermann (2010)). We add to this body of evidence using data on cross-sectional asset prices.

cross-industry variation. The value premium is high in the oil (17.34% per annum) and the chemicals (17.49%) industries, but is low in the car (2.94%) industry. The average value premium across all industries is 11.75%. The magnitude of the value spread also varies across the industries. It is high among the consumer goods industry (5.40) and low in the oil (0.77) and steel (0.86) industries. The average value spread across all industries is 1.99.

The average m.a.r.e. for the CAPM across the industries is 5.22% per annum. The CAPM alpha of the high-minus-low quintile, α_{H-L}, is typically large (on average, 10.96%) and significant across all but two industries. The average m.a.r.e. for the Fama-French model (4.12%) and the Carhart model (3.43%) are similar. Although smaller than the errors for the CAPM, the alphas of the high-minus-low quintile for the Fama-French and Carhart models are also large, with cross-industry averages being 6.91% and 6.53%, respectively, and are significant across many industries.

2.4.2.2 Point Estimates

Panel A of Table 8 reports the parameter estimates and GMM tests when we use the investment model to match the average Q moments of the book-to-market quintiles within each industry. The parameter estimates vary across industries and seem economically reasonable. The slope adjustment cost parameter, η, is significantly positive, and the curvature adjustment cost parameter, ν, is always above two. Confirming the results from the full cross section of firms, the importance of curvature for matching Tobin's Q is clear. The curvature parameter is estimated to be significantly above two across most industries. The implied magnitudes of adjustment costs are small across most industries. On average, the estimated adjustment costs represent about 2.20% of sales. The average adjustment costs are high in the consumer goods industry, about 7.90% of sales, and low in the steel and the oil industries, on average 0.07% and 0.25% of sales, respectively.

Panel B reports the parameter estimates and GMM tests when we match average stock returns of the book-to-market quintiles within each industry. In contrast with the results for the Tobin's Q moments, the parameter estimates are in general imprecisely estimated, and some estimates even take extreme values. The slope adjustment cost parameter, η, hits the lower bound of zero for four industries (mines, construction, cars, and retail). With η estimated to be zero, the curvature adjustment cost parameter, ν, is not identifiable from the expected return moments for these four industries. The ν estimate also hits the upper bound of 15 for four other industries (durables, chemicals, steel, and fabricated paper). Panel C reports the parameter estimates and GMM tests when we use the investment model to match both average Tobin's Q and average stock returns of the book-to-market quintiles within each industry. Because Tobin's Q moments are included, the parameter estimates are precisely estimated. The η parameter is estimated to be significantly positive across all but one industries. The ν parameter is estimated to be above two, except for the durables and car industries. The average adjustment costs continue to be low, on average about 2.24% of sales.

2.4.2.3 Overall Model Performance and Individual Model Errors

From Panel A of Table 9, the investment model produces small Q errors across all the industries when matching the Q moments. The cross-industry average m.a.q.e. is 0.20, which is slightly above 10% of the average value spread across the industries. The Q errors for the high-minus-low quintile, $e_H^Q - e_L^Q$, are insignificant for all but three industries (oil, clothes, and steel). The model is rejected by the χ^2 test in only two out of the fourteen industries: oil and transportation. Given the parsimonious investment model with only one capital input, the rejection of the model across some industries is perhaps not surprising. For example, other inputs such as intangible capital or quasi-fixed labor (due to staggered labor contracts, for example) are omitted for parsimony, but these inputs can contribute to the measured Tobin's Q. What is perhaps more surprising, at least to us, is the economically small Q errors for many industries achieved by this parsimonious model.

Figure 3 illustrates the good fit of the investment model in matching the Q moments in most industries. We plot the average predicted Tobin's Q against the average realized Tobin's Q for the book-to-market quintiles. The portfolios are mostly aligned with the 45-degree line. The fit of the model is good in the clothes, durable goods, chemicals, construction, machinery and retail industries, but is more modest in the mines, oil, steel, fabricated paper and transportation industries.

When the model is estimated to match the cross section of average stock returns, the model produces average model errors that are lower than those from standard asset pricing models. The average m.a.r.e. across industries is only 2.31% per annum in the investment model. This error compares favorably with the average pricing errors of the CAPM (5.22%), the Fama-French model (4.12%), and the Carhart model (3.43%) (see Table 7). Also, all but two industries have insignificant expected return errors of the high-minus-low quintile ($e^R_H - e^R_L$) in the investment model.

The model produces small return and Q errors even when matching average Tobin's Q and expected returns simultaneously. Both expected return errors and the Tobin's Q errors increase somewhat, as expected, because the model is forced to match more moments. The m.a.r.e. increases from 2.31% (when matching return moments only) to 3.60%. These average return errors are still smaller in magnitude than the errors from the Fama-French model (4.12%), even though the Fama-French model is not required to match the Q moments. The average Tobin's Q error increases somewhat, from 0.20 (when matching Tobin's Q moments only) to 0.25. Also, when both Tobin's Q and return moments are included, the χ^2 test does not reject the model in any of the industries.

Taken together, the industry level analysis provides robust evidence that the cross section of Tobin's Q is a useful dimension of the data that should be taken seriously in estimating the neoclassical investment model. The cross section of average returns provides a set of moments that is imprecisely estimated. The imprecision is more severe when the tests are performed at the more disaggregated industry level, at which industry-specific idiosyncratic variance is not diversified away. As a result, the statistical tests have lower power, and the moment conditions are not precise enough to identify the parameters. The low precision can also lead to extreme parameter estimates occasionally. Adding the Tobin's Q moments in the estimation significantly increases the model's ability to identify the structural parameters and the statistical power of the tests.

2.5 Conclusion

The neoclassical investment model matches cross-sectional asset prices both in first differences and in *levels* simultaneously. When confronted with average Tobin's Q and average stock returns moments across the book-to-market deciles, the model predicts a Tobin's Q spread of 2.79 and an average return spread of 15.92% per annum. The valuation error of 0.22 is about 7% of the Tobin's Q spread (3.01) observed in the data, and the expected return error of -1.08% is also about 7% in magnitude of the value premium (14.84%) observed in the data. The model matches these key moments with reasonable parameter estimates for the production and capital adjustment technologies. In particular, the implied adjustment costs are low, about 1.66% of sales.

By providing the technological underpinnings of asset prices, our work has some implications on the popular view that the market value of equity often deviates from the intrinsic value of equity. In an endowment economy, because quantities are fixed, investor irrationality will fully impact on asset prices. At the other extreme, in a linear technologies economy without adjustment costs, investor irrationality will only impact on quantities through the optimal investment behavior of firms, leaving no trace in asset prices. The adjustment costs economy, which is what we model, lies somewhere in between the two extremes. Investor irrationality could put a short term dent on asset prices, but rational firms will eventually enter the economy, pay up adjustment costs, and flood any "fire" of asset pricing bubble with the "water" of investment. In the long run, the "water" extinguishes any impact of irrationality on asset prices. Our evidence seems consistent with this interpretation.

We view our work as a first step toward integrating asset pricing with the equity valuation and fundamental analysis literature in accounting. The quantitative results from the first step are encouraging! Ultimately, valuation should be done at the firm level. Additional productive inputs such as labor and intangible assets should be incorporated into the neoclassical model. Nonconvex adjustment technologies that are likely relevant at the firm level should be incorporated as in, for example, Abel and Eberly (1994). More generally, a deep unification between asset pricing and the standard valuation framework in accounting (e.g., Koller, Goedhart, and Wessles (2010)) should be pursued.

Table 2.1 Descriptive Statistics of Ten Book-to-Market Deciles

For each book-to-market decile, we report the following statistics: the time series average, $\bar{Q}_{it}$, and the annualized standard deviation, σ_i^Q, of Tobin's Q; the average stock return in annualized percent, $\bar{r}^S_{it+1}$; the annualized volatility in percent of stock return, σ_i^R; the average growth rate of investment-to-capital from time t and $t+1$, $\overline{\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}}$; the average investment-to-capital at t, $\overline{I_{it}/K_{it}}$; the average market leverage, $\bar{w}_i$; and the average sales-to-capital over $t+1$, $\overline{Y_{it+1}/K_{it+1}}$. The H−L is the high-minus-low book-to-market decile, and Avg. is the averages across deciles.

	Low	2	3	4	5	6	7	8	9	High	H−L	Avg.
$\bar{Q}_{it}$	3.83	2.40	1.92	1.63	1.30	1.11	0.99	0.93	0.89	0.82	−3.01	1.58
σ_i^Q	1.28	0.83	0.81	0.75	0.50	0.38	0.33	0.31	0.33	0.34	1.13	0.59
$\bar{r}^S_{it+1}$	9.22	11.18	13.38	15.47	16.15	16.59	18.05	18.17	20.06	24.06	14.84	16.23
σ_i^R	27.16	24.78	24.59	24.55	24.94	24.15	25.22	23.86	24.07	28.30	20.14	25.16
$\overline{\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}}$	0.98	0.97	1.00	0.99	1.00	1.01	0.99	1.00	0.99	1.01	0.03	0.99
$\overline{I_{it}/K_{it}}$	0.17	0.14	0.13	0.12	0.11	0.10	0.10	0.10	0.09	0.07	−0.09	0.11
$\bar{w}_{it}$	0.11	0.17	0.22	0.25	0.27	0.29	0.31	0.37	0.43	0.56	0.45	0.30
$\overline{Y_{it+1}/K_{it+1}}$	1.93	1.89	1.77	1.65	1.55	1.44	1.33	1.36	1.32	1.34	−0.60	1.56

Table 2.2 Parameter Estimates and Tests of Overidentification

The table reports the estimation results via GMM on the Tobin's Q moments and the expected return moments given by equations (2.9) and (2.10), respectively, using ten book-to-market deciles as the testing portfolios. κ is the capital's share, η is the slope adjustment cost parameter, and ν is the curvature adjustment cost parameter. The t-statistics, denoted $[t]$, test that a given estimate equals zero. Φ/Y is the ratio (in percent) of the implied capital adjustment costs-to-sales ratio. m.a.r.e. is the mean absolute return error in percent, and m.a.q.e. is the mean absolute valuation error. χ^2, d.f., and p-val are the statistic, the degrees of freedom, and the p-value testing that all the errors are jointly zero. The Q column is for estimating the Q moments only, the r column for estimating the expected return moments only, and the $Q + r$ column for estimating the Q moments and expected return moments jointly.

	Q	r	$Q+r$
Panel A: Point Estimates			
η	5.15	4.58	5.15
$[t]$	15.78	2.59	14.71
ν	5.65	4.17	5.55
$[t]$	11.17	1.97	8.53
κ		0.24	0.23
$[t]$		5.43	6.45
Panel B: Adjustment Costs			
Φ/Y	1.61	1.67	1.66
Panel C: Tests and Pricing Errors			
m.a.q.e.	0.17		0.17
m.a.r.e.		1.81	1.96
χ^2	10.46	6.72	10.93
d.f.	8	7	17
p-val	0.23	0.46	0.86

Table 2.3 Euler Equation Errors

The table reports the Euler equation errors implied by the estimation of the investment model via GMM on the Q moments and the return moments given by equations (2.9) and (2.10), using ten book-to-market deciles as the test portfolios. e_i^Q is the Tobin's Q error defined in equation (2.11). e_i^R is the expected return error defined in equation (2.12). α_i is the intercept in annual percent from monthly CAPM regressions, α_i^{FF} is the intercept in annual percent from monthly Fama-French (1993) three-factor regressions, and α_i^{CARH} is the intercept in annual percent from the Carhart (1997) four-factor model that includes the Fama-French factors and the momentum factor. The data for the risk-free rate and the factor returns are from Kenneth French's Web site. m.a.e. is the mean absolute error computed as the mean of the absolute value of the corresponding row variable.

	Low	2	3	4	5	6	7	8	9	High	H−L	m.a.e.
	Panel A: Matching Average Q Moments Only											
e_i^Q	−0.06	0.10	0.31	0.11	−0.05	−0.13	−0.22	−0.25	−0.24	−0.24	−0.18	0.17
[t]	−2.46	1.21	2.95	1.46	−1.10	−2.23	−2.85	−2.88	−2.94	−2.72	−2.19	
	Panel B: Matching Expected Return Moments Only											
e_i^R	−1.04	−1.09	−3.77	0.27	0.74	−0.45	4.26	1.45	2.80	−2.25	−1.21	1.81
[t]	−0.54	−0.72	−1.81	0.21	0.60	−0.31	2.00	0.75	1.33	−1.67	−0.60	
α_i	−4.07	−1.66	0.62	2.70	3.34	4.02	5.26	5.70	7.41	10.53	14.61	4.53
[t]	−2.22	−1.11	0.39	1.51	2.10	2.69	3.06	3.29	4.31	4.85	7.65	
α_i^{FF}	−2.45	−1.85	−0.96	0.11	0.08	0.18	1.31	1.11	2.28	4.26	6.71	1.46
[t]	−2.37	−2.43	−1.17	0.13	0.10	0.23	1.39	1.25	2.89	3.76	5.63	
α_i^{CARH}	−2.37	−1.34	−0.96	−0.18	−0.25	0.77	1.26	0.76	2.60	4.45	6.82	1.50
[t]	−2.24	−1.66	−1.15	−0.21	−0.32	0.95	1.34	0.85	2.94	3.68	5.45	
	Panel C: Matching Average Q Moments and Expected Return Moments Jointly											
e_i^Q	−0.02	0.09	0.3	0.09	−0.07	−0.14	−0.23	−0.26	−0.25	−0.25	−0.22	0.17
[t]	−0.29	0.89	1.94	0.79	−0.59	−1.47	−2.1	−2.6	−2.75	−2.72	−1.72	
e_i^R	−0.85	−0.56	−4.50	−0.40	0.60	−1.46	4.24	1.76	3.31	−1.93	−1.08	1.96
[t]	−0.22	−0.10	−1.65	−0.16	0.38	−0.89	1.82	1.00	1.42	−0.55	−0.17	

Table 2.4 Parameter Estimates and Tests of Overidentification: Subsample Analysis

The table reports the estimation results using GMM on the average Q moments and the expected return moments given by equations (2.9) and (2.10), using ten book-to-market deciles as the testing portfolios. κ is the capital's share, η is the slope adjustment cost parameter, and ν is the curvature adjustment cost parameter. The t-statistics, denoted [t], test that a given estimate equals zero. Φ/Y is the ratio (in percent) of the implied capital adjustment costs-to-sales ratio. m.a.q.e. is the mean absolute Tobin's Q error, and m.a.r.e. is the mean absolute return error. χ^2, d.f., and p-val are the statistic, the degrees of freedom, and the p-value testing that all the errors are jointly zero. The Q columns report the results from estimating the average Q moments only, the r columns report the results from estimating the expected return moments only, and the $Q+r$ columns report the results from estimating the average Q moments and the expected return moments jointly.

	Subsample: 1965–1990			Subsample: 1983–2008		
	Q	r	$Q+r$	Q	r	$Q+r$
Panel A: Point Estimates						
η	4.47	3.13	4.36	6.43	8.15	6.39
[t]	18.15	3.83	13.73	24.29	1.05	21.74
ν	6.87	3.47	8.17	6.55	3.14	5.88
[t]	8.59	1.23	3.98	10.27	1.53	8.77
κ		0.21	0.20		0.57	0.22
[t]		4.12	5.13		0.45	5.89
Panel B: Adjustment Costs						
Φ/Y	0.79	0.91	0.51	1.59	13.6	1.85
Panel C: Tests and Pricing Errors						
m.a.q.e.	0.19		0.21	0.23		0.26
m.a.r.e.		1.86	2.2		3.95	4.84
χ^2	6.75	5.65	6.87	6.33	5.16	6.79
d.f.	8	7	17	8	7	17
p-val	0.56	0.58	0.99	0.61	0.64	0.99

Table 2.5 Time Series of Parameter Estimates from Recursive Estimation

We estimate the model's parameters recursively using a series of expanding windows. The expanding windows start from 1965. T denotes the terminal year from which accounting variables are used in the estimation in a given expanding window. We estimate only the average Tobin's Q moments in Panel A, only the expected return moments in Panel B, and both the Q moments and expected return moments in Panel C. η is the slope adjustment cost parameter, ν is the curvature adjustment cost parameter, and κ is the capital's share parameter. The last three rows report, for each corresponding column, the mean, standard deviation, and the coefficient of variation in percent, denoted C.V.%, which is defined as standard deviation/mean times 100.

	Panel A: Q		Panel B: r			Panel C: $Q+r$		
T	η	ν	η	ν	κ	η	ν	κ
1989	4.47	6.87	3.13	3.47	0.21	4.37	8.09	0.20
1990	4.51	6.80	3.33	3.57	0.22	4.44	7.52	0.20
1991	4.54	6.77	3.50	3.76	0.22	4.49	7.21	0.21
1992	4.58	6.75	3.64	4.26	0.22	4.53	7.33	0.22
1993	4.62	6.66	4.03	4.99	0.22	4.60	6.83	0.22
1994	4.65	6.54	4.10	5.14	0.22	4.63	6.69	0.22
1995	4.67	6.47	4.04	5.06	0.22	4.64	6.69	0.22
1996	4.70	6.33	4.32	5.75	0.22	4.69	6.42	0.22
1997	4.73	6.23	4.28	5.16	0.23	4.72	6.27	0.22
1998	4.77	6.09	4.16	4.67	0.22	4.76	6.15	0.22
1999	4.81	6.07	4.12	5.28	0.22	4.79	6.24	0.22
2000	4.85	6.05	4.35	7.90	0.21	4.81	6.40	0.22
2001	4.90	6.09	4.31	6.22	0.21	4.87	6.29	0.22
2002	4.94	6.08	4.22	5.35	0.21	4.91	6.24	0.22
2003	4.96	6.05	4.23	4.82	0.23	4.95	6.12	0.23
2004	5.01	5.91	4.34	4.64	0.23	5.00	5.90	0.23
2005	5.06	5.82	4.46	4.83	0.23	5.05	5.82	0.23
2006	5.11	5.72	4.55	4.32	0.24	5.11	5.62	0.23
2007	5.15	5.65	4.58	4.17	0.24	5.15	5.55	0.23
Mean	4.79	6.26	4.09	4.91	0.22	4.76	6.49	0.22
Std	0.21	0.38	0.41	1.01	0.01	0.23	0.67	0.01
C.V.%	4.35	6.12	9.93	20.63	3.93	4.77	10.24	3.41

Table 2.6 Parameter Estimates, Tests of Overidentification, and Euler Equation Errors, Quadratic Adjustment Costs

Panel A reports the GMM estimation results on the Tobin's Q moments and the expected return moments given by equations (2.9) and (2.10), respectively, in which $\nu = 2$. The testing portfolios are ten book-to-market deciles. κ is the capital's share, and η is the slope adjustment cost parameter. The t-statistics, denoted $[t]$, test that a given estimate equals zero. Φ/Y is the ratio (in percent) of the implied capital adjustment costs-to-sales ratio. m.a.r.e. is the mean absolute return error in percent, and m.a.q.e. is the mean absolute valuation error. χ^2, d.f., and p-val are the statistic, the degrees of freedom, and the p-value testing that all the errors are jointly zero. The Q column is for estimating the Q moments only, the r column for estimating the expected return moments only, and the $Q + r$ column for estimating the Q moments and expected return moments jointly. Panel B reports the Euler equation errors. e_i^Q is the Tobin's Q error defined in equation (2.11), in which $\nu = 2$. e_i^R is the expected return error defined in equation (2.12), in which $\nu = 2$. m.a.e. is the mean absolute error computed as the mean of the absolute value of the corresponding row variable.

Panel A: Parameter Estimates and Tests of Overidentification

	Q	r	$Q + r$
η	3.33	5.04	3.59
$[t]$	9.94	1.29	7.37
κ		0.45	0.33
$[t]$		1.26	6.04
Φ/Y	4.88	11.21	5.69
m.a.q.e.	0.62		0.66
m.a.r.e.		2.36	2.41
χ^2	10.65	6.94	11.17
d.f.	9	8	18
p-val	30.01	54.27	88.7

Panel B: Euler Equation Errors

	Low	2	3	4	5	6	7	8	9	High	H−L	m.a.e.
	Matching Average Q Moments Only											
e_i^Q	1.77	0.48	0.11	−0.16	−0.43	−0.55	−0.66	−0.70	−0.69	−0.67	−2.44	0.62
$[t]$	3.16	2.98	1.26	−1.63	−3.11	−3.23	−3.20	−3.21	−3.21	−3.23	−3.20	
	Matching Expected Return Moments Only											
e_i^R	−2.79	−2.28	−2.67	1.19	1.41	0.92	4.88	1.38	2.96	−3.11	−0.33	2.36
$[t]$	−1.35	−1.71	−1.56	0.97	1.06	0.58	2.09	0.72	1.17	−1.90	−0.26	
	Matching Average Q Moments and Expected Return Moments Jointly											
e_i^Q	1.59	0.33	−0.02	−0.28	−0.55	−0.66	−0.77	−0.81	−0.79	−0.75	−2.35	0.66
$[t]$	3.01	2.10	−0.15	−1.75	−2.51	−2.80	−2.83	−2.87	−2.90	−2.98	−3.19	
e_i^R	−4.13	−3.61	−3.30	0.37	0.94	0.93	4.65	1.72	3.24	−1.18	2.95	2.41
$[t]$	−1.58	−1.67	−1.64	0.24	0.64	0.68	2.27	1.02	1.47	−0.36	0.62	

Table 2.7 Descriptive Statistics of Five Book-to-Market Quintiles Within Each Industry

The table reports the averages of selected characteristics of five book-to-market quintiles within each industry. For each industry, we report the value premium, measured as the average stock return of the high-minus-low book-to-market quintile, $\bar{r}^S_{H-L}$, the value spread, measured as the average Tobin's Q of the growth quintile minus the average Q of the value quintile, $\bar{Q}_L - \bar{Q}_H$. m.a.e. is the mean absolute error using the CAPM, the Fama-French (1993) model, and the Carhart (1997) model in each industry. α_{H-L} is the intercept for the high-minus-low book-to-market quintile. Ave. is the average of the absolute value of the variable in each column.

	Averages		CAPM			Fama-French			Carhart		
Industry	$\bar{r}^S_{H-L}$	$\bar{Q}_L - \bar{Q}_H$	m.a.e.	α_{H-L}	$[t]$	m.a.e.	α_{H-L}	$[t]$	m.a.e.	α_{H-L}	$[t]$
Food	11.80	3.16	5.04	10.46	3.26	3.00	7.28	2.33	3.03	8.13	2.53
Mines	13.24	1.63	6.13	10.80	1.89	4.82	8.89	1.54	3.66	5.69	1.00
Oil	17.34	0.77	7.30	14.51	5.02	5.04	12.69	4.21	4.46	12.27	3.94
Clothes	10.39	3.55	4.19	10.43	2.98	4.59	7.11	2.06	3.13	5.19	1.49
Durables	11.10	1.59	4.72	10.67	3.16	4.13	5.65	1.84	2.96	5.35	1.69
Chemicals	17.49	1.24	6.39	14.68	4.52	4.25	9.37	3.05	4.15	9.28	3.01
Consumers	11.52	5.40	6.16	10.25	2.27	4.88	4.19	0.97	4.38	4.31	1.01
Construction	7.52	1.28	3.75	7.15	2.61	3.58	2.58	0.99	2.49	1.61	0.54
Steel	14.74	0.86	5.94	14.11	3.50	4.74	10.08	2.51	5.00	12.63	2.98
Fab Paper	14.50	1.53	6.32	14.72	3.25	4.64	11.44	2.57	4.51	10.55	2.43
Machinery	14.98	2.68	7.27	15.78	6.02	4.01	9.03	4.11	3.31	6.88	3.20
Cars	2.94	1.03	2.10	3.53	0.84	3.78	−1.47	−0.38	1.80	−0.80	−0.20
Transportation	8.35	1.05	3.98	8.74	3.55	3.41	6.68	2.88	2.89	6.21	2.53
Retail	8.31	2.07	3.75	7.60	2.23	2.80	3.28	1.08	2.20	4.11	1.28
Avg.	11.73	1.99	5.22	10.96		4.12	6.91		3.43	6.53	

Table 2.8 Parameter Estimates from Industry-by-Industry Estimation

The table reports the estimation results using GMM on the valuation and return moments given by equations (2.9) and (2.10), using five book-to-market quintiles as the test portfolios within each industry. κ is the share of capital in the production function, η is the slope adjustment cost parameter, and ν is the curvature adjustment cost parameter. The t-statistics denoted $[t]$ test that a given estimate equals zero. Φ/Y is the ratio (in percent) of the implied capital adjustment costs-to-sales ratio, measured as $\Phi(I_{it}, K_{it})/Y_{it}$.

	Panel A: Matching Tobin's Q					Panel B: Matching Expected Returns							Panel C: Matching Tobin's Q and Expected Returns						
Industry	η	$[t]$	ν	$[t]$	Φ/Y	η	$[t]$	ν	$[t]$	κ	$[t]$	Φ/Y	η	$[t]$	ν	$[t]$	κ	$[t]$	Φ/Y
Food	6.24	32.78	7.89	4.25	1.02	5.50	10.92	8.30	1.31	0.10	6.47	0.35	6.21	24.83	7.74	4.80	0.09	5.30	1.00
Mines	3.55	17.05	3.27	4.64	5.23	0.00	0.00	–	–	0.16	5.03	0.00	2.77	5.90	6.30	1.95	0.16	3.73	0.60
Oil	2.51	7.30	10.79	0.43	0.25	2.91	14.97	9.75	1.94	0.30	7.35	1.23	2.63	34.01	8.78	2.07	0.31	7.59	0.50
Clothes	5.65	20.68	4.33	9.13	1.51	4.28	3.54	2.53	1.37	0.13	2.26	1.74	5.64	21.59	4.31	11.56	0.09	2.71	1.50
Durables	5.51	24.23	4.15	6.99	2.91	3.49	3.38	15.00	0.22	0.10	6.05	0.01	3.25	4.72	1.64	5.69	0.18	4.56	4.97
Chemicals	5.10	24.73	8.94	2.65	0.37	4.63	1.59	15.00	0.13	0.23	9.93	0.03	4.87	85.05	15.00	1.85	0.23	9.60	0.07
Consumer	7.00	26.05	4.75	6.16	7.90	7.36	2.04	4.71	2.36	0.02	0.15	10.01	6.99	20.96	4.85	5.49	0.03	0.66	7.82
Construction	5.67	12.03	3.57	2.66	1.98	0.00	0.00	–	–	0.10	4.82	0.00	4.55	6.98	2.37	2.91	0.13	2.95	2.78
Steel	5.15	20.41	8.65	1.24	0.07	5.08	2.30	15.00	0.20	0.19	5.91	0.01	5.09	51.69	15.00	0.94	0.19	6.07	0.01
Fab Paper	5.45	22.48	6.48	3.08	0.90	4.19	6.36	15.00	0.29	0.13	8.77	0.02	5.02	8.68	3.92	3.18	0.11	2.79	1.44
Machinery	4.98	14.87	3.31	14.10	5.59	3.58	13.80	11.59	0.59	0.14	8.36	0.23	4.90	13.52	3.79	5.72	0.18	5.77	4.58
Cars	4.76	13.25	4.95	2.70	1.35	0.00	0.00	–	–	0.10	7.71	0.00	1.01	0.55	1.00	1.11	0.18	4.02	4.55
Transportation	4.29	11.81	11.52	0.40	0.20	4.89	2.00	2.69	1.64	0.26	3.55	5.48	3.72	5.38	3.70	2.71	0.20	7.17	1.06
Retail	4.05	20.41	4.04	7.71	1.49	0.00	0.00	–	–	0.07	5.97	0.00	3.70	19.13	8.85	2.30	0.07	5.60	0.44
Ave.	4.99	19.15	6.19	4.73	2.20	3.28	4.35	9.96	1.01	0.15	5.88	1.37	4.31	21.64	6.23	3.73	0.15	4.89	2.24

Table 2.9 Tests of Overidentification and Euler Equation Errors in Industry-by-Industry Estimation

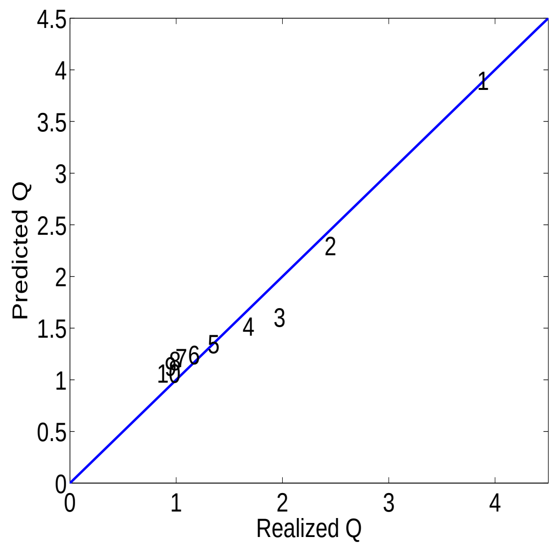
The table reports the estimation results via GMM on the valuation and return moments given by equations (2.9) and (2.10), using five book-to-market quintiles as the test portfolios within each industry. χ^2 and p-val are the statistic and the p-value, respectively, testing that all the errors are jointly zero. m.a.r.e. is the mean absolute return error, and m.a.q.e. is the mean absolute valuation error. $e^Q_H - e^Q_L$ is the difference in the valuation error between the high and low quintiles. $e^R_H - e^R_L$ is the difference in the expected return error between the high and low quintiles. Significant values of $e^Q_H - e^Q_L$ and $e^R_H - e^R_L$ at the 5% significant level are underlined. Ave. is the average absolute value of the variable in each column.

	Panel A: Matching Tobin's Q				Panel B: Matching expected returns				Panel C: Matching Tobin's Q and expected returns					
Industry	χ^2	p-val	m.a.q.e.	$e^Q_H - e^Q_L$	χ^2	p-val	m.a.r.e.	$e^R_H - e^R_L$	χ^2	p-val	m.a.q.e.	$e^Q_H - e^Q_L$	m.a.r.e.	$e^R_H - e^R_L$
Food	3.41	33.26	0.17	−0.11	1.23	54.09	1.97	0.33	5.12	64.58	0.20	−0.27	2.97	9.08
Mines	2.88	41.03	0.31	−0.45	1.77	41.32	3.72	−3.47	5.48	60.15	0.27	−0.25	5.91	−7.52
Oil	10.81	1.28	0.19	<u>−0.44</u>	2.52	28.34	1.04	0.78	10.94	14.11	0.20	−0.33	1.22	−0.67
Clothes	8.17	4.26	0.09	<u>−0.22</u>	1.10	57.58	2.47	1.92	9.00	25.29	0.09	<u>−0.26</u>	4.12	−0.06
Durables	3.54	31.60	0.10	−0.03	1.16	55.95	1.65	−0.93	8.94	25.70	0.39	<u>−1.25</u>	4.25	<u>−10.03</u>
Chemicals	3.49	32.20	0.06	−0.11	2.14	34.33	1.88	3.53	7.69	36.08	0.07	−0.09	2.17	6.73
Consumer	2.59	45.97	0.52	0.12	2.32	31.34	4.13	0.66	4.90	67.19	0.52	0.23	4.60	−0.64
Construction	3.56	31.27	0.13	0.03	6.61	3.68	2.81	−3.37	7.96	33.64	0.22	<u>−0.52</u>	5.54	−8.37
Steel	7.08	6.94	0.24	<u>−0.60</u>	0.11	94.57	3.22	<u>13.03</u>	9.74	20.39	0.25	<u>−0.67</u>	3.22	<u>13.04</u>
Fab Paper	3.37	33.80	0.28	−0.69	0.03	98.44	2.65	<u>6.98</u>	8.16	31.91	0.31	<u>−0.95</u>	3.39	4.48
Machinery	5.01	17.10	0.11	−0.11	1.74	41.86	0.88	−0.72	8.32	30.48	0.17	0.12	3.40	−7.67
Cars	8.65	3.44	0.29	−0.59	0.57	75.03	1.38	−3.11	10.97	13.98	0.34	<u>−1.03</u>	1.46	−3.68
Transportation	10.50	1.48	0.21	−0.43	3.72	15.54	4.03	7.31	10.72	15.15	0.27	<u>−0.61</u>	6.49	<u>19.57</u>
Retail	7.84	4.94	0.09	−0.22	0.30	86.01	0.52	−0.39	9.91	19.37	0.22	−0.07	1.65	−0.65
Ave.	5.78	20.61	0.20	0.30	1.81	51.29	2.31	3.32	8.42	32.72	0.25	0.48	3.60	6.59

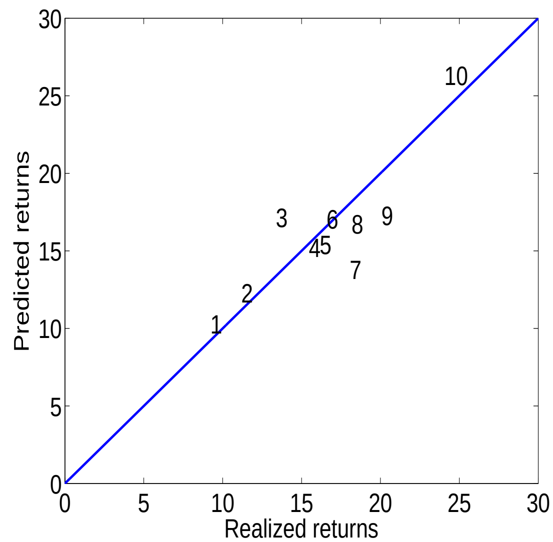
Figure 2.1 Average Predicted Tobin's Q versus Average Realized Tobin's Q and Average Predicted Returns versus Average Realized Returns, Separate and Joint Estimations

The results are from estimating the model via GMM using the average Tobin's Q moments given by equation (2.9), the expected return moments given by equation (2.10), or both sets of moments simultaneously. The test portfolios are ten book-to-market deciles. Portfolio 1 is the growth decile, and 10 is the value decile.

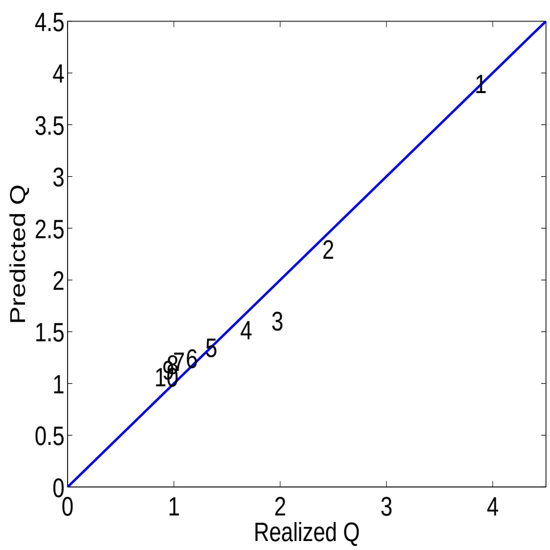
Panel A: Tobin's Q Errors, Matching Average Tobin's Q Only



Panel B: Expected Return Errors, Matching Expected Returns Only



Panel C: Tobin's Q Errors, Matching Expected Returns and Average Tobin's Q Jointly



Panel D: Expected Return Errors, Matching Expected Returns and Average Tobin's Q Jointly

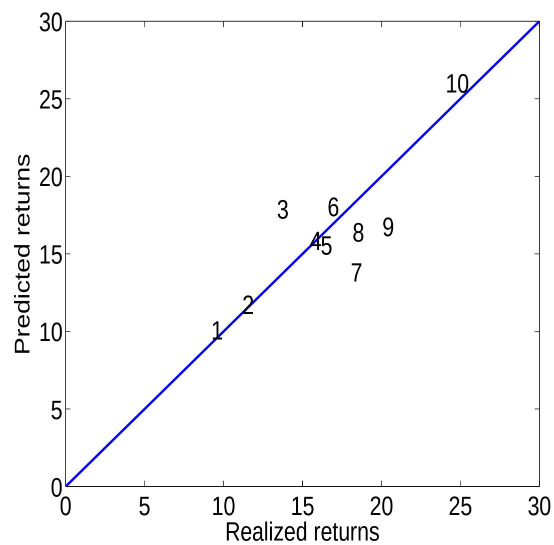
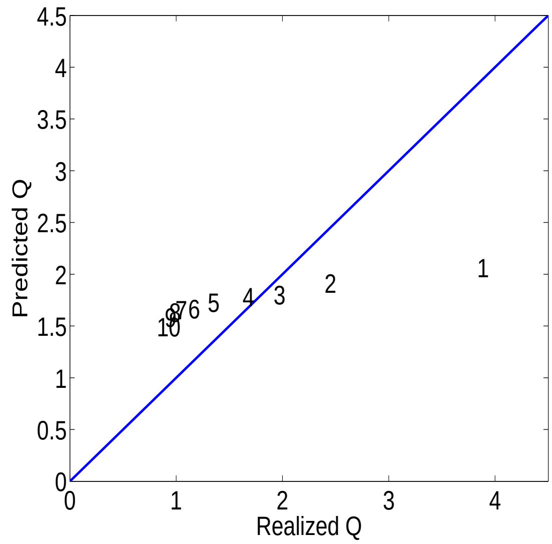


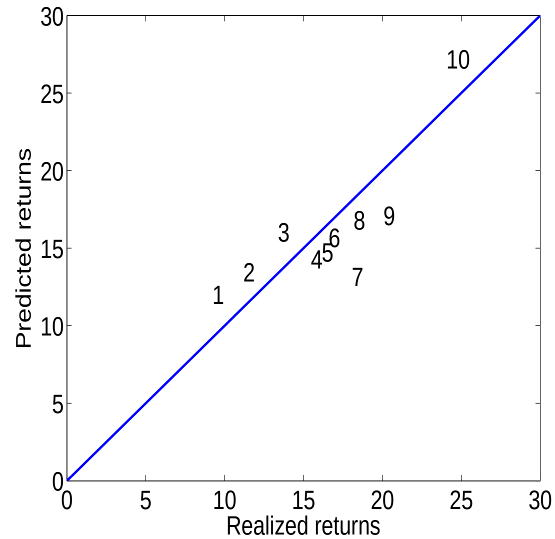
Figure 2.2 Average Predicted Tobin's Q versus Average Realized Tobin's Q and Average Predicted Returns versus Average Realized Returns, Separate and Joint Estimations, Quadratic Adjustment Costs

The results are from estimating the model via GMM using the average Tobin's Q moments given by equation (2.9), the expected return moments given by equation (2.10), or both sets of moments simultaneously. The curvature parameter ν is restricted to be 2. The test portfolios are ten book-to-market deciles. Portfolio 1 is the growth decile, and 10 is the value decile.

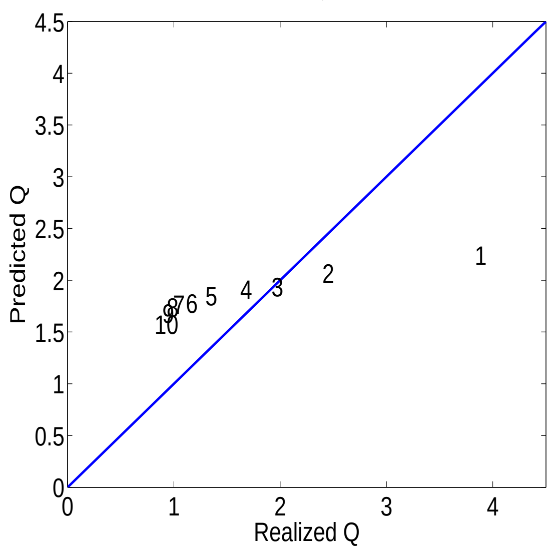
Panel A: Tobin's Q Errors, Matching Average Tobin's Q Only



Panel B: Expected Return Errors, Matching Expected Returns Only



Panel C: Tobin's Q Errors, Matching Expected Returns and Average Tobin's Q Jointly



Panel D: Expected Return Errors, Matching Expected Returns and Average Tobin's Q Jointly

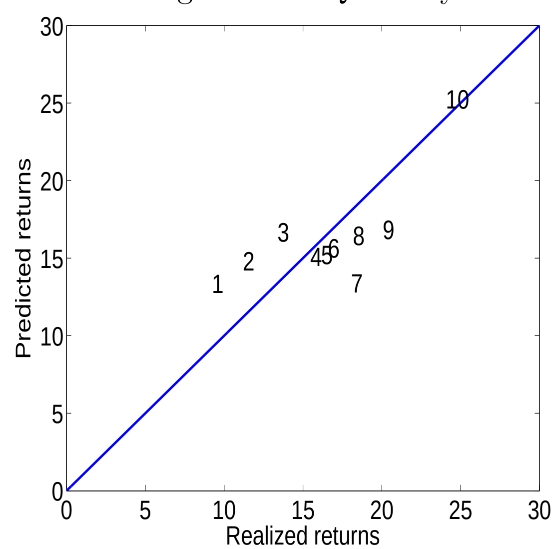
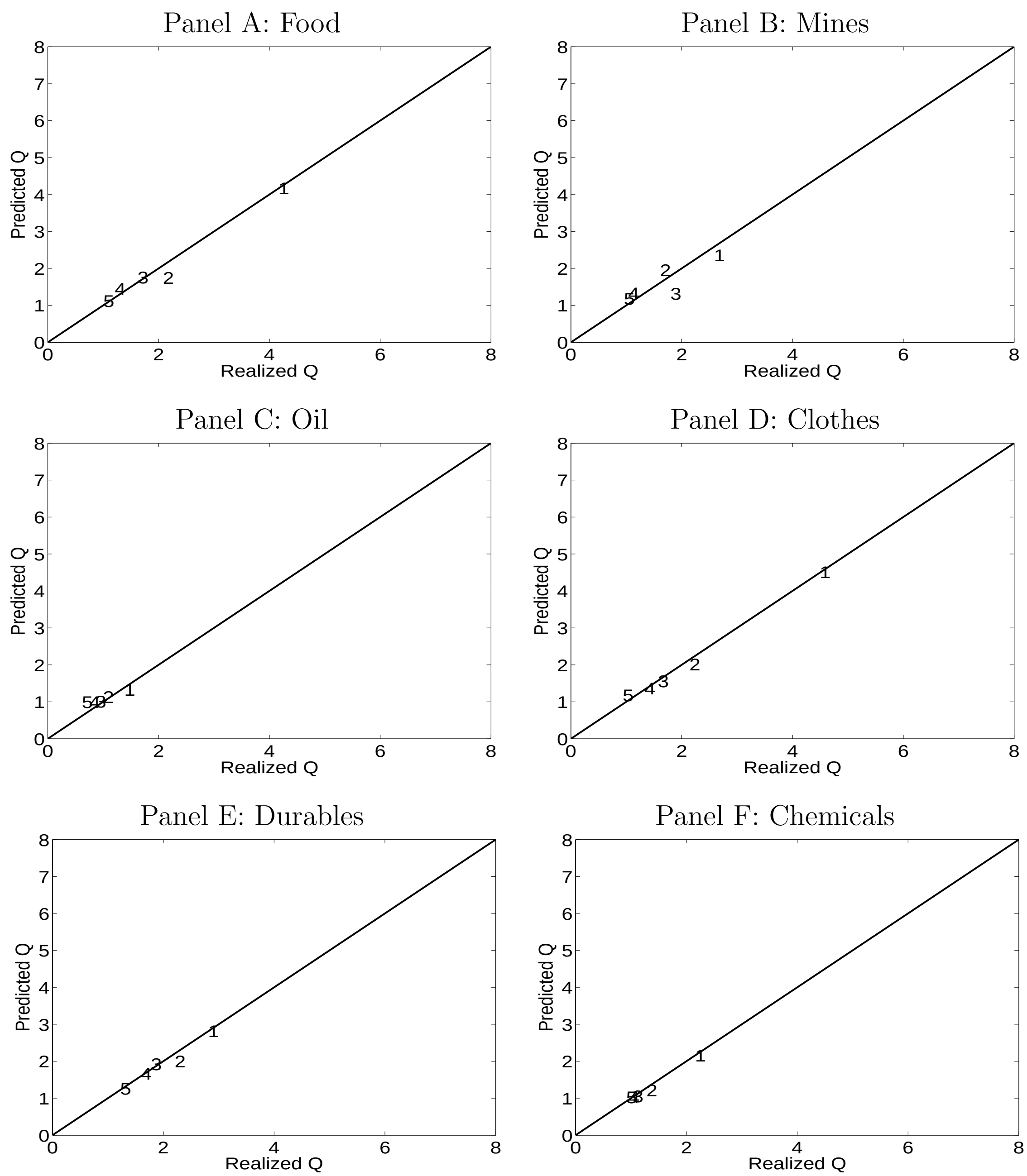
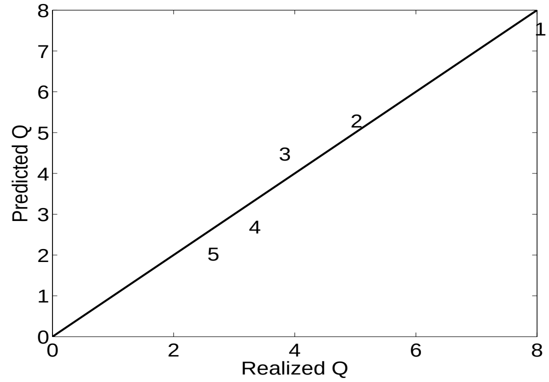


Figure 2.3 Average Predicted versus Realized Tobin's Q Within Each Industry

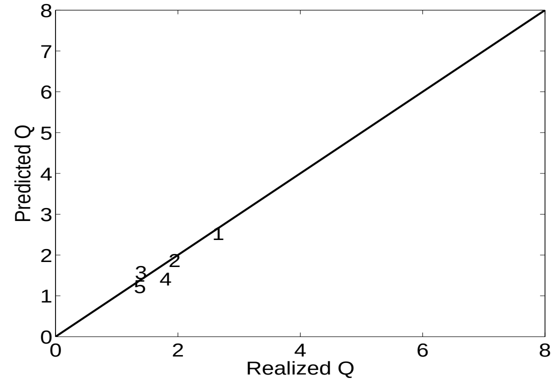
The testing portfolios are five book-to-market quintiles within each industry. The results are from estimating the model via GMM in each industry with the Tobin's Q moments in equation (2.9). Portfolio 1 is the growth quintile, and portfolio 5 is the value quintile.



Panel G: Consumer

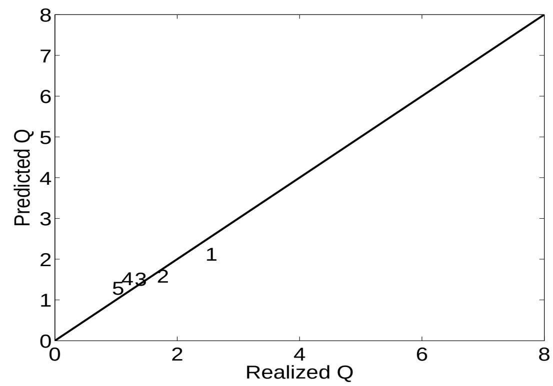


Panel H: Construction

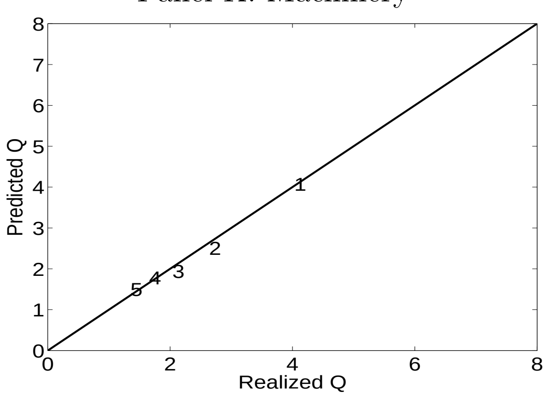


Panel I: Steel

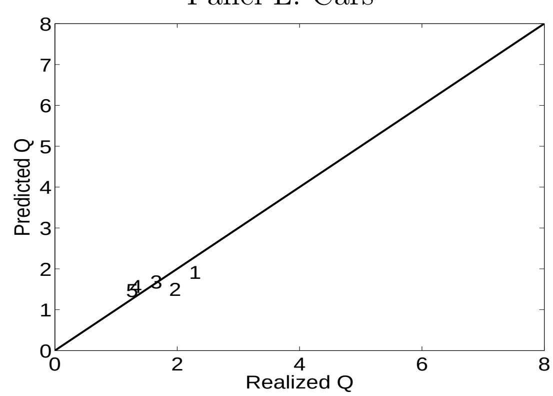
Panel J: Fab paper



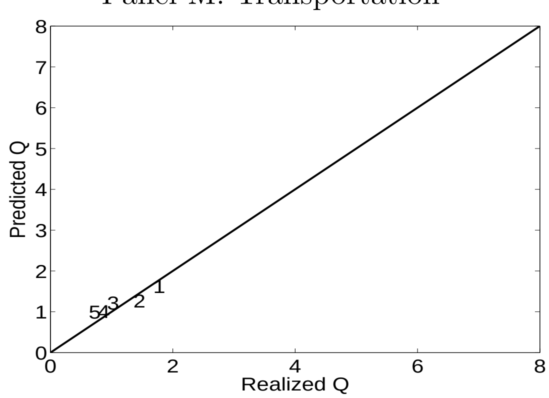
Panel K: Machinery



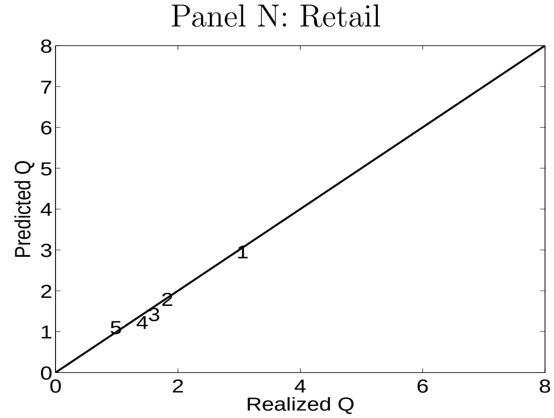
Panel L: Cars



Panel M: Transportation



Panel N: Retail



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