The Dissertation Committee for Denys Maslov
certifies that this is the approved version of the following dissertation:

Asset Pricing Anomalies: Persistence, Aggregation, and Monotonicity

Committee:

Clemens Sialm, Supervisor

Andres Donangelo

Travis Johnson

Shimon Kogan

Stathis Tompaidis

Asset Pricing Anomalies: Persistence, Aggregation, and Monotonicity

by

Denys Maslov, B.S.; M.S.; M.S.; M.S.Fin.

DISSERTATION

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT AUSTIN

May 2014

To N

Acknowledgments

I am deeply indebted to my advisor Clemens Sialm for his patient guidance and support. I am also thankful to my committee members Andres Donangelo, Travis Johnson, Shimon Kogan, and Stathis Tompaidis for their valuable insight and encouragement. I am grateful to Oleg Rytchkov for his mentorship and friendship. This work greatly benefited from valuable discussions with Andres Almazan, Aydogan Alti, Fernando Anjos, Jonathan Cohn, John Griffin, Jay Hartzell, Jan Schneider, Sheridan Titman, and fellow PhD students, particularly, Chao Bian, Sergey Maslennikov, Jeremy Page, Chishen Wei, and Miao (Ben) Zhang. Parker Hund carefully proofread the manuscript several times.

In addition, Chapter 1 was improved from insights from seminar participants at Menta Capital, Moody's Analytics, and PanAgora Asset Management. Chapter 2 is jointly written with Nathaniel Light and Oleg Rytchkov. We are grateful to Naresh Bansal, Sudipta Basu, Tarun Chordia, Revansiddha Khanapure, Igor Makarov, Anna Obizhaeva, Pavel Savor, Elizaveta Shevyakhova, and seminar participants at Temple University, as well as to participants of the 2013 MFA Meetings and 2013 FMA Meetings for helpful comments.

Chapter 3 is written together with Oleg Rytchkov. We are grateful to Jules van Binsbergen, Alan Huang, Marie Lambert, Igor Makarov, Elizaveta Shevyakhova, Mitch Warachka, Yuzhao Zhang, and participants of the 1st World Finance Conference, 2010 FMA Meetings, 2010 EFA Meetings, 2010 NFA Meetings, as well as to seminar participants at Temple University and the University of Pennsylvania for helpful comments.

Asset Pricing Anomalies: Persistence, Aggregation, and Monotonicity

Denys Maslov, Ph.D.
The University of Texas at Austin, 2014

Supervisor: Clemens Sialm

In Chapter 1, I investigate whether returns of strategies based on asset pricing anomalies exhibit time series persistence which can be attributed to flow-induced trading by mutual funds. I find persistence for thirteen characteristics, which is statistically significant for five including size, corporate investment, and bankruptcy likelihood. The persistence is not explained by individual stock momentum and is not limited to certain calendar months. The return predictability can be used to construct new trading strategies, which on average earn 4.5% annually. A price pressure measure of mutual fund flow-driven trading explains a substantial part of the strategy performance persistence.

In Chapter 2, we propose a new approach for estimating expected returns on individual stocks from firm characteristics. We treat expected returns as latent variables and develop a procedure that filters them out using the characteristics as signals and imposing restrictions implied by a one factor asset pricing model. The estimates of expected returns obtained by applying our method to thirteen asset pricing anomalies generate a wide cross-sectional dispersion of realized returns. Our

results provide evidence of strong commonality in the anomalies. The use of portfolios based on the filtered expectations as test assets increases the power of asset pricing tests.

In Chapter 3, we examine the sensitivity of fourteen asset pricing anomalies to extreme observations using robust regression methods. We find that although all anomalies except size are strong and robust for stocks with presumably low returns, most of them are sensitive to individual influential observations for stocks with presumably high returns. For some anomalies, extreme observations distort regression results for all stocks and even portfolio returns. When the impact of such observations is mitigated, eight anomalies become positively related to expected returns for stocks with low characteristics meaning that these anomalies have an inverted J-shaped form. Chapter 4 concludes by summarizing the main contributions of three chapters and their implications.

Table of Contents

List of Tables

List of Figures

Chapter 1

Strategy Performance Persistence and Mutual Fund Price Pressure

1.1 Introduction

Predictability of asset prices is one of the most important and challenging questions in financial economics. In particular, substantial work has focused on the understanding of the relative performance of common stocks of US companies. Beginning with the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), rational models have postulated that differences in expected stock returns should reflect only their loadings on risk factors. However, research has uncovered a substantial number of characteristics which predict future stock returns, even after controlling for known measures of risk.[1] Whether capturing additional sources of risk or originating from behavioral biases, these characteristics can be used to create implementable strategies. Such strategies are becoming increasingly popular among institutional and retail investors.

In this study, I investigate whether flow-induced trading by mutual funds generates persistence in returns of fourteen characteristic-based strategies. Specifically,

[1] Subrahmanyam (2010) surveys the literature and cites more than 50 variables used to forecast returns. McLean and Pontiff (2013) study the robustness of 82 anomalies following the initial publication, and Hand, Green, and Zhang (2012) study the properties of more than 330 predictive variables.

when a particular strategy performs well, retail clients invest in the funds following this strategy. In turn, funds increase their holdings of the strategy, creating price pressure and driving up its future performance. As a consequence, the future returns of a strategy can be predicted by its past returns and a measure of expected price pressure based on the mutual fund prior performance and holdings.

The strategy performance arises as a consequence of institutional frictions faced by mutual fund managers. Previous literature shows that fund flows are predictable, as retail clients, due to rational or behavioral reasons, tend to invest in funds based on their past performance.[1] Hence, returns of a particular strategy predict flows into funds, to the extent that these funds follow this strategy. However, mutual funds are restricted in their ability to respond to expected inflows and outflows as they are constrained in borrowing to scale up their positions or to return cash to their investors. As fund managers are also discouraged from keeping any part of their portfolio in cash, they can only react to flows by increasing or decreasing their existing stock holdings. As funds are likely to maintain the same portfolio weights, their flow-driven buying or selling of a particular strategy is predictable by its past performance. In the presence of imperfect stock liquidity this flow-induced trading may create price pressure, which may explain the continuation in the performance of the strategy.

To test the prediction of short-term strategy performance persistence, for each characteristic I regress the return of the strategy in the current month on its

[1]See Chevalier and Ellison (1997) and Sirri and Tufano (1998)

cumulative return over the past twelve months. The coefficient is positive for almost all fourteen anomalies and economically and statistically significant for five including strategies based on size, asset growth, investment-to-assets ratio, abnormal capital investments, and bankruptcy likelihood. The continuation is also not concentrated in any particular calendar month, although it is most strong in December. On average, the persistence is significant for four lags and insignificant for higher lags, which is consistent with the short-term underreaction.

The strategy performance persistence is not explained by the momentum of individual stocks as I still find it after adjusting strategy returns for momentum in stocks comprising the strategy. In addition, I randomly split the set of all firms into two nonoverlapping samples and for each characteristic construct two strategies based on these two subsamples. Then, I use the past return of one subsample strategy to predict the current return of the other one. I find very similar predictability, which implies that most of the persistence comes from strategy stocks predicting returns of one another and not only from stocks predicting their own returns.

I conduct these analyses for fourteen prominent asset pricing anomalies which can be divided into five groups. The first group contains the three most researched anomalies: size, book-to-market, and momentum. The second group contains three corporate investment anomalies: total asset growth, investments-to-assets ratio, and abnormal capital investments. The third group contains two financing anomalies: net stock issues and composite stock issuance. The fourth group contains three accounting anomalies: accruals, net operating assets, and profitability. The fifth and last group contains three anomalies broadly related to uncertainty about the firm: idiosyncratic volatility, Ohlson's score measuring the bankruptcy likelihood, and dispersion in analysts' forecasts.[1]

To gauge the economic significance of performance persistence, I investigate whether it can be used to create new trading strategies based upon the underlying strategies. I construct new persistence strategies, which consist of buying underlying strategies following positive prior returns and selling them otherwise. I adjust the prior twelve month return by its trailing median to ensure that a persistence strategy holds and shorts the underlying strategy in equal proportion. Otherwise, a positive or negative average exposure to the base strategy will imply significant average returns for a persistence strategy even in the absence of return predictability. The persistence strategy with the highest average return of 72 bps per month (t-statistic=3.28) is based on size. Across all characteristics, the average raw return for the new strategies is 37 bps (t-statistic=3.40), and the book-to-market-size-momentum adjusted return is 24 bps (t-statistic=2.98).

Next, I examine whether flow-induced trading by mutual funds is responsible for the strategy performance persistence. I compute a measure of expected price pressure for each strategy. I use previous fund performance as a predictor of future flows and assume that flows are allocated in accordance with prior portfolio weights. Since the strategy performance and price pressure are highly correlated, I first regress the return of the strategy on the price pressure, and then I regress residuals from this regression on the prior strategy return. I find that for all characteristics the coefficient

[1]A very similar set of characteristics is studied in different contexts by Stambaugh, Yu, and Yuan (2012), Lewellen (2013), and Hou, Xue, and Zhang (2012).

on the prior strategy return becomes lower, and, on average, its magnitude is reduced by two-thirds. The findings are stronger in the second half of the sample, when mutual funds became more important. In this subperiod, expected price pressure renders prior strategy return insignificant and close to zero.

Among institutional investors, mutual funds are particularly sensitive to capital flow shocks. Hence, other institutions such as hedge funds, pension funds, and insurance companies may provide liquidity to mutual funds by taking the other side of flow-induced trades. I investigate this possibility by considering the aggregate institutional investors' demand in response to the past strategy performance. Specifically, I regress the institutional demand for each strategy on the prior twelve month cumulative return of the strategy. I find the coefficient to be positive for almost all characteristics and statistically significant for ten out of fourteen. Thus, in aggregate, institutional investors appear to trade in the same direction as mutual funds, possibly contributing to the price pressure.

The research in this chapter is related to several strands of literature. One strand studies the price impact of institutional flows on individual stocks (Coval and Stafford, 2007; Frazzini and Lamont, 2008; Lou, 2012). I build on these results by looking at the implications of fund flows at the strategy level. I argue that the same mechanism is responsible for the persistence in returns of strategies. I show that this persistence is different from individual stock momentum, which previous research also attempted to explain with flows (Lou, 2012). Another strand of literature studies the predictability of returns of characteristic-based portfolios. Moskowitz and Grinblatt (1999) find momentum in industry portfolios: the past winning industries continue to outperform past losing industries. Lewellen (2002) uncovers momentum among book-to-market and size sorted portfolios.[1] To my knowledge, all previous research only considered book-to-market and size anomalies, and this is the first study to show that the time series performance persistence of strategies is pervasive among a much larger set of characteristics.

The rest of this chapter is organized as follows. Section 1.2 describes the data and characteristic-based portfolios. Section 1.3 establishes strategy performance persistence. Section 1.4 explores the connection between strategy performance persistence and trading by mutual funds and institutional investors.

1.2 Characteristics, Data, and Average Strategy Returns

1.2.1 Characteristics

The fourteen characteristics are divided into five groups. The classical group consists of size S, book-to-market B/M, and momentum Mom. These three characteristics underlie the Fama and French (1993) three factor model and are used to construct DGTW benchmark portfolios. Size anomaly captures the tendency for small stocks to outperform large stocks (Banz, 1981; Reinganum, 1981). Book-to-market ratio is a measure of the fundamental value to the market price. High value stocks have on average higher returns than low value (growth) stocks (Rosenberg, Reid, and Lanstein, 1985). Jegadeesh and Titman (1993) documented the intermediate term momentum, i.e. the ability of stocks with relatively high prior returns

[1] See also Chen and Bondt (2004) and Wahal and Yavuz (2013).

(winners) to continue outperforming stocks with relatively low prior returns (losers).

Investment variables capture the firm's capital investment. This group consists of total asset growth AG, abnormal capital investments CI, and investments-to-assets ratio I/A. Cooper, Gulen, and Schill (2008) suggested total asset growth as a comprehensive measure of investment, while abnormal capital investments (Titman, Wei, and Xie, 2004) is equal to the deviation of the recent capital expenditures from their historical mean, and investments-to-assets ratio (Lyandres, Sun, and Zhang, 2008) is the capital investment in the prior year. All three characteristics are negatively related to future stock returns.

Issuance characteristics capture the firm's equity issuance activity with net stock issues NS and composite stock issuance ι. Net stock issues (Pontiff and Woodgate, 2008) measures the issuance in the previous year and composite stock issuance (Daniel and Titman, 2006) in the previous five years. Both are negatively related to future stock returns.

Two accounting anomalies capture the firm's earnings management and its cumulative effect on the balance sheet with accruals Acc (Sloan, 1996) and net operating assets NOA (Hirshleifer, Hou, Teoh, and Zhang, 2004), respectively. Both are negatively related to future stock returns. Return on assets ROA (Fama and French, 2006, 2008; Chen, Novy-Marx, and Zhang, 2010), an accounting measure of the firm's performance, also belongs to this group, but is positively related to stock returns. Idiosyncratic volatility $IdVol$, Ohlson's O-score, and dispersion in analysts' forecasts D are grouped together as they broadly quantify uncertainty about the firm. The idiosyncratic volatility anomaly was first documented by Ang, Hodrick, Xing, and

Zhang (2006) as the tendency of stocks with high residual daily return volatility to deliver relatively low future returns. Ohlson's O-score measures the likelihood of financial distress. Dichev (1998) found that distressed firms underperform healthier firms on average. Diether, Malloy, and Scherbina (2002) demonstrate that firms with more disagreement among analysts about future earnings tend to have lower future returns. The details of the construction of all characteristics are provided in the Appendix.

1.2.2 Data and Sample Construction for Characteristics and Stocks

This subsection describes the data sources and sample construction for stock characteristics and returns. All characteristics except dispersion in analysts' forecasts are constructed using Center for Research in Security Prices (CRSP) and Compustat datasets. Dispersion in analysts' forecasts is based on the data from Institutional Brokers Estimate System (I/B/E/S).

The CRSP sample includes only firms traded on NYSE, AMEX, and NASDAQ (CRSP EXCHCD = 1, 2, or 3) with common stocks (CRSP SHRCD = 10 or 11). The sample excludes financial firms (CRSP SICCD between 6000 and 6999) as they are excluded for the majority of the considered characteristic variables. These screens are set for returns in month t based on the data available at the end of month $t-1$. Portfolio returns are based on the monthly individual stock returns with dividends (CRSP RET) adjusted by the delisting return (CRSP DLRET).

In some tests, individual stock returns are adjusted for their size, book-to-market, and momentum benchmarks following the methodology of Daniel, Grinblatt, Titman, and Wermers (1997) (abbreviated DGTW) and Wermers (2004).[1] The resulting returns are denoted DGTW-adjusted. The basic methodology is as follows: DGTW create 125 benchmark portfolios by sorting sequentially stocks into five groups based on size, book-to-market, and momentum. They use only NYSE firms to compute portfolio breakpoints for each characteristic variable and value-weight portfolio returns. The DGTW-adjusted return for each stock is equal to its raw return minus the return of the corresponding benchmark.

Compustat annual data in calendar year t are taken from reports with fiscal year ends in year $t-1$ (based on the Compustat date variable DATADATE). I use a six month gap to allow for the possible late submission of accounting statements. Thus, annual accounting variables are used from the end of June of year t through the end of May of year $t+1$. All characteristics based on the Compustat annual data follow this rule with the addition of composite stock issuance. Compustat quarterly data are taken from the most recent quarterly earnings report (based on the Compustat date variable RDQ) and are used for the following three months or until the next report, whichever comes sooner. All characteristic variables are separately matched with the stock returns in the current month to compute portfolio returns. Therefore, the sample of firms used to construct portfolios varies by the characteristic.

Characteristics book-to-market, total asset growth, abnormal capital investments, investments-to-assets ratio, net stock issues, composite stock issuance, accruals, and net operating assets are updated annually at the end of June. Size, mo-

[1]The DGTW benchmarks are available for download on Russ Wermers' website.

mentum, idiosyncratic volatility, and dispersion in analysts' forecasts are updated monthly, and return on assets and O-score quarterly. Portfolio returns are computed from July 1976 to December 2011 for all characteristics except O-score and dispersion in analysts' forecasts. For these characteristics, the time-series of returns start in January 1977 and 1978, respectively.

To reduce the dataset errors for abnormal capital investments and total asset growth, the samples of these two characteristics are truncated each month by discarding the one percent of observations with the lowest and the one percent with the highest values of these variables. To reduce the effect of bid-ask bounce on momentum and idiosyncratic volatility, stocks with prices below or equal to \$5 at the end of the previous month are excluded for the samples of these two characteristics.

Daily and monthly risk-free rate RF_t, Fama and French (1993) factors $MKTRF_t$, SMB_t, HML_t, and the Carhart (1997) momentum factor UMD_t are downloaded from Wharton Research Data Services (WRDS).[1]

1.2.3 Mutual Fund and Institutional Data

This subsection explains mutual fund and institutional holdings data sources. Mutual fund equity holdings come from Thomson Financial, and mutual fund returns and characteristics are taken from the CRSP Survivor-Bias-Free Mutual Fund database. These two datasets are combined using the Mutual Fund Links (MFLINKS) matching dataset originally constructed by Russ Wermers.

[1] WRDS obtained these data from Ken French's website.

Thomson Financial compiled holdings from SEC N–30D form filings, which are required to be submitted semi-annually, although some funds voluntarily report quarterly. If the recorded report date is different from the end-of-quarter filing date, I assume that the manager did not trade between the report and filing dates.

Mutual fund gross monthly return is equal to the sum of the net return (CRSP MRET) and 1/12 of the expense ratio (CRSP EXP_RATIO). CRSP data are aggregated for funds with multiple share classes. Specifically, fund's total net assets (CRSP TNA) is equal to the sum of the TNAs of all share classes. Similarly, the fund return is the average of returns of its share classes weighted by their TNA. The time period for mutual fund holdings starts in the quarter ending in December 1979 and ends in the quarter ending in September 2011 for a total of 128 quarters.

Institutional equity holdings come from Thomson Financial, which collects quarterly 13F filings of investment managers to the SEC. According to Securities Exchange Act Section 3(a)(9) and Section 13(f)(5)(A), an institutional investment manager is an entity that has investment discretion over the funds that it does not directly own. This broad definition captures banks, insurance companies, mutual fund companies, pension funds, and university endowments. Companies managing several mutual funds file holdings aggregated across all their funds and other accounts. Only managers with a portfolio valued at $100 million or more are required to file 13F form to disclose their holdings. They can omit small holdings (less than 10,000 shares or $200,000) and securities not included on the 13F disclosure list, which mostly consists of equities. To use the most recent holdings only reports filed at the end of the quarter are used, which eliminates about 5% of the observations.

The time period for 13F holdings starts in the quarter ending in March 1980 and ends in the quarter ending in December 2011 for a total of 128 quarters.

1.2.4 Average Returns of Characteristic-based Portfolios

This subsection reports average portfolio returns for characteristic-based portfolios. Using a particular characteristic, firms are sorted at the end of month $t-1$ to form quintile portfolios P1 to P5. Following Fama and French (2008), portfolio breakpoints are determined using all stocks except for the micro group. The market capitalization of micro stocks is in the lowest market capitalization quintile of firms traded on the NYSE. Equal-weighted average raw and DGTW–adjusted returns are computed at the end of month t for each portfolio and characteristic. Long-short zero-cost portfolio P1-P5 is created by investing \$1 in portfolio P1 and selling \$1 of portfolio P5. As I explained in the construction of the characteristics, standard definitions of book-to-market, momentum, and return on assets are multiplied by negative one to make the return of portfolio P1-P5 consistently positive across all anomalies.

This methodology is a compromise between equal-weighting and value-weighting portfolios using all stocks for breakpoints. As firm size is highly skewed, value-weighting tends to put the most weight on a few very large firms. Hence, for most characteristics, average returns are sensitive to the value-weighting methodology, which may reduce statistical power in the tests below. On the other hand, equal-weighted portfolios are likely to consist mostly of extremely small less liquid stocks, which account for 60% of all stocks, but only for 3% of aggregate market capitalization (Fama and French, 2008). Since the dispersion in the characteristic variables is higher among micro stocks, excluding them from the breakpoint sample ensures that they do not dominate portfolios P1 and P5, therefore these portfolios contain more medium and large firms.

Panel A of Table 1.1 shows average raw monthly returns for each portfolio. To be included in the sample, each portfolio is required to have twelve months of previous returns. Thus, the sample period is the same as in tests which use the cumulative return over the previous twelve months as an independent variable. In line with the previous research, all considered characteristics are strongly negatively related to raw stock returns, as evidenced by the highly statistically significant average returns for almost all long-short portfolios P1-P5. As discussed previously, since the sample used to set portfolio breakpoints excludes micro stocks, the extreme portfolios contain more large stocks with lower returns, making the average return of portfolio P1-P5 lower in some cases. Notably, the return spread for S is 33 bps per month with a t-statistic of 1.36. If all stocks are used for setting portfolio breakpoints, then the spread for the size is much higher at 93 bps with a t-statistic of 3.14 for the same time period. Similarly, the return spread for $IdVol$ is 41 bps, which is lower than found in the previous literature. The returns decrease relatively monotonically from portfolio P1 to P5 for most characteristics. However, the characteristic-return relationship tends to be nonlinear with the most variation coming from portfolios P1 and P5, and much less from P2 to P4. For example, for book-to-market B/M the average return for P1-P5 is 105 bps, but for P2-P4 is 39 bps. Thus, the rest of the chapter focuses on the returns of portfolios P1-P5.

Panel B shows the average portfolio returns adjusted for size, book-to-market, and momentum. The DGTW-adjusted returns of portfolios P1 to P5 noticeably decrease, but the average return of P1-P5 does not decrease as much and is still significant for most characteristics. For example, for *AG*, the average return of portfolio P1 decreases from 172 bps to 47 bps and P5 from 74 bps to -29 bps, but P1-P5 is reduced from 98 bps to a still high 76 bps. Overall, all examined characteristics are different from the three prominent anomalies forming the basis for the most popular factor model of Fama and French (1993).

Both average raw and DGTW-adjusted returns vary across fourteen characteristics, even though they are computed almost over the same periods. This is not surprising in light of varying economic motivations and explanations for considered anomalies. Hence, studying only one time-series of average characteristic-based portfolios P1-P5 is likely to ignore the variation across these portfolios for different anomalies. Thus, in the subsequent analysis the time-series properties of portfolios P1-P5 are investigated separately for each of the fourteen characteristics as well as in combination.

1.3 Persistence in the Performance of Characteristic-based Strategies

1.3.1 Short-term Performance Persistence of Strategies

This subsection considers whether the cumulative return of portfolio P1-P5 over the previous twelve months can predict its return in the current month. For each characteristic the following regression model is estimated

$$R_t = \alpha_0 + \alpha_1 * R_{t-12,t-1} + \epsilon_t,$$

where R_t is the return of the long-short portfolio P1-P5 in month t, and $R_{t-12,t-1}$ is the cumulative return over the previous twelve months of this portfolio. Table 1.2 presents the intercept α_0 and regression coefficient α_1 (both multiplied by 100) from this regression. In the first two columns raw returns are used both on the left-hand side and right-hand side. Thus, this specification is headed (*raw*, *raw*). Standard errors are adjusted for autocorrelation in residuals for up to three lags following Newey and West (1987).[1]. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

The null hypothesis of no predictability is rejected for five characteristics (size S, total asset growth AG, abnormal capital investments CI, investments-to-assets ratio I/A, and Ohlson's O-score O) by the corresponding statistically significant coefficients α_1. The coefficient is positive but insignificant for eight more characteristics (book-to-market B/M, momentum Mom, net stock issues NS, composite stock issuance ι, accruals Acc, net operating assets NOA, return on assets ROA, and dispersion in analysts' forecasts D). The remaining characteristic, idiosyncratic volatility $IdVol$, has a negative but statistically insignificant coefficient.

Significant α_1 estimates vary from 1.49 for net operating assets NOA to 3.23 for total asset growth AG. A coefficient of persistence α_1 of 2.27 for size S implies that

[1]Regression residuals are heteroskedastic so weighted least squares may improve the efficiency of estimates, which is what I find, when the weights are set to be inversely proportional to the residuals.

if its prior twelve month return $R_{t-12,t-1}$ increases by its standard deviation of 23%, current month return R_t increases by 52.2 bps on average. The last row *All* shows coefficients from panel regressions using all fourteen strategies with year-month fixed effects and standard errors clustered by strategy. This methodology controls both for possible cross sectional correlation and serial correlation in regression residuals (Petersen, 2009). The null hypothesis of no persistence for all strategies is rejected at a 1% level with a coefficient of 1.65 and a t-statistic of 5.88. Overall, the short-term persistence in the performance of strategies is pervasive and economically meaningful.

The average portfolio return, reported in Table 1.1, is equal to the sum of α_0 and α_1 multiplied by the average return in the previous twelve months. It follows that how much the intercept α_0 is lower than the average return depends on the strength of the persistence and the magnitude of the prior twelve month return. This intuition is confirmed in the first column, showing the reduced intercept α_0 for most characteristics.

When the cumulative return of portfolio P1-P5 over the previous twelve months $R_{t-12,t-1}$ is positive, portfolios P1 and P5 tend to hold individual stocks with high and low cumulative returns, respectively. A similar intuition applies when $R_{t-12,t-1}$ is negative. Thus, it appears that the persistence in the returns of the strategies may be driven by the momentum in individual stocks (Jegadeesh and Titman, 1993). In addition, the persistence may come from the correlation with size S and book-to-market B/M, which themselves exhibit persistence with coefficients of 2.27 and 2.26, respectively.[1] Some evidence for this correlation, discussed in sub-

[1]Specifically, suppose that $R_t = a_t + \gamma * f_t$, where f_t is a risk factor, and a_t is the residual.

section 1.2.4, is that average returns of characteristic-based portfolios P1-P5 are still significant, but are slightly lower after adjustment for size, book-to-market, and momentum.

To address this possibility in the next specification, the left-hand side returns are adjusted for size, book-to-market, and momentum (DGTW-adjusted). Hence, this specification is denoted ($DGTW$, raw) with size S, book-to-market B/M, and momentum Mom excluded. While the magnitude of the α_1 coefficients is somewhat lower, the same characteristics remain significant. The panel regression confirms that persistence is robust to this adjustment with only a slightly lower coefficient of 1.33 (t-statistic=5.01). To explore this adjustment further, the next specification ($DGTW$, $DGTW$) uses DGTW-adjusted on both the left-hand side and right-hand side with consistent results.

Conceptually, strategy performance persistence is different from momentum in individual stocks if it can be substantially attributed to strategy stocks predicting returns of one another and not only to stocks predicting their own returns. To test this explanation the set of all firms is randomly split into two nonoverlapping samples to construct two strategies R_t^1 and R_t^2 for each characteristic. Then, the following time series regression for each characteristic is executed

$$R_t^1 = \alpha_0 + \alpha_1 * R_{t-12,t-1}^2 + \epsilon_t$$

along with a panel regression using all fourteen strategies with year-month fixed

$Cov(R_t, R_{t-1}) = Cov(a_t, a_{t-1}) + \gamma(Cov(f_t, a_{t-1}) + Cov(f_{t-1}, a_t)) + \gamma^2 Cov(f_t, f_{t-1})$. Hence, portfolio P1-P5 persistence $Cov(R_t, R_{t-1}) > 0$ can stem from the factor portfolio persistence $Cov(f_t, f_{t-1}) > 0$.

effects. R_t^1 is the return in month t of the long-short portfolio P1-P5 based on the first sample, and $R_{t-12,t-1}^2$ is the cumulative return over the previous twelve months of the long-short portfolio based on the second sample. This procedure is repeated 1000 times. Table 1.3 reports average coefficients and average t-statistics of the corresponding 1000 estimates. For most characteristics coefficients α_1 are virtually identical to the full sample estimates reported in Table 1.2. For example, in the (raw,raw) specification for size S the average persistence coefficient is 2.24, which is very close to 2.27 for the whole sample test results. For the same specification the panel coefficient estimate is 1.58, similarly close to 1.65 for the whole sample. The Figure 1.1 shows histograms of coefficients from 1000 repetitions. The plots display tight distributions of estimates with only a small proportion being negative, which implies that strong persistence is found in most random splits. Overall, strategy performance persistence cannot be fully attributed to individual stock momentum and is robust to the adjustment for size and book-to-market anomalies.

1.3.2 Persistence Strategies based on Characteristic-based Strategies

To gauge the economic significance of performance persistence, I investigate whether it can be used to construct new persistence strategies based upon the underlying strategies. Perhaps the simplest persistence trading strategy consists of buying the underlying strategy following positive prior returns and selling it otherwise. However, positive or negative average exposure to the base strategy implies significant average returns for the new strategy even in the absence of persistence. Hence, it is important that a persistence strategy holds and shorts the underlying strategy in equal proportion.

Motivated by this observation, in Panel A of Table 1.4 I test an alternative specification for the short-term persistence

$$R_t = \alpha_0 + \alpha_1 * sign(R_{t-12,t-1} - Med_{R_{t-12,t-1}}) + \epsilon_t,$$

where R_t is the return in month t of the long-short portfolio P1-P5, and $sign(R_{t-12,t-1} - Med_{R_{t-12,t-1}})$ is the sign of the cumulative return over the previous twelve months of this portfolio after subtracting its time-series median. Raw portfolio returns are used on the left-hand side and right-hand side. In the 'In Sample' specification the median is computed using the full time series of cumulative returns. Thus, by construction, the sign of the median-adjusted prior return is equal to 1 or -1 exactly half the time. Based on this specification, the average return of holding the underlying strategy is equal to $.5(\alpha_0 + \alpha_1) + .5(\alpha_0 - \alpha_1) = \alpha_0$. Thus, the intercepts α_0 are equal exactly to the average strategy returns, which were previously reported in Table 1.1. The average return of a persistence strategy is equal to $.5(\alpha_0 + \alpha_1) - .5(\alpha_0 - \alpha_1) = \alpha_1$. Intuitively, half the time the return of the strategy is higher by α_1 than the average α_0, and half the time it is lower by α_1. Note that the average return of the persistence strategy is independent of the average return of the underlying strategy.

The results in Table 1.4 are consistent with the evidence in the previous subsection. For the 'In Sample' specification coefficients α_1 are positive for all characteristics and significant for six (size S, total asset growth AG, investments-to-assets ratio I/A, net operating assets NOA, return on assets ROA, and Ohlson's O-score O). The coefficient α_1 estimates vary from 11 bps for net stock issues NS to 72 bps for size S. The panel coefficient is 30 bps (t-statistic=5.31).

However, the persistence strategies implied by these results are not implementable as they require knowledge of the future data. To address this issue in the 'Out of Sample' specification the median is based only on the cumulative returns available in month $t-1$. For the first five years of cumulative returns, the 'Out of Sample' median is set equal to zero. The 'Out of Sample' coefficients α_1 in the fourth column differ only slightly from the 'In Sample' estimates.

Panel B shows the raw and DGTW-adjusted average returns of persistence strategies. The median is computed as in the 'Out of Sample' specification. As previously argued, if the median is computed precisely, a persistence strategy holds the underlying strategy exactly half the time, and its average return is equal to the corresponding coefficient α_1 in Panel A. Column 'months long' displays the percentage of months a given persistence strategy buys the underlying strategy. The average across all characteristics is 53.1% (row 'Average') with the lowest 44.4% for net stock issues NS and the highest 62.2% for total asset growth AG. Thus, on average, implementable persistence strategies have a slight exposure to the underlying strategy. The 'Average' persistence strategy every month averages the returns of fourteen persistence strategies. The average raw and DGTW-adjusted returns of this persistence strategy are statistically significant 37 bps and 24 bps, respectively. Overall, the short-term performance persistence of characteristic-based strategies is economically significant, as evidenced by significant average returns for the persistence strategies.

To explore the time series dynamics of characteristic-based strategies and persistence strategies, Table 1.5 shows their average returns in various subperiods.

In Panel A for each characteristic the full sample is split based on the publication date of the first academic study describing the anomaly. More attention to the characteristic may reduce its predictive power, particularly if it arises from behavioral biases of investors. Column 'first post year' shows the first year of the post period which is set to the year before the publication date. One year adjustment is due to papers typically receiving significant publicity before appearing in journals. On average, strategies continue to earn significant returns after the publication, with the average return decreasing slightly from 67 bps to 56 bps. Similarly, the average performance of persistence strategies shows a minor change from 40 bps to 39 bps.

However, it is difficult to interpret the returns of the *Average* strategy, because the number of anomalies it contains changes over time. This explains why the average of the reported persistence strategy returns is 54 bps before the publication and 13 bps after it. To address this concern, in Panel B the time series is divided into pre and post 1995 subperiods for all characteristics. Interestingly, for characteristic-based strategies the results are similar with a slight decrease in the post 1995 period from 68 bps to 57 bps. However, the decline is more dramatic for the persistence strategies from 44 bps to 29 bps. The potential explanation for this decline is explored in further analysis below.

1.3.3 Seasonal Patterns

Next, I consider whether there are seasonal patterns in the predictability in returns of strategies. For example, in January the size effect is particularly strong (Keim, 1983; Reinganum, 1983), and momentum is particularly weak (Jegadeesh and

Titman, 1993). To the extent that persistence correlates with these effects, January results may be weaker or stronger. Since Compustat annual data are updated at the end of June, returns of Compustat-based characteristics (book-to-market B/M, total asset growth AG, abnormal capital investments CI, investments-to-assets ratio I/A, net stock issues NS, composite stock issuance ι, accruals Acc, and net operating assets NOA) in July may be higher, improving the predictability. Overall, it is interesting to see whether persistence is restricted to or stronger in certain calendar months.

To this end, Table 1.6 displays average returns of persistence strategies in each calendar month. For each characteristic a persistence strategy buys an underlying strategy when its 'Out of Sample' median-adjusted prior cumulative return $R_{t-12,t-1} - Med_{R_{t-12,t-1}}$ is positive and sells it otherwise. Raw portfolio returns are used on the left-hand side and right-hand side. Note that as the number of months in each regression is reduced by a factor of twelve, the statistical power is substantially lowered.

In January, six characteristics are positive with two being significant (total asset growth AG and investments-to-assets ratio I/A), making the return of the average strategy close to zero with 4 bps. In July ten are positive with four of them significant (total asset growth AG, net operating assets NOA, return on assets ROA, and dispersion in analysts' forecasts D). For the *Average* strategy, the strongest months are February (109 bps), September (56 bps), and December (107 bps). The high return in December may be the result of window dressing by mutual fund managers at the strategy level at the end of the year. Overall, despite some variation, the persistence does not appear to be concentrated in a single month or a small subset of months with ten months showing positive returns for the *Average* strategy.

1.3.4 Long-term Performance Persistence of Strategies

In this subsection I test whether persistence of characteristic-based strategies exists over a horizon of more than one month. Specifically, Panel A of Table 1.7 and Figure 1.2 show the regression coefficient α_1 for each characteristic from the time series monthly regression

$$R_t = \alpha_0 + \alpha_1 * R_{t-11-k,t-k} + \epsilon_t,$$

where R_t is the return in month t of the long-short portfolio P1-P5, and $R_{t-11-k,t-k}$ is the cumulative return of this portfolio over the period $t-11-k$ to $t-k$ with the lag number k varying from 1 to 12. In both panels, raw returns are used on the left-hand side and right-hand side. The first column reproduces coefficients α_1 from Table 1.2.

Eleven characteristics continue to be positive at the second lag, and three are significant (total asset growth AG, investments-to-assets ratio I/A, and Ohlson's O-score). The panel regression coefficient is .76 for the second lag, .81 for the third, and .70 for the fourth. For lags five through seven, I cannot reject the null hypothesis that the coefficient is zero. Beginning with lag eight there is evidence of reversal with significantly negative coefficients.

Panel B shows average returns of the persistence strategies, discussed in subsection 1.3.2. For each characteristic, a persistence strategy buys an underlying strategy when its median-adjusted prior cumulative return $R_{t-11-k,t-k} - Med_{R_{t-11-k,t-k}}$ is positive and sells it otherwise. The median is based only on the data available in month $t-k$. For the first five years of cumulative returns the median is set equal to zero. The last row shows returns of the *Average* persistence strategy, which every month averages the returns of fourteen persistence strategies for a given lag. The returns of the *Average* persistence strategy decrease almost monotonically from a statistically significant 37 bps at lag 1 to an insignificant -3 bps at lag 12. A similar pattern is observed for individual strategies. However, there is no reversal at higher lags, suggesting that this is not a robust finding. Overall, characteristic-based strategies exhibit significant performance persistence for four to six months.

1.4 Mutual Fund Price Pressure and Institutional Demand

1.4.1 Strategy Performance Persistence and Mutual Fund Price Pressure

Next, I examine more directly the relation between prior strategy returns, expected fund flows into strategies, and subsequent strategy returns. In order to do so, I need to compute a measure of mutual fund trading in response to flows. I follow Lou, 2012 and Shive and Yun, 2013 in the construction of flow-induced trading at the stock level. Under the assumption that all flows and trading occur at the end of the quarter, the dollar flow into the mutual fund i in the current quarter is defined as

$$fund\_flow_{i,t+2} = TNA_{i,t+2} - TNA_{i,t-1} * (1 + ret_{i,t+2}),$$

where TNA is measured at the end of months $t-1$ and $t+2$, and $ret_{i,t+2}$ is the fund return measured over the current quarter, i.e. over three months t, $t+1$, and $t+2$.

To construct a measure of flow-driven trading for a given fund, I also assume that managers invest all flows in accordance with prior portfolio weights, and the stock price does not change over the quarter. Under these assumptions, the dollar value of additional holdings is equal to the product of dollar flows and portfolio weight. Thus, the number of shares of stock j that may be bought or sold due to the flows is

$$stock\_flow_{i,j,t+2} = \frac{w_{i,j,t-1} * fund\_flow_{i,t+2}}{price_{i,j,t-1}},$$

where $w_{i,j,t-1}$ is the weight of stock j in the mutual fund portfolio and $price_{i,j,t-1}$ is the stock price at the end of month $t-1$.

To capture the overall trading due to flows, I aggregate flow-driven buys and sells across all funds holding a given stock. I scale it by the prior total mutual fund ownership to control for the liquidity of the stock as mutual funds tend to hold more liquid assets (Lou, 2012). Therefore, the aggregate flow-driven trading of stock j is

$$stock\_flow_{j,t+2} = \sum_i \frac{stock\_flow_{i,j,t+2}}{\sum_i shares_{i,j,t-1}} = \sum_i \frac{shares_{i,j,t-1} * fund\_flow\_TNA_{i,t+2}}{\sum_i shares_{i,j,t-1}},$$

where $fund\_flow\_TNA_{i,t+2}$ is $fund\_flow_{i,t+2}$ scaled by $TNA_{i,t-1}$, and $shares_{i,j,t-1}$ is the number of shares of stock j owned by fund i at the end of month $t-1$.

I use the prior fund performance as a predictor of fund flows. Thus, the expected aggregate flow into stock j is

$$E_{t-1}[stock\_flow_{j,t+2}] = \sum_i \frac{shares_{i,j,t-1} * E_{t-1}[fund\_flow\_TNA_{i,t+2}]}{\sum_i shares_{i,j,t-1}},$$

where $E_{t-1}[fund\_flow\_TNA_{i,t+2}]$ is equal to the fund four factor alpha $\alpha_{i,t-1}$ from the rolling-window regression over the previous twelve months. Specifically, $\alpha_{i,t-1}$

comes from the regression

$$ret^m - RF^m = \alpha_{i,t-1} + \beta_{i,t-1}^{MKTRF} MKTRF^m + \beta_{i,t-1}^{SMB} SMB^m + \beta_{i,t-1}^{HML} HML^m + \beta_{i,t-1}^{UMD} UMD^m + \epsilon^m,$$

where month $m = t-12$ to $t-1$, ret^m is the gross monthly fund return, RF^m is the monthly risk-free rate, $MKTRF^m$, SMB^m, HML^m are Fama and French (1993) factors, and UMD^m is the Carhart (1997) momentum factor.

The expected fund flow into a characteristic-based strategy $E_{t-1}[Strategy\_Flow_t]$ is calculated as follows: first, the individual stock level measure is averaged across all firms in portfolios P1 and P5. Then, portfolio level measure P5 is subtracted from P1. This procedure mimics the computation of returns for the long-short portfolio P1-P5. Fund holdings are updated quarterly and returns monthly.

To test whether price pressure from fund flow-driven trading explains the performance persistence of strategies, I estimate the following two time-series regression models for each characteristic

$$R_t = \alpha_0^1 + \alpha_1 * E_{t-1}[Strategy\_Flow_t] + \epsilon_t^1,$$

$$\epsilon_t^1 = \alpha_0^2 + \alpha_2 * R_{t-12,t-1} + \epsilon_t,$$

where R_t is the return in month t of the long-short portfolio P1-P5, and $R_{t-12,t-1}$ is the cumulative return of this portfolio over previous twelve months. Raw or DGTW-adjusted returns are used on the left-hand side and raw returns on the right-hand side. Table 1.8 presents intercepts α_0^1 and α_0^2 and regression coefficients α_1 and α_2 from these regressions.

Panel A reports estimates based on the full sample 1980-2011. The coefficient α_1 is positive for thirteen characteristics and statistically significant for four (total asset growth AG, abnormal capital investments CI, investments-to-assets ratio I/A, and net operating assets NOA). The panel regression coefficient in column *All* is equal to 2.31 with a t-statistic of 4.60. At the same time, the coefficient α_2 on the prior strategy return is reduced by two-thirds to .58 compared with Table 1.2. Similar results are obtained when DGTW-adjusted portfolio returns are used on the left-hand side.

In Panel B estimation is performed separately for pre 1995 and post 1995 periods. In the second half of the sample mutual funds became more important market participants as evidenced by the share of the market they held (Lou, 2012). Accordingly, I find that the price pressure measure in this subperiod renders the prior return close to zero.[1] It is possible that several factors are responsible for strategy return persistence before 1995, which explains the significant coefficient on the prior return in the earlier period and overall. However, in the latter subperiod trading by mutual funds is the dominant explanation for the persistence, which makes the prior return a noisier predictor of future strategy returns. Overall, this evidence implies that the price pressure measure substantially reduces the predictive power of prior strategy returns. These findings support the conjecture that predictable flow-driven trading is at least partially responsible for the strategy performance persistence.

[1] Without controlling first for the price pressure, the coefficient on the prior return is 1.00 (t-statistic=4.1).

1.4.2 Aggregate Institutional Demand and Prior Strategy Performance

Institutions such as hedge funds, pension funds, and insurance companies are not as sensitive to the return chasing flows as mutual funds. Hence, they may alleviate the flow-induced price pressure by trading with mutual funds. To explore this possibility, I compute the institutional demand for each characteristic-based strategy, and examine how it depends on the prior strategy returns.

For a given stock i, total institutional ownership $shares_{i,t}$ is equal to the sum of the number of shares (Thomson SHARES) held by all 13F institutions at the end of month t. Institutional holdings are updated quarterly. The institutional demand for stock i in the current quarter is calculated as

$$Demand_{i,t+2} = 100 * \frac{shares\_adj_{i,t+2} - shares_{i,t-1}}{shrout_{i,t-1}}$$

where $shares\_adj_{i,t+2}$ is $shares_{i,t+2}$ corrected for stock splits and stock dividends in the current quarter using the CRSP adjustment factor (CRSP CFACSHR). $shrout_{i,t-1}$ is the number of shares outstanding at the end of month $t-1$ (CRSP SHROUT).

The institutional demand for a characteristic-based strategy $Strategy\_Demand_{t+2}$ is calculated as follows: first, the individual stock demand is averaged across all firms in portfolios P1 and P5. Then, portfolio level demand P5 is subtracted from P1. This procedure mimics the computation of returns and expected price pressure for the long-short portfolio P1-P5.

To study how the institutional demand for a strategy depends on its prior return, the following regression model is estimated for each characteristic

$$Strategy\_Demand_{t+2} = \alpha_0 + \alpha_1 * R_{t-12,t-1} + \epsilon_t,$$

where $R_{t-12,t-1}$ is the cumulative return of the long-short portfolio P1-P5 over the previous twelve months. Table 1.9 presents the intercept α_0 and regression coefficient α_1 (both multiplied by 100) from this regression.

Panel A reports estimates based on the full sample 1980-2011. In the second column the coefficient α_1 is positive for all but one characteristic (abnormal capital investments CI) and is significant for eleven (book-to-market B/M, momentum Mom, total asset growth AG, net stock issues NS, composite stock issuance ι, accruals Acc, net operating assets NOA, idiosyncratic volatility $IdVol$, Ohlson's O-score, and dispersion in analysts' forecasts D). The panel regression coefficient is 1.22 (t-statistic=4.87). The coefficient $\alpha_1 = 1.14$ for book-to-market implies that an increase in one standard deviation of prior returns $R_{t-12,t-1}$ equal to 19% leads to an increase in the aggregate demand of .22% of shares outstanding.

The intercept α_0 is the fitted institutional demand when the prior returns of a strategy are zero. It is negative and significant for nine characteristics (book-to-market B/M, total asset growth AG, investments-to-assets ratio I/A, net stock issues NS, composite stock issuance ι, net operating assets NOA, idiosyncratic volatility $IdVol$, Ohlson's O-score, and dispersion in analysts' forecasts D). This implies that institutional investors tend to sell the strategy when it underperforms in the previous twelve months.

To test whether the demand for strategies based on size S, book-to-market B/M, and momentum Mom may explain the results for other characteristics, the demand for each stock is adjusted for the average demand for these three characteristics. Following a methodology similar to Daniel, Grinblatt, Titman, and Wermers

(1997), I use Wermers' individual stock assignments to size, book-to-market, and momentum quintile portfolios and compute average institutional demand for each of the 125 portfolios. Then, from each stock's individual demand I subtract the corresponding size-book-to-market-momentum portfolio demand to calculate the adjusted demand. The results are shown in the specification 'Adjusted' of Table 1.9. The α_1 coefficients are reduced in magnitude, but four out of nine individual characteristics and the panel regression coefficient remain statistically significant. In Panel B, estimation is performed separately for pre 1995 and post 1995 periods with results being consistent across both subperiods. Overall, institutional demand for strategies is economically and statistically higher following positive strategy returns.

Table 1.1: Mean Returns of Characteristic-based Portfolios

Each month stocks are sorted on each of fourteen variables into quintile portfolios P1 to P5 with portfolio breakpoints based on the sample of all but micro stocks. The market capitalization of micro stocks is in the lowest market capitalization quintile of firms traded on the NYSE. For portfolios P1 to P5 and zero-cost portfolio P1-P5 equal-weighted raw and DGTW-adjusted returns are calculated. Panel A and Panel B display averages of monthly time-series of raw and DGTW-adjusted returns for each portfolio, respectively. Returns are multiplied by 100. Standard errors of the means are adjusted for autocorrelation in residuals for up to three lags following Newey and West (1987). The t-statistics are shown in parentheses.

Panel A: Mean Raw Portfolio Returns

	S	$-B/M$	$-Mom$	AG	CI	I/A	NS	ι	Acc	NOA	$-ROA$	$IdVol$	O	D
P1	1.33	1.70	1.73	1.72	1.46	1.60	1.32	1.48	1.41	1.68	1.83	1.18	1.41	1.38
	(3.43)	(5.11)	(4.67)	(4.48)	(4.17)	(4.29)	(4.18)	(6.20)	(3.69)	(4.02)	(5.75)	(6.39)	(4.50)	(5.03)
P2	1.25	1.45	1.40	1.46	1.45	1.58	1.43	1.39	1.55	1.56	1.56	1.35	1.48	1.26
	(3.86)	(4.70)	(5.17)	(5.25)	(4.90)	(5.18)	(4.82)	(5.52)	(5.06)	(4.65)	(5.53)	(5.47)	(4.96)	(4.55)
P3	1.21	1.39	1.26	1.42	1.39	1.41	1.54	1.47	1.40	1.46	1.46	1.38	1.51	1.22
	(4.08)	(4.34)	(5.09)	(5.13)	(4.94)	(4.73)	(4.78)	(5.06)	(4.84)	(4.86)	(5.35)	(4.91)	(4.81)	(3.91)
P4	1.10	1.06	1.12	1.28	1.34	1.33	1.34	1.51	1.39	1.29	1.31	1.38	1.32	1.20
	(4.05)	(2.98)	(4.23)	(4.22)	(4.63)	(4.31)	(3.72)	(4.40)	(4.53)	(4.27)	(4.52)	(4.17)	(4.12)	(3.46)
P5	1.00	0.65	0.62	0.74	1.27	0.80	0.77	1.07	1.17	0.77	0.82	0.77	1.05	0.90
	(4.30)	(1.52)	(1.83)	(1.97)	(3.94)	(2.21)	(1.90)	(2.76)	(3.33)	(2.28)	(1.82)	(1.94)	(2.61)	(2.16)
P1-P5	0.33	1.05	1.11	0.98	0.19	0.80	0.54	0.41	0.24	0.91	1.01	0.41	0.36	0.47
	(1.36)	(5.07)	(4.39)	(6.51)	(2.40)	(6.65)	(3.60)	(1.85)	(2.42)	(4.38)	(4.37)	(1.43)	(1.94)	(2.18)

Panel B: Mean DGTW-adjusted Portfolio Returns

	S	$-B/M$	$-Mom$	AG	CI	I/A	NS	ι	Acc	NOA	$-ROA$	$IdVol$	O	D
P1				0.47	0.25	0.35	0.28	0.20	0.24	0.58	0.72	-0.01	0.36	0.25
				(3.70)	(3.04)	(3.27)	(4.15)	(2.52)	(2.16)	(3.47)	(12.73)	(-0.15)	(5.10)	(3.82)
P2				0.22	0.21	0.37	0.20	0.12	0.32	0.32	0.41	0.15	0.38	0.16
				(3.92)	(3.76)	(3.42)	(3.18)	(1.67)	(4.68)	(4.09)	(8.80)	(2.80)	(7.23)	(2.98)
P3				0.21	0.18	0.22	0.36	0.22	0.21	0.20	0.25	0.18	0.32	0.14
				(4.06)	(3.64)	(3.87)	(3.66)	(3.38)	(3.20)	(3.39)	(4.83)	(4.00)	(5.69)	(2.45)
P4				0.14	0.16	0.18	0.24	0.33	0.17	0.06	0.08	0.21	0.14	0.17
				(2.67)	(2.81)	(3.00)	(2.64)	(4.47)	(3.07)	(0.93)	(1.33)	(4.68)	(2.35)	(2.20)
P5				-0.29	0.07	-0.26	-0.26	-0.01	0.03	-0.32	-0.21	-0.26	-0.05	-0.07
				(-2.68)	(1.01)	(-2.54)	(-1.93)	(-0.14)	(0.35)	(-3.42)	(-1.22)	(-3.13)	(-0.36)	(-0.57)
P1-P5				0.76	0.18	0.61	0.54	0.21	0.21	0.90	0.94	0.24	0.40	0.32
				(6.18)	(2.77)	(5.87)	(3.95)	(1.46)	(2.24)	(4.98)	(5.25)	(1.57)	(3.12)	(2.02)

Table 1.2: Short-term Performance Persistence of Characteristic-based Strategies

The table presents the intercept α_0 and regression coefficient α_1 for each characteristic from the time series monthly regression $R_t = \alpha_0 + \alpha_1 * R_{t-12,t-1} + \epsilon_t$, where R_t is the return in month t of the long-short portfolio P1-P5, and $R_{t-12,t-1}$ is the cumulative return over the previous twelve months of this portfolio. (raw, raw) indicates that raw portfolio returns are used on the left-hand and right-hand side. Similarly, $(DGTW, raw)$ indicates that DGTW-adjusted portfolio returns are used on the left-hand and raw portfolio returns on the right-hand side. The intercept α_0 and regression coefficient α_1 are multiplied by 100. The last row *All* shows coefficients from panel regressions using all fourteen strategies with year-month fixed effects and standard errors clustered by strategy. For individual characteristics, standard errors are adjusted for autocorrelation in residuals for up to three lags following Newey and West (1987). The t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Anomaly	(raw, raw)		$(DGTW, raw)$		$(DGTW, DGTW)$	
	int	$R_{t-12,t-1}$	int	$R_{t-12,t-1}$	int	$R_{t-12,t-1}$
S	0.20	2.27**				
	(0.83)	(2.40)				
$-B/M$	0.72**	2.26				
	(2.07)	(1.49)				
$-Mom$	1.01***	0.67				
	(3.28)	(0.36)				
AG	0.51***	3.23***	0.42***	2.35***	0.46***	3.17***
	(2.94)	(3.30)	(3.10)	(3.40)	(3.38)	(2.92)
CI	0.12	2.15*	0.11	2.04**	0.10	3.26**
	(1.46)	(1.68)	(1.63)	(2.14)	(1.44)	(2.39)
I/A	0.46***	2.87**	0.32**	2.47**	0.33**	3.84**
	(2.83)	(2.11)	(2.30)	(2.00)	(2.33)	(1.98)
NS	0.46**	1.15	0.45**	1.20	0.48***	0.91
	(2.16)	(0.62)	(2.57)	(0.71)	(2.72)	(0.38)
ι	0.36	0.89	0.18	0.61	0.20	0.61
	(1.33)	(0.47)	(1.06)	(0.52)	(1.22)	(0.30)
Acc	0.20**	1.18	0.16*	1.27	0.15*	2.02
	(2.14)	(0.86)	(1.94)	(0.95)	(1.83)	(1.30)
NOA	0.71***	1.49	0.69***	1.50	0.55***	3.05
	(3.35)	(0.77)	(3.87)	(0.95)	(2.96)	(1.42)
$-ROA$	0.80**	1.70	0.78***	1.23	0.79**	1.33
	(2.27)	(1.01)	(3.00)	(1.03)	(2.23)	(0.60)
$IdVol$	0.41	-0.02	0.28	-0.72	0.32	-2.84
	(1.13)	(-0.01)	(1.42)	(-0.48)	(1.55)	(-0.86)
O	0.27	2.55***	0.33***	1.91***	0.28**	2.66**
	(1.59)	(2.75)	(2.90)	(2.87)	(2.38)	(2.14)
D	0.38	1.56	0.26	1.00	0.24	2.24
	(1.59)	(1.11)	(1.53)	(1.02)	(1.40)	(1.38)
All		1.65***		1.33***		2.60***
		(5.88)		(5.01)		(9.18)

Table 1.3: Short-term Performance Persistence, Sample Split Test

The set of all firms is randomly split into two nonoverlapping samples to construct two strategies R_t^1 and R_t^2 for each characteristic. Then, the following time series regression for each characteristic is executed $R_t^1 = \alpha_0 + \alpha_1 * R_{t-12,t-1}^2 + \epsilon_t$ along with a panel regression using all fourteen strategies with year-month fixed effects. R_t^1 is the return in month t of the long-short portfolio P1-P5 based on the first sample, and $R_{t-12,t-1}^2$ is the cumulative return over the previous twelve months of the long-short portfolio based the second sample. This procedure is repeated 1000 times. The table reports average coefficients and average t-statistics of the corresponding 1000 estimates. The intercept α_0 and regression coefficient α_1 are multiplied by 100. The t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Anomaly	(raw, raw)		$(DGTW, raw)$		$(DGTW, DGTW)$	
	int	$R_{t-12,t-1}$	int	$R_{t-12,t-1}$	int	$R_{t-12,t-1}$
S	0.20	2.24**				
	(0.83)	(2.37)				
$-B/M$	0.72**	2.27				
	(2.08)	(1.51)				
$-Mom$	1.02***	0.64				
	(3.32)	(0.36)				
AG	0.54***	3.00***	0.44***	2.21***	0.48***	2.92**
	(2.96)	(3.05)	(2.94)	(3.00)	(3.25)	(2.56)
CI	0.13	1.96	0.12	1.80*	0.12	2.70*
	(1.40)	(1.56)	(1.52)	(1.77)	(1.43)	(1.91)
I/A	0.48***	2.75**	0.34**	2.35**	0.35**	3.50*
	(2.83)	(2.07)	(2.33)	(1.96)	(2.47)	(1.93)
NS	0.47**	1.02	0.46***	1.06	0.48***	0.82
	(2.23)	(0.57)	(2.58)	(0.66)	(2.77)	(0.36)
ι	0.36	0.86	0.19	0.58	0.20	0.58
	(1.35)	(0.46)	(1.06)	(0.48)	(1.23)	(0.29)
Acc	0.21**	0.90	0.18*	0.96	0.17*	1.53
	(2.04)	(0.95)	(1.86)	(1.03)	(1.77)	(1.23)
NOA	0.71***	1.43	0.69***	1.44	0.57***	2.86
	(3.35)	(0.76)	(3.77)	(0.94)	(3.10)	(1.40)
$-ROA$	0.79**	1.73	0.77***	1.28	0.77**	1.48
	(2.28)	(1.07)	(2.94)	(1.09)	(2.23)	(0.68)
$IdVol$	0.44	-0.03	0.30	-0.73	0.34	-2.77
	(1.19)	(-0.01)	(1.49)	(-0.49)	(1.64)	(-0.88)
O	0.28	2.48***	0.34***	1.86***	0.29**	2.51**
	(1.57)	(2.66)	(2.78)	(2.70)	(2.34)	(1.98)
D	0.39	1.60	0.27	1.05	0.25	2.22
	(1.61)	(1.17)	(1.52)	(1.07)	(1.41)	(1.39)
All		1.58***		1.27***		2.38***
		(5.58)		(4.73)		(7.23)

Table 1.4: Persistence Strategies based on Characteristic-based Strategies

Panel A presents coefficients from the regression $R_t = \alpha_0 + \alpha_1 * sign(R_{t-12,t-1} - Med_{R_{t-12,t-1}}) + \epsilon_t$, where $sign(R_{t-12,t-1} - Med_{R_{t-12,t-1}})$ is the sign of the cumulative return over the previous twelve months of the left-hand side long-short portfolio P1-P5 after subtracting its time-series median. In the 'In Sample' specification the median is computed using the full time series of cumulative returns. In the 'Out of Sample' specification the median is based only on the data available in month $t-1$. Raw portfolio returns are used on the left-hand side and right-hand side. The last row *All* shows coefficients from panel regressions using all fourteen strategies with year-month fixed effects. Panel B shows the raw and DGTW-adjusted average returns of new persistence strategies. For each characteristic a persistence strategy buys an underlying strategy, when its 'Out of Sample' median-adjusted prior cumulative return $R_{t-12,t-1} - Med_{R_{t-12,t-1}}$ is positive and sells it otherwise. Column 'months long' displays the percentage of months a given persistence strategy buys the underlying strategy. The last row *Average* shows the average percentage across all characteristics. The other two columns of the last row show returns of the *Average* persistence strategy, which every month averages the returns of fourteen persistence strategies. Returns are multiplied by 100. Standard errors are adjusted for autocorrelation in residuals for up to three lags following Newey and West (1987) except for panel regressions, where they are clustered by strategy. The t-statistics are shown in parentheses.

Panel A: Short-term Performance Persistence

Anomaly	In Sample		Out of Sample	
	int	$sign(R_{t-12,t-1})$	*int*	$sign(R_{t-12,t-1})$
S	0.33	0.72***	0.37	0.74***
	(1.45)	(3.34)	(1.63)	(3.40)
$-B/M$	1.05***	0.33	1.02***	0.41**
	(5.21)	(1.64)	(4.95)	(1.98)
$-Mom$	1.11***	0.36	1.14***	0.31
	(4.48)	(1.45)	(4.45)	(1.26)
AG	0.98***	0.52***	0.87***	0.44***
	(7.22)	(3.66)	(6.42)	(3.08)
CI	0.19**	0.11	0.20**	0.12
	(2.46)	(1.40)	(2.55)	(1.52)
I/A	0.80***	0.44***	0.75***	0.40***
	(7.29)	(3.83)	(6.77)	(3.52)
NS	0.54***	0.11	0.55***	0.09
	(3.64)	(0.75)	(3.68)	(0.61)
ι	0.41*	0.25	0.40*	0.27
	(1.88)	(1.18)	(1.83)	(1.22)
Acc	0.24**	0.13	0.23**	0.13
	(2.47)	(1.29)	(2.42)	(1.34)
NOA	0.91***	0.40*	0.88***	0.40**
	(4.51)	(1.96)	(4.54)	(2.11)
$-ROA$	1.01***	0.37*	0.93***	0.40
	(4.49)	(1.68)	(3.79)	(1.64)
$IdVol$	0.41	0.17	0.40	0.11
	(1.44)	(0.64)	(1.33)	(0.37)
O	0.36**	0.44***	0.30*	0.47***
	(2.04)	(2.67)	(1.71)	(2.82)
D	0.47**	0.31	0.46**	0.28
	(2.23)	(1.58)	(2.15)	(1.47)
All		0.30***		0.32***
		(5.31)		(5.81)

Table 1.4: (Continued)

Panel B: Persistence Strategies			
Anomaly	months long	raw	DGTW
S	47.2%	0.72**	
		(3.28)	
$-B/M$	53.5%	0.48**	
		(2.17)	
$-Mom$	46.5%	0.23	
		(0.89)	
AG	62.2%	0.65**	0.46**
		(4.04)	(3.58)
CI	47.2%	0.11	0.08
		(1.36)	(1.27)
I/A	56.1%	0.49**	0.37**
		(3.72)	(3.34)
NS	44.4%	0.03	-0.03
		(0.18)	(-0.21)
ι	51.4%	0.28	0.17
		(1.27)	(1.13)
Acc	52.8%	0.14	0.16*
		(1.43)	(1.71)
NOA	54.0%	0.47**	0.36*
		(2.20)	(1.85)
$-ROA$	60.1%	0.59**	0.51**
		(2.52)	(2.75)
$IdVol$	56.6%	0.16	-0.02
		(0.57)	(-0.12)
O	56.4%	0.51**	0.40**
		(3.01)	(3.44)
D	52.7%	0.31	0.21
		(1.57)	(1.44)
$Average$	53.1%	0.37**	0.24**
		(3.40)	(2.98)

Table 1.5: Persistence Strategies, Subperiods

The table shows average returns of characteristic-based strategies and persistence strategies based on them in various subperiods. For each characteristic a persistence strategy buys an underlying strategy, when its 'Out of Sample' median-adjusted prior cumulative return $R_{t-12,t-1} - Med_{R_{t-12,t-1}}$ is positive and sells it otherwise. In Panel A, for each characteristic the full sample is split based on the publication date of the academic study describing the anomaly. Column 'first post year' shows the first year of the post period which is set to the year before the publication date. In Panel B, the time series is divided into pre and post 1995 subperiods for all characteristics. The last row shows the returns of the *Average* persistence strategy, which every month averages the returns of fourteen persistence strategies. Returns are multiplied by 100. Standard errors are adjusted for autocorrelation in residuals for up to three lags following Newey and West (1987). The t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Pre and Post Publication

Anomaly	first post year	raw returns				DGTW-adjusted returns			
		strategy		persistence		strategy		persistence	
		pre	post	pre	post	pre	post	pre	post
S	1980	2.02**	0.15	2.02**	0.58**				
		(3.79)	(0.57)	(3.79)	(2.49)				
$-B/M$	1979	0.88**	1.07**	0.88**	0.45*				
		(2.25)	(4.81)	(2.25)	(1.91)				
$-Mom$	1992	1.46**	0.85**	0.33	0.16				
		(6.03)	(2.08)	(1.14)	(0.39)				
AG	2007	1.07**	0.42	0.74**	0.07	0.83**	0.37	0.53**	0.06
		(6.65)	(1.08)	(4.24)	(0.19)	(6.14)	(1.30)	(3.69)	(0.23)
CI	2003	0.25**	0.03	0.15	-0.02	0.22**	0.07	0.10	0.02
		(2.63)	(0.22)	(1.60)	(-0.15)	(2.85)	(0.56)	(1.35)	(0.13)
I/A	2007	0.88**	0.28	0.55**	0.13	0.67**	0.29	0.41**	0.16
		(6.87)	(0.92)	(3.79)	(0.44)	(6.02)	(0.98)	(3.38)	(0.56)
NS	2007	0.57**	0.41	0.14	-0.64**	0.57**	0.34	0.09	-0.79**
		(3.40)	(1.21)	(0.79)	(-2.24)	(3.78)	(1.16)	(0.57)	(-2.39)
ι	2005	0.36	0.58	0.41	-0.27	0.16	0.45	0.27	-0.24
		(1.42)	(1.46)	(1.60)	(-0.75)	(0.92)	(1.57)	(1.56)	(-0.93)
Acc	1995	0.16	0.33**	0.11	0.18	0.11	0.31**	0.12	0.21
		(1.14)	(2.33)	(0.82)	(1.21)	(0.85)	(2.47)	(0.88)	(1.60)
NOA	2003	1.11**	0.33	0.55**	0.25	1.07**	0.38	0.44*	0.13
		(4.57)	(0.85)	(2.09)	(0.75)	(5.06)	(1.18)	(1.84)	(0.44)
$-ROA$	1995	1.25**	0.75*	0.76**	0.41	1.19**	0.66*	0.62**	0.39
		(7.14)	(1.70)	(3.54)	(0.94)	(11.78)	(1.87)	(4.00)	(1.12)
$IdVol$	2005	0.38	0.53	0.29	-0.38	0.23	0.31	0.03	-0.22
		(1.14)	(1.04)	(0.92)	(-0.71)	(1.27)	(1.02)	(0.17)	(-0.71)
O	1997	0.39**	0.33	0.57**	0.43	0.42**	0.39	0.36**	0.46**
		(2.04)	(0.92)	(3.22)	(1.34)	(3.41)	(1.51)	(3.10)	(2.02)
D	2001	0.66**	0.07	0.33	0.26	0.47**	0.02	0.27*	0.10
		(2.98)	(0.14)	(1.56)	(0.64)	(2.90)	(0.06)	(1.68)	(0.33)
Average		0.67**	0.56**	0.40**	0.39**	0.51**	0.50**	0.27**	0.20
		(7.47)	(5.61)	(2.99)	(2.76)	(7.86)	(3.70)	(2.76)	(1.28)

Table 1.5: (Continued)

Panel B: Pre and Post 1995

Anomaly	raw returns				DGTW-adjusted returns			
	strategy		persistence		strategy		persistence	
	1976-1994	1995-2011	1976-1994	1995-2011	1976-1994	1995-2011	1976-1994	1995-2011
S	0.30	0.36	0.88***	0.54				
	(0.98)	(0.95)	(3.18)	(1.58)				
$-B/M$	1.11***	0.99***	0.63**	0.32				
	(4.45)	(2.92)	(2.34)	(0.90)				
$-Mom$	1.39***	0.81*	0.12	0.36				
	(6.28)	(1.72)	(0.46)	(0.76)				
AG	0.84***	1.13***	0.62***	0.68**	0.64***	0.89***	0.41**	0.53**
	(4.57)	(4.70)	(3.26)	(2.57)	(4.04)	(4.72)	(2.54)	(2.54)
CI	0.21**	0.17	0.24**	-0.03	0.18**	0.17*	0.17**	-0.02
	(2.01)	(1.40)	(2.40)	(-0.22)	(2.05)	(1.87)	(2.11)	(-0.22)
I/A	0.84***	0.76***	0.51***	0.46**	0.59***	0.64***	0.28**	0.48**
	(6.53)	(3.63)	(3.35)	(2.13)	(6.38)	(3.29)	(2.51)	(2.40)
NS	0.70***	0.38	0.19	-0.15	0.57***	0.51*	0.05	-0.12
	(6.07)	(1.31)	(1.35)	(-0.50)	(5.45)	(1.93)	(0.39)	(-0.41)
ι	0.49**	0.31	0.58***	-0.05	0.24	0.18	0.39***	-0.07
	(2.26)	(0.80)	(2.80)	(-0.13)	(1.63)	(0.71)	(2.77)	(-0.27)
Acc	0.16	0.33**	0.11	0.18	0.11	0.31**	0.12	0.21
	(1.14)	(2.33)	(0.82)	(1.21)	(0.85)	(2.47)	(0.88)	(1.60)
NOA	0.81***	1.02**	0.49***	0.46	0.74***	1.07***	0.39**	0.33
	(5.35)	(2.53)	(2.88)	(1.12)	(4.91)	(3.18)	(2.30)	(0.91)
$-ROA$	1.25***	0.75*	0.76***	0.41	1.19***	0.66*	0.62***	0.39
	(7.14)	(1.70)	(3.54)	(0.94)	(11.78)	(1.87)	(4.00)	(1.12)
$IdVol$	0.35	0.48	0.12	0.19	0.27*	0.21	-0.03	-0.01
	(1.32)	(0.91)	(0.47)	(0.39)	(1.94)	(0.73)	(-0.18)	(-0.04)
O	0.37*	0.36	0.63***	0.37	0.43***	0.38	0.40***	0.41*
	(1.83)	(1.11)	(3.49)	(1.30)	(3.52)	(1.62)	(3.47)	(1.95)
D	0.75***	0.19	0.28	0.34	0.60***	0.04	0.22	0.21
	(4.06)	(0.50)	(1.39)	(0.99)	(4.49)	(0.15)	(1.42)	(0.83)
$Average$	0.68***	0.57***	0.44***	0.29	0.50***	0.46***	0.27***	0.21
	(10.78)	(4.38)	(5.19)	(1.41)	(8.88)	(4.03)	(5.52)	(1.31)

Table 1.6: Short-term Performance Persistence by Calendar Month

The table shows raw average returns of persistence strategies in each calendar month. For each characteristic a persistence strategy buys an underlying strategy when its 'Out of Sample' median-adjusted prior cumulative return $R_{t-12,t-1} - Med_{R_{t-12,t-1}}$ is positive and sells it otherwise. The last row shows the returns of the *Average* persistence strategy, which every month averages the returns of fourteen persistence strategies. Returns are multiplied by 100. Standard errors are adjusted for autocorrelation in residuals for up to three lags following Newey and West (1987). The t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Anomaly	calendar month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
S	-0.03	0.07	0.57	0.08	1.11	0.89	0.14	1.19**	0.87**	0.53	1.63***	1.52**
	(-0.02)	(0.12)	(1.00)	(0.12)	(1.43)	(1.61)	(0.35)	(2.43)	(2.16)	(0.84)	(3.19)	(2.19)
$-B/M$	-0.25	2.19**	0.90**	0.10	0.62	-0.01	-0.09	-0.07	0.46	-0.18	1.05	1.05*
	(-0.38)	(2.24)	(2.15)	(0.18)	(1.37)	(-0.02)	(-0.22)	(-0.11)	(1.09)	(-0.27)	(1.11)	(1.68)
$-Mom$	0.48	0.68	-1.09**	-0.28	-0.42	1.24	-0.80*	0.98**	0.26	-0.14	0.28	1.61*
	(0.65)	(0.66)	(-2.22)	(-0.26)	(-0.58)	(0.97)	(-1.67)	(2.15)	(0.57)	(-0.23)	(0.29)	(1.93)
AG	1.87***	1.55**	0.40	0.51	0.74*	0.51	1.06**	-0.46	0.81**	0.50	0.25	0.08
	(2.66)	(2.14)	(0.99)	(1.48)	(1.93)	(1.25)	(2.17)	(-1.12)	(2.07)	(0.69)	(0.61)	(0.25)
CI	0.35	0.33**	-0.22	-0.02	-0.18	0.18	-0.13	0.27	-0.00	-0.01	0.32*	0.43
	(1.05)	(2.10)	(-0.91)	(-0.10)	(-1.00)	(1.05)	(-0.62)	(1.64)	(-0.02)	(-0.03)	(1.74)	(1.27)
I/A	0.85*	0.62	0.51	0.49*	0.83***	0.25	0.52	-0.31	0.00	0.65*	1.01**	0.44
	(1.88)	(1.37)	(1.64)	(1.95)	(3.08)	(0.73)	(1.44)	(-0.88)	(0.00)	(1.86)	(2.20)	(1.58)
NS	0.11	0.96	0.15	-0.66	-0.76	0.69	-0.33	0.51	0.35	-0.70*	-0.92*	0.95**
	(0.22)	(1.25)	(0.41)	(-1.55)	(-1.54)	(1.62)	(-0.83)	(1.18)	(0.84)	(-1.76)	(-1.77)	(2.32)
ι	-0.92	1.52	0.53	-0.42	0.10	0.27	-0.00	1.01**	1.18*	-0.99	-0.13	1.16
	(-0.79)	(1.47)	(1.42)	(-0.75)	(0.15)	(0.40)	(-0.01)	(2.05)	(1.84)	(-1.41)	(-0.15)	(1.60)
Acc	-0.22	0.49*	0.46**	0.33	-0.24	0.24	0.28	-0.02	0.51***	-0.36	-0.44*	0.71***
	(-0.79)	(1.82)	(2.04)	(1.41)	(-1.05)	(1.06)	(0.83)	(-0.09)	(2.59)	(-0.68)	(-1.95)	(3.74)
NOA	0.76	1.32	0.31	-0.62	0.30	0.96**	0.66**	0.63**	0.58*	0.36	0.33	0.13
	(1.21)	(1.23)	(0.85)	(-0.87)	(0.77)	(2.12)	(1.97)	(2.13)	(1.77)	(0.58)	(0.67)	(0.23)
$-ROA$	-1.33	1.32	0.62*	0.41	-0.13	0.69	0.96**	-0.05	0.44	0.60	1.12	2.36***
	(-1.29)	(1.27)	(1.72)	(0.56)	(-0.19)	(1.39)	(2.57)	(-0.12)	(0.77)	(1.08)	(1.48)	(3.10)
$IdVol$	-0.03	2.78*	-0.17	-1.60	-1.14	-0.14	0.14	0.92	0.60	-1.71*	1.06	1.13
	(-0.04)	(1.71)	(-0.29)	(-1.44)	(-1.46)	(-0.15)	(0.22)	(1.04)	(1.07)	(-1.95)	(0.88)	(1.60)
O	-0.43	0.04	0.10	0.10	0.45	0.80	0.11	0.25	1.03***	1.29**	0.55	1.81***
	(-0.34)	(0.09)	(0.30)	(0.20)	(0.92)	(1.57)	(0.41)	(0.45)	(2.86)	(2.20)	(1.06)	(2.73)
D	-0.76	1.38	-0.06	-0.82	0.46	0.93	1.00*	0.31	0.92	-0.62	-0.63	1.63***
	(-1.45)	(1.61)	(-0.20)	(-1.22)	(0.93)	(1.45)	(1.87)	(0.62)	(1.47)	(-1.01)	(-0.59)	(3.40)
Average	0.04	1.09*	0.22	-0.17	0.13	0.53	0.25	0.37	0.56**	-0.06	0.40	1.07***
	(0.10)	(1.70)	(1.42)	(-0.51)	(0.51)	(1.24)	(1.47)	(1.46)	(2.37)	(-0.21)	(1.10)	(2.89)

Table 1.7: Long-term Performance Persistence of Characteristic-based Strategies

Panel A presents coefficients from the time series monthly regression $R_t = \alpha_0 + \alpha_1 * R_{t-11-k,t-k} + \epsilon_t$, where R_t is the return in month t of the long-short portfolio P1-P5, and $R_{t-11-k,t-k}$ is the cumulative return of this portfolio over the period $t-11-k$ to $t-k$ with the lag number k varying from 1 to 12. Panel B shows average returns of the persistence strategies. For each characteristic, a persistence strategy buys an underlying strategy when its median-adjusted prior cumulative return $R_{t-11-k,t-k} - Med_{R_{t-11-k,t-k}}$ is positive and sells it otherwise. In both panels raw returns are used on the left-hand side and right-hand side. Regression coefficients in Panel A and returns in Panel B are multiplied by 100.

Panel A: Long-term Performance Persistence

Anomaly	lag number											
	1	2	3	4	5	6	7	8	9	10	11	12
S	2.27**	1.27	1.03	0.88	0.67	0.53	0.56	0.32	0.24	0.52	0.53	0.28
	(2.40)	(1.31)	(1.04)	(0.90)	(0.69)	(0.56)	(0.58)	(0.34)	(0.24)	(0.47)	(0.48)	(0.28)
$-B/M$	2.26	1.12	0.92	0.32	-0.55	-0.65	-0.84	-1.14	-1.33	-0.71	-1.06	-2.03
	(1.49)	(0.70)	(0.57)	(0.22)	(-0.39)	(-0.44)	(-0.55)	(-0.65)	(-0.74)	(-0.45)	(-0.67)	(-1.29)
$-Mom$	0.67	-0.04	-0.11	0.17	-1.21	-0.03	-0.96	-1.00	-1.10	-1.43	-1.46	-0.88
	(0.36)	(-0.02)	(-0.07)	(0.12)	(-0.97)	(-0.03)	(-0.81)	(-0.83)	(-0.86)	(-1.17)	(-1.04)	(-0.89)
AG	3.23***	2.47***	2.28**	2.13**	1.68**	1.60*	1.46*	1.55**	1.58**	1.12	0.91	0.57
	(3.30)	(2.58)	(2.44)	(2.41)	(2.01)	(1.95)	(1.88)	(2.02)	(2.05)	(1.41)	(1.08)	(0.63)
CI	2.15*	1.42	1.19	1.25	1.00	1.12	1.00	0.57	0.78	0.60	0.41	-0.05
	(1.68)	(1.08)	(0.99)	(1.10)	(0.92)	(1.13)	(1.03)	(0.56)	(0.76)	(0.57)	(0.38)	(-0.04)
I/A	2.87**	2.23*	2.03*	1.91**	1.49*	1.28	1.29*	1.17	1.13	1.27	1.22	0.77
	(2.11)	(1.78)	(1.88)	(2.00)	(1.69)	(1.55)	(1.67)	(1.44)	(1.36)	(1.53)	(1.45)	(0.85)
NS	1.15	0.04	0.17	-0.07	-0.25	-0.44	-1.12	-1.54	-1.87	-1.21	-1.13	-1.68
	(0.62)	(0.02)	(0.11)	(-0.05)	(-0.17)	(-0.32)	(-0.76)	(-0.92)	(-1.14)	(-0.73)	(-0.66)	(-1.19)
ι	0.89	-0.20	0.04	-0.37	-0.41	-0.37	-1.19	-1.52	-1.41	-0.65	-0.29	-1.05
	(0.47)	(-0.11)	(0.03)	(-0.25)	(-0.28)	(-0.27)	(-0.80)	(-0.93)	(-0.88)	(-0.41)	(-0.19)	(-0.88)
Acc	1.18	0.54	0.09	-0.50	-0.87	-1.05	-0.65	-0.69	-1.01	-0.48	-0.18	-0.56
	(0.86)	(0.46)	(0.07)	(-0.48)	(-0.83)	(-1.02)	(-0.79)	(-0.90)	(-1.30)	(-0.55)	(-0.19)	(-0.58)
NOA	1.49	0.85	0.82	0.61	-0.15	-0.20	-0.69	-1.03	-1.32*	-0.83	-0.69	-1.13*
	(0.77)	(0.47)	(0.58)	(0.50)	(-0.15)	(-0.20)	(-0.91)	(-1.36)	(-1.76)	(-1.12)	(-0.99)	(-1.67)
$-ROA$	1.70	0.69	1.14	1.03	0.43	0.16	-0.40	-1.54	-2.07	-0.49	0.34	-1.17
	(1.01)	(0.38)	(0.80)	(0.90)	(0.40)	(0.16)	(-0.30)	(-0.92)	(-1.11)	(-0.30)	(0.20)	(-0.97)
$IdVol$	-0.02	-1.80	-1.12	-0.78	-1.68	-0.64	-1.96	-2.98	-2.77	-1.63	-2.20	-3.15
	(-0.01)	(-0.65)	(-0.52)	(-0.42)	(-1.01)	(-0.41)	(-1.02)	(-1.19)	(-1.12)	(-0.91)	(-1.23)	(-1.49)
O	2.55***	2.32**	1.93*	1.68	0.82	0.94	0.59	0.45	-0.06	0.06	-0.07	-0.08
	(2.75)	(2.46)	(1.94)	(1.58)	(0.74)	(0.88)	(0.58)	(0.46)	(-0.06)	(0.07)	(-0.08)	(-0.10)
D	1.56	0.46	0.57	0.32	0.11	-0.10	-0.63	-1.12	-1.49	-0.77	-0.70	-1.61
	(1.11)	(0.31)	(0.44)	(0.27)	(0.10)	(-0.10)	(-0.57)	(-0.85)	(-1.05)	(-0.59)	(-0.54)	(-1.33)
All	1.65***	0.76**	0.81***	0.70***	0.05	0.20	-0.30	-0.73**	-0.87**	-0.37	-0.39	-0.82**
	(5.88)	(2.30)	(2.89)	(2.91)	(0.16)	(0.91)	(-1.01)	(-2.09)	(-2.46)	(-1.22)	(-1.09)	(-2.40)

Table 1.7: (Continued)

Panel B: Persistence Strategies

Anomaly	lag number											
	1	2	3	4	5	6	7	8	9	10	11	12
S	0.72***	0.44*	0.52**	0.51**	0.51**	0.41*	0.35	0.27	0.28	0.18	0.06	0.15
	(3.28)	(1.79)	(2.22)	(2.16)	(2.17)	(1.67)	(1.45)	(1.09)	(1.11)	(0.72)	(0.24)	(0.62)
$-B/M$	0.48**	0.23	0.40*	0.23	0.10	0.12	0.08	0.07	0.09	0.06	-0.03	-0.09
	(2.17)	(0.98)	(1.70)	(1.06)	(0.46)	(0.52)	(0.34)	(0.31)	(0.38)	(0.28)	(-0.12)	(-0.41)
$-Mom$	0.23	0.21	0.00	0.05	-0.02	-0.11	0.04	0.03	-0.21	-0.21	0.08	-0.17
	(0.89)	(0.79)	(0.00)	(0.19)	(-0.07)	(-0.39)	(0.15)	(0.10)	(-0.76)	(-0.80)	(0.28)	(-0.66)
AG	0.65***	0.67***	0.60***	0.58***	0.57***	0.68***	0.70***	0.70***	0.48***	0.40**	0.40**	0.38**
	(4.04)	(3.99)	(3.69)	(3.48)	(3.50)	(4.36)	(4.34)	(4.22)	(2.85)	(2.20)	(2.38)	(2.32)
CI	0.11	0.09	0.04	0.00	-0.01	0.04	0.01	0.05	0.05	0.07	0.01	0.02
	(1.36)	(1.15)	(0.49)	(-0.02)	(-0.11)	(0.45)	(0.11)	(0.67)	(0.66)	(0.88)	(0.08)	(0.26)
I/A	0.49***	0.47***	0.40***	0.36***	0.31**	0.29**	0.25*	0.26*	0.27**	0.28**	0.22	0.23
	(3.72)	(3.63)	(3.04)	(2.68)	(2.31)	(2.11)	(1.79)	(1.87)	(1.97)	(1.97)	(1.59)	(1.60)
NS	0.03	0.00	0.10	-0.03	-0.04	-0.01	-0.02	-0.13	-0.06	-0.03	0.04	0.05
	(0.18)	(-0.02)	(0.58)	(-0.17)	(-0.27)	(-0.06)	(-0.15)	(-0.83)	(-0.37)	(-0.19)	(0.21)	(0.32)
ι	0.28	0.13	0.18	0.05	0.10	0.18	0.21	0.09	-0.03	-0.32	-0.19	-0.20
	(1.27)	(0.54)	(0.81)	(0.24)	(0.43)	(0.81)	(1.01)	(0.45)	(-0.17)	(-1.33)	(-0.78)	(-0.86)
Acc	0.14	0.18*	0.07	-0.01	-0.04	-0.09	-0.05	-0.04	0.04	0.11	0.07	0.10
	(1.43)	(1.93)	(0.77)	(-0.06)	(-0.40)	(-0.92)	(-0.53)	(-0.39)	(0.36)	(1.11)	(0.66)	(0.99)
NOA	0.47**	0.47**	0.38*	0.31	0.30	0.34	0.21	0.19	0.01	0.00	0.01	0.01
	(2.20)	(2.24)	(1.73)	(1.41)	(1.42)	(1.62)	(0.96)	(0.85)	(0.04)	(0.02)	(0.06)	(0.04)
$-ROA$	0.59**	0.66***	0.47*	0.35	0.46*	0.42*	0.24	0.18	0.05	0.16	0.03	-0.02
	(2.52)	(2.86)	(1.93)	(1.28)	(1.86)	(1.78)	(1.01)	(0.74)	(0.22)	(0.62)	(0.13)	(-0.07)
$IdVol$	0.16	0.12	-0.03	-0.04	-0.12	0.02	-0.07	-0.42	-0.27	-0.64**	-0.53**	-0.45
	(0.57)	(0.44)	(-0.09)	(-0.15)	(-0.41)	(0.06)	(-0.28)	(-1.60)	(-1.01)	(-1.98)	(-1.96)	(-1.59)
O	0.51***	0.40**	0.34*	0.28	0.22	0.34*	0.27	0.09	0.12	0.10	0.05	0.04
	(3.01)	(2.35)	(1.90)	(1.58)	(1.17)	(1.75)	(1.40)	(0.46)	(0.63)	(0.53)	(0.29)	(0.22)
D	0.31	0.09	0.27	0.02	-0.03	-0.05	-0.10	-0.03	-0.17	-0.35*	-0.34	-0.45**
	(1.57)	(0.40)	(1.18)	(0.08)	(-0.15)	(-0.21)	(-0.48)	(-0.16)	(-0.80)	(-1.66)	(-1.52)	(-2.14)
$Average$	0.37***	0.30***	0.27**	0.19*	0.17	0.19*	0.15	0.10	0.05	-0.01	-0.01	-0.03
	(3.40)	(2.69)	(2.38)	(1.80)	(1.56)	(1.78)	(1.55)	(0.97)	(0.49)	(-0.10)	(-0.07)	(-0.31)

Table 1.8: Strategy Performance Persistence and Mutual Fund Price Pressure

The table presents intercepts α_0^1 and α_0^2 and regression coefficients α_1 and α_2 for each characteristic from the time series monthly regressions $R_t = \alpha_0^1 + \alpha_1 * E_{t-1}[Strategy\_Flow_t] + \epsilon_t^1$ and $\epsilon_t^1 = \alpha_0^2 + \alpha_2 * R_{t-12,t-1} + \epsilon_t$, where R_t is the return in month t of the long-short portfolio P1-P5, $R_{t-12,t-1}$ is the cumulative return over the previous twelve months of this portfolio, and $E_{t-1}[Strategy\_Flow_t]$ is the measure of price pressure created by mutual fund flow-driven trading at the strategy level. This measure uses fund performance as a predictor of future flows and assumes that flows are allocated in accordance with prior portfolio weights. Panel A reports estimates based on the full sample 1980-2011. In Panel B estimation is performed separately for pre 1995 and post 1995 periods. Raw and DGTW-adjusted portfolio returns are used on the left-hand and raw portfolio returns on the right-hand side. Intercepts α_0^1 and α_0^2 and regression coefficients α_1 and α_2 are multiplied by 100. The last row *All* shows coefficients from panel regressions using all fourteen strategies with year-month fixed effects and standard errors clustered by strategy. For individual characteristics, standard errors are adjusted for autocorrelation in residuals for up to three lags following Newey and West (1987). The t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: The Full Sample, 1980-2011

Anomaly	raw				DGTW-adjusted			
	int	$E[Flow]$	*int*	$R_{t-12,t-1}$	*int*	$E[Flow]$	*int*	$R_{t-12,t-1}$
S	0.16	0.68	-0.05	1.50				
	(0.62)	(0.43)	(-0.20)	(1.51)				
$-B/M$	1.10***	1.18	-0.24	1.65				
	(4.77)	(0.86)	(-0.66)	(1.07)				
$-Mom$	0.64	3.09	0.03	-0.19				
	(1.54)	(0.87)	(0.09)	(-0.10)				
AG	1.06***	2.09*	-0.43**	2.81***	0.83***	1.73*	-0.31**	2.01***
	(6.65)	(1.89)	(-2.31)	(2.89)	(6.30)	(1.70)	(-2.07)	(2.92)
CI	0.22**	5.59***	-0.02	0.84	0.22***	4.62***	-0.03	1.12
	(2.51)	(3.32)	(-0.28)	(0.59)	(3.14)	(3.42)	(-0.46)	(1.06)
I/A	0.84***	2.28**	-0.29*	2.38*	0.66***	1.86**	-0.25*	2.05*
	(6.56)	(2.21)	(-1.70)	(1.79)	(5.89)	(2.33)	(-1.69)	(1.68)
NS	0.41*	3.04	-0.01	0.20	0.46**	2.91	-0.03	0.40
	(1.94)	(1.25)	(-0.06)	(0.11)	(2.54)	(1.39)	(-0.14)	(0.23)
ι	0.40	1.77	-0.01	0.25	0.20	1.42	-0.01	0.12
	(1.37)	(0.75)	(-0.05)	(0.13)	(1.09)	(1.00)	(-0.04)	(0.10)
Acc	0.23**	0.92	-0.04	1.08	0.19*	0.30	-0.04	1.25
	(2.11)	(0.61)	(-0.38)	(0.78)	(1.87)	(0.21)	(-0.48)	(0.92)
NOA	0.91***	8.78***	-0.09	0.61	0.91***	7.54***	-0.11	0.73
	(4.67)	(2.84)	(-0.39)	(0.32)	(5.49)	(2.80)	(-0.55)	(0.48)
$-ROA$	0.77**	3.91	-0.13	0.94	0.71***	3.28*	-0.09	0.67
	(2.36)	(1.63)	(-0.33)	(0.55)	(2.81)	(1.76)	(-0.32)	(0.55)
$IdVol$	0.52*	-0.10	0.01	-0.14	0.28*	0.61	0.05	-0.85
	(1.76)	(-0.03)	(0.02)	(-0.05)	(1.74)	(0.33)	(0.24)	(-0.55)
O	0.35*	1.95	-0.08	1.70*	0.34***	1.47	-0.07	1.50**
	(1.92)	(1.15)	(-0.47)	(1.80)	(2.76)	(1.21)	(-0.59)	(2.31)
D	0.41	3.67	-0.05	0.85	0.25	3.17*	-0.03	0.41
	(1.59)	(1.34)	(-0.21)	(0.59)	(1.33)	(1.69)	(-0.14)	(0.43)
All		2.31***		0.58**		2.75***		0.55**
		(4.60)		(2.48)		(5.23)		(2.53)

Table 1.8: (Continued)

Panel B: Subperiods								
	raw returns				DGTW-adjusted returns			
Anomaly	1980-1994		1995-2011		1980-1994		1995-2011	
	$E[Flow]$	$R_{t-12,t-1}$	$E[Flow]$	$R_{t-12,t-1}$	$E[Flow]$	$R_{t-12,t-1}$	$E[Flow]$	$R_{t-12,t-1}$
S	3.48*	0.80	-1.58	1.14				
	(1.87)	(0.42)	(-0.68)	(0.98)				
$-B/M$	0.34	3.08	2.62	0.24				
	(0.24)	(1.38)	(0.97)	(0.12)				
$-Mom$	-2.39	-1.00	5.46	-0.90				
	(-1.32)	(-0.54)	(0.99)	(-0.36)				
AG	1.03	2.65**	4.47**	3.22**	0.93	1.63*	3.54*	2.46***
	(0.78)	(2.19)	(2.03)	(2.49)	(0.71)	(1.86)	(1.89)	(2.74)
CI	6.29***	3.14**	5.24*	-2.28	5.23***	2.74**	4.32**	-1.06
	(3.17)	(2.35)	(1.89)	(-1.11)	(2.95)	(2.18)	(2.04)	(-0.85)
I/A	1.52	2.13	4.67**	2.66	1.13	1.09	3.82**	2.66
	(1.30)	(1.63)	(2.36)	(1.49)	(1.44)	(1.21)	(2.04)	(1.57)
NS	2.31**	0.91	3.62	-0.31	2.04**	0.45	3.55	0.24
	(2.11)	(0.70)	(0.90)	(-0.13)	(2.04)	(0.36)	(1.02)	(0.10)
ι	1.39	3.67**	1.83	-1.20	0.52	2.49**	2.09	-0.94
	(0.93)	(2.50)	(0.45)	(-0.47)	(0.53)	(2.49)	(0.85)	(-0.59)
Acc	-0.70	-0.93	7.08***	2.22	-1.14	-1.37	5.73**	2.66**
	(-0.42)	(-0.33)	(2.60)	(1.52)	(-0.71)	(-0.48)	(2.18)	(2.08)
NOA	2.54	0.48	13.29***	0.56	2.30	0.76	11.23***	0.65
	(1.30)	(0.34)	(2.81)	(0.27)	(1.16)	(0.58)	(2.75)	(0.39)
$-ROA$	-0.61	1.73	10.75*	0.05	-0.62	-0.11	8.92*	0.06
	(-0.44)	(0.98)	(1.73)	(0.02)	(-0.74)	(-0.10)	(1.87)	(0.04)
$IdVol$	-0.25	0.20	-0.04	-0.22	-0.22	-0.84	1.09	-0.91
	(-0.13)	(0.10)	(-0.01)	(-0.07)	(-0.20)	(-0.74)	(0.38)	(-0.47)
O	1.65	2.35	2.10	1.54	0.06	1.93*	2.83	1.22*
	(1.36)	(1.29)	(0.61)	(1.37)	(0.07)	(1.73)	(1.20)	(1.66)
D	0.98	0.68	6.56	0.50	0.84	0.32	5.61	0.06
	(0.70)	(0.41)	(1.06)	(0.28)	(0.70)	(0.26)	(1.39)	(0.05)
All	1.41***	1.32***	3.27**	0.01	0.83**	0.94**	4.98***	0.23
	(2.66)	(3.36)	(2.55)	(0.03)	(2.34)	(2.01)	(4.41)	(1.20)

Table 1.9: Aggregate Institutional Demand and Prior Strategy Performance

The table presents the intercept α_0 and regression coefficient α_1 for each characteristic from the time series quarterly regression $Strategy\_Demand_{t+2} = \alpha_0 + \alpha_1 * R_{t-12,t-1} + \epsilon_t$, where $Strategy\_Demand_{t+2}$ is the institutional demand in the current quarter for the long-short portfolio P1-P5, and $R_{t-12,t-1}$ is the cumulative return over the previous twelve months of this portfolio. The portfolio demand is computed by averaging demand for stocks comprising the portfolio. The institutional demand $Demand_{t+2}$ for a given stock is equal to the change in the number of shares held by all 13F institutions over the quarter, adjusted for stock splits and scaled by the number of shares outstanding. Panel A reports estimates based on the full sample 1980-2011. In Panel B estimation is performed separately for pre 1995 and post 1995 periods. In the 'adjusted' specification the individual stock demand is adjusted for the average demand for the size, book-to-market, and momentum. Raw portfolio returns are used on the right-hand side. The intercept α_0 and regression coefficient α_1 are multiplied by 100. The last row *All* shows coefficients from panel regressions using all fourteen strategies with year-month fixed effects and standard errors clustered by strategy. For individual characteristics, standard errors are adjusted for autocorrelation in residuals for up to three lags following Newey and West (1987). The t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: The Full Sample, 1980-2011

Anomaly	raw		adjusted	
	int	$R_{t-12,t-1}$	*int*	$R_{t-12,t-1}$
S	0.38***	0.72		
	(2.64)	(0.91)		
$-B/M$	-0.70***	1.14**		
	(-5.46)	(2.27)		
$-Mom$	1.41***	0.90*		
	(10.92)	(1.82)		
AG	-0.25**	0.90**	-0.28***	0.14
	(-2.41)	(2.11)	(-2.97)	(0.47)
CI	0.22***	-1.11	0.03	-1.44
	(3.03)	(-1.15)	(0.42)	(-1.30)
I/A	-0.16*	0.37	-0.27***	0.09
	(-1.72)	(0.69)	(-3.30)	(0.24)
NS	-0.82***	1.85***	-0.61***	1.08***
	(-10.4)	(5.16)	(-10.1)	(4.15)
ι	-0.70***	1.03**	-0.37***	0.27
	(-7.82)	(2.57)	(-6.55)	(1.00)
Acc	0.03	1.73***	-0.05	1.44**
	(0.48)	(3.32)	(-0.87)	(2.41)
NOA	-0.15*	0.90***	-0.25***	0.59***
	(-1.74)	(4.09)	(-3.84)	(3.04)
$-ROA$	0.21	1.02	0.21**	0.28
	(1.61)	(1.58)	(2.38)	(0.67)
$IdVol$	-1.05***	1.48*	-0.22***	0.42
	(-7.97)	(1.92)	(-3.23)	(0.95)
O	-0.27**	1.62***	0.00	0.64
	(-2.46)	(2.76)	(0.01)	(1.45)
D	-0.23**	1.57***	0.00	0.62*
	(-2.12)	(3.02)	(0.02)	(1.81)
All	-0.46	1.22***	-0.45**	0.36***
	(-1.37)	(4.87)	(-2.25)	(3.41)

Table 1.9: (Continued)

Panel B: Pre and Post 1995

Anomaly	raw				adjusted			
	1980-1994		1995-2011		1980-1994		1995-2011	
	int	$R_{t-12,t-1}$	*int*	$R_{t-12,t-1}$	*int*	$R_{t-12,t-1}$	*int*	$R_{t-12,t-1}$
S	0.36***	0.12	0.38	1.01				
	(2.86)	(0.19)	(1.45)	(0.89)				
$-B/M$	-0.58***	1.05	-0.81***	1.17*				
	(-3.17)	(1.37)	(-4.72)	(1.93)				
$-Mom$	1.05***	1.20*	1.67***	1.09*				
	(5.72)	(1.82)	(10.10)	(1.83)				
AG	-0.15	0.86	-0.37**	1.03*	-0.13	0.11	-0.44***	0.32
	(-1.08)	(1.26)	(-2.39)	(1.94)	(-0.90)	(0.16)	(-3.79)	(1.02)
CI	0.24**	-2.28	0.19**	0.33	0.09	-1.94	-0.04	-0.77
	(2.19)	(-1.60)	(2.47)	(0.32)	(0.78)	(-1.10)	(-0.71)	(-1.05)
I/A	-0.11	0.73	-0.22**	0.18	-0.18	0.41	-0.37***	-0.10
	(-0.81)	(1.16)	(-1.99)	(0.30)	(-1.35)	(0.65)	(-3.86)	(-0.25)
NS	-0.70***	1.90**	-0.93***	1.66***	-0.51***	0.72	-0.68***	1.08***
	(-6.08)	(2.55)	(-8.19)	(3.62)	(-4.05)	(1.10)	(-10.2)	(3.39)
ι	-0.50***	1.27	-0.90***	0.77*	-0.29***	0.54	-0.47***	0.09
	(-3.98)	(1.62)	(-7.37)	(1.76)	(-2.64)	(0.84)	(-6.67)	(0.34)
Acc	0.04	0.33	-0.02	2.61***	0.01	0.16	-0.14*	2.39***
	(0.55)	(0.33)	(-0.27)	(6.16)	(0.17)	(0.18)	(-1.90)	(4.68)
NOA	-0.10	0.22	-0.11	0.96***	-0.19***	0.10	-0.26**	0.63***
	(-1.19)	(0.47)	(-0.72)	(4.02)	(-3.18)	(0.26)	(-2.27)	(3.03)
$-ROA$	0.12	1.77***	0.18	0.85	-0.01	1.53**	0.19**	0.07
	(0.67)	(2.80)	(1.15)	(1.14)	(-0.03)	(2.43)	(1.99)	(0.15)
$IdVol$	-0.69***	2.46***	-1.45***	1.22*	-0.08	0.96***	-0.38***	0.29
	(-4.98)	(3.18)	(-8.19)	(1.74)	(-1.30)	(2.91)	(-3.71)	(0.67)
O	-0.23*	2.37**	-0.36**	1.31**	-0.15	1.86**	0.06	0.35
	(-1.80)	(2.54)	(-2.13)	(2.02)	(-1.64)	(2.42)	(0.56)	(0.85)
D	0.02	1.07	-0.40**	1.37**	-0.03	1.29**	-0.04	0.46
	(0.11)	(1.11)	(-2.51)	(2.18)	(-0.46)	(2.21)	(-0.45)	(1.24)
All	-0.21	1.31*	-0.45	1.19***	-0.21**	0.54*	-0.44**	0.31**
	(-1.21)	(1.90)	(-1.37)	(8.00)	(-2.11)	(1.71)	(-2.21)	(2.34)

Figure 1.1: Short-term Performance Persistence, Sample Split Test

The figure presents a histogram of coefficients α_1 for each characteristic from 1000 repetitions of a time series monthly regression $R^1_t = \alpha_0 + \alpha_1 * R^2_{t-12,t-1} + \epsilon_t$, where R^1_t is the return in month t of the long-short portfolio P1-P5 constructed using one randomly selected half of all firms, and $R^2_{t-12,t-1}$ is the cumulative return over the previous twelve months of the long-short portfolio based on the second subsample. The Panel *All* shows coefficients from panel regressions using all fourteen strategies with year-month fixed effects.

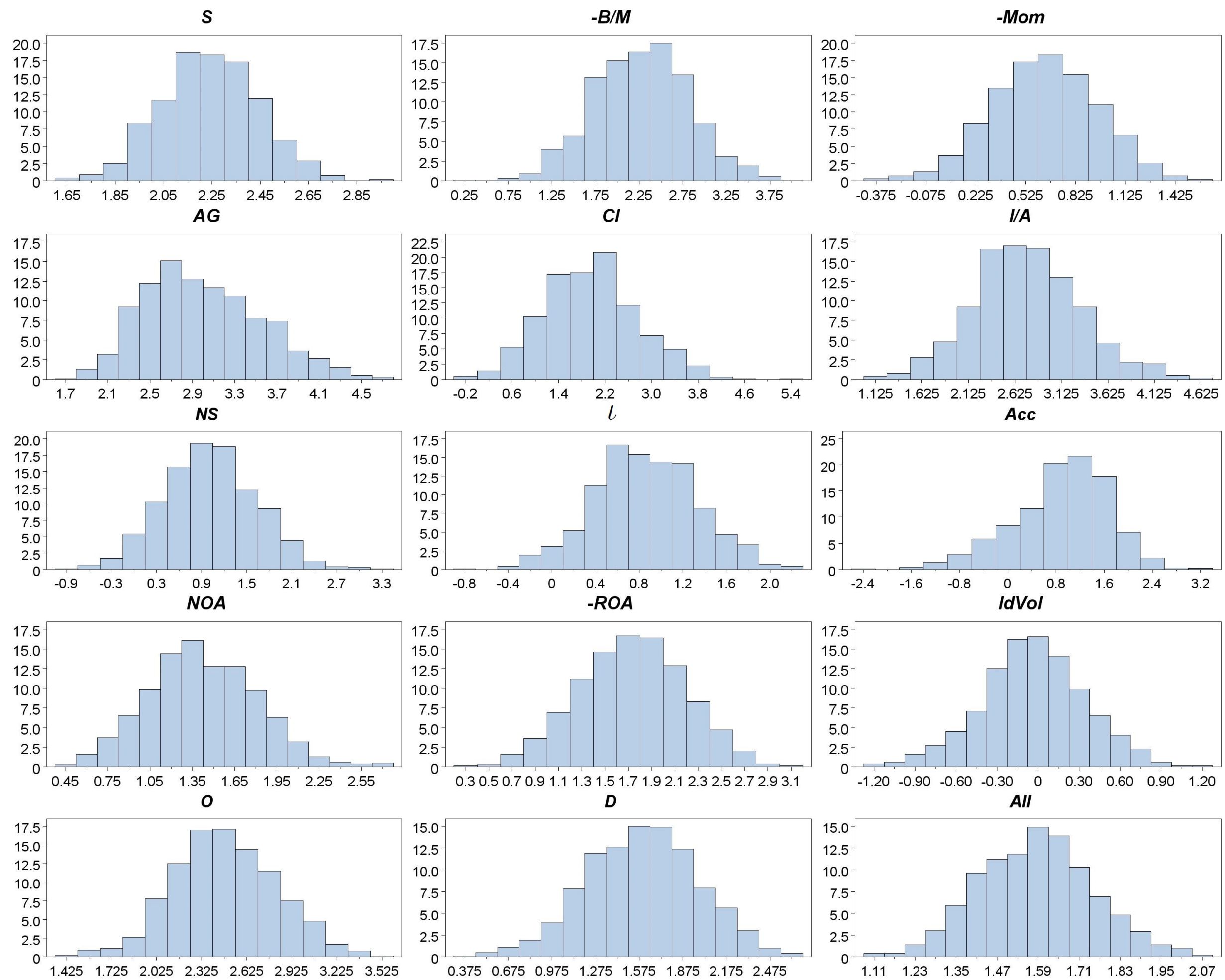
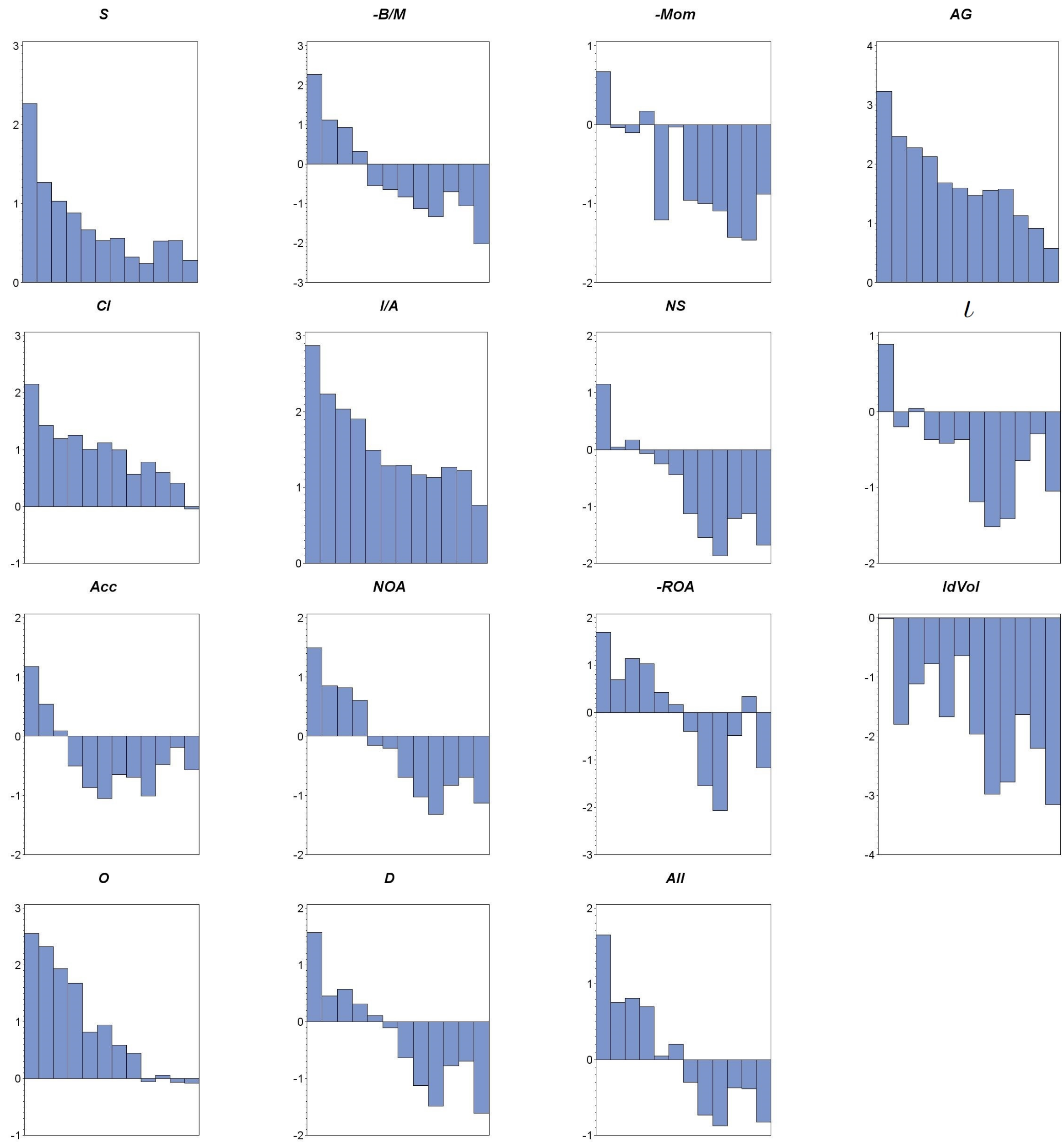


Figure 1.2: Long-term Performance Persistence of Characteristic-based Strategies

The figure presents the regression coefficient α_1 (y-axis) for each characteristic from the time series monthly regression $R_t = \alpha_0 + \alpha_1 * R_{t-11-k,t-k} + \epsilon_t$, where R_t is the return in month t of the long-short portfolio P1-P5, and $R_{t-11-k,t-k}$ is the cumulative twelve month return of this portfolio over the period $t-11-k$ to $t-k$ with the lag number k varying from 1 to 12 (x-axis). The Panel *All* shows coefficients from panel regressions using all fourteen strategies with year-month fixed effects.



Chapter 2

Aggregation of Information About the Cross Section of Stock Returns: A Latent Variable Approach
(joint with Nathaniel Light and Oleg Rytchkov)

2.1 Introduction

Any rational asset pricing theory implies that expected stock returns admit a beta representation, where betas are computed with respect to a discount factor (Cochrane, 2005). However, the nature of the discount factor remains elusive despite several decades of active academic research: many initially promising theories such as the CAPM or the Fama-French three-factor model cannot fully explain the cross section of stock returns. Instead, there is a large and still growing body of empirical evidence suggesting that expected returns tend to line up with various firm characteristics. Such patterns, known as asset pricing anomalies, have received much attention in the literature and now seem ubiquitous. Subrahmanyam (2010) reviews the literature and finds that more than 50 variables are correlated with future stock returns in the cross section. Harvey, Liu, and Zhu (2013) catalogue 314 different factors, although some of them are highly correlated. Green, Hand, and Zhang (2013) conduct an extensive search for "return predictive signals" in the accounting and finance literature and find that 330 of them have been reported.

In his AFA 2011 Presidential Address, Cochrane (2011) argues that the existence of multiple anomalies is a multidimensional challenge and conjectures that to address many questions on the relation between firm characteristics and expected stock returns "... in the zoo of new variables ... we will have to use different methods." Specifically, the variety of variables related to expected returns poses two main questions neither of which has a complete answer in the literature. First, which firm characteristics contain complementary information about returns? Numerous papers compared various characteristics pairwise and in small groups but the big picture is frustratingly missing.[1] Nevertheless, there is some evidence that many anomalies are distinct from each other. Fama and French (2008) find that all seven characteristics that they consider have unique information about future returns. The most comprehensive up-to-date study of this question is Green, Hand, and Zhang (2014) who simultaneously examine almost 100 "return predictive signals" and document that 24 of them are not subsumed by the others.

The second question stemming from the variety of the anomalies and their complementarity is how to aggregate information contained in various firm characteristics and construct the most precise estimates of expected returns on individual stocks. Such aggregation can facilitate the study of the properties of expected re-

[1]This literature is voluminous but often inconclusive. For example, Anderson and Garcia-Feijóo (2006) provide evidence that the value anomaly weakens substantially after controlling for growth in capital expenditures. In contrast, Cooper, Gulen, and Schill (2008) and Fama and French (2008) find that the asset growth effect explains little of the book-to-market effect and that the anomalies are distinct. Desai, Rajgopal, and Venkatachalam (2004) show that the ability of accruals to explain future returns is subsumed by the operating cash flows-to-price ratio and claim that the accruals anomaly is closely related to the value anomaly. However, Cheng and Thomas (2006) demonstrate that abnormal accruals relate to future annual returns even after controlling for the operating cash flows-to-price ratio.

turns in the cross section (e.g., Lewellen, 2013), provide a characteristic-based cost of capital as well as a benchmark for portfolio performance evaluation (e.g., Chan, Dimmock, and Lakonishok, 2009), allow researchers to form basis assets that would increase the power of asset pricing tests (e.g., Haugen and Baker, 1996), and help to identify possible mispricing (e.g., Cao and Han, 2013; Stambaugh, Yu, and Yuan, 2013). The most common approach to aggregation is to use fitted values from Fama-MacBeth regressions of realized returns on all available characteristics. However, this approach has several shortcomings when the number of characteristics to be aggregated is large. First, the regression coefficients are estimated imprecisely because their computation effectively requires the estimation of the variance-covariance matrix of all regressors, whose size grows quadratically with the number of regressors. Second, the regression requires the availability of all regressors for the same observation and this is a very restrictive condition on firm characteristics. Third, many characteristics are highly correlated and the regression suffers from the multicollinearity problem.

In this chapter, we propose a novel approach to aggregating information about stock returns from a large number of firm characteristics, which does not have the above limitations. The approach is based on two main premises. First, we explicitly acknowledge that conditional expected returns on individual stocks and their conditional betas are unobservable to an econometrician.[1] Unobservability of true betas

[1]The unobservability of betas and risk factors is also explicitly recognized in asset pricing models with latent variables (e.g., Gibbons and Ferson, 1985; Ferson, 1990; Ferson, Foerster, and Keim, 1993). However, this literature attempts to explain the time series of expected returns using a small number of expected risk premia, whereas our analysis investigates the cross section of expected stock

is recognized in the literature as one of the possible origins of asset pricing anomalies (e.g., Lin and Zhang, 2012) and can be caused by either mismeasurement of risk factors (e.g., Black, Jensen, and Scholes, 1972; Roll, 1977), or imprecision of the beta estimates themselves. True betas of conditional linear factor models are theoretically infeasible because they depend on the information available to investors, but not to an econometrician (Hansen and Richard, 1987). Moreover, betas tend to vary over time (e.g., Harvey, 1989; Ferson and Harvey, 1991; Lewellen and Nagel, 2006; Li and Yang, 2011; Ang and Kristensen, 2012) and this further complicates their estimation.

The cornerstone of our approach is the second assumption that unobservable expected returns are described by a single-beta rational asset pricing model and numerous observable firm characteristics can be viewed as proxies for the *same* unobservable beta. This assumption is motivated by the literature that establishes theoretical links between various firm characteristics and betas and shows that many characteristics can predict future returns even when the expected returns are described by a single-beta model. For example, Gomes, Kogan, and Zhang (2003) and Carlson, Fisher, and Giammarino (2004) relate size and book-to-market to conditional betas. Within a q-theory framework, the expected returns have been linked to book-to-market (Zhang, 2005), investments (Cochrane, 1996), equity issuance (Li, Livdan, and Zhang, 2009), and accruals (Wu, Zhang, and Zhang, 2010). In a recent paper, Babenko, Boguth, and Tserlukevich (2013) argue that cash flow shocks change conditional betas because they change relative weights of various firm divisions with different betas and, as a result, any characteristic correlated with the history of cash

---

returns.

flow shocks can be successful in explaining expected stock returns.[1]

Under our assumptions, the problem of an econometrician is to use firm characteristics as signals to construct the best estimate of the latent expected returns on individual stocks. To solve it, we propose an intuitive and easily implementable procedure, which delivers consistent estimates (up to a common multiplicative factor) when the number of stocks and characteristics is sufficiently large. Because this procedure reveals a cross section of a latent variable by combining a large number of observables, we refer to it as the high-dimensional cross-sectional filter (HCF). HCF is implemented as a sequence of two regressions. In the first step, realized returns are regressed on each lagged standardized characteristic individually (these are cross-sectional regressions that use all stocks for which the characteristic is available). The obtained slopes, whose number is equal to the number of characteristics, are used in the second step: for each individual stock, all currently available firm characteristics are regressed on the slopes obtained in the first step. We prove that the slopes from the second-step regressions are asymptotically proportional to cross-sectionally demeaned expected returns on individual stocks. It should be emphasized that HCF is a purely cross-sectional procedure that does not rely on the availability of a long history of characteristics.

Our approach to estimation of expected returns deserves several comments. First, our assumptions are broad and valid irrespective of which single-beta asset pric-

[1]Although our approach is motivated by a beta representation of expected returns, it is also valid when characteristics are related to future returns because they are all associated with the same psychological bias responsible for multiple anomalies.

ing model really explains expected returns. Moreover, they are consistent with the heterogeneous information quality of characteristics (the loadings of characteristics on betas as well as the amount of noise in them can vary across the characteristics). Nevertheless, HCF explicitly uses the restrictions implied by the underlying asset pricing model, which allows only one common component of the characteristics to be related to expected returns in the cross section. The incorporation of this model restriction into estimation of expected returns is the unique feature of our approach, which is responsible for its advantages over aggregation using the Fama-MacBeth regression.

Our estimator relies on the existence of the common component in characteristics that is related to expected returns. On the one hand, this may reduce the applicability of our approach and make it less efficient than the aggregation by the Fama-MacBeth regression if our model is misspecified. On the other hand, the ability of the HCF estimates to predict future returns would unambiguously indicate the presence of the common component in at least some of the characteristics. Thus, our approach also provides a test for the commonality in asset pricing anomalies. Note that the presence of a common component does not mean that all characteristics have the same information about returns, so using all of them is likely to make the estimates of expected returns more precise.

Having developed the aggregation procedure, we apply it to thirteen firm characteristics that are known to be related to stock returns and associated with the most prominent asset pricing anomalies. The first group of considered characteristics contains the three most researched anomalies: size, book-to-market, and momentum.

The second group contains two corporate investment anomalies: total asset growth and abnormal capital investments. The third group contains two financing anomalies: net stock issues and composite stock issuance. The fourth group contains three accounting anomalies: accruals, net operating assets, and profitability. The fifth and last group contains three anomalies broadly related to uncertainty about the firm: idiosyncratic volatility, Ohlson's score measuring the bankruptcy likelihood, and dispersion in analysts' forecasts. From these characteristics, we construct a new variable that aggregates information from all of them, and we refer to it as the aggregate filtered expected returns ($AFER$). To examine the cross-sectional dispersion of stock returns produced by $AFER$, we form portfolios based on $AFER$ and compute average returns on them. We find that the difference in monthly returns on top and bottom decile equally-weighted $AFER$ portfolios is around 3%. This spread is highly statistically significant (the t-statistic is 10.98) and substantially exceeds those produced by individual characteristics. The result is weaker for value-weighted portfolios, but the spread is still wide (2% per month with the t-statistic of 6.98).

Our empirical results have several implications. First of all, it is already remarkable that $AFER$ has at least some predictive power for future returns. By construction, the HCF procedure estimates the common component in the characteristics that is related to stock returns. Hence, the dispersion of returns on the $AFER$ portfolios implies that such a component exists and there is a strong commonality in the considered anomalies. The presence of the common component also alleviates the concern that asset pricing anomalies represent a result of data mining:

it is very unlikely that spurious anomalies would have a common component even if each of the characteristics were correlated with returns. Second, the dispersion of returns produced by $AFER$ is larger than that produced by individual anomalies meaning that various firm characteristics do contain complementary information and its aggregation is fully justified. Third, in many specifications of the model $AFER$ is more informative about future returns than fitted values of the Fama-MacBeth regression, so the additional theory-motivated assumptions used by HCF can help to improve the estimation efficiency.

Our estimation approach is applicable not only to all considered characteristics, but also to a subsample of them. In particular, it can be used for testing whether a group of anomalies have a common origin (the filtered expectations would be useless for predicting returns in the absence of a common component in the characteristics) and examining whether the information in the characteristics is complementary (when the characteristics are subsumed by each other, the filtered expected returns would not be better than individual characteristics for predicting returns). We conduct such an analysis on the characteristics related to firm growth. Using HCF, we construct a new variable dubbed the growth-based filtered expected returns ($GFER$) that aggregates information about expected returns from total asset growth, abnormal capital investments, accruals, net stock issues, and composite stock issuance. We find that the spread in returns produced by $GFER$ is statistically detectable but comparable with that produced by its individual components and is typically below 1% per month. Thus, various growth-associated anomalies are likely to capture different aspects of the same phenomenon.[1]

We also perform numerous additional tests to demonstrate the validity and robustness of our results. In particular, we i) build filtered expectations and perform tests using both raw returns and Fama-French risk adjusted returns; ii) explore the strength of $AFER$ and $GFER$ in various subsamples of stocks and time periods; iii) consider alternative model specifications; iv) conduct the Gibbons, Ross, and Shanken (1989) test (GRS test) of several standard asset pricing models using $AFER$ portfolios as test assets to show that the latter can help to increase the power of the test.

This study is related to several strands in the literature. In particular, it is close to the papers that examine the joint ability of multiple firm characteristics to predict stock returns (e.g., Haugen and Baker, 1996; Hanna and Ready, 2005; Lewellen, 2013; Green, Hand, and Zhang, 2014). In contrast to these papers, which primarily rely on Fama-MacBeth regressions, our study develops a new econometric approach to aggregating information from multiple firm characteristics. Also, our analysis is related to several studies that examine various trading strategies based on firm fundamentals. For example, Ou and Penman (1989) show how a logit model that aggregates numerous items from financial statements can predict future earnings and returns. Abarbanell and Bushee (1998) employ OLS regression to build portfolios that take into account a number of fundamental signals. Piotroski (2000) constructs

[1]This conclusion is consistent with Lipson, Mortal, and Schill (2012) who examine a variety of asset growth measures and argue that the total asset growth measure of Cooper, Gulen, and Schill (2008) largely subsumes the majority of them.

a new variable (F_SCORE) that combines nine accounting signals and has an ability to predict returns of value firms. A similar score ($GSCORE$) has been developed by Mohanram (2005) for growth stocks. Compared to these studies, our approach has a better theoretical motivation. Brandt, Santa-Clara, and Valkanov (2009) solve a portfolio optimization problem by allowing portfolio weights to depend directly on the size, book-to-market, and momentum characteristics. Thus, they do not construct estimates of expected returns of individual stocks using characteristics, which is the focus of our method.

This study also belongs to the growing literature that promotes a holistic approach to asset pricing anomalies. Fama and French (2008) examine the strength of seven anomalies across size groups. Stambaugh, Yu, and Yuan (2012) find that eleven anomalies appear to be stronger following periods of high investor sentiment. Avramov, Chordia, Jostova, and Philipov (2010) document that many anomalies are concentrated in firms with low credit ratings and the profitability of those anomalies (except asset growth) derives from credit rating downgrades. Chordia, Subrahmanyam, and Tong (2013) reconsider twelve popular anomalies and argue that their returns diminished in recent years because of a decline in trading costs and an increase in trading activity. McLean and Pontiff (2013) compare pre- and post-publication returns on 82 anomalies and find that the profitability of anomalies tends to decline after their publication. Kogan and Tian (2012) examine how easy it is to explain 27 asset pricing anomalies by a three-factor model in which two factors are return spreads produced by anomalous characteristics.

The idea that expected returns are unobservable variables that should be filtered out from available signals makes this study close to the recent literature on time series predictability of aggregate stock returns by filtered expectations.[1] In contrast to this literature, we use disaggregated firm characteristics for predicting the cross-sectional distribution of expected stock returns rather than the level of aggregate stock returns.

The rest of this chapter is organized as follows. In Section 2.2 we present our framework. We construct the HCF estimators of unobservable expected returns, discuss their properties, and compare them with several alternative aggregation techniques. Section 2.3 contains the results of our empirical analysis, in which we apply the methodology to a set of characteristics and construct filtered expected returns.

2.2 Methodology

2.2.1 Latent Variable Approach

Consider a set of N stocks whose characteristics and returns are observed in T periods. By definition, the best predictor of returns on stock i at time t is expected return $\mu_{it} = E[R_{it+1}|\mathcal{F}_t]$, where $\mathcal{F}_t$ is all information available to market participants. We assume that expected returns are described by an asset pricing model that admits a single-beta representation:

$$\mu_{it} - r_t = \beta_{it}\gamma_t,$$

[1] An incomplete list of papers includes Conrad and Kaul (1988), Brandt and Kang (2004), Pástor and Stambaugh (2009), van Binsbergen and Koijen (2010), Piatti and Trojani (2012), Romero (2012), Rytchkov (2012), Kelly and Pruitt (2012a), and Kelly and Pruitt (2012b). Various expectations are modeled as unobservable state variables also in Hamilton (1985), Balke and Wohar (2002), and Rytchkov (2010).

where β_{it} is the beta with respect to some risk factor, γ_t is the factor risk premium, and r_t is the risk-free rate. By definition of the expectation, the realized return on stock i can be written as

$$R_{it+1} = \mu_{it} + \varepsilon_{it+1}, \tag{2.1}$$

where $E[\varepsilon_{it+1}|\mathcal{F}_t] = 0$, but in general $E[\varepsilon_{it+1}\varepsilon_{jt+1}|\mathcal{F}_t] \neq 0$ for $i \neq j$. We assume that econometricians lack some information contained in $\mathcal{F}_t$ and do not know the nature of the priced factor, so neither μ_{it} nor β_{it} are observable to them.[1] Instead, they observe A firm characteristics X^a_{it}, $a = 1, \ldots, A$, such that $\{X^a_{it-s},\ s \geq 0,\ a = 1, \ldots, A,\ i = 1, \ldots, N\} \subset \mathcal{F}_t$. In practice, relevant firm characteristics may describe different aspects of a firm and have incomparable measurement scales. To take this into account, the following discussion assumes that all characteristics have been cross-sectionally demeaned and standardized, so that each of them has a unit cross-sectional variance at each moment. Implementing the interpretation of firm characteristics as proxies for conditional betas, we assume that the demeaned characteristics X^a_{it}, $a = 1, \ldots, A$ are related to demeaned betas $\beta_{it} - \bar{\beta}_t$ as

$$X^a_{it} = \delta^a_t \gamma_t (\beta_{it} - \bar{\beta}_t) + u^a_{it}, \tag{2.2}$$

where $\delta^a_t \gamma_t$ measures the sensitivity of characteristic a to current betas and $\bar{\beta}_t$ is the cross-sectional average of betas at time t. By construction, the cross-sectional average of the components u^a_{it} is zero. Note that the parameters δ^a_t and γ_t are allowed to change from period to period, so the informativeness of characteristics may vary

[1] We are agnostic about whether market participants observe the parameters of the asset pricing model, which is the main issue in Adrian and Franzoni (2009) and Armstrong, Banerjee, and Corona (2013).

over time. This flexibility makes our framework consistent with abundant empirical evidence that the strength of market anomalies varies over time.

The definition of the slope in Eq. (2.2) deliberately includes γ_t because without losing generality Eq. (2.2) can be rewritten in terms of demeaned expected returns:

$$X^a_{it} = \delta^a_t(\mu_{it} - \bar{\mu}_t) + u^a_{it}, \tag{2.3}$$

where $\bar{\mu}_t$ is the cross-sectional average of expected returns at time t. The latter representation of characteristics is more convenient for subsequent analysis. Note that the characteristics can be equivalently interpreted as signals about betas or signals about expected returns only if expected returns are described by a one-factor model.

For future convenience, we introduce the following notation. Denote the sample cross-sectional variance and covariance as $\overline{Var}$ and $\overline{Cov}$, respectively, and reserve $\widetilde{Var}$ and $\widetilde{Cov}$ for the sample variance and covariance in the characteristic space. Note that the standardization of characteristics implies that $\overline{Var}(X^a_{it}) = 1$ in each period t. To make the model identifiable, we need the following additional assumptions:

Assumption 1. (Distribution of expected returns) *In each period t, $t = 1, \ldots, T$,*

$$\bar{\mu}_t = \frac{1}{N}\sum_{i=1}^{N}\mu_{it} \xrightarrow{p} \mu_t \quad \textit{and} \quad \overline{Var}(\mu_{it}) = \frac{1}{N}\sum_{i=1}^{N}(\mu_{it} - \bar{\mu}_t)^2 \xrightarrow{p} V_t \quad \textit{as} \quad N \to \infty,$$

where $V_t > 0$.

Assumption 2. (Distribution of characteristic loadings) *In each period* t*,* $t = 1, \ldots, T$*,*

$$\tilde{\delta}_t = \frac{1}{A}\sum_{a=1}^{A} \delta_t^a \xrightarrow{p} \delta_t \quad \textit{and} \quad \widetilde{Var}(\delta_t^a) = \frac{1}{A}\sum_{a=1}^{A}(\delta_t^a - \tilde{\delta}_t)^2 \xrightarrow{p} \Lambda_{t,\,t} \quad \textit{as} \quad A \to \infty,$$

where $\Lambda_{t,\,t} > 0$*. Also, for consecutive periods* $t-1$ *and* t

$$\widetilde{Cov}(\delta_{t-1}^a, \delta_t^a) = \frac{1}{A}\sum_{a=1}^{A}(\delta_{t-1}^a - \tilde{\delta}_{t-1})(\delta_t^a - \tilde{\delta}_t) \xrightarrow{p} \Lambda_{t-1,\,t} \quad \textit{as} \quad A \to \infty,$$

where $\Lambda_{t-1,\,t} > 0$*.*

Assumption 3. (Orthogonality of errors and expected returns) *In each period* t*,* $t = 1, \ldots, T$ *and for each characteristic* a*,* $a = 1, \ldots, A$*,*

$$\overline{Cov}(\mu_{it}, u_{it}^a) = \frac{1}{N}\sum_{i=1}^{N}(\mu_{it} - \bar{\mu}_t)(u_{it}^a - \bar{u}_t^a) \xrightarrow{p} 0 \quad \textit{as} \quad N \to \infty.$$

Assumption 4. (Orthogonality of errors and characteristic loadings) *In each period* t*,* $t = 2, \ldots, T$ *and for each stock* i*,* $i = 1, \ldots, N$*,*

$$\widetilde{Cov}(\delta_{t-1}^a, u_{it}^a) = \frac{1}{A}\sum_{a=1}^{A}(\delta_{t-1}^a - \tilde{\delta}_{t-1})(u_{it}^a - \tilde{u}_{it}) \xrightarrow{p} 0 \quad \textit{as} \quad A \to \infty.$$

Assumption 1 formalizes a natural condition that the cross-sectional distribution of expected stock returns has a finite expectation and a positive standard deviation. Similarly, Assumption 2 implies that the population distribution of the vector of characteristic loadings $(\delta_{t-1}^a, \delta_t^a)$ has finite and non-zero second moments. It can be interpreted as a condition that when the number of characteristics increases, their average informativeness stays the same.[1] Assumption 3 states that there is no cross-sectional relation between u^a_{it} and the individual expected stock returns. In other words, all available information about the cross-section of stock returns is captured by μ_{it}. Assumption 4 implies that there is no systematic relation between the past sensitivity of each characteristic to expected returns and the part of the characteristic unrelated to expected returns. Given that typically the time variation in the characteristic loadings is low, the assumption is also likely to hold for the contemporaneous loadings δ^a_t.

It should be emphasized that our assumptions impose restrictions on neither the cross-sectional correlations of ε_{it} nor the cross-characteristic or cross-sectional correlations of u^a_{it}. In general, the error components can be correlated even asymptotically. In particular, ε_{it} may have a factor structure underlying the cross-sectional correlations of realized returns (e.g., with the return on the market as a factor). The correlations between u's imply that X^a_{it} may have a complex correlation structure with multiple factors in the characteristics space and that μ_{it} is just one of them. Note that because of the correlations between the returns-unrelated components of the characteristics, a simple averaging of the characteristics in general would provide an inconsistent estimate for expected stock returns.

The main problem of an econometrician is to estimate μ_{it} using all observable characteristics X^a_{it}. In order to solve it, we propose a simple procedure, which can be implemented as a sequence of standard OLS regressions. Because it uncovers a

[1] A disproportionate number of useless characteristics would shift the density of the distribution of δ_t to zero and decrease $\Lambda_{t,\,t}$.

cross-section of latent variables using a large number of observables, we refer to it as the high-dimensional cross-sectional filter (HCF). The main steps of HCF at time t are as follows:

Step 1. Run separate cross-sectional regressions of R_{it}, $i = 1, \ldots, N$, on each individual firm characteristic X^a_{it-1}, $i = 1, \ldots, N$ for $a = 1, \ldots, A$ and denote the obtained slopes as λ^a_t.

Step 2. For each firm i, $i = 1, \ldots, N$ run a regression of X^a_{it} on λ^a_t, $a = 1, \ldots, A$, and denote the obtained slopes as $\hat{\mu}_{it}$.

The steps of the HCF procedure admit an intuitive interpretation. Running regressions of current returns on each past characteristic at Step 1, we effectively estimate the loadings of characteristics on expected returns in the previous time period (up to a scalar multiplicative factor), so λ^a_t can be viewed as a proxy for δ^a_{t-1}. If the loadings are persistent, they represent good estimates for current loadings δ^a_t. Running a regression of current characteristics of each stock on the estimated loadings at Step 2, we find the slope in Eq. (2.3) (again, up to a multiplicative factor that is the same for all stocks), which coincides with the current demeaned expected return on the stock.

Note that λ^a_t and $\hat{\mu}_{it}$ are determined only by realized returns on all stocks at time t and all characteristics of all stocks at times t and $t-1$. Obviously, all needed information is available when the expected returns are estimated. Hence, the procedure does not suffer from a look-ahead bias, and all computations are performed in real time. Also note that the HCF procedure uses information on characteristics and returns from two periods only, so it does not rely on the availability of a long history of observations.

The following Proposition states one the main econometric results of this chapter.

Proposition 1. *If Assumptions 1 – 4 hold, the described two-step procedure (HCF) asymptotically uncovers the cross section of expected stock returns up to an unobservable time-varying factor F_t, which is the same for all stocks, i.e.,*

$$\operatorname*{plim}_{A\to\infty}\operatorname*{plim}_{N\to\infty}\hat{\mu}_{it} = F_t(\mu_{it} - \mu_t), \qquad \textit{where} \qquad F_t = \frac{\Lambda_{t-1,t}}{\Lambda_{t-1,t-1}V_{t-1}},$$

and $\Lambda_{t-1,t}$, $\Lambda_{t,t}$, and V_{t-1} are defined in Assumptions 1 and 2.

Proof. See Appendix, Section 2.4.

Proposition 1 implies that when the number of stocks and characteristics is sufficiently large, the HCF estimates $\hat{\mu}_{it}$ contain all information about the cross-sectional dispersion of expected stock returns up to a scaling factor. Thus, asymptotically the cross-sectional ranking of stocks based on $\hat{\mu}_{it}$ coincides with that of based on μ_{it}, and sorting stocks in portfolios using $\hat{\mu}_{it}$ should deliver the highest dispersion of future realized portfolio returns.

Proposition 1 says that the expected returns are revealed in a sequential limit: N goes to infinity first, and then the limit with respect to A is taken. Note that in general this limit may differ from that obtained when the limits are taken in the opposite order or when N and A tend to infinity simultaneously.[1] However, this does not diminish the relevance of our analysis. In practice the number of firms typically exceeds the number of their characteristics, and this is consistent with taking the limit with respect to N first.

For the next step of our analysis, we introduce matrix notation. Denote by R_t, μ_{t-1}, and ε_t the $N \times 1$ matrices of all realized returns at time t, all expected returns at time $t-1$, and all unexpected returns at time t, respectively. The vector of HCF estimates of expected returns at time t is $\hat{\mu}_t$. The $N \times A$ matrix X_t represents all characteristics available at time t and the characteristic loadings are denoted by an $1 \times A$ vector δ_t.

We previously described the construction of $\hat{\mu}_{it}$ in terms of a sequence of OLS regressions. However, when all characteristics are available for all stocks, $\hat{\mu}_{it}$ admits an explicit analytical representation, which is given by Proposition 2.

Proposition 2. *The vector $\hat{\mu}_t$ can be found as*

$$\hat{\mu}_t = N(R_t' M_N X_{t-1} M_A X_{t-1}' M_N R_t)^{-1} X_t M_A X_{t-1}' M_N R_t, \tag{2.4}$$

where M_N and M_A are standard projectors on the spaces orthogonal to N- and A-dimensional vectors of ones ι_N and ι_A:

$$M_N = I_N - \frac{1}{N}\iota_N \iota_N', \qquad M_A = I_A - \frac{1}{A}\iota_A \iota_A'.$$

I_N and I_A are identity matrices of the sizes N and A, respectively.

[1] See Bai (2003) for a discussion of various types of asymptotic convergence when random variables are labeled by two indexes.

Proof. See Appendix, Section 2.4.

Proposition 2 implies that $\hat{\mu}_t$ is proportional to $X_t M_A X'_{t-1} M_N R_t$, and only this matrix needs to be computed to estimate the cross-section of stock returns (the factor $N(R'_t M_N X_{t-1} M_A X'_{t-1} M_N R_t)^{-1}$ is a scalar, which is irrelevant because $\hat{\mu}_t$ estimates μ_t up to a multiplicative factor). This reduces the computational intensity of the procedure and facilitates the simulation analysis discussed below.

Our methodology admits multiple modifications and extensions. To predict the dispersion of returns at time $t+1$, the baseline procedure uses only realized returns at time t and characteristics measured at times t and $t-1$. However, in practice much longer time series of characteristics and returns are available, and their use may increase the efficiency of the estimates. Extensions 1 and 2 describe the two major ways in which the availability of observations in other periods can be exploited.

Extension 1. If the relative relations among expected returns in the cross section are stable over time, past realizations of the characteristics X^a_{it-s}, $s = 1, \ldots, L-1$ can also be used on par with X^a_{it} (if Assumptions 2, 3, and 4 hold for them). This multiplies the number of observables A and makes the asymptotic result from Proposition 1 more reliable.

Extension 2. If the relations between characteristics and expected returns are stable over time or have a particular time series pattern (e.g., δ^a_t is constant for all i), a modification of Step 2 can improve the efficiency of the whole procedure.

Indeed, instead of using λ_t^a at Step 2 it is possible to use averages of λ_s^a that take the time series pattern in to account. In particular, when δ_t^a is constant we can average the lambdas computed for all previous periods. Because λ_t^a is a proxy for δ_t^a, an average of lambdas is a better estimate for the constant δ^a, and its use improves the precision of the estimates.

In practice, it is unlikely that the assumptions of Extensions 1 and 2 hold exactly. However, expected returns on individual stocks are highly persistent and it is reasonable to assume that there are no abrupt changes in the relations between characteristics and expected returns. In this case, past characteristics can be added as observables, but their history should be limited. In our empirical analysis, we assume that expected returns can be treated as constant on horizons of up to one year. Thus, we set $L = 12$ and use X_{it-s}^a, $s = 1, \ldots, L$ at Step 1 and X_{it-s}^a, $s = 0, \ldots, L-1$ at Step 2. In our applications, we also use Extension 2. In particular, we average lambdas computed at the same month in all previous years (we also add the most recent lambdas when we compute the averages). There is evidence of a seasonal variation in the factor risk premia (Keloharju, Linnainmaa, and Nyberg, 2013), and in the absence of seasonal variation in firm characteristics the suggested averaging takes the seasonality in the risk premia into account.

Eq. (2.3) assumes a linear relation between characteristics and expected returns (i.e., δ_t^a does not depend on i). However, it is well known that the strength of many asset pricing anomalies depends on the range of the anomalous characteristic. For example, many anomalies tend to be stronger in the short end (e.g., Stambaugh, Yu, and Yuan, 2012) and for small stocks (e.g., Fama and French, 2008). It means that practically, the slopes δ_t^a can depend on characteristic a itself as well as on other characteristics (denote them as $-a$). Our procedure can be modified to take into account this possibility, and this modification is described in Extension 3.

Extension 3. Assume that $\delta_t^a(X_{it}^a, X_{it}^{-a})$ is piece-wise constant in the characteristic space. Then, its components are estimated at Step 1 by running regressions on each subsample of stocks for which δ_t^a is constant. In this way, several estimates of λ_t^a are obtained for each characteristic that correspond to different ranges of the characteristics' values. At Step 2, for each stock i with the set of characteristics X_{it}^a the appropriate lambdas corresponding exactly to X_{it}^a should be chosen.

The implementation of Extension 3 brings up an important tradeoff. On the one hand, it may improve the quality of the estimates because the non-linear model is likely to suffer less from misspecification compared to its linear analog and better capture the information from each characteristic. On the other hand, a non-linear model is more demanding in terms of the availability of data and the noise may offset the benefits of improved specification.

2.2.2 HCF and Alternative Aggregation Techniques

The most common approach to estimating expected returns from multiple characteristics is to use fitted values from the Fama-MacBeth regression (effectively, a cross-sectional OLS regression) of realized returns on all available characteristics (e.g., Haugen and Baker, 1996; Chan, Dimmock, and Lakonishok, 2009; Lewellen, 2013). On the one hand, the OLS regression, which does not rely on any factor structure of the characteristics, is more robust and may deliver consistent estimates even when the assumptions of our model are violated and HCF may demonstrate poor performance. On the other hand, HCF has several advantages over OLS, which become particularly pronounced when the number of characteristics is large.

The key assumption of our approach is that all characteristics are proxies to the *same* beta, so there is only one factor in the space of all characteristics that is related to expected returns. This restriction is formalized by Eqs. (2.1) and (2.3) together with Assumptions 3 and 4 and the returns-related factor is denoted by μ_{it}. Even though there may exist multiple factors in the characteristic space and there are no restrictions on the covariances of the characteristics, our assumption puts more structure on the model than the standard linear regression does. When our assumption actually holds, HCF explicitly exploits it and is likely to provide asymptotically more efficient estimates than the OLS regression.

HCF is particularly advantageous over OLS when the number of characteristics is large. The coefficients of the OLS regression $(X'_{t-1}X_{t-1})^{-1}X'_{t-1}R_t$ effectively require the estimation of the variance-covariance matrix of all regressors $X'_{t-1}X_{t-1}$, whose size grows with the number of characteristics as A^2. When A is relatively large, the estimate becomes imprecise and even does not exist when there are more characteristics than stocks.[1] In contrast, HCF does not involve the variance-covariance

[1] The techniques designed to deal with a large number of regressors include sliced inverse regression (e.g., Li, 1991), and sparse regression models (e.g., Huang, Horowitz, and Ma, 2008; Belloni, Chernozhukov, and Hansen, 2011). The methods of forecasting of a single time series when there are many predictors are reviewed by Stock and Watson (2006).

matrix of all characteristics but estimates only the loadings δ_a and expected returns themselves. As a result, it even benefits from a large number of characteristics. Meanwhile, when there are only few characteristics the estimates of their common component may be imprecise and HCF may be dominated by OLS.

Another detrimental consequence for the OLS regression from including $X'_{t-1}X_{t-1}$ is the inability to handle highly correlated characteristics due to the multicollinearity problem. As a result, a researcher should make a judgment about which characteristic among those that are highly correlated is the most informative about returns and use only this characteristic in the regression. HCF does not suffer from this issue and can easily aggregate information about expected returns from two characteristics even when the characteristics are highly correlated.

The OLS regression has an undesirable requirement that all characteristics are available for each stock. This is a very restrictive condition because the elimination of stocks with missing characteristics significantly reduces the sample size.[1] In contrast, HCF can naturally handle stocks with only a few characteristics. Indeed, the first step of our approach considers the characteristics one by one and, hence, uses all stocks for which the given characteristic is available. As a result, the estimates of lambdas are based on the maximum amount of information. The second step of our procedure runs a regression of all characteristics *available for the given stock* at the given moment on the slopes of these characteristics obtained at the first step. This

[1] To alleviate this problem, it is common to impute missing observations by assigning cross-sectional averages of non-missing observations to them (e.g., Haugen and Baker, 1996; Green, Hand, and Zhang, 2014).

is again a univariate regression in which the number of characteristics corresponds to the number of observations. If several characteristics are missing for the given stock, this simply reduces the sample size in the regression (and possibly the precision of the inference) but does not prevent running the regression as in the case of OLS regressions of returns on all characteristics.

The objective of HCF to uncover a common component from a set of characteristics resembles the objective of factor analysis. However, these techniques are different in terms of their applicability as well as their outcomes. Factor analysis uses the covariance structure of characteristics only, so it may reveal a factor that explains the commonality in characteristics but is silent about expected returns. In contrast, HCF by construction focuses only on the common component in characteristics that is related to future returns, even though there may exist other factors in characteristics that strongly affect the correlations among the characteristics themselves. Because of that, HCF and factor analysis generally would deliver different estimates for expected returns, and those provided by factor analysis are inconsistent unless the characteristics are described by a one-factor model.

The HCF procedure also bears some relation to a partial least squares regression (PLS).[1] Similar to the main framework of PLS, the dependent variable (realized returns) and independent variables (characteristics) are related to each other through a latent structure (expected returns). However, in contrast to the classic PLS technique, our results rely on the availability of a large number of observables. Our pro-

[1]Various aspects of PLS are presented in Vinzi, Chin, Henseler, and Wang (2010).

cedure also resembles the three-pass regression filter developed by Kelly and Pruitt (2012b) but has a different objective: the latter is designed to find the best predictor for one time series having a long history of multiple observables, whereas HCF uncovers the cross-sectional distribution of unobservable expected stock returns.

2.2.3 Simulation Analysis

Our theoretical results show how the proposed estimator of expected returns behaves for a large number of characteristics and stocks. To assess its behavior in finite samples and to examine how the estimator quality depends on model parameters such as the signal to noise ratio of observables and the distribution of the slopes δ, we use Monte Carlo simulations. We also compare the performance of our estimator with that of fitted OLS values and factors revealed by the factor analysis and illustrate how a large number of anomalies improves the performance of HCF.

We assume that the cross-sectional distribution of expected returns is normal with a mean of 1% and a standard deviation of $\sigma(\mu_i) = 0.8\%$. This calibration is consistent with the estimates obtained for actual monthly expected returns on stocks (e.g., Lewellen, 2013). Unexpected returns ε_i are assumed to be normally distributed with a zero mean and a standard deviation of 10%, which is the order of magnitude for a monthly volatility of individual stock returns. In the baseline analysis we ignore the cross-sectional correlation of unexpected returns and model them as i.i.d. shocks.

It is harder to calibrate the loadings of characteristics δ_t^a and the distribution of the returns-unrelated components u_{it}^a. Given that the relations between characteristics and expected returns tend to be relatively stable, we treat δ^a as constant over time, i.e., $\delta^a_{t-1} = \delta^a_t$. We also assume that the distribution of δ^a is normal with a unit mean and a standard deviation of σ_δ. To examine how σ_δ affects the quality of the HCF estimates, we consider three specifications for it: $\sigma_\delta = 0.5$, $\sigma_\delta = 1$, and $\sigma_\delta = 2$. The components u^a_{it} have a normal distribution as well with zero mean. In the simplest case, they are independent across characteristics and across stocks. The standard deviation of u^a_{it} determines the informativeness of a characteristics about expected stock returns. However, for each characteristic this informativeness is also affected by the realized δ^a (for each characteristic a, the signal-to-noise ratio is $\theta^a = \sigma(\delta^a\mu_i)/\sigma(u^a_{it})$). To separate these two effects, we set $\sigma(u^a_{it}) = |\delta^a|\sigma(\mu_i)/\theta$ and consider three values for the parameter θ: 0.2, 0.5, and 1.

To study the impact of the number of observations and characteristics on the HCF performance, we examine various combinations of N and A. In particular, we consider 100, 500, $1,000$, and $3,000$ as the values of N and 10, 50, 100, and 500 as the values of A. For each combination of the model parameters and for the chosen N and A, we generate $B = 1,000$ pseudo-samples of characteristics X^a_{it-1}, X^a_{it}, and returns R_{it}, and compute the HCF estimates of expected returns $\hat{\mu}^{(b)}_i$, $b = 1, \ldots, B$.

As a metric of the estimation precision, we use an average cross-sectional correlation between the estimated expected returns $\hat{\mu}^{(b)}_i$ and the actual expected returns μ_i. In particular, we compute $\rho^{(b)} = corr(\hat{\mu}^{(b)}_i, \mu^{(b)}_i)$ for each simulated sample $b = 1, \ldots, B$ and then find their average: $\rho = \sum_{b=1}^{B} \rho^{(b)}/B$. Note that the correlation is the most appropriate metric in our framework because HCF reveals expected returns up to a multiplicative factor which has no effect on the correlations. The average correlations obtained by HCF and OLS in the baseline model are reported in Table 2.1.

Table 2.1 delivers several observations. First, the quality of the HCF estimates increases with the number of characteristics. For example, when $\sigma_\delta = 1$, $\theta = 0.5$, and $N = 1,000$ the correlation of the HCF estimates with the true values increases from 0.48 to 0.97 as A increases from 10 to 500. Moreover, HCF provides reasonable estimates even when A exceeds N.

Second, Table 2.1 shows how the quality of the HCF estimates depends on the dispersion of characteristic loadings σ_δ. Because the second step of HCF is a regression of firm characteristics on the proxies for characteristic loadings, the obtained estimates should be more precise when the dispersion of the loadings is high. This is clearly demonstrated by the correlations in Table 2.1. When $\sigma_\delta = 0.5$ the HCF correlations are relatively small, especially when only few characteristics are available (they do not exceed 0.13 for $A = 10$). However, all HCF correlations are much higher when $\sigma_\delta = 2$. For example, they increase from 0.13 to 0.75 when $N = 3,000$ and $A = 10$, and they approach 0.99 when $N = 3,000$ and $A = 500$.

Third, Table 2.1 illustrates the dependence of the HCF correlations on the signal-to-noise ratio θ. When θ is high, the characteristics are more informative about expected returns, so the correlations should increase with θ. This intuition is confirmed by Table 2.1: the HCF estimates become more precise with θ. For example, when $N = 1,000$ and $A = 10$ the HCF correlation rises from 0.13 to 0.71 as θ increases from 0.2 to 1.

Table 2.1 also compares the performance of HCF and OLS estimates for expected returns, where the latter are obtained by running cross-sectional regressions of realized returns R_{it} on the past characteristics X^a_{it-1} and using the fitted values based on X^a_{it} as the estimates. Our results show that in the vast majority of cases the estimates obtained by HCF are more precise than those based on OLS and the difference can be dramatic. For example, when $\theta = 0.5$, $\sigma_\delta = 1$, $N = 1,000$, and $A = 500$ the HCF correlation is 0.97, whereas the corresponding correlation of the OLS estimate is only 0.08. Moreover, in contrast to HCF the quality of the OLS estimates notably decreases with the number of characteristics. In particular, when $\sigma_\delta = 1$, $\theta = 0.5$, $N = 1,000$, and A increases from 10 to 500 the correlation drops from 0.48 to 0.08. When A exceeds N, OLS estimates do not exist.

The OLS estimates also demonstrate different dependence on model parameters. In stark contrast to the HCF estimates, the OLS estimates have no sensitivity to σ_δ. Even though both HCF and OLS estimates become more precise with θ, the improvement is much less pronounced for OLS than for HCF, and for the former it almost disappears when the number of characteristics is large. In the case when $N = 1,000$ and $A = 10$ the OLS correlation rises only from 0.21 to 0.56 as θ increases from 0.2 to 1. A similar HCF gain is from 0.13 to 0.71.

Although in the baseline simulations we assume that the realized returns are independent, actual returns are strongly correlated with returns on the market being the dominant common factor. To examine how this correlation affects the quality of the HCF estimates, we repeat the simulations assuming that the unexpected returns are generated as $\varepsilon_i = f^\varepsilon + \nu_i$, where f^ε is a normally distributed common factor with a zero mean and a standard deviation of $\sigma(f^\varepsilon)$. The idiosyncratic unexpected returns ν_i are also normally distributed with zero mean and are uncorrelated with the factor and with each other. We characterize the importance of the factor with the ratio $\theta_f = \sigma(f^\varepsilon)/\sigma(\nu_i)$, where $\sigma(\nu_i)$ is the standard deviation of the idiosyncratic component. We consider three values for the parameter θ_f: 0.2, 0.5, and 1. To ensure that the total volatility of returns is the same as in the baseline case (10%), we set $\sigma(f^\varepsilon) = 0.1\theta_f/\sqrt{1+\theta_f^2}$ and $\sigma(\nu_i) = 0.1/\sqrt{1+\theta_f^2}$. The other parameters are $\sigma_\delta = 1$ and $\theta = 0.5$.

The correlations between $\hat{\mu}_i$ and μ_i in the presence of a factor in unexpected returns are also reported in Table 2.1. In general, the obtained correlations are similar to those without the factor and all previous conclusions hold. The only new observation is that the quality of the estimates tends to increase with the importance of the factor. This finding admits an intuitive explanation: when the proportion of the volatility of returns attributed to the factor is high, the cross-sectional dispersion of realized returns is determined largely by the cross-sectional dispersion of expected returns rather than by the cross-sectional dispersion of the realized idiosyncratic returns. Hence, the confounding effect of the unexpected returns decreases, and the estimates of expected returns become more precise.

A common factor unrelated to expected returns can also be present in the characteristics. We assume that $u_{it}^a = f_{it}^u + \eta_{it}^a$, where f_{it}^u is an additional factor in the characteristics of stock i uncorrelated with η_{it}^a. This factor is normally distributed with zero mean and standard deviation $\sigma(f_{it}^u)$. Neither the factors nor the idiosyncratic components η_{it}^a are correlated across stocks or over time. As before, we measure the strength of the factor by the ratio $\theta_f = \sigma(f_{it}^u)/\sigma(\eta_{it})$, where $\sigma(\eta_{it})$ is the standard deviation of the idiosyncratic component. To avoid confounding effects, we assume that the total volatility of u_{it}^a is the same for all stocks and characteristics and set to be $\sigma(u_{it}^a) = 0.05$. Note that in contrast to the baseline specification, $\sigma(u_{it}^a)$ is assumed to be independent of the realizations of δ^a. To maintain the same volatility of u_{it}^a for different values of θ_f, the volatilities of the factor and the idiosyncratic component are computed as $\sigma(f_{it}^u) = \sigma(u_{it}^a)\theta_f/\sqrt{1+\theta_f^2}$ and $\sigma(\eta_{it}) = \sigma(u_{it}^a)/\sqrt{1+\theta_f^2}$. As before, we set $\sigma_\delta = 1$ and consider three values for θ_f: 0.2, 0.5, and 1.

Table 2.2 reports the correlations between actual expected returns and their estimates obtained by HCF in the presence of an additional factor in characteristics. It shows that the quality of the HCF estimates tends to increase with the strength of the additional factor θ_f, and this pattern has an intuitive explanation. A common factor in u's has no effect on the outcome of the cross-sectional regressions of returns on individual characteristics that are run at Step 1. However, it reduces the cross-characteristic dispersion of errors u_{it}^a for each stock, and this affects the regression slopes at Step 2. When the factor is strong, the dispersion in observed characteristics of stock i should be largely attributed to the dispersion of factor loadings rather than to the errors u_{it}^a. As a result, the regression slope, which is proportional to the expected return on stock i, is estimated more precisely, and this explains the increase in the correlations between $\hat{\mu}_i$ and μ_i.

Under our assumption that there is only one factor in the characteristics related to expected returns, a viable alternative to HCF could be extracting a common factor from firm characteristics by factor analysis and considering it as a proxy for expected returns. This approach would obviously provide consistent estimates when there is only one factor in characteristics that corresponds to expected returns (i.e., the errors u^a_{it} are uncorrelated across characteristics), although it is more computationally intensive than HCF, especially when the number of available characteristics is large. However, when firm characteristics contain several common factors (e.g., there is also a common factor in u^a_{it} for each stock), the comparison of HCF and factor analysis is non-trivial. On the one hand, HCF extracts only the factor related to expected returns and ignores all others. On the other hand, HCF uses realized returns and characteristics from the past period, so when returns-unrelated factors are weak it may be less precise than factor analysis, which extracts the factor directly from the current characteristics.

To compare HCF and factor analysis, we augment Table 2.2 with the correlations between actual expected returns and their estimates obtained by factor analysis in the presence of an additional factor in characteristics. A comparison of these estimates with their HCF analogs reveals that factor analysis produces more precise estimates than HCF when the common factor in the errors u^a_{it} is weak (when θ_f is low), but tends to underperform when the common factor is strong. Indeed, when the relation to expected stock returns is the main source of correlations among characteristics of a stock, the factor analysis uncovers the common component associated with expected returns relatively precisely. However, when the returns-irrelevant factor in characteristics is strong, it erroneously dominates the estimate of expected returns produced by factor analysis and makes the estimate less precise. In contrast, HCF uncovers only the common factor in characteristics that contains information about future returns and ignores all others.

Table 2.2 also demonstrates how the quality of the HCF and factor analysis estimates changes with the number of stocks and characteristics. Not surprisingly, both of them become more precise as N grows, but the effect is stronger for the HCF estimates: they are consistent and tend to converge to the true values, whereas the factor analysis estimates are misspecified. A similar pattern holds for the number of available characteristics A.

2.3 Empirical Analysis

In this section, we illustrate how HCF works for real data by applying it to thirteen firm characteristics that are known to be related to expected stock returns.

2.3.1 Data

Our data come from standard sources. Stock returns, stock prices, and the number of shares outstanding are from CRSP monthly files, while accounting data are from Compustat Fundamentals annual files. We exclude financial firms and consider only NYSE, AMEX, and NASDAQ firms with common stocks. Returns are monthly stock returns with dividends adjusted for delisting. We consider both raw and risk-adjusted returns, and use the Fama-French three-factor model to adjust for risk. We compute risk-adjusted returns $\tilde{r}_{it}$ on security i in month t following Brennan, Chordia, and Subrahmanyam (1998) and Avramov and Chordia (2006):

$$\tilde{r}_{it} = r_{it} - r_t^f - \beta_i^{MKT} \times MKT_t - \beta_i^{HML} \times HML_t - \beta_i^{SMB} \times SMB_t.$$

Individual stock betas are estimated every month by regressing excess stock returns on a constant and the Fama-French factors. We use the previous 60 months of observations, requiring that at least 24 months of return data are available.

As signals about expected stock returns, we use thirteen characteristics that are associated with prominent asset pricing anomalies. The characteristics can be divided into five groups. The classical group consists of size S, book-to-market B/M, and momentum Mom. Investment variables capture the firm's capital investment. This group consists of total asset growth AG and abnormal capital investments CI. Issuance characteristics capture the firm's equity issuance activity with net stock issues NS and composite stock issuance ι. Two accounting anomalies capture the firm's earnings management and its cumulative effect on the balance sheet with accruals Acc and net operating assets NOA, respectively. Return on assets ROA, an accounting measure of the firm's performance, also belongs to this group. Idiosyncratic volatility $IdVol$, Ohlson's O-score O, and dispersion in analysts' forecasts D are grouped together as they broadly quantify uncertainty about the firm. The detailed construction of each characteristic is described in the Appendix.

Our sample covers the period from January 1965 to December 2012 for all characteristics except the return on assets, O-score, and analysts' forecast dispersion, for which the sample starts in January 1975, January 1976, and January 1983, respectively.

2.3.2 Individual Anomalies

We start our analysis by confirming that the selected characteristics are related to expected stock returns. We sort stocks with respect to each characteristic, form decile portfolios, and compute average raw and risk-adjusted monthly returns on them. For the book-to-market, asset growth, abnormal capital investments, accruals, net operating assets, net stock issues, and composite stock issuance the portfolios are formed once a year at the end of June. They are held for one year and rebalanced at the end of next June. Portfolios based on size, momentum, idiosyncratic volatility, and dispersion in analysts forecasts are created at the end of each month, whereas portfolios based on return on assets and O-score are updated quarterly. Anomalous returns are produced by a strategy with a long position in the top portfolio and a short position in the bottom portfolio. In order to identify the contribution of small stocks into abnormal returns, we compute both equal-weighted and value-weighted portfolio returns. Table 2.3 reports the results.

In general, Table 2.3 confirms the existence of the considered anomalies and implies that the thirteen characteristics contain some information about future returns. For instance, Panel A shows that all hedge returns based on equal-weighted portfolios are highly statistically significant and the majority of them exceed 50 basis points per month. In the considered sample, the widest dispersion of raw returns is produced by size, momentum, and the value anomalies. The absolute values of t-statistics range from 3.00 for the O-score to 7.30 for the total asset growth, and more than half of them are greater than 4. Note that this variation in the t-statistics across anomalies is driven by the dispersion both in expected returns and in the volatility of anomalous returns, which ranges from 2.24% for abnormal capital investments to 7.58% for size.

Panel B shows that the anomalies survive the adjustment for risk based on the Fama-French three factor model. Moreover, the risk adjustment does not eliminate the dispersion in expected returns even across size and book-to-market portfolios, although it halves the value premium. This result echoes the findings of Brennan, Chordia, and Subrahmanyam (1998) and shows that the conclusions are sensitive to whether the risk adjustment is conducted at the portfolio level or at the level of individual securities.

Consistent with the literature, Panels C and D show that the abnormal returns tend to be weaker when computed for value-weighted portfolios. The reduction in hedge returns is particularly pronounced for the value anomaly, the total asset growth anomaly, and the abnormal capital investments anomaly, which even becomes statistically insignificant for risk-adjusted returns. Also note that the distress anomaly and the analysts' forecasts anomaly disappear for raw returns and value-weighted portfolios but retain their strength for risk-adjusted returns.

2.3.3 Filtered Expected Returns

In order to aggregate information on individual expected stock returns contained in multiple characteristics, we apply the HCF procedure. We construct the estimates of expected returns $\hat{\mu}_{it}$ using the two-step procedure described in Subsection 2.2.1. These estimates can be viewed as new firm characteristics related to actual stock returns, and we refer to them as filtered expected returns.

We introduce two types of filtered expected returns. First, we construct a proxy for expected returns that unifies the information from all thirteen characteristics discussed above and denote it as $AFER$ (the abbreviation stands for "aggregate filtered expected returns"). It aggregates the information from different sources (fundamental data, price data, analysts' forecasts data, etc.) and it may be hard to give it a particular economic interpretation. However, this is exactly the characteristic that investors should optimally use to build portfolios with the highest dispersion of expected return.

Our second aggregate estimate of expected returns captures the information associated with various aspects of firms' growth. Conceivably, the relations between various growth-related firm characteristics and expected returns have the same economic explanation, and various growth anomalies capture its different aspects. To some extent, this logic is the same as in Cooper, Gulen, and Schill (2008), where the authors motivate the use of the total asset growth as a single variable that unifies many subcomponents of growth from both the financing and investment sides. To construct the characteristic that aggregates various growth anomalies (we denote it as $GFER$, which is an abbreviation for growth-based filtered expected returns), we combine asset growth, accruals, capital investments, net stock issues, and composite stock issuance.

To aggregate characteristics, we use their ability to predict raw returns. However, many of the considered characteristics have become prominent due to their ability to predict returns adjusted for risk using the Fama-French three factor model. Because of that, we also consider versions of aggregate expected returns that are built as predictors of risk-adjusted returns. The latter filtered returns are denoted as $AFER(a)$ and $GFER(a)$ (a stands for "adjusted"), whereas the expectations based on raw returns are denoted as $AFER(r)$ and $GFER(r)$ (r stands for "raw").

In the practical implementation, we augment the two-step procedure with several additional conventions. First, as mentioned in Subsection 2.2.1, we use not only the values of the characteristics available in month t for predicting returns in month $t+1$ but also the values of the characteristics from $L-1$ previous months as additional signals (although not all lagged characteristics contain new information because several of them are revised annually). In the baseline case we set $L = 12$ and consider the sensitivity of the results to this choice among other robustness tests in Subsection 2.3.5. Second, we adjust the procedure for a seasonal variation in the strength of anomalies and use averaged lambdas, i.e., for predicting returns in month m we average lambdas computed for all previous months m and the most recent lambda computed in month $m-1$. Third, we run the regression at Step 2 only if the sample of available characteristics of firm i and the corresponding lambdas computed at Step 1 contains more than seven data points. Otherwise, the expected return for firm i in the given period is deemed unavailable.

Table 2.4 reports the average returns on decile portfolios formed on the basis of the four filtered expected returns constructed by HCF. To ensure that our results are not driven by risk adjustment, we examine the predictability of both raw returns and risk-adjusted returns. Also, as in the case of individual anomalies, we compute equal-weighted and value-weighted portfolio returns.

Table 2.4 provides several observations. First, both $AFER$ and $GFER$ produce a strong dispersion in expected stock returns, and the average portfolio returns tend to increase monotonically with the portfolio number. The only exception is the risk-adjusted returns on $GFER(r)$ computed for value-weighted portfolios, which can be explained by poor behavior of the total asset growth anomaly and the abnormal capital investments anomaly on risk-adjusted returns and value-weighted portfolios (cf. Table 2.3).

Second, the comparison of Tables 2.3 and 2.4 reveals that $AFER$ produces hedge returns that substantially exceed those on individual anomalies. In particular, Panel A of Table 2.4 shows that the spread between top and bottom decile portfolios for $AFER(r)$ is 3.02% per month with the t-statistic of 10.98, whereas the highest return on individual anomaly is 1.88% (the size anomaly). The result is robust and holds for both $AFER(r)$ and $AFER(a)$, raw and risk-adjusted returns, and equal-weighted and value-weighted portfolios. Moreover, the hedge returns on $AFER$ tend to have higher t-statistics, implying that high expected returns are generated without a commensurate increase in the volatility of returns. Thus, various firm characteristics indeed contain complementary information about stock returns, and the HCF procedure reveals it.

Third, the result is different for $GFER$. Even though the dispersion of returns produced by it is statistically detectable in the majority of specifications, it does not generate hedge returns that are larger than those on its individual components. For example, the spreads in raw returns on equal-weighted decile portfolios for $GFER(r)$ and $GFER(a)$ are 1.06% and 0.78%, respectively, whereas the similar spread produced by total asset growth alone is 1.13%. This lack of improvement can occur for several reasons. First, different components of growth might not contain substantial complementary information about future returns. Second, the model may be misspecified due to non-linearities in the relations between characteristics and returns, and the misspecification reduced the forecasting power of the filtered expected returns. Third, the individual growth-related anomalies may be largely driven by individual influential returns whose impact is reduced in the two-step procedure. Fourth, the HCF procedure may bring additional noise to the estimation of expected returns. To identify the exact reason, more research is needed.

Consistent with the pattern in hedge returns for individual anomalies, the prediction power of filtered expectations is weaker for risk-adjusted returns and value-weighted portfolios. For example, $AFER(r)$ produces a spread of 3.02% per month for raw returns and equal-weighted portfolios, but only 1.31% for risk-adjusted returns and value portfolios. Nevertheless, the latter is still comparably high and statistically significant with the t-statistic of 6.24. Hence, the dispersion of expected stock returns produced by filtered expectations is not confined to small stocks and cannot be explained by the Fama-French three-factor model.

2.3.4 Estimation of Expected Stock Returns using Fama-MacBeth Regressions

As discussed above, the HCF estimates of expected returns have several theoretical advantages compared to fitted values from cross-sectional OLS regressions. To juxtapose them using actual data, we run Fama-MacBeth regressions in each month using the history of characteristics and returns available in that month and construct estimates for expected returns as fitted values. As before, we separately aggregate all characteristics and only those related to growth, and predict both raw and risk-adjusted returns. Using the obtained estimates for expected returns, we sort stocks into decile portfolios, compute equal-weighted returns on them, and examine the difference in returns on top and bottom portfolios. The results are presented in Table 2.5.

The columns of Table 2.5 correspond to different types of averaging of regression slopes over time. We consider four of them that use i) all history; ii) 5-year rolling windows, iii) 10-year rolling windows, and iv) all estimates for the same calendar month and the most recent month. Overall, the constructed fitted values do contain information about future returns (all t-statistics are large), and for expected returns based on only growth-related characteristics the results are similar to those of HCF. The latter is additional evidence that the growth-related characteristics do not contain complementary information about returns. However, the results for all characteristics are consistently weaker than those produced by HCF. In particular, for all characteristics and raw returns the decile hedge returns do not exceed 1.2% per month, whereas for HCF these returns can be as high as 3%. These results illustrate the benefits of HCF compared to the OLS-based aggregation.

Our results for the Fama-MacBeth fitted values are weaker than those in Lewellen (2013) and Green, Hand, and Zhang (2014), who also estimate expected stock returns using the Fama-MacBeth regression but find a wider dispersion of realized returns. The discrepancy is likely to be explained by the use of different sets of characteristics as well as the way of their construction. For example, in contrast to Lewellen (2013), we include the analysts' forecasts dispersion, which reduces the sample size in the regression approach and affects the quality of the estimates for expected returns. When this characteristic is excluded, hedge returns become close to 1.5% per month. We also do not impute missing values of the characteristics, as

Green, Hand, and Zhang (2014) do.

2.3.5 Robustness Tests

Our baseline analysis shows that HCF does a good job aggregating information from various firm characteristics. In this Subsection we explore whether this conclusion is sensitive to alternative specifications of the HCF procedure.

In the main analysis it is assumed that twelve lags of each firm characteristic are used as signals, i.e., $L = 12$. Panel A of Table 2.6 shows the difference in returns on top and bottom decile portfolios for alternative choices $L = 2$, $L = 6$, and $L = 24$. To save space, we report only the results for raw returns and equal-weighted portfolios.

Overall, Panel A of Table 2.6 demonstrates that the choice of L only weakly affects the size of hedge returns and its statistical significance. In particular, the dispersion of returns produced by $AFER$ slightly decreases with L, whereas the returns on $GFER$ are remarkably stable. The former effect is likely to be explained by the increase in the number of weak signals about expected returns when distant lags of characteristics are added to the model. As a result, the dispersion of characteristic loadings $\Lambda_{t,\,t}$ shrinks, and this makes the estimates of $\hat{\mu}_{it}$ obtained at Step 2 of the HCF procedure less precise. In contrast, the growth-related characteristics are more stable over time and preserve their informativeness about expected returns on longer horizons.

Another choice that we make while constructing $AFER$ and $GFER$ is how to average over time the slopes λ^a obtained at the first step. In the main analysis, we use the estimates from the same calendar month and the most recent month to exploit the seasonality of considered anomalies. Panel B of Table 2.6 shows hedge returns for alternative specifications in which we average λ^a obtained i) in all past months, ii) in the past 5 years, and iii) in the past 10 years. For $GFER$, the results are surprisingly consistent across the specifications and again indicate that the growth-related characteristics have a common returns-related component but do not contain complementary information. In contrast, the results for $AFER$ are weaker for alternative specifications, although the hedge returns are still relatively high (higher than 1.5% per month) and exceed those produced by fitted values of Fama-MacBeth regressions and reported in Table 2.5. This observation suggests that the commonality in anomalies inherits seasonal variation from the factor risk premia and the averaging of slopes from the same calendar month takes this into account.

The next modification of the estimation procedure that we consider pertains to the specification of cross-sectional regressions that we run at Step 1. In the baseline case, we use individual stocks. However, extreme realizations of characteristics or returns may affect the estimated slopes λ_t^a and, as a result, decrease the precision of $\hat{\mu}_t$ obtained at Step 2. One of the possible remedies is to group stocks into P portfolios and then run a regression of average portfolio returns on average values of characteristics in the portfolios.[1] We implement this approach as a second robustness test. We consider the cases $P = 20$, $P = 50$, $P = 100$, and $P = 200$. In order to ensure that each portfolio contains at least several stocks, we consider a sample that

[1]The idea to run cross-sectional regressions on portfolios goes back to Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973), where portfolios are formed to mitigate the errors-in-variables problem in the estimated betas.

starts in January 1975. The results are presented in Panel C of Table 2.6. Again, only the spread in equal-weighted raw returns on decile portfolios is reported.

The obtained results show that the regressions on portfolios at Step 1 produce almost the same decile hedge returns and their t-statistics as the regressions on individual stocks. For example, the spread on $AFER(r)$ with $P = 20$ is 2.97%, which is almost identical to 3.02% reported in Table 2.4. Thus, we can conclude that either the effects of outliers are unimportant or the gain produced by the robustness of the cross-sectional regressions to outliers is offset by the loss in efficiency produced by the decrease in the dispersion of characteristics that results from portfolio formation (Ang, Liu, and Schwarz, 2008).

The theoretical literature suggests that one of the reasons why both betas and characteristics appear to be related to stock returns is a nonlinear relation between them. To take into account this possibility, we consider a specification of the model with $L = 1$ in which observables contain characteristics and all possible quadratic terms formed from them. Thus, instead of 13 and 5 observables there are 104 and 20 observables for $AFER$ and $GFER$, respectively. The hedge returns on decile equal-weighted portfolios and their t-statistics obtained in this specification are presented in Panel D of Table 2.6. Our results show that the presence of nonlinearities does not change the ability of $AFER$ and $GFER$ to capture expected returns: both hedge returns and their t-statistics are very close to their counterparts from the baseline specification. Thus, the higher order terms neither help nor hurt our analysis.

So far in the analysis, all characteristics were given equal weight. It may be interesting to explore whether putting more weight on characteristics that better predict stock returns may increase the precision of $AFER$ estimates and the spread in $AFER$-sorted long short portfolio returns. Table 2.7 presents the results of several tests aimed at over-weighting higher 'quality' characteristics. For simplicity, each characteristic a is multiplied by the sign of its average λ^a, so that for all characteristics average λ^as are positive. As in the previous table, this table shows the differences in monthly returns on top and bottom decile portfolios formed by the filtered expected returns. In Panel A, each month the characteristics with the lowest first stage estimates of λ^as are excluded from the second stage. For example, excluding one characteristic leads to a drop in average equal-weighted returns to 2.7 % per month. There appears to be a negative monotonic relation between the number of excluded characteristics and average returns. This pattern implies that it is important to use all characteristics for the construction of filtered expected returns. This finding may be specific to the set of chosen prominent anomalies, which were previously established as strong predictors of stock returns. The weak predictability in a particular month may come from the estimation error in the first stage, but excluded λ^as still contain useful information for the second stage. Thus, leaving out these λ^as leads to a loss of power in estimating $AFER$ and lower spread in the decile portfolio returns.

In Panel B, in the first two columns λ^as are weighted in the second stage by the inverse of their time series standard deviations. In the third and fourth columns, weights are inversely proportional to the time series averages of the cross sectional errors from the first stage. Index 1 corresponds to using the whole previous history for computing weights, and index 2 corresponds to using only the twelve previous months. Similarly to Panel B, the results are weaker compared with equal weighting all anomalies. The difference may be attributed to the weak small sample properties of weighted least squares as only fourteen characteristics are used.

2.3.6 Filtered Expected Returns in Subsamples

Lastly, we explore the dispersion of expected returns produced by $AFER$ and $GFER$ within subsamples based on time period, firm capitalization, and idiosyncratic volatility of stock returns. Each of these subsamples is motivated by recent literature. In the case of firm capitalization, Fama and French (2008) highlight the potential for microcaps to dominate any regression and recommend testing anomalies with separate regressions for microcaps, small stocks, and big stocks. Pontiff (1996, 2006) argue that idiosyncratic volatility can be thought of as a proxy for arbitrage costs that dissuade rational arbitrageurs from exploiting mispricing, and that anomalies therefore are more likely to exist among stocks with high idiosyncratic volatility. Finally, the consideration of anomalies in different time periods is motivated by their likely tendency to become weaker or even disappear after their academic discovery. A number of recent papers look at these issues, and the general conclusion is that some anomalies do, indeed, tend to be more pronounced on small stocks, on stocks with high idiosyncratic volatility, and in earlier time periods.[1]

[1] Fama and French (2008) find that the size anomaly, the value anomaly, the profitability anomaly, and the asset growth anomaly are mainly produced by small stocks whereas the net stock issues anomaly, the accruals anomaly, and the momentum anomaly are pervasive across size groups. The idiosyncratic volatility has been found to affect the strength of book-to-market (Ali, Hwang, and Trombley, 2003), accruals (Mashruwala, Rajgopal, and Shevlin, 2006), and asset growth (Lipson, Mortal, and Schill, 2012). A decrease in returns on various anomalies in the recent period is reported in Horowitz, Loughran, and Savin (2000), Schwert (2003), Green, Hand, and Soliman

Following the literature, we measure the idiosyncratic volatility as the standard deviation of the error term in the time series regression of daily returns on the Fama-French three factors. We split all stocks into three groups based on idiosyncratic volatility (low, medium, high). As breakpoints, we use the 30th percentile and 70th percentile, i.e., the stocks whose idiosyncratic volatility are below the 30th percentile are in a low group, etc. Since idiosyncratic volatility is measured on a monthly basis, we rebalance the volatility groups each month. To form size portfolios, we follow Fama and French (2008) and classify stocks as microcaps, small stocks, and big stocks. The breakpoints are the 20th and 50th percentiles of end-of-June market capitalization for NYSE stocks.

Table 2.8 shows the difference in returns on top and bottom decile portfolios formed by each constructed estimate of expected returns within various subsamples. To save space, we report the results only for raw returns and equal-weighted portfolios. The three panels correspond to subsamples based on sample period, size, and idiosyncratic volatility, respectively.

Each of the three panels yields interesting results. First, all filtered expected returns preserve their statistical significance in all periods and the size of hedge returns even slightly increases after 1995. Although the t-statistics are lower in the late period, the stability of the forecasting power demonstrated by filtered returns across time periods indicates that they represent an actual phenomenon and not a statistical fluke.

(2011), McLean and Pontiff (2013), Chordia, Subrahmanyam, and Tong (2013), among others.

Second, the breakdown along market capitalization reveals that the filtered expected returns have more power to predict actual returns for microcap stocks than for large stocks. For example, $AFER(r)$ and $AFER(a)$ generate 3.01% and 2.74% per month for microcaps, but their hedge returns drop to 0.81% and 0.63% for large stocks. A similar pattern is observed for t-statistics. However, all filtered expectations have a detectable forecasting power for large stocks, so their relation to actual returns is not confined to tiny and illiquid stocks.

Finally, Table 2.8 presents the hedge returns across the idiosyncratic volatility portfolios and reveals an anticipated pattern: in general, the dispersion of returns appears to be wider among high volatility stocks than among low volatility ones. In particular, for $AFER(r)$ the difference in returns on top and bottom decile portfolios reaches 3.39% for stocks with high idiosyncratic volatility, but is only 1.22% for low volatility stocks. Again, the t-statistics show a similar pattern. However, the forecasting power of all filtered expectations is detected for stocks with low idiosyncratic volatility, so it cannot be explained by limits to arbitrage.

2.3.7 Application: Testing Asset Pricing Models

The constructed filtered expected returns can be used for testing asset pricing theories. Because they produce a high dispersion of expected returns, quintile or decile portfolios based on them are likely to be good test assets whose returns are hard to explain. Thus, $AFER$-based portfolios may help to increase the power of asset pricing tests. To demonstrate that this is indeed the case, we test the CAPM, the Fama-French three-factor model (Fama and French, 1993), and the Carhart model

(Carhart, 1997) by using the Gibbons, Ross, and Shanken (1989) F-statistic (GRS test) computed for the decile value-weighted $AFER$ portfolios.[1] The results are presented in Table 2.9.

Table 2.9 reports alphas from the time series regressions of excess portfolio returns on the excess market returns (CAPM), on the excess market returns, HML, and SMB (FF3), and on the excess market returns, HML, SMB, and the momentum factor (Carhart). Also the table shows the GRS statistics and their p-values. Overall, the patterns in alphas for all models are similar to those in expected portfolio returns, so the factor betas do not help to explain the cross section of returns. This conclusion is supported by the GRS statistics whose p-values show that all three models are unambiguously rejected. More importantly, the values of the GRS statistics are much higher than those reported in the literature when the test assets are portfolios formed on the book-to-market ratio, size (e.g., Fama and French, 1996; Fama and French, 2012), earnings-to-price ratio, cash flow-to-price ratio, sales rank (e.g., Fama and French, 1996), dispersion of analysts' forecasts (Diether, Malloy, and Scherbina, 2002) or portfolios of mutually correlated stocks (Ahn, Conrad, and Dittmar, 2009).[2] Thus, the $AFER$ portfolios help to increase the power of the GRS test and we can conclude that the considered models are rejected much more reliably than when more standard test assets are used.

[1] The null hypothesis of the GRS test is that all alphas in the time series regressions of excess returns on the factors are jointly equal to zero.

[2] Typically, the GRS statistics do not exceed 4.

2.4 Appendix

Proof of Proposition 1. The cross-sectional standardization of characteristics implies that $\overline{Var}(X_{it}^a) = 1$ for all t, $t = 1, \ldots, T$ and a, $a = 1, \ldots, A$. Hence, the slope in the cross-sectional regression of R_{it} on X_{it-1}^a (Step 1) is

$$\lambda_t^a = \frac{\overline{Cov}(R_{it}, X_{it-1}^a)}{\overline{Var}(X_{it-1}^a)} = \overline{Cov}(R_{it}, X_{it-1}^a).$$

Taking the first limit $N \to \infty$, we have

$$\overline{Cov}(R_{it}, X_{it-1}^a) = \overline{Cov}(\mu_{it-1} + \varepsilon_{it}, \delta_{t-1}^a(\mu_{it-1} - \bar{\mu}_{t-1}) + u_{it-1}^a) \xrightarrow{p} \delta_{t-1}^a V_{t-1},$$

where we use Assumptions 1 and 3 along with the independence of ε_{it} from all variables available at time $t-1$.

At Step 2, the characteristics X_{it}^a are regressed on λ_t^a in the characteristics space for each stock and the obtained slopes are

$$\hat{\mu}_{it} = \frac{\widetilde{Cov}(X_{it}^a, \lambda_t^a)}{\widetilde{Var}(\lambda_t^a)}.$$

Using the Slutsky's theorem,

$$\begin{aligned}\widetilde{Cov}(X_{it}^a, \lambda_t^a) = \widetilde{Cov}(\delta_t^a(\mu_{it} - \bar{\mu}_t) + u_{it}^a, \lambda_t^a) &\xrightarrow[N\to\infty]{p} \widetilde{Cov}(\delta_t^a(\mu_{it} - \mu_t) + u_{it}^a, \delta_{t-1}^a V_{t-1}) \\ &= (\widetilde{Cov}(\delta_{t-1}^a, \delta_t^a)(\mu_{it} - \mu_t) + \widetilde{Cov}(u_{it}^a, \delta_{t-1}^a))V_{t-1},\end{aligned}$$

$$\widetilde{Var}(\lambda_t^a) \xrightarrow[N\to\infty]{p} \widetilde{Var}(\delta_{t-1}^a V_{t-1}) = \widetilde{Var}(\delta_{t-1}^a)V_{t-1}^2.$$

Taking the second limit $A \to \infty$ and applying the rules for probability limits we get

$$\begin{aligned}\operatorname*{plim}_{A\to\infty}\operatorname*{plim}_{N\to\infty} \hat{\mu}_{it} &= \operatorname*{plim}_{A\to\infty}\operatorname*{plim}_{N\to\infty} \frac{\widetilde{Cov}(X_{it}^a, \lambda_t^a)}{\widetilde{Var}(\lambda_t^a)} \\ &= \operatorname*{plim}_{A\to\infty} \frac{\widetilde{Cov}(\delta_{t-1}^a, \delta_t^a)(\mu_{it} - \mu_t) + \widetilde{Cov}(u_{it}^a, \delta_{t-1}^a)}{\widetilde{Var}(\delta_{t-1}^a)V_{t-1}} = \frac{\Lambda_{t-1,t}}{\Lambda_{t-1,t-1}V_{t-1}}(\mu_{it} - \mu_t).\end{aligned}$$

The computation of the last limit uses Assumptions 2 and 4. After denoting the factor $\Lambda_{t-1,t}/(\Lambda_{t-1,t-1}V_{t-1})$ as F_t, we get the statement of the proposition. Q.E.D.

Proof of Proposition 2. The slope of the first step regression is

$$\lambda_t^a = \overline{Cov}(R_{it}, X_{it-1}^a) = \frac{1}{N} X_{t-1}^a{}' M_N R_t,$$

or in a matrix form,

$$\lambda_t = \frac{1}{N} X_{t-1}' M_N R_t.$$

The slope of the second step regression is

$$\hat{\mu}_{it} = (\lambda_t' M_A \lambda_t)^{-1} \lambda_t' M_A X_{it}'.$$

Putting it in a matrix form and plugging in λ_t, we get the result:

$$\hat{\mu}_t = (\lambda_t' M_A \lambda_t)^{-1} X_t M_A \lambda_t = N(R_t' M_N X_{t-1} M_A X_{t-1}' M_N R_t)^{-1} X_t M_A X_{t-1}' M_N R_t.$$

This completes the proof. Q.E.D.

Table 2.1: Simulations: HCF and OLS

This table shows average cross-sectional correlations between the estimated expected returns $\hat{\mu}_i$ and the actual expected returns μ_i. The estimates are obtained using HCF and OLS. The errors ε_i are i.i.d. or have a one-factor structure. N is the number of stocks, A is the number of available characteristics, σ_δ is the dispersion of the characteristic loadings, and θ is the signal-to-noise ratio of the characteristics. The parameter θ_f measures the contribution of the factor in the volatility of returns. In the simulations with a factor in unexpected returns we set $\sigma_\delta = 1$ and $\theta = 0.5$. All other model parameters are specified in Subsection 2.2.3.

N	A	$\theta = 0.5$						$\sigma_\delta = 1$						one factor in unexpected returns ε_i					
		HCF			OLS			HCF			OLS			HCF			OLS		
		$\sigma_\delta = 0.5$	$\sigma_\delta = 1$	$\sigma_\delta = 2$	$\sigma_\delta = 0.5$	$\sigma_\delta = 1$	$\sigma_\delta = 2$	$\theta = 0.2$	$\theta = 0.5$	$\theta = 1$	$\theta = 0.2$	$\theta = 0.5$	$\theta = 1$	$\theta_f = 0.2$	$\theta_f = 0.5$	$\theta_f = 1$	$\theta_f = 0.2$	$\theta_f = 0.5$	$\theta_f = 1$
100	10	0.04	0.20	0.27	0.18	0.17	0.17	0.05	0.20	0.35	0.07	0.17	0.20	0.19	0.21	0.25	0.16	0.18	0.22
	50	0.11	0.41	0.47	0.07	0.08	0.08	0.10	0.41	0.52	0.05	0.08	0.08	0.35	0.41	0.51	0.07	0.08	0.11
	100	0.15	0.45	0.47	—	—	—	0.15	0.45	0.51	—	—	—	0.42	0.48	0.59	—	—	—
	500	0.27	0.51	0.56	—	—	—	0.29	0.51	0.60	—	—	—	0.54	0.60	0.69	—	—	—
500	10	0.07	0.39	0.54	0.35	0.36	0.36	0.09	0.39	0.59	0.14	0.36	0.45	0.40	0.43	0.48	0.36	0.39	0.47
	50	0.20	0.68	0.79	0.21	0.22	0.22	0.23	0.68	0.87	0.16	0.22	0.22	0.69	0.73	0.80	0.22	0.24	0.29
	100	0.29	0.78	0.85	0.15	0.15	0.15	0.32	0.78	0.89	0.13	0.15	0.15	0.78	0.82	0.88	0.15	0.17	0.21
	500	0.55	0.88	0.90	—	—	—	0.57	0.88	0.92	—	—	—	0.91	0.92	0.97	—	—	—
1000	10	0.11	0.48	0.66	0.47	0.48	0.48	0.13	0.48	0.71	0.21	0.48	0.56	0.48	0.50	0.55	0.47	0.51	0.59
	50	0.28	0.81	0.89	0.30	0.30	0.30	0.31	0.81	0.95	0.22	0.30	0.32	0.81	0.84	0.88	0.31	0.34	0.42
	100	0.40	0.88	0.93	0.22	0.22	0.23	0.42	0.88	0.97	0.18	0.22	0.23	0.89	0.91	0.93	0.23	0.25	0.31
	500	0.69	0.97	0.98	0.08	0.08	0.08	0.70	0.97	0.98	0.08	0.08	0.08	0.97	0.97	0.99	0.08	0.09	0.11
3000	10	0.13	0.58	0.75	0.65	0.65	0.64	0.20	0.58	0.76	0.31	0.65	0.77	0.58	0.58	0.62	0.65	0.68	0.73
	50	0.39	0.89	0.94	0.50	0.49	0.49	0.46	0.89	0.98	0.37	0.49	0.52	0.90	0.90	0.91	0.50	0.53	0.62
	100	0.53	0.94	0.97	0.38	0.38	0.38	0.59	0.94	0.99	0.32	0.38	0.40	0.95	0.95	0.95	0.39	0.42	0.50
	500	0.85	0.99	0.99	0.18	0.18	0.17	0.86	0.99	1.00	0.17	0.18	0.18	0.99	0.99	0.99	0.18	0.19	0.24

Table 2.2: Simulations: HCF and Factor Analysis

This table shows average cross-sectional correlations between the estimated expected returns $\hat{\mu}_i$ and the actual expected returns μ_i. The estimates are obtained using HCF and factor analysis. The errors u_i^a have a one-factor structure. N is the number of stocks, A is the number of available characteristics, and the parameter θ_f measures the contribution of the factor in the dispersion of returns-unrelated components of the characteristics. In all simulations we set $\sigma_\delta = 1$ and $\sigma(u_{it}^a) = 0.05$. All other model parameters are specified in Subsection 2.2.3.

N	A	HCF			factor analysis		
		$\theta_f = 0.2$	$\theta_f = 0.5$	$\theta_f = 1$	$\theta_f = 0.2$	$\theta_f = 0.5$	$\theta_f = 1$
100	10	0.04	0.06	0.10	0.39	0.30	0.21
	50	0.13	0.15	0.21	0.67	0.36	0.23
	100	0.15	0.18	0.28	—	—	—
500	10	0.12	0.13	0.19	0.47	0.32	0.21
	50	0.26	0.30	0.40	0.68	0.36	0.23
	100	0.35	0.40	0.52	0.72	0.36	0.23
1000	10	0.15	0.19	0.27	0.48	0.32	0.22
	50	0.34	0.39	0.53	0.69	0.36	0.23
	100	0.46	0.52	0.65	0.73	0.37	0.23
3000	10	0.24	0.28	0.39	0.49	0.31	0.22
	50	0.50	0.56	0.70	0.68	0.36	0.23
	100	0.64	0.69	0.81	0.73	0.37	0.23

Table 2.3: Individual Anomalies

This table reports statistical properties of hedge returns defined as a difference in monthly returns on top and bottom decile portfolios formed on the basis of thirteen anomalous characteristics. The anomaly variables are denoted as follows: B/M is book-to-market, S is size, Mom is momentum, $IdVol$ is idiosyncratic volatility, AG is total asset growth, CI is abnormal capital investments, ROA is return on assets, Acc is accruals, NOA is net operating assets, NS is net stock issues, ι is composite stock issuance, O is Ohlson's (1980) O-score, D is analysts' forecasts dispersion. A detailed description of characteristics is given in the Appendix. The sample covers the period from January 1965 to December 2012 for all characteristics, except the return on assets, O-score, and analysts' forecasts dispersion, for which the sample periods start in January 1975, January 1976, and January 1983, respectively. Means and standard deviations of returns are multiplied by 100.

Panel A: Raw Returns, Equal-Weighted Portfolios

	B/M	S	Mom	$IdVol$	AG	CI	ROA	Acc	NOA	NS	ι	O	D
Means	1.31	-1.88	1.64	-0.86	-1.13	-0.34	1.22	-0.57	-1.02	-0.41	-0.67	-0.71	-0.70
Stds	4.40	7.58	5.76	6.36	3.70	2.24	6.42	2.93	4.05	2.44	4.86	5.02	4.38
t-stats	7.16	-5.94	6.82	-3.24	-7.30	-3.68	4.07	-4.67	-6.02	-4.03	-3.13	-3.00	-3.31

Panel B: Risk-Adjusted Returns, Equal-Weighted Portfolios

	B/M	S	Mom	$IdVol$	AG	CI	ROA	Acc	NOA	NS	ι	O	D
Means	0.76	-1.69	1.14	-0.95	-0.82	-0.27	1.21	-0.41	-0.84	-0.81	-0.70	-0.96	-0.85
Stds	2.91	6.63	4.70	2.77	3.31	2.15	5.30	2.73	3.29	2.74	3.52	4.56	3.32
t-stats	6.26	-6.11	5.79	-8.26	-5.94	-3.04	4.86	-3.63	-6.16	-7.12	-4.53	-4.42	-5.32

Panel C: Raw Returns, Value-Weighted Portfolios

	B/M	S	Mom	$IdVol$	AG	CI	ROA	Acc	NOA	NS	ι	O	D
Means	0.65	-1.31	1.46	-0.85	-0.34	-0.29	0.88	-0.41	-0.41	-0.42	-0.61	-0.28	-0.34
Stds	5.15	7.24	7.17	7.06	3.88	3.53	6.05	4.50	4.25	3.01	4.25	4.93	5.62
t-stats	3.04	-4.33	4.87	-2.87	-2.08	-1.95	3.10	-2.19	-2.29	-3.38	-3.27	-1.20	-1.24

Panel D: Risk-Adjusted Returns, Value-Weighted Portfolios

	B/M	S	Mom	$IdVol$	AG	CI	ROA	Acc	NOA	NS	ι	O	D
Means	-0.17	-0.98	0.84	-1.03	0.11	-0.06	1.02	-0.29	-0.47	-0.64	-0.39	-0.70	-0.70
Stds	3.55	5.82	5.88	3.72	3.06	3.41	4.44	3.81	3.68	2.67	2.98	3.50	3.91
t-stats	-1.15	-4.06	3.44	-6.68	0.87	-0.41	4.93	-1.85	-3.05	-5.78	-2.96	-4.23	-3.71

Table 2.4: Decile Portfolio Returns on $AFER$ and $GFER$ Portfolios

This table shows averages of monthly equal-weighted and value-weighted stock returns and returns adjusted for risk using the Fama-French three-factor model for decile portfolios formed by sorting firms on the filtered expectations. The last two columns report the difference between returns on portfolio 10 and portfolio 1 and its t-statistic. $AFER$ and $GFER$ stand for aggregate filtered expected returns and growth-based filtered expected returns, respectively. The index in parentheses indicates whether the filtered expectations are formed using raw returns (r) or risk-adjusted returns (a). The sample is from January 1970 to December 2012. All returns are reported in percentage points.

Panel A: Raw Returns, Equal-Weighted Portfolios												
	1	2	3	4	5	6	7	8	9	10	(10-1)	t-stat
$AFER(r)$	-0.58	0.23	0.44	0.90	1.07	1.34	1.65	1.91	2.13	2.44	3.02	10.98
$AFER(a)$	-0.21	0.41	0.75	1.05	1.35	1.46	1.65	1.88	2.03	2.33	2.55	9.25
$GFER(r)$	0.52	0.89	0.92	1.24	1.26	1.32	1.48	1.62	1.75	1.58	1.06	8.48
$GFER(a)$	0.69	0.93	1.12	1.37	1.33	1.37	1.41	1.61	1.57	1.47	0.78	6.53
Panel B: Risk-Adjusted Returns, Equal-Weighted Portfolios												
	1	2	3	4	5	6	7	8	9	10	(10-1)	t-stat
$AFER(r)$	-1.18	-0.49	-0.49	-0.14	0.02	0.20	0.44	0.68	0.89	1.23	2.41	11.24
$AFER(a)$	-1.17	-0.66	-0.39	-0.13	0.16	0.24	0.42	0.67	0.84	1.21	2.38	11.12
$GFER(r)$	-0.52	-0.19	-0.14	0.16	0.15	0.18	0.31	0.38	0.54	0.35	0.87	7.76
$GFER(a)$	-0.46	-0.21	-0.04	0.22	0.19	0.21	0.23	0.42	0.38	0.29	0.75	7.11
Panel C: Raw Returns, Value-Weighted Portfolios												
	1	2	3	4	5	6	7	8	9	10	(10-1)	t-stat
$AFER(r)$	-0.54	0.15	0.46	0.72	0.98	1.11	1.26	1.50	1.54	1.46	2.00	6.98
$AFER(a)$	-0.22	0.34	0.71	0.96	1.14	1.15	1.37	1.35	1.47	1.49	1.71	6.04
$GFER(r)$	0.57	0.85	0.83	0.94	1.05	0.98	1.03	1.05	1.06	1.07	0.50	3.21
$GFER(a)$	0.60	0.87	0.93	0.98	1.06	0.94	1.06	1.08	0.91	1.06	0.45	2.98
Panel D: Risk-Adjusted Returns, Value-Weighted Portfolios												
	1	2	3	4	5	6	7	8	9	10	(10-1)	t-stat
$AFER(r)$	-1.05	-0.54	-0.46	-0.31	-0.10	0.05	0.05	0.28	0.36	0.26	1.31	6.24
$AFER(a)$	-1.08	-0.71	-0.46	-0.19	-0.03	-0.08	0.10	0.12	0.31	0.37	1.46	7.86
$GFER(r)$	-0.19	-0.09	0.02	0.06	0.08	0.06	0.04	0.00	-0.02	-0.06	0.13	0.96
$GFER(a)$	-0.33	-0.11	0.01	0.02	0.12	0.02	0.09	0.11	-0.13	0.04	0.36	2.64

Table 2.5: Aggregation using Fama-MacBeth Regressions

This table shows the differences in monthly returns on top and bottom equal-weighted decile portfolios formed by fitted values from Fama-MacBeth regressions of returns on characteristics. The rows of the table correspond to different sets of characteristics (all or growth-related only) and types of returns used for constructing the fitted values (raw or risk-adjusted). The columns indicate the way of how the slopes are averaged (all history, 5-year window, 10-year window, all history with the same month). All returns are reported in percentage points. The sample is January 1978 – December 2012 for fitted values based on all characteristics and January 1971 – December 2012 for fitted values based on growth-related characteristics.

	Hedge returns				t-stats			
	all	5 years	10 years	same month	all	5 years	10 years	same month
All, raw returns	1.18	1.04	1.10	0.90	5.20	3.97	4.54	3.84
All, adjusted returns	1.18	1.09	1.15	0.54	5.65	4.84	5.76	2.45
Growth, raw returns	0.96	0.87	0.95	0.64	7.21	5.71	6.41	3.67
Growth, adjusted returns	1.03	0.97	1.04	0.52	7.18	6.82	7.59	3.15

Table 2.6: Alternative Specifications

This table shows the differences in monthly returns on top and bottom equal-weighted decile portfolios formed by the filtered expectations constructed in several alternative ways. In Panel A, columns correspond to different numbers of lags of each characteristic used in the aggregation. In Panel B, the estimates are constructed using alternative averaging of λ^a over time. In Panel C, the expectations are constructed by running cross-sectional regressions on the specified number of portfolios rather than on individual stocks. In Panel D, the observations include characteristics as well as all possible quadratic terms constructed from them. $AFER$ and $GFER$ stand for aggregate filtered expected returns and growth-based filtered expected returns, respectively. The index in parentheses indicates whether the filtered expectations are formed using raw returns (r) or risk-adjusted returns (a). All returns are reported in percentage points. The sample is January 1970 – December 2012 in Panels A, B, and D and January 1975 – December 2012 in Panel C.

Panel A: Alternative number of lags

	Hedge returns				t-stats			
	$L=2$	$L=6$	$L=12$	$L=24$	$L=2$	$L=6$	$L=12$	$L=24$
$AFER(r)$	3.27	3.11	3.02	3.03	10.69	10.97	10.98	11.01
$AFER(a)$	2.99	2.72	2.55	2.44	10.41	9.74	9.25	8.84
$GFER(r)$	1.10	1.12	1.06	1.06	7.30	7.79	8.48	8.50
$GFER(a)$	0.73	0.81	0.78	0.67	5.05	5.81	6.53	5.71

Panel B: Alternative time series averaging of λ^a

	Hedge returns				t-stats			
	all	5 years	10 years	same month	all	5 years	10 years	same month
$AFER(r)$	1.90	1.55	1.54	3.02	8.99	6.40	7.52	10.97
$AFER(a)$	1.88	1.69	1.72	2.55	9.65	7.81	8.89	9.24
$GFER(r)$	0.99	1.07	1.01	1.06	7.61	7.89	7.88	8.47
$GFER(a)$	0.81	0.87	0.83	0.78	7.38	6.40	6.37	6.52

Panel C: Cross-sectional regressions on portfolios

	Hedge returns				t-stats			
	$P=20$	$P=50$	$P=100$	$P=200$	$P=20$	$P=50$	$P=100$	$P=200$
$AFER(r)$	2.97	2.95	3.01	2.91	10.81	10.21	10.44	9.96
$AFER(a)$	2.54	2.76	2.74	2.84	9.02	9.83	9.63	9.16
$GFER(r)$	1.12	1.12	1.15	1.13	8.16	8.10	8.22	7.98
$GFER(a)$	0.76	0.87	0.87	0.84	5.31	6.00	6.08	5.98

Panel D: Nonlinear specification

	Hedge returns	t-stats
$AFER(r)$	3.31	12.60
$AFER(a)$	2.96	11.62
$GFER(r)$	1.14	7.71
$GFER(a)$	0.91	6.41

Table 2.7: Quality Test

This table shows the differences in monthly returns on top and bottom equal-weighted (EW) and value-weighted (VW) decile portfolios formed by the aggregate filtered expected returns $AFER$, constructed by weighting characteristics in several ways. In this table, each characteristic a is multiplied by the sign of its average λ^a, so that for all characteristics average λ^as are positive. In Panel A, each month the characteristics with the lowest first stage estimates of λ^as are excluded from the second stage. Columns correspond to different numbers of characteristics excluded. In Panel B, in the first two columns λ^as are weighted in the second stage by the inverse of their time series standard deviations. In the third and fourth columns, weights are inversely proportional to the time series averages of the cross sectional errors from the first stage. Index 1 corresponds to using the whole previous history for computing weights, and index 2 corresponds to using only the twelve previous months. The index in parentheses indicates whether the $AFER$ portfolio returns are raw (r) or risk-adjusted (a). $AFER$ construction is based on raw returns. All returns are reported in percentage points. The sample is January 1970 – December 2012.

Panel A: Excluding Characteristics

	Hedge returns						t-stats					
	1	2	3	4	5	6	1	2	3	4	5	6
EW(r)	2.70	2.50	2.43	2.34	2.25	2.21	9.48	8.95	8.82	8.83	8.72	8.54
EW(a)	2.67	2.47	2.40	2.33	2.24	2.17	9.57	9.05	8.93	9.06	8.88	8.63
VW(r)	1.90	1.74	1.44	1.32	1.03	1.06	6.52	6.12	5.02	4.63	3.77	4.13
VW(a)	2.03	1.89	1.57	1.50	1.21	1.19	6.88	6.60	5.42	5.29	4.46	4.68

Panel B: Weighted Least Squares

	Hedge returns				t-stats			
	TS 1	TS 2	CS 1	CS 2	TS 1	TS 2	CS 1	CS 2
EW(r)	2.30	2.23	3.01	2.85	8.42	8.77	9.90	8.85
EW(a)	2.26	2.22	2.96	2.75	8.31	8.69	9.82	8.63
VW(r)	1.78	1.83	2.09	2.25	6.87	7.53	6.90	7.16
VW(a)	1.82	1.86	2.16	2.34	6.99	7.57	7.07	7.35

Table 2.8: Filtered Expected Returns in Subsamples

This table reports the differences in monthly equal-weighted raw returns on top and bottom decile portfolios and their t-statistics for the filtered expectations in subsamples. To denote subsamples we use the following notation: sample periods: (1) – full sample (January 1970 – December 2012), (2) – early sample (January 1970 – December 1995), (3) – late sample (January 1996 – December 2012); size portfolios: (1) – microcap stocks, (2) – small stocks; (3) – large stocks; idiosyncratic volatility portfolios: (1) – low volatility, (2) – medium volatility, (3) – high volatility. $AFER(r)$ and $AFER(a)$ are aggregate filtered expected returns, $GFER(r)$ and $GFER(a)$ are growth-based filtered expected returns. All returns are reported in percentage points.

	Sample periods					
	Hedge return			t-stats		
	(1)	(2)	(3)	(1)	(2)	(3)
$AFER(r)$	3.02	2.96	3.10	10.98	10.41	5.71
$AFER(a)$	2.55	2.29	2.93	9.25	7.53	5.67
$GFER(r)$	1.06	0.94	1.23	8.48	7.07	5.13
$GFER(a)$	0.78	0.66	0.96	6.53	5.47	4.04

	Size portfolios						Idiosyncratic volatility portfolios					
	Hedge return			t-stats			Hedge return			t-stats		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$AFER(r)$	3.01	1.50	0.81	12.25	5.76	3.57	1.22	2.29	3.39	3.72	11.59	11.67
$AFER(a)$	2.74	1.15	0.63	11.26	5.12	3.30	1.10	1.83	2.80	6.11	9.08	9.33
$GFER(r)$	1.17	0.57	0.44	8.20	3.47	3.32	0.48	0.77	1.28	4.32	6.79	6.15
$GFER(a)$	0.84	0.45	0.28	6.24	3.11	2.17	0.24	0.70	0.69	2.17	6.08	3.49

Table 2.9: GRS Test

This table shows the results of the GRS test applied to the CAPM, the Fama-French three-factor model (Fama and French, 1993), and the Carhart model (Carhart, 1997) when the $AFER$-based decile portfolios are used as test assets. The first ten columns contain portfolio alphas (in percentage points); the last two columns report the value of the GRS statistic and its p-value. The sample is from January 1970 to December 2012.

	1	2	3	4	5	6	7	8	9	10	GRS	p-value
CAPM	-1.63	-0.95	-0.61	-0.37	-0.08	0.07	0.23	0.49	0.57	0.52	8.50	0.0000
FF3	-1.56	-0.90	-0.60	-0.38	-0.11	0.01	0.13	0.41	0.52	0.53	8.12	0.0000
Carhart	-1.38	-0.73	-0.57	-0.34	-0.08	0.05	0.15	0.47	0.53	0.53	6.84	0.0000

Chapter 3

Monotonicity of Asset Pricing Anomalies (joint with Oleg Rytchkov)

3.1 Introduction

An asset pricing anomaly is a pattern in expected stock returns that cannot be explained by a particular asset pricing model. Many anomalies are associated with firm characteristics and typically thought of as a monotonic relation between a characteristic and future abnormal stock returns. To identify anomalies, researchers usually compare average returns on characteristic-based portfolios or run a linear cross-sectional regression of realized returns on firm characteristics. However, these methods are silent about how abnormal returns are generated. In particular, they cannot distinguish whether the anomaly pertains to the majority of stocks whose expected returns are monotonically related to the given firm characteristic or abnormal returns are produced by a small number of special stocks, and there is no detectable monotonic relation between characteristics and returns for all other stocks. Although these two patterns are not mutually exclusive, it is important to identify the role of influential observations to better understand the origin of anomalies. In particular, the existing theoretical explanations of anomalies typically justify the first pattern, i.e. predict a robust monotonic relation between characteristics and returns (e.g., Johnson, 2004; Li, Livdan, and Zhang, 2009; Avramov, Cederburg, and Hore, 2010). Testing this prediction is a natural way to test the theories themselves.

In this chapter, we systematically explore whether fourteen prominent asset pricing anomalies are driven by extreme observations. As a main tool, we use robust regressions, such as rank regression, least trimmed squares (LTS) regression, and iterated reweighted least squares (IRLS) regression incorporated in the Fama-MacBeth approach (Fama and MacBeth, 1973). Robust regressions are much less sensitive to outliers than the standard OLS regression, so any discrepancy in the results of linear and robust regressions should be attributed to the impact of influential observations on the linear regression.

The key idea of rank regression is to compare two stock rankings: one is produced by a firm characteristic and the other is associated with stock alphas. For an anomaly, these rankings must be similar, i.e., statistical tests should reject the null hypothesis of their independence. The main advantage of rank regression is that to some extent it combines the benefits of portfolio sorts and OLS regression. On the one hand, like linear regressions, rank regressions deal with individual stocks and, hence, use all available information quite efficiently. On the other hand, like portfolio sorts, rank regression is nonparametric and does not assume a specific functional form of the relation between characteristics and returns. As a result, it is much more robust than linear regression to influential observations and even functional misspecification.

Another robust technique that we use in our analysis is LTS regression (Rousseeuw and LeRoy, 1987). It trims a certain proportion of influential observations with the largest residuals and then fits the remaining observations using the minimization of a sum of squared residuals. If an anomaly exists for the majority of stocks, the results of LTS and OLS regressions must be similar. It should be emphasized that we do not consider the trimmed stocks outliers and do not claim that LTS regression provides a better description of the relation between characteristics and expected stock returns. We use LTS regression as a diagnostic tool that allows us to study the prevalence of anomalies across stocks and identify the impact of individual influential observations on the standard linear regression results.

The drawback of LTS regression is that it completely discards information contained in the trimmed stocks. This problem is mitigated in iterated reweighted least squares (IRLS) regression which we employ as an alternative to LTS regression (e.g., Holland and Welsch, 1977). Effectively, IRLS regression is a weighted least squares (WLS) regression in which weights are determined by a recursive procedure and depend on regression residuals. Thus, IRLS regression uses information more efficiently and, in addition, takes into account possible heteroskedasticity of regression errors.

We apply robust techniques to all stocks as well as stocks within quintile portfolios formed on the anomalous characteristic. As emphasized by Fama and French (2008), the cross-sectional dispersion of anomaly variables within extreme portfolios is much higher than within interior portfolios. As a result, expected returns do not vary much across stocks in the interior portfolios, and many anomalies are detected for extreme ranges of characteristics only. Our analysis of anomalies within quintile portfolios takes this pattern into account and allows us to study the impact of influential observations separately for stocks with high and low characteristics. Thus, the consideration of quintile portfolios effectively allows us to conduct a test for monotonicity of the given anomaly. Indeed, if the anomaly is monotonic, the regression slopes in extreme portfolios should have the same sign. If the relations between the characteristic and abnormal returns in any two portfolios appear to be statistically significant with *opposite* signs, the hypothesis of monotonicity should be rejected.

As a benchmark for computing abnormal returns, we choose the Fama-French three-factor model. Since the list of known anomalies is too long to be comprehensively examined in one study, we limit our analysis to fourteen of them which can be classified in several groups. The first group contains the three most researched anomalies: size, book-to-market, and momentum. The second group contains three corporate investment anomalies: total asset growth, investments-to-assets ratio, and abnormal capital investments. The third group contains two financing anomalies: net stock issues and composite stock issuance. The fourth group contains three accounting anomalies: accruals, net operating assets, and profitability. The fifth and last group contains three anomalies broadly related to uncertainty about the firm: idiosyncratic volatility, Ohlson's score measuring the bankruptcy likelihood, and dispersion in analysts' forecasts.

This chapter contains several empirical results. First, we document that for several anomalies, cross-sectional OLS regression and robust regressions of returns on anomalous characteristics deliver opposite results: all OLS slopes are negative and statistically significant, but the slopes in robust regressions can be positive and even statistically significant. In particular, we observe it in rank regressions of returns on size and abnormal capital investments. For other anomalies such as total asset growth, investments-to-assets ratio, accruals, and net operating assets anomaly, rank regression slopes are statistically indistinguishable from zero.

Second, we run robust regressions within quintile portfolios formed on anomalous characteristics. We find that all considered anomalies except size tend to be strong and robust within the portfolio with presumably low returns (portfolio 5), and this is consistent with the idea that high transaction costs of short selling prevent arbitrage and make anomalies more pronounced (e.g., Nagel, 2005). However, the results are surprising in portfolio 1: the slopes of robust regressions for many anomalies appear to be *positive* and statistically significant. In particular, we document it for momentum, idiosyncratic volatility, asset growth, abnormal capital investments, investments-to-assets ratio, accruals, net operating assets, and composite stock issuance. For all these anomalies except momentum and accruals the positive relation between characteristics and returns is detected by all robust regressions that we use. Note that the linear regression produces insignificant slopes in portfolio 1 for almost all anomalies. Thus, comparing the results of linear and robust regressions we can conclude that for stocks with presumably high returns, the linear regression may be unduly influenced by extreme individual stocks and may fail to capture the prevailing relation between characteristics and returns. When the impact of few influential stocks is mitigated, the relation between characteristics and returns may appear to have an opposite sign.

Influential observations may affect not only slopes in regressions, but also portfolio returns themselves. As an additional exercise, we recompute average returns on extreme quintile portfolios formed on anomalous characteristics excluding only one or two stocks in each period: we drop the stocks with the highest returns in the given period in portfolio 1 or the stocks with the lowest returns in portfolio 5. We demonstrate that the exclusion of only one stock from portfolio 1 substantially reduces the difference in returns between extreme portfolios and even makes it statistically insignificant for momentum, idiosyncratic volatility, abnormal capital investments, and accruals. When the two stocks are excluded, only five anomalies (size, profitability, net stock issues, distress, and analysts' forecasts dispersion) remain statistically significant. Consistent with our regression results, we also find that anomalies are more robust in the portfolio 5: only four anomalies (momentum, idiosyncratic volatility, abnormal capital investments, and accruals) disappear when two stocks with the lowest returns are excluded. This analysis illustrates the importance of individual stocks in producing anomalous returns.

The results of robust regressions within quintile portfolios can be used for testing the monotonicity of anomalies. Having established that past returns, idiosyncratic volatility, asset growth, abnormal capital investments, investments-to-assets ratio, accruals, net operating assets, and composite stock issuance are negatively related to future returns in portfolio 5 and positively in portfolio 1, we can conclude that these anomalies are non-monotonic and effectively have an inverted J-shaped form. A unique pattern is observed for size. In contrast to other anomalies, it appears to have a strong negative relation to expected returns on microcap stocks (in portfolio 1), but the relation is positive and statistically significant for the rest of the stocks. Thus, the prevailing relation between size and risk-adjusted expected returns has a U-shaped form.

It should be emphasized that the relation between a firm characteristic and expected returns does not cease to be anomalous if it appears to be non-monotonic: for a subsample of stocks we still observe an anomalous pattern in expected returns unexplained by the Fama-French three-factor model. Moreover, our findings should not be interpreted as evidence of impossibility to develop a profitable trading strategy based on a given anomaly. In many cases, the discovered reversed relation between characteristics and returns is confined to portfolio 1 and not sufficiently pronounced to eliminate the difference in returns on extreme portfolios. The main implication of our results is that they challenge theoretical explanations of anomalies predicting monotonic relations between characteristics and returns at the stock level and emphasize the role of a small number of very special stocks in producing abnormal returns. For anomalies having an inverted J-shaped form, the prevailing increasing relation between characteristics and returns in portfolio 5 requires a separate theoretical explanation.

Our study falls into a large literature studying asset pricing anomalies (see Subrahmanyam (2010) for a recent review). In particular, there is a lot of research on how the strength of asset pricing anomalies varies across stocks: it may be different for firms with different size (Fama and French, 2008), distress risk (Griffin and Lemmon, 2002; Vassalou and Xing, 2004), credit rating (Avramov, Chordia, Jostova, and Philipov, 2010), idiosyncratic volatility (Ali, Hwang, and Trombley, 2003; Lipson, Mortal, and Schill, 2012), measures of financing constraints (Li and

Zhang, 2010), measures of limits-to-arbitrage and higher investment frictions (Lam and Wei, 2011), institutional ownership (Nagel, 2005), institutional trading (Jiang, 2010), proportion of short-term institutional investors (Cremers and Pareek, 2010), and measures of stock overvaluation (Cao and Han, 2013). In contrast to these papers, we focus on how the strength of anomaly varies with its own characteristic.

The closest to our study is Fama and French (2008) where the authors also look separately at various ranges of anomalous characteristics. However, Fama and French (2008) do not explore the impact of influential observations and monotonicity of anomalies. Other related papers are Knez and Ready (1997) which studies the robustness of the size and value anomalies using the LTS regression and Kraft, Leone, and Wasley (2006) which tests the monotonicity of the accruals anomaly. In this chapter, the list of anomalies is much longer and we use a variety of methods in addition to the LTS regression. Patton and Timmermann (2010) examine average raw returns on decile portfolios formed on the size, book-to-market ratio, cash flow-price ratio, earnings-price ratio, dividend-price ratio, momentum, short-term reversal, and long-term reversal and find that only the book-to-market ratio, cash flow-price ratio, earnings-price ratio, and long-term reversal exhibit a monotonic relation to returns. We consider a different list of anomalies and, more importantly, focus on individual stocks instead of portfolios. In a contemporaneous paper, Stambaugh, Yu, and Yuan (2012) explore separately the returns on short and long legs of various anomalies and show that time variation in anomaly returns is mostly driven by stocks with presumably low returns.

The rest of this chapter is organized as follows. In Section 3.2 we present robust regressions. Section 3.3 contains our empirical results.

3.2 Methodology: Robust Regressions

Many anomalies are associated with firm characteristics, so the characteristics that contain information about alphas for at least a subsample of stocks are called anomalous. To test whether a given characteristic is anomalous, two major procedures are employed in the literature. The first approach is to assign stocks to portfolios based on the characteristic and examine alphas of these portfolios (e.g., Fama and French, 1993; Daniel and Titman, 1997). In particular, it is common to form quintile or decile portfolios and test whether the difference in abnormal returns on the top and bottom portfolios is statistically significant or whether portfolio alphas are jointly significant (e.g., Gibbons, Ross, and Shanken, 1989; Fama and French, 1996). The second approach is to run a linear Fama-MacBeth regression (Fama and MacBeth, 1973) of realized returns on betas and characteristics. The significance of the characteristic slope reveals the anomaly.

The main objective of our analysis is to study whether the asset pricing anomalies are still monotonic, when few unusual observations are downweighted. To achieve this goal, we employ robust econometric techniques: along with standard OLS regressions, we use rank regressions, least trimmed squares (LTS) regressions, and iteratively reweighted least squares (IRLS) regressions. To study monotonicity, we separately examine the presence of anomalies for all stocks and for individual quintile portfolios formed on anomalous characteristics. Robust methods are particularly appealing since the number of stocks within quintile portfolios is relatively small and the OLS regression can be unduly influenced by few stocks with extreme characteristics and returns.

The use of rank regression is motivated by the following logic. Consider two cross-sectional stock rankings (i.e., two ways to order stocks): one is produced by a firm characteristic, the other is based on alphas with respect to a selected asset pricing model. These two rankings should be statistically independent if the characteristic is unrelated to alphas or if all alphas are zero and the estimated alphas rank stocks randomly. This hypothesis can be tested using the Spearman rank correlation.[1] If it is rejected, the characteristic contains some information about stock alphas and should be considered anomalous. Note that by construction the variances of two rankings are identical, so the Spearman correlation coincides with the regression slope when one ranking is regressed on the other.

The rank regression approach deserves several comments. First, it captures the intuition that an anomalous characteristic should be aligned with abnormal returns. For example, if they were linearly related, both the linear and rank regressions would detect it, and conclusions of rank-based tests would be identical to those obtained using the standard linear regression. In addition, this approach is consistent with the standard portfolio-based tests: for example, if rankings produced by the

[1] The family of rank statistics designed to test the independence of two rankings is quite large (Hájek, Šidák, and Sen, 1999). We use the Spearman correlation as one of the simplest and intuitive. Its another advantage is in assigning higher weights to those objects which are located distantly according to two rankings (as opposed to the Kendall rank correlation for example, which counts the pairs of objects ordered differently in two rankings but ignores the quantitative difference in ranks).

characteristic and expected returns are positively related, the portfolio of stocks with higher characteristics outperforms the portfolio with lower characteristics. Thus, the rank regression can be viewed as a compromise between the linear regression and the portfolio-based analysis, and to some extent it combines the advantages of both methods. On the one hand, similar to the linear regression, the rank regression uses information on individual stocks making the inference more precise than in the analysis of portfolio returns which ignores the dispersion of characteristics and returns within portfolios. Moreover, rank regression is applicable to stocks in various ranges of the anomalous characteristic. On the other hand, similar to the portfolio analysis, the rank regression is non-parametric. It does not impose any functional restrictions on the relation between anomalous variables and stock returns and, hence, is much more robust to misspecifications than the linear regression. In addition, it is less sensitive to outliers than the linear regression, which may produce misleading results in finite samples, especially when characteristics or returns have highly skewed distributions.

The benefits of the rank regression may be particularly noticeable when the actual relation between the characteristic and expected returns is non-linear and the standard linear regression is misspecified. From the theoretical point of view, it would be quite natural to expect that this is the case for the majority of anomalous characteristics. Although in rational asset pricing models the expected returns are exclusively determined by loadings on risk factors, these loadings are often unobservable and proxied by firm characteristics. In addition, characteristics may be helpful for explaining expected returns if the dynamics of factor loadings are misspecified (Berk, Green, and Naik, 1999) or conditional factor loadings are measured imprecisely (Gomes, Kogan, and Zhang, 2003). Although in such cases the theoretical relation between expected stock returns and anomalous characteristics is almost always monotonic, it is typically non-linear. For instance, Livdan, Sapriza, and Zhang (2009) demonstrate how financial constraints produce a convex relation between market leverage and expected returns.

The comparison of slopes in the linear and rank regressions can be used as a diagnostic tool: any substantial difference between them (e.g., when both of them are statistically significant but have opposite signs) indicates that the sample size is small enough to allow for influential individual observations. Indeed, the rank regression captures the prevailing relation between the characteristic and stock returns which likely involves a broad group of stocks. In particular, it is more robust to outliers, ensuring that the conclusions are not driven by highly unusual stocks with extreme characteristics or returns. Empirically, most anomalous characteristics have very skewed distributions resulting in a potentially high impact of extreme stocks. For instance, even if the characteristic is negatively related to returns for the vast majority of stocks, a small number of outliers with extremely high characteristics and returns (or extremely low characteristics and returns) can make the slope of the linear regression statistically indistinguishable from zero or even positive. Thus, a zero slope in the linear regression does not mean that there is no relation between the characteristic and returns. Such relation in some cases can be uncovered using rank regressions.

Even though rank-based tests are robust and less affected by outliers, they also have drawbacks. In particular, the use of ranks causes a partial loss of information imbedded in magnitudes of characteristics and returns. Thus, in terms of information utilization, the rank-based approach is somewhere in between the parametric regression and portfolio formation. As a result, it may be inappropriate for improving the profitability of trading strategies based on anomalous characteristics. The objective of using rank regression is to capture the prevailing relation between characteristics and returns, but not to identify stocks with the highest (or lowest) returns.

Another robust technique used in our analysis is the least trimmed squares (LTS) regression. Given the observations (y_i, x_i), $i = 1, \ldots, N$, it defines the estimator for the regression slope β as

$$\hat{\beta}_{LTS} = \arg\min_{\beta} \sum_{i=1}^{h} r_{[i]}^2(\beta),$$

where $r_{[i]}^2(\beta)$ represents the ith order statistic of squared residuals $r_i = y_i - x_i\beta$. The parameter h determines the trimming level and must satisfy $N/2 < h \leq N$. In subsequent analysis, we set h such that approximately 1% of observations are trimmed. Intuitively, the LTS approach prescribes to find a certain proportion of observations with the highest squared residuals and eliminate them from the sample.

The LTS regression complements the rank regression. Although the latter one reduces the impact of outliers, it does not provide an estimate of the proportion of extreme observations that explain the difference between the results of linear and robust regressions. The LTS regression fills this gap. Similar to the rank regression slopes, the LTS estimates are more robust to extreme observations than their OLS counterparts. Almost by construction, the LTS regression ignores highly unusual observations and captures the relation between characteristics and returns pertaining to a large number of stocks. However, given that the number of trimmed observations is an exogenous parameter, the LTS regression quantifies the fraction of observations that potentially influence the OLS results.

The third robust technique that we apply to anomalies is the iteratively reweighted least squares (IRLS) regression (e.g., Holland and Welsch, 1977). The main drawback of the LTS regression is that it discards certain data points, so the information contained in them is lost. In contrast, the IRLS regression utilizes all observations, but put different weights on them. In this sense, the IRLS is a compromise between the OLS regression, which weighs all observations equally, and the LTS regression, which gives a zero weight to some of them. The IRLS regression is a special case of the weighted least squares (WLS) regression, and the weights are determined recursively by regression residuals. Thus, the IRLS also takes into account the heteroskedasticity of regression errors.

More specifically, given the observations (y_i, x_i), $i = 1, \ldots, N$, the IRLS estimator $\hat{\beta}_{IRLS}$ is defined as a limit of the following iteration:

$$\hat{\beta}^{(n+1)} = \arg\min_{\beta} \sum_{i=1}^{N} w_i^{(n)} (y_i - x_i\beta)^2,$$

where the weights $w_i^{(n)}$ are determined by the residuals $r_i^{(n)} = y_i - x_i\beta^{(n)}$, obtained at the previous iteration step: $w_i^{(n)} = w(r_i^{(n)})$. Common specifications of the weighting function $w(\,\cdot\,)$ are discussed in Holland and Welsch (1977) and Huber (1981) and include Huber's function, Tukey's bi-square function, Cauchy function, Andrews' function, logistic function, and others. In our empirical analysis, we use the logistic specification

$$w(x) = \frac{\tanh(x)}{x} = \frac{1}{x}\frac{e^{2x}-1}{e^{2x}+1},$$

and we check that the results are not sensitive to this choice. All weighting functions contain a scale parameter (effectively, the normalization of residuals) which is usually set to be proportional to the median absolute deviation of the residuals from their median (Hogg, 1979; Street, Carroll, and Ruppert, 1988). In addition, residuals are normalized by $\sqrt{1-h_i}$, where h_i is the "leverage" of observation i and the tuning constant (Huber, 1981).

To implement the described robustness tests empirically, we use an analog of the Fama-MacBeth procedure in which a robust cross-sectional regression is substituted for the OLS regression. This approach equally applies to all stocks and characteristic-based quintile portfolios. For example, to run a rank regression, we construct two stock rankings based on a given characteristic and realized abnormal returns in the next period in each time period t and compute Spearman rank correlations ρ_t between them. As mentioned above, the Spearman correlation is exactly equal to the slope of rank regression, i.e. an OLS regression with ranks used instead of magnitudes. Then, as in the standard Fama-MacBeth procedure, we compute the average of ρ_t across all periods and use the obtained statistic ρ to test whether the slope is different from zero. Since the serial correlation is negligible for returns, it is safe to assume that the estimated slopes from different periods are independent.[1]

[1]In our empirical analysis, we have checked that this assumption is innocuous. Unreported

Because of that, we estimate the standard deviation of ρ as a sample standard deviation and use the t-statistic to test the hypothesis $\rho = 0$. When the number of stocks N_t in period t is sufficiently large and the rankings are independent, ρ_t is normally distributed: $\rho_t \sim N(0, 1/(N_t - 1))$ (Hájek, Šidák, and Sen, 1999). Hence, ρ is also normally distributed and under the null the t-statistic has a conventional distribution. LTS and IRLS regressions are implemented in a very similar manner.

The robust regressions discussed above use individual stocks, so they can be applied for all stocks as well as for various subsamples of stocks. In particular, we form quintile portfolios based on the characteristic and explore the relation between the characteristic and returns *within* each portfolio. This analysis has two major objectives. First, it allows us to examine the variation of the strength of the anomaly and its reliance on exceptional observations across various ranges of characteristics. Second, it provides a way to test the monotonicity of the anomaly which is based on the following simple idea: if the relation between firm characteristic and future stock returns is monotonic, it should have the same sign in all ranges of the characteristic.[1] The test is complicated by the fact that cross-sectional dispersions of characteristics within each portfolio substantially vary across portfolios (Fama and French, 2008). In those portfolios where characteristics are not sufficiently dispersed, the slopes of regressions may be statistically insignificant even in the presence of the anomaly. However, statistically significant slopes with opposite signs in two different portfo-

---

estimations show that the results are essentially unaffected if the Newey and West (1987) standard errors are used for construction of t-statistics.

[1]Another monotonicity test applicable to asset pricing anomalies is developed by Patton and Timmermann (2010) and based on portfolio returns instead of individual stocks.

lios would clearly indicate that the monotonicity hypothesis should be rejected. This would have important theoretical implications since by testing the monotonicity of the anomaly we effectively test the theories explaining anomalies that predict monotonic relations between characteristics and returns. The lack of monotonicity would imply that such theories do not capture the whole picture and should be revised.

3.3 Empirical Results

3.3.1 Data

Our data come from standard sources. Stock returns, stock prices, and the number of shares outstanding are from CRSP monthly files, while accounting data are from Compustat Fundamentals annual files. We exclude financial firms and consider only NYSE, AMEX, and NASDAQ firms with common stocks. Returns are monthly stock returns with dividends adjusted for delisting. We consider both raw and risk-adjusted returns, and use the Fama-French three-factor model to adjust for risk. We compute risk-adjusted returns $\tilde{r}_{it}$ on security i in month t following Brennan, Chordia, and Subrahmanyam (1998) and Avramov and Chordia (2006):

$$\tilde{r}_{it} = r_{it} - r_t^f - \beta_i^{MKT} \times MKT_t - \beta_i^{HML} \times HML_t - \beta_i^{SMB} \times SMB_t.$$

Individual stock betas are estimated every month by regressing excess stock returns on a constant and the Fama-French factors. We use the previous 60 months of observations, requiring that at least 24 months of return data are available.

As signals about expected stock returns, we use fourteen characteristics that are associated with prominent asset pricing anomalies. The characteristics can be divided into five groups. The classical group consists of size S, book-to-market B/M, and momentum Mom. Investment variables capture the firm's capital investment. This group consists of total asset growth AG, abnormal capital investments CI, and investments-to-assets ratio I/A. Issuance characteristics capture the firm's equity issuance activity with net stock issues NS and composite stock issuance ι. Two accounting anomalies capture the firm's earnings management and its cumulative effect on the balance sheet with accruals Acc and net operating assets NOA, respectively. Return on assets ROA, an accounting measure of the firm's performance, also belongs to this group. Idiosyncratic volatility $IdVol$, Ohlson's O-score O, and dispersion in analysts' forecasts D are grouped together as they broadly quantify uncertainty about the firm. The detailed construction of each characteristic is described in the Appendix.

3.3.2 Characteristics and Portfolio Returns

First, we confirm that all selected characteristics are indeed anomalous, i.e. that the differences in returns on stocks with high and low characteristics are statistically different from zero. For each characteristic, we form quintile portfolios and compute average portfolio raw returns and Fama-French risk-adjusted returns. For the book-to-market, asset growth, abnormal capital investments, investments-to-assets ratio, accruals, net operating assets, net stock issues, and composite stock issuance the portfolios are formed once a year at the end of June. They are held for one year and rebalanced at the end of next June. Portfolios based on size, momentum, idiosyncratic volatility, and dispersion in analysts' forecasts are created at the end of each month, whereas portfolios based on return on assets and O-score are updated quarterly.

For each characteristic, portfolio breakpoints are determined using all stocks for which the characteristic is available at the moment of portfolio formation. Since we examine individual stocks in our subsequent analysis, we focus on equal-weighted portfolios. The sample period is from January 1965 to December 2007 for all characteristics except the return on asset, O-score, and dispersion in analysts' forecasts, for which sample periods start in January 1975, January 1976, and January 1983, respectively.

From the previous research we know that all characteristics under consideration except book-to-market, momentum, and return on assets are supposed to be negatively related to abnormal stock returns. For the uniformity of the analysis, we switch the sign of B/M, Mom, and ROA so that the first portfolio always has the highest return and the fifth portfolio has the lowest one.

Panel A of Table 3.1 reports averages of monthly raw returns on the constructed quintile portfolios. As expected, all characteristics (except idiosyncratic volatility $IdVol$) appear to be negatively related to raw stock returns. Moreover, portfolio 1 earns substantially higher returns than portfolio 5, and the difference is highly statistically significant. The only characteristic that does not produce a large dispersion of returns across equal-weighted portfolios is idiosyncratic volatility, and this result is consistent with Bali and Cakici (2008) who argue that the choice of a weighting scheme used to compute average portfolio returns is critical for detecting the idiosyncratic volatility anomaly.

As mentioned above, we define anomalies relative to the Fama-French 3-factor model. Panel B of Table 3.1 shows averages of risk-adjusted returns on quintile portfolios, which measure the cross-sectional variation in expected returns not captured by the loadings on the market, HML, and SMB factors. Although the risk adjustment substantially reduces average returns, all differences in returns on extreme portfolios are still statistically significant confirming that the characteristics under consideration indeed capture patterns in non-zero alphas. Compared to raw returns, the differences in risk-adjusted returns for the majority of anomalies stay almost the same, and notably increase for the idiosyncratic volatility anomaly. Surprisingly, the correction for the Fama-French factors does not eliminate the dispersion of returns even across size and book-to-market portfolios, although it halves the value premium. This result echoes the findings of Brennan, Chordia, and Subrahmanyam (1998) and seems to manifest the sensitivity of conclusions to whether the risk adjustment is conducted at the portfolio level or at the level of individual securities.

3.3.3 Robustness of Anomalies: Evidence from Individual Stocks

In this section, we compare the results of the standard OLS Fama-MacBeth regression and robust regressions of risk-adjusted returns on anomalous characteristics for all stocks and for stocks from quintile portfolios formed on anomalous characteristics. The results are reported in Table 3.2.

Panel A of Table 3.2 shows the slopes from the standard OLS Fama-MacBeth regression for quintile portfolios and all stocks, and their t-statistics reveal several patterns. First, the slopes for all anomalies in the whole sample are negative and highly statistically significant. This is exactly what we should expect from the analysis of portfolio returns and is additional evidence that the characteristics under consideration are anomalous. The negative relation is observed even for size and the book-to-market ratio supporting the findings of Brennan, Chordia, and Subrahmanyam (1998) who demonstrate that the correction for the Fama-French factors cannot eliminate the size and book-to-market effects for individual stocks.

Second, the slopes of the OLS regression in portfolio 5 (the portfolio with supposedly low stock returns) are negative and statistically significant at the conventional level for six anomalies out of fourteen (they are only marginally significant for book-to-market, abnormal capital investments, accruals, and net stock issues and positive for size). Given that the number of stocks within each portfolio is relatively small, this result means that either the anomalies are very strong for stocks with presumably low returns or the regression results are substantially affected by outliers. To distinguish these hypotheses, we need to run robust regressions.

Third, the majority of slopes in other portfolios are not statistically significant and some of them are positive. In particular, only the book-to-market ratio and size are significantly related to stock returns in portfolio 1, and this relation is particularly strong for the size anomaly which is known to be driven by small stocks.[1] The insignificance of slopes in intermediate portfolios can be explained by low dispersion of characteristics within such portfolios resulting in large standard errors of slopes (e.g., Fama and French, 2008). Thus, even if anomalies exist for intermediate stocks,

[1]Fama and French (2007) conclude that the size premium stems almost entirely from small stocks that earn extreme positive returns and become big stocks.

our tests may lack statistical power to detect them. The insignificant slopes in portfolio 1 can result from either a low power of the t-test or the lack of the anomalous relation in this range of characteristics. In particular, the low test power may be due to the impact of outliers that strongly affects the estimates of slopes and conceal the prevailing anomalous relation between characteristics and returns.

To distinguish these explanations, we repeat all computations using rank regression instead of standard OLS regression in the Fama-MacBeth cross sections. Since rank regression is less influenced by extreme stocks, the difference in results between rank and linear regressions would demonstrate the impact of outliers on the linear regression slope. The results of rank Fama-MacBeth regression of risk-adjusted returns on fourteen characteristics for all stocks and within quintile portfolios are reported in Panel B of Table 3.2.

In contrast to OLS regression results, the results of rank Fama-MacBeth regression when all stocks are used in the analysis substantially vary across anomalies. Panel B of Table 3.2 shows that the relation between returns and book-to-market, momentum, idiosyncratic volatility, return on assets, net stock issues, composite stock issuance, O-score, and analysts' forecasts dispersion is still negative and statistically significant. It means that these anomalies pertain to many stocks and the slopes in OLS regressions are not driven by outliers. However, the slopes for all other anomalies are either statistically insignificant or, as in the case of size and abnormal capital investments, even positive and significant. This is direct evidence that the latter group of anomalies may be produced by influential observations.

To get a better understanding of the rank regression results for all stocks, we also repeat the analysis for stocks from individual quintile portfolios. In line with the OLS regression results, the slopes are negative for all characteristics (except size) in portfolio 5 and all of them are statistically significant at a 1% level. It means that in portfolio 5 there is an actual robust relation between characteristics and stock returns, and negative slopes in the OLS regressions are not the result of influence of several stocks with abnormally low returns. However, the slopes in the OLS and rank regressions substantially differ in portfolio 1. In contrast to the OLS regression, the majority of slopes in the rank regression are *positive*. Moreover, they are highly significant for Mom, $IdVol$, AG, CI, I/A, Acc, NOA, and ι. The only anomalies that preserve negative slopes are size and distress anomalies. These results are unexpected and cannot be anticipated from returns on portfolios or results of OLS regression.

Positive slopes in portfolio 1 have important implications. First, they indicate that many anomalies are not robust for stocks with presumably high returns. The fragility of anomalies for these stocks can be explained by easiness to exploit them: these stocks are underpriced, and investors need to take a long position to profit from the mispricing. In contrast, stocks in portfolio 5 are overpriced, and investors would short them. This is more costly and not all investors can do that. As a result, the anomaly is much more pronounced there.

Second, the non-robustness of anomalies in portfolio 1 can explain the results in rank regressions for all stocks. In particular, the asset growth, investments-to-assets ratio, accruals, and net operating assets anomalies, whose rank regression slopes are not unambiguously negative for all stocks, tend to have positive and statistically significant rank slopes in portfolio 1. Similarly, for the abnormal capital investments anomaly the positive relation observed in portfolio 1 is strong enough to dominate in the whole sample. The story is a bit different for size: the slope of size for all stocks is positive and statistically significant due to the positive relation between this characteristic and returns in all portfolios except portfolio 1. For all other anomalies, the decreasing part from portfolio 5 dominates and the slopes are negative and statistically significant in the whole sample. Partially, this result can also be attributed to a strong negative relation between characteristics and returns not only in portfolio 5, but also in some intermediate portfolios.

Third, the opposite signs of rank regression slopes in portfolios 1 and 5 represent stark evidence of non-monotonicity in the relations between characteristics and expected returns. In particular, we can conclude that the prevailing relations between returns and past returns, idiosyncratic volatility, asset growth, abnormal capital investments, investments-to-assets ratio, accruals, net operating assets, and composite stock issuance have a hump-shaped form: returns increase with characteristics in portfolio 1 and decrease in portfolio 5. In other words, stocks with extreme magnitudes of these characteristics (no matter high or low) tend to have lower returns.

It should be emphasized that the discovered non-monotonicity does not contradict the monotonicity of average portfolio returns documented in Tables 3.1. The surprising increasing relation between characteristics and returns is confined to the lowest quintile portfolio and the total portfolio return can still be higher than the return on the adjacent portfolio. Thus, the overall relations between characteristics and returns can be described as having an inverse J-shaped form.

For the book-to-market ratio, return on assets, net stock issues, and analysts' forecasts dispersion the picture is similar but positive coefficients in portfolio 1 are statistically insignificant. However, the size anomaly demonstrates a completely different pattern: it is strongly negatively related to returns in portfolio 1 containing small stocks, but the relation is inverse for medium and large stocks. Thus, in contrast to other anomalies, size demonstrates a U-shaped form. The decreasing part is consistent with Fama and French (2008), who also document that the negative relation between size and average returns is particularly strong for microcap stocks. The increasing part of the relation confirms the conclusion of Knez and Ready (1997) who argue that the size effect is driven by extreme positive returns on a limited number of small stocks. When the impact of such influential points is eliminated, the relation between size and returns appears to be positive.[1]

The difference in slopes between linear and rank regressions in portfolio 1 can be explained by the strong influence of a few highly unusual stocks with low values of characteristics and very high returns which drive up portfolio returns and make the slope of the OLS Fama-MacBeth regression negative. To demonstrate this, we repeat the Fama-MacBeth procedure but run cross-sectional least trimmed squares (LTS) regression at the first stage instead of rank regression or linear regression (a detailed description of LTS regression is provided in Section 3.2). Following conventions in the literature, we set the cutoff in LTS regression at the 1% level, so only a few

[1]Fu and Yang (2011) show that a positive relation between size and returns also arises after controlling for idiosyncratic volatility.

observations are trimmed. By construction, LTS regression is robust to outliers and any divergence in the results of OLS and LTS regressions indicates a presence of influential observations.

The results are reported in Panel C of Table 3.2. Overall, the t-statistics from LTS regression are close to their counterparts in the rank regression. In portfolio 1, the slopes of LTS regression are positive and significant for the anomalies that are discovered to have an inverted J-shaped form. Also, the coefficient of size is negative and significant. In portfolio 5, the vast majority of characteristics (except size, returns on assets, and accruals) are negatively related to future stock returns even after trimming exceptional observations confirming the results from the linear and rank regressions. Thus, we can conclude that many anomalies look monotonic in the linear regression only because of a few stocks with low values of the characteristics and high returns. When the impact of such stocks is diminished, the prevailing relation between characteristics and returns appears to have an inverted J-shaped form.[1]

The impact of unusual stocks and the resulting discrepancy between the linear and rank regressions in portfolio 1 also can explain why for the whole sample the slope can be positive in the rank regression but negative in the linear regression. If abnormal expected returns decline strongly with a characteristic in one of the extremes but have a positive relation to the characteristic for the majority of stocks, the slope in the rank regression can be high and positive (it captures the prevailing

[1] We have also explored the sensitivity of results to stocks with extreme characteristics. We find that the elimination of such stocks does not produce a noticeable change in regression slopes.

relation) whereas the slope in the linear regression is zero or negative (it is strongly influenced by extreme stocks).

Another robust regression that we use in our analysis is iteratively reweighted least squares (IRLS) regression. Its main advantage relative to LTS regression is that the information from all observations is used for constructing the slope estimate (see the discussion of IRLS regression in Section 3.2). The results of IRLS regression are reported in Panel D of Table 3.2. Overall, the slopes and their t-statistics produced by LTS and IRLS regressions are comparable and support our previous conclusions. In particular, the vast majority of slopes in portfolio 5 are negative and statistically significant, whereas the slopes of all characteristics except size and O-score are positive in portfolio 1 and five of them are statistically significant. Because IRLS regression puts non-zero weights on influential observations, the results are slightly weaker in than in the case of LTS regression, but still indicate that many anomalies are non-robust in portfolio 1 and non-monotonic for all stocks.

The influential observations may affect not only slopes in regressions, but also portfolio returns themselves. To illustrate this point, we recompute average returns on extreme quintile portfolios when one or two stocks with abnormal returns are excluded in each period. Since we are interested in the role of these stocks in generating the difference in returns on portfolios 1 and 5, we drop stocks with the highest returns from portfolio 1 and stocks with the lowest returns from portfolio 5. Table 3.3 reports how this truncation affects the profitability of each anomaly.

Column (2) of Table 3.3 shows that only one stock with the highest return in portfolio 1 is responsible on average for almost one half of the spread in returns on portfolios 1 and 5. Moreover, four anomalies (momentum, idiosyncratic volatility, abnormal capital investments, and accruals) become insignificant when only one stock is excluded from portfolio 1. When two stocks with the highest returns are excluded from portfolio 1 (column (4) of Table 3.3), the number of disappeared anomalies increases to nine (only size, profitability, net stock issues, distress, and analysts' forecasts dispersion anomalies survive) and two of them (abnormal capital investments and accruals) become significant with the opposite sign. Consistent with our previous analysis, the disappearing anomalies are those that tend to have positive and significant robust regression slopes in portfolio 1.

The result is different for portfolio 5. Columns (3) and (5) of Table 3.3 show that only three anomalies disappear when one stock with the lowest return is excluded and four anomalies disappear when two extreme stocks are excluded. This supports our conclusion that anomalies tend to be more robust in portfolio 5.

To visualize the impact of individual stocks on portfolio returns, we plot average risk-adjusted returns on quintile portfolios without truncation and with one stock truncated from either portfolio 1 or portfolio 5. Figure 3.1 presents the obtained graphs. After dropping the worst stock, returns on portfolio 5 increase, but for the vast majority of anomalies they are still lower than the returns on portfolio 4. It means that the monotonicity of average returns at the portfolio level survives. The results are strikingly different for portfolio 1. First, for the majority of anomalies the change in returns due to truncation in portfolio 1 is larger than in portfolio 5, and this is exactly what Table 3.3 reports. Second, returns on portfolio 1 are substantially lower than the returns on portfolio 2 for the majority of the anomalies, and in particular for the anomalies losing statistical significance after truncation. This means that the pattern of portfolio returns becomes non-monotonic, and the non-monotonicity is particularly strong for the anomalies based on idiosyncratic volatility, asset growth, capital investments, investments-to-assets ratio, accruals, net operating assets, net stock issues, and composite stock issuance. Except the net stock issues anomaly, all these anomalies exhibit an inverse J-shaped form according to robust regressions. Thus, this test illustrates the impact of influential observations in portfolio 1.

Overall, we can conclude that all considered characteristics are indeed anomalous, and the anomalies are very robust for stocks with presumably low returns (the only exception is the size anomaly, which is robust for stocks with expected high returns). However, in the opposite extreme high returns are produced by influential stocks, and the prevailing relation between characteristics and returns for many anomalies has an opposite sign indicating the presence of non-monotonicity.

3.3.4 Size Portfolios

Fama and French (2008) explore the strength of various anomalies across firm size groups and document that the anomalies associated with net stock issues, accruals, and momentum are detectable for firms with all sizes whereas the asset growth anomaly is absent for big stocks. Thus, we anticipate that robustness and monotonicity may also vary with the firm size and repeat the analysis separately for different size groups. Following Fama and French (2008), we split all stocks into three categories: microcaps, small stocks, and big stocks. As the breakpoints, we use the 20th and 50th percentiles of the end-of-June market cap for NYSE stocks.

Table 3.4 collects the results. To save space, we report only slopes and t-statistics for Fama-MacBeth rank regressions of risk-adjusted returns on firm characteristics.

Panel A of Table 3.4 shows that the pattern of slopes and t-statistics for microcap stocks closely resembles the pattern for all stocks from Table 3.2. Five anomalies (size, asset growth, abnormal capital investments, accruals, and net operating assets) are not robust for all microcap stocks, but all characteristics except size are negatively related to returns in portfolio 5. Moreover, the slopes for momentum, asset growth, abnormal capital investments, investments-to-assets ratio, and accruals are positive and significantly different from zero in portfolio 1, indicating that these anomalies preserve their inverted J-shaped form in microcap stocks.

For big stocks, the results are presented in Panel C of Table 3.4. Consistent with Fama and French (2008), momentum, net stock issues and composite stock issuance have negative slopes for all stocks. Meanwhile, the significance of book-to-market, asset growth, abnormal capital investments, investments-to-assets ratio, and accruals disappear. The disappearance of the value anomaly (the slopes of B/M are significant neither for all big stocks nor for quintile portfolios) is not surprising either, given that the existing literature demonstrates the ability of Fama-French factors to explain the value premium for big stocks. We already know that the size effect is presumably driven by microcaps and demonstrates a positive relation to returns for all other stocks. This observation is also confirmed by Panel C of Table 3.4.

It is more interesting that all characteristics except book-to-market, size, and net stock issues are negatively and statistically significantly related to returns in portfolio 5. Thus, although some anomalies are undetectable for all big stocks, they are still present in portfolio 5. This result illustrates the benefits of examining anomalies within quintile portfolios.

The slopes of the rank regression in portfolio 1 are different from their counterparts for microcaps and all stocks. Except for total asset growth, all of them are statistically indistinguishable from zero. This means that the discovered inverted J-form of anomalies is mainly produced by microcaps and small stocks (Panel B of Table 3.4 reports the results for small stocks which are qualitatively consistent with those for microcaps). For the asset growth anomaly, the positive slope in portfolio 1 suggests the presence of non-monotonicity even when only big stocks are considered. Given the finding of Fama and French (2008) that the asset growth anomaly is undetectable for big stocks, we can speculate that this happens because the positive relation between the characteristic and returns in portfolio 1 is strong enough to offset the negative relation in portfolio 5.

To summarize, firm's size indeed affects the form of many anomalies. In particular, the inverted J-shaped form of several anomalies documented above is mostly confined to microcap and small stocks. Nevertheless, all considered anomalies except value, size, and net stock issues are present in the portfolio 5 in all size groups.

Table 3.1: Raw Returns and Fama-French Risk-Adjusted Returns

This table shows averages of monthly equal-weighted stock returns (Panel A) and returns adjusted for risk using the Fama-French 3-factor model (Panel B) for quintile portfolios formed by sorting firms on fourteen anomalous characteristics. The column (1-5) reports the difference between returns on portfolio 1 and portfolio 5. To ensure that for all anomalies expected returns decrease with the portfolio number (i.e., portfolio 1 contains stocks with abnormally high returns), the signs of B/M, Mom, and ROA have been inverted. All coefficients are multiplied by 100.

Panel A: Raw Returns

	Returns						t-stats					
	1	2	3	4	5	(1-5)	1	2	3	4	5	(1-5)
$-B/M$	1.70	1.47	1.29	1.12	0.80	0.90	7.99	6.75	5.28	3.95	2.26	4.13
S	2.11	1.06	1.09	1.13	1.02	1.09	6.29	3.71	3.95	4.37	4.76	4.21
$-Mom$	1.83	1.47	1.26	1.08	0.98	0.85	6.23	6.39	5.51	4.10	2.59	3.21
$IdVol$	1.16	1.40	1.42	1.26	0.93	0.24	7.42	6.66	5.43	3.93	2.31	0.75
AG	1.70	1.48	1.34	1.25	0.72	0.99	5.20	6.47	6.01	5.00	2.26	7.33
CI	1.47	1.41	1.33	1.30	1.19	0.27	4.99	5.63	5.79	5.54	4.51	3.45
I/A	1.65	1.48	1.40	1.22	0.82	0.83	5.62	6.00	6.04	4.89	2.79	8.69
$-ROA$	1.76	1.50	1.38	1.05	0.69	1.06	6.39	6.04	5.64	3.49	1.61	3.88
Acc	1.52	1.52	1.42	1.38	1.03	0.49	4.87	6.14	5.98	5.28	3.34	5.29
NOA	1.60	1.51	1.44	1.24	0.80	0.81	4.80	5.60	5.92	5.16	2.90	5.38
NS	1.31	1.32	1.37	1.09	0.63	0.69	5.58	5.32	5.00	3.77	2.01	5.49
ι	1.43	1.36	1.37	1.36	0.99	0.44	7.61	6.49	5.62	4.58	3.13	2.40
O	1.61	1.57	1.51	1.28	0.95	0.66	5.40	5.51	5.14	4.17	2.61	3.57
D	1.39	1.30	1.21	1.06	0.66	0.73	5.33	4.65	3.84	2.98	1.58	2.98

Panel B: Risk-Adjusted Returns

	Returns						t-stats					
	1	2	3	4	5	(1-5)	1	2	3	4	5	(1-5)
$-B/M$	0.33	0.18	0.11	0.08	-0.16	0.50	4.62	2.88	1.63	0.78	-1.22	4.08
S	1.05	-0.17	-0.17	-0.04	-0.03	1.09	5.16	-1.44	-2.31	-0.79	-0.70	4.94
$-Mom$	0.37	0.19	0.07	-0.10	-0.10	0.47	3.87	3.33	1.22	-1.16	-0.47	2.00
$IdVol$	0.15	0.24	0.23	0.07	-0.26	0.41	2.35	5.08	3.85	0.71	-1.28	1.98
AG	0.35	0.24	0.17	0.07	-0.36	0.71	2.27	3.36	3.18	1.15	-3.74	6.00
CI	0.18	0.18	0.14	0.11	-0.02	0.20	1.62	2.58	2.48	1.92	-0.20	2.66
I/A	0.24	0.25	0.20	0.05	-0.30	0.54	2.12	2.81	3.41	0.79	-3.56	6.06
$-ROA$	0.48	0.21	0.10	-0.21	-0.45	0.93	5.56	2.80	1.18	-1.77	-1.96	4.19
Acc	0.24	0.29	0.21	0.20	-0.13	0.37	1.94	3.68	3.20	2.75	-1.30	4.41
NOA	0.39	0.26	0.19	0.06	-0.31	0.70	2.71	3.00	2.82	0.98	-3.49	5.92
NS	0.11	0.21	0.18	-0.07	-0.52	0.64	1.53	2.28	2.17	-0.78	-4.05	6.85
ι	0.19	0.16	0.19	0.12	-0.29	0.48	4.36	3.06	2.68	1.32	-2.49	4.21
O	0.31	0.20	0.15	0.01	-0.34	0.64	3.83	2.46	1.52	0.06	-1.87	3.89
D	0.22	0.08	0.05	-0.09	-0.49	0.71	2.42	1.07	0.61	-0.88	-3.23	4.24

Table 3.2: Characteristics and Risk-Adjusted Stock Returns Within Quintile Portfolios

This table reports slopes and t-statistics from the OLS regression (Panel A), the rank regression (Panel B), the least trimmed squares (LTS) regression (Panel C), and the iteratively reweighted least squares (IRLS) regression (Panel D) of risk-adjusted returns on several anomalous characteristics. The regressions are run within individual quintile portfolios formed using sorts on anomalous variables (columns 1 – 5) and for the whole sample (column *All*). The column (1-5) reports the difference between returns on portfolio 1 and portfolio 5.

Panel A: OLS Fama-MacBeth Regression

	Slope						t-stats					
	1	2	3	4	5	All	1	2	3	4	5	All
$-B/M$	-0.0040	0.0036	0.0002	-0.0041	-0.0016	-0.0021	-3.10	1.42	0.08	-1.09	-1.78	-4.04
S	-0.0242	0.0006	0.0004	-0.0002	0.0004	-0.0018	-15.13	0.57	0.41	-0.32	1.83	-4.95
$-Mom$	-0.0001	-0.0107	-0.0089	-0.0045	0.0112	-0.0032	-0.12	-3.36	-1.82	-0.89	1.22	-2.39
$IdVol$	-0.1913	0.2797	-0.1703	-0.3223	-0.1593	-0.1525	-0.72	2.04	-1.35	-3.04	-3.93	-4.97
AG	-0.0052	-0.0092	-0.0141	-0.0208	-0.0041	-0.0039	-0.98	-0.66	-1.13	-2.98	-4.99	-6.06
CI	-0.0041	0.0028	-0.0037	0.0010	-0.0004	-0.0004	-0.97	0.65	-0.89	0.38	-1.64	-4.38
I/A	-0.0057	0.0106	-0.0113	-0.0156	-0.0069	-0.0070	-1.45	0.39	-0.51	-1.16	-4.23	-6.00
$-ROA$	-0.0583	-0.2708	-0.5142	-0.3319	-0.0702	-0.0676	-1.04	-1.12	-1.59	-1.11	-0.63	-3.14
Acc	-0.0087	-0.0287	0.0758	0.0280	-0.0187	-0.0116	-0.80	-0.70	1.10	0.60	-1.61	-4.42
NOA	-0.0044	0.0047	-0.0141	-0.0199	-0.0043	-0.0044	-1.48	0.56	-1.25	-1.94	-3.01	-5.75
NS	0.2162	0.2227	0.0453	-0.0528	-0.0054	-0.0126	0.50	1.03	0.53	-2.06	-1.77	-6.34
ι	0.0002	0.0040	0.0019	0.0124	-0.0028	-0.0035	0.15	0.49	0.20	1.14	-3.24	-5.16
O	-0.0003	-0.0007	-0.0029	-0.0033	0.0004	-0.0005	-0.78	-0.58	-1.87	-2.21	1.03	-1.95
D	-0.0971	-0.0176	0.0435	-0.0288	-0.0012	-0.0013	-1.36	-0.29	1.03	-1.81	-3.30	-4.06

Panel B: Rank Fama-MacBeth Regression

	Slope						t-stats					
	1	2	3	4	5	All	1	2	3	4	5	All
$-B/M$	0.0033	0.0027	-0.0036	-0.0081	-0.0279	-0.0265	1.40	1.34	-1.85	-3.68	-9.91	-9.78
S	-0.0156	0.0116	0.0103	0.0070	0.0095	0.0449	-5.63	5.30	4.52	3.22	3.77	10.36
$-Mom$	0.0113	-0.0048	-0.0074	-0.0138	-0.0487	-0.0428	3.69	-2.37	-3.58	-6.43	-13.64	-10.03
$IdVol$	0.0122	-0.0021	-0.0133	-0.0212	-0.0499	-0.0712	3.99	-1.05	-6.67	-10.05	-16.72	-19.07
AG	0.0295	0.0078	-0.0014	-0.0096	-0.0284	0.0017	10.13	3.53	-0.73	-4.99	-11.77	0.75
CI	0.0217	0.0101	0.0005	-0.0028	-0.0257	0.0050	7.17	4.18	0.21	-1.19	-8.79	3.14
I/A	0.0172	0.0091	0.0011	-0.0067	-0.0218	-0.0014	6.97	4.04	0.50	-3.12	-8.52	-0.66
$-ROA$	0.0004	-0.0083	-0.0112	-0.0195	-0.0325	-0.0604	0.09	-2.44	-3.11	-5.25	-7.14	-14.86
Acc	0.0217	0.0051	0.0051	-0.0032	-0.0261	-0.0033	4.98	1.36	1.04	-0.74	-5.97	-1.48
NOA	0.0115	0.0101	0.0021	-0.0072	-0.0261	-0.0013	4.21	4.37	0.95	-2.98	-9.70	-0.62
NS	0.0012	0.0020	-0.0010	-0.0134	-0.0204	-0.0275	0.48	0.80	-0.42	-5.09	-7.23	-13.40
ι	0.0078	-0.0080	-0.0082	0.0008	-0.0236	-0.0373	3.07	-3.20	-3.42	0.29	-9.73	-13.31
O	-0.0099	-0.0087	-0.0084	-0.0130	-0.0213	-0.0500	-4.05	-4.15	-3.79	-5.75	-7.81	-15.56
D	0.0011	-0.0068	0.0001	-0.0157	-0.0237	-0.0428	0.35	-2.47	0.03	-4.92	-6.12	-9.67

Table 3.2: (Continued)

Panel C: LTS Fama-MacBeth Regression

	Slope						t-stats					
	1	2	3	4	5	All	1	2	3	4	5	All
$-B/M$	0.0029	0.0033	-0.0031	-0.0073	-0.0081	-0.0052	2.94	1.73	-1.59	-4.05	-10.85	-11.71
S	-0.0021	0.0063	0.0055	0.0024	0.0010	0.0034	-2.23	6.50	5.91	4.00	4.57	12.88
$-Mom$	0.0028	-0.0051	-0.0152	-0.0301	-0.0731	-0.0092	2.94	-1.77	-3.73	-6.67	-11.19	-7.19
$IdVol$	0.4244	-0.2255	-0.8846	-1.0411	-0.5283	-0.6355	4.81	-1.98	-7.61	-11.03	-16.99	-22.62
AG	0.0397	0.0363	0.0000	-0.0293	-0.0054	-0.0021	9.65	3.02	0.00	-4.89	-7.52	-3.27
CI	0.0286	0.0169	-0.0002	-0.0019	-0.0010	-0.0005	9.05	4.91	-0.07	-0.87	-4.74	-4.94
I/A	0.0162	0.0876	-0.0048	-0.0239	-0.0096	-0.0010	5.42	4.75	-0.27	-2.23	-6.96	-0.92
$-ROA$	0.0816	-0.3903	-1.0383	-0.5480	-0.1165	-0.1778	1.32	-1.42	-3.18	-2.07	-1.14	-7.67
Acc	0.0257	0.0528	-0.0078	-0.0098	-0.0163	-0.0070	2.67	1.49	-0.13	-0.20	-1.33	-2.51
NOA	0.0071	0.0325	0.0143	-0.0188	-0.0076	-0.0013	2.85	4.65	1.60	-2.36	-5.85	-1.70
NS	0.0803	0.3500	0.0423	-0.0768	-0.0156	-0.0243	0.22	1.89	0.57	-3.23	-6.43	-14.25
ι	0.0039	-0.0260	-0.0401	0.0105	-0.0062	-0.0087	4.11	-3.56	-4.63	1.08	-7.92	-14.42
O	-0.0010	-0.0049	-0.0048	-0.0072	-0.0014	-0.0031	-2.53	-5.07	-3.96	-6.61	-4.15	-14.24
D	0.0818	-0.1734	-0.0115	-0.0697	-0.0012	-0.0028	1.39	-3.11	-0.33	-4.88	-3.46	-7.21

Panel D: IRLS Fama-MacBeth Regression

	Slope						t-stats					
	1	2	3	4	5	All	1	2	3	4	5	All
$-B/M$	0.0012	0.0034	-0.0021	-0.0054	-0.0061	-0.0039	1.27	1.80	-1.16	-3.16	-8.30	-9.08
S	-0.0072	0.0044	0.0037	0.0016	0.0008	0.0021	-7.47	4.77	4.12	2.84	3.79	7.71
$-Mom$	0.0018	-0.0072	-0.0128	-0.0215	-0.0495	-0.0078	1.88	-2.68	-3.29	-5.02	-7.27	-6.12
$IdVol$	0.4061	-0.0213	-0.6278	-0.7778	-0.4040	-0.4797	4.77	-0.19	-5.62	-8.49	-12.52	-17.31
AG	0.0269	0.0241	-0.0048	-0.0233	-0.0049	-0.0027	6.79	2.17	-0.49	-4.08	-7.11	-4.23
CI	0.0198	0.0130	0.0005	-0.0018	-0.0009	-0.0004	6.39	3.95	0.15	-0.90	-4.35	-5.10
I/A	0.0104	0.0601	0.0012	-0.0246	-0.0083	-0.0027	3.67	3.41	0.07	-2.44	-6.24	-2.55
$-ROA$	0.0319	-0.3476	-0.6684	-0.4589	-0.1342	-0.1382	0.59	-1.51	-2.31	-1.88	-1.25	-7.14
Acc	0.0134	0.0302	0.0772	-0.0035	-0.0219	-0.0083	1.36	0.97	1.24	-0.08	-1.88	-3.64
NOA	0.0047	0.0235	0.0026	-0.0201	-0.0064	-0.0022	1.98	3.48	0.30	-2.58	-5.08	-3.08
NS	0.0958	0.2705	0.0506	-0.0663	-0.0133	-0.0213	0.27	1.56	0.73	-2.94	-5.50	-12.90
ι	0.0027	-0.0188	-0.0229	0.0096	-0.0052	-0.0069	3.04	-2.73	-2.85	0.99	-6.93	-11.47
O	-0.0009	-0.0035	-0.0044	-0.0057	-0.0009	-0.0024	-2.43	-3.78	-3.89	-5.48	-2.72	-11.71
D	0.0200	-0.1107	0.0073	-0.0546	-0.0012	-0.0025	0.36	-2.21	0.22	-4.00	-3.73	-7.31

Table 3.3: Impact of Individual Stocks on Portfolio Returns

This table shows average differences between monthly equal-weighted stock returns on portfolios 1 and 5 and their t-statistics. All returns are adjusted for risk using the Fama-French 3-factor model. Portfolios are formed by sorting firms on fourteen anomalous characteristics. The columns correspond to the following cases: (1) – no truncation; (2) – one stock with the highest return is excluded from portfolio 1; (3) – one stock with the lowest return is excluded from portfolio 5; (4) – two stocks with the highest returns are excluded from portfolio 1; (5) – two stocks with the lowest returns are excluded from portfolio 5. To ensure that for all anomalies expected returns decrease with the portfolio number (i.e., portfolio 1 contains stocks with abnormally high returns), the signs of B/M, Mom, and ROA have been inverted. All coefficients are multiplied by 100.

	Returns					t-stats				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
$-B/M$	0.50	0.30	0.38	0.17	0.28	4.08	2.45	3.11	1.42	2.33
S	1.09	0.75	1.03	0.53	0.98	4.94	3.48	4.69	2.49	4.48
$-Mom$	0.47	0.32	0.36	0.21	0.26	2.00	1.34	1.50	0.86	1.09
$IdVol$	0.41	0.25	0.29	0.17	0.19	1.98	1.18	1.38	0.80	0.90
AG	0.71	0.39	0.61	0.20	0.52	6.00	3.61	5.11	1.91	4.39
CI	0.20	-0.09	0.08	-0.28	-0.02	2.66	-1.23	1.04	-4.01	-0.25
I/A	0.54	0.26	0.43	0.08	0.33	6.06	3.04	4.77	0.92	3.73
$-ROA$	0.93	0.71	0.76	0.55	0.63	4.19	3.19	3.40	2.46	2.79
Acc	0.37	0.00	0.19	-0.26	0.04	4.41	-0.03	2.30	-3.27	0.47
NOA	0.70	0.38	0.59	0.19	0.49	5.92	3.52	4.93	1.81	4.13
NS	0.64	0.39	0.48	0.23	0.35	6.85	4.17	5.13	2.43	3.76
ι	0.48	0.32	0.35	0.21	0.24	4.21	2.78	3.02	1.81	2.09
O	0.64	0.49	0.51	0.39	0.41	3.89	2.97	3.12	2.34	2.49
D	0.71	0.57	0.56	0.47	0.43	4.24	3.38	3.33	2.77	2.59

Table 3.4: Characteristics and Stock Returns Within Quintile Portfolios, Size Groups

This table reports slopes and t-statistics from the rank Fama-MacBeth regression of risk-adjusted returns on various anomalous characteristics for microcap stocks (Panel A), small stocks (Panel B), and big stocks (Panel C). The regressions are run within individual quintile portfolios formed on anomaly variables (columns 1 – 5) and for all stocks from the appropriate size group (column All).

Panel A: Microcap Stocks

	Slope						t-stats					
	1	2	3	4	5	All	1	2	3	4	5	All
$-B/M$	0.0000	-0.0018	-0.0065	-0.0129	-0.0274	-0.0445	-0.01	-0.62	-2.40	-4.37	-8.92	-13.87
S	-0.0234	0.0059	0.0057	0.0069	0.0027	0.0178	-7.44	2.38	2.21	2.57	1.05	5.03
$-Mom$	0.0123	-0.0052	-0.0064	-0.0107	-0.0359	-0.0411	3.79	-1.97	-2.42	-4.00	-9.88	-9.86
$IdVol$	0.0047	-0.0144	-0.0130	-0.0204	-0.0372	-0.0734	1.51	-5.40	-5.38	-8.02	-11.08	-19.84
AG	0.0249	0.0133	0.0020	-0.0114	-0.0324	-0.0030	7.59	4.26	0.67	-4.10	-9.84	-1.26
CI	0.0153	0.0007	-0.0019	-0.0079	-0.0216	0.0044	3.16	0.18	-0.46	-1.82	-5.06	2.06
I/A	0.0107	0.0060	-0.0001	-0.0097	-0.0244	-0.0072	3.36	1.94	-0.03	-3.27	-7.26	-3.32
$-ROA$	0.0009	-0.0067	-0.0231	-0.0270	-0.0294	-0.0722	0.23	-1.68	-6.45	-7.10	-7.43	-19.57
Acc	0.0204	0.0036	-0.0007	-0.0041	-0.0261	-0.0042	4.20	0.79	-0.14	-0.88	-5.44	-1.81
NOA	0.0045	0.0034	-0.0003	-0.0061	-0.0231	-0.0025	1.04	1.04	-0.08	-1.84	-5.37	-1.03
NS	-0.0029	-0.0026	-0.0108	-0.0141	-0.0128	-0.0340	-0.71	-0.75	-2.63	-3.16	-3.01	-14.49
ι	0.0015	-0.0094	-0.0121	-0.0124	-0.0141	-0.0458	0.38	-2.28	-3.23	-3.15	-3.92	-14.07
O	-0.0053	-0.0094	-0.0079	-0.0113	-0.0107	-0.0460	-1.84	-3.07	-2.60	-3.87	-3.38	-17.42
D	0.0034	-0.0083	-0.0079	-0.0135	-0.0125	-0.0502	0.61	-1.48	-1.44	-2.41	-2.32	-12.01

Panel B: Small Stocks

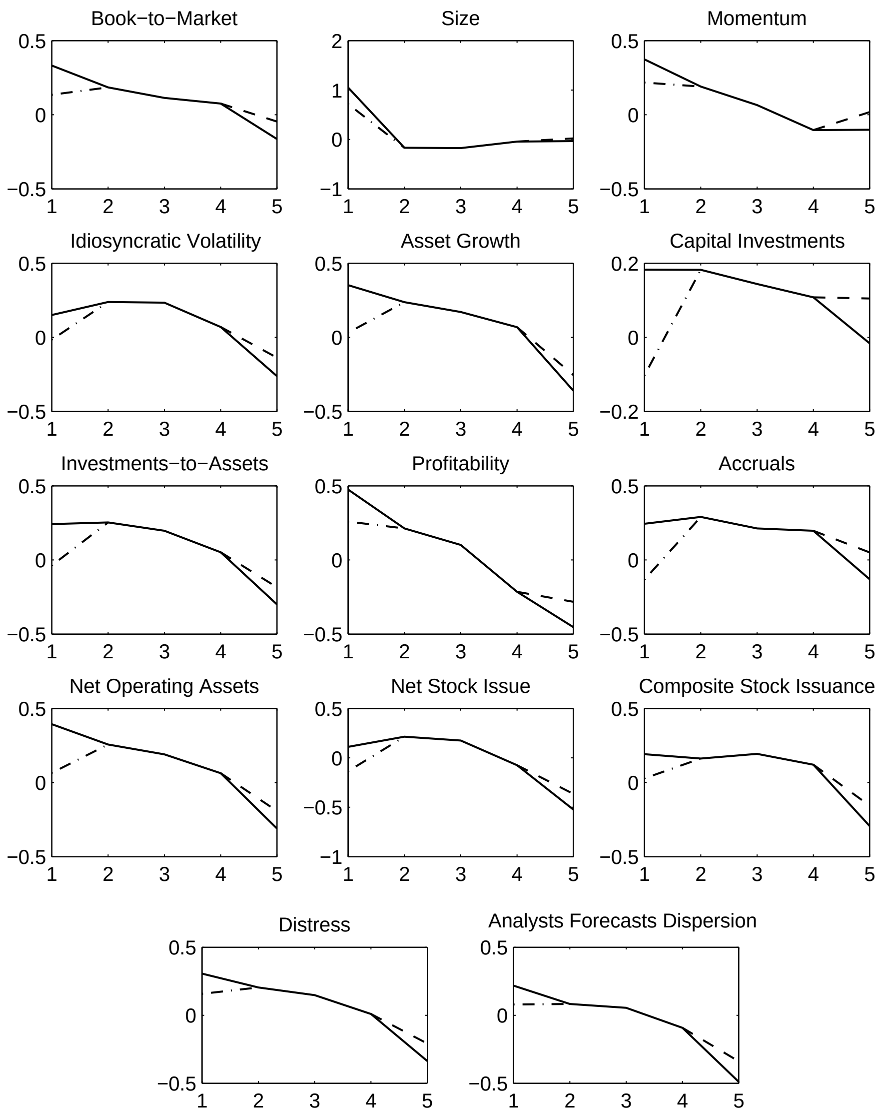
	Slope						t-stats					
	1	2	3	4	5	All	1	2	3	4	5	All
$-B/M$	0.0041	0.0064	0.0034	-0.0055	-0.0102	-0.0163	0.82	1.51	0.75	-1.21	-2.26	-4.73
S	-0.0019	-0.0012	0.0004	0.0070	0.0065	0.0118	-0.45	-0.29	0.12	1.73	1.63	5.31
$-Mom$	0.0160	-0.0012	0.0010	-0.0045	-0.0330	-0.0259	3.21	-0.28	0.23	-1.03	-6.44	-5.18
$IdVol$	0.0064	-0.0067	-0.0122	-0.0137	-0.0466	-0.0497	1.50	-1.63	-2.98	-3.28	-10.56	-12.94
AG	0.0153	0.0015	-0.0018	-0.0144	-0.0191	-0.0068	3.10	0.34	-0.40	-3.40	-4.17	-2.20
CI	0.0180	0.0039	0.0027	0.0004	-0.0108	-0.0031	3.04	0.72	0.51	0.08	-2.02	-1.26
I/A	0.0132	-0.0001	-0.0049	0.0006	-0.0081	-0.0064	2.78	-0.03	-1.09	0.13	-1.63	-2.20
$-ROA$	-0.0015	-0.0088	-0.0081	-0.0132	-0.0314	-0.0423	-0.28	-1.75	-1.53	-2.49	-5.04	-10.92
Acc	0.0268	-0.0090	-0.0126	-0.0029	-0.0245	-0.0040	3.86	-1.32	-1.91	-0.40	-3.49	-1.10
NOA	0.0105	0.0005	0.0036	-0.0014	-0.0101	-0.0052	1.89	0.10	0.69	-0.28	-1.88	-1.66
NS	0.0044	0.0113	0.0062	-0.0119	-0.0192	-0.0134	0.81	2.03	1.15	-2.34	-3.60	-4.38
ι	0.0030	0.0023	-0.0041	-0.0012	-0.0140	-0.0262	0.59	0.49	-0.88	-0.25	-2.73	-7.98
O	-0.0055	-0.0003	-0.0008	-0.0059	-0.0147	-0.0211	-1.07	-0.06	-0.18	-1.27	-2.93	-6.53
D	-0.0011	-0.0011	-0.0044	-0.0046	-0.0161	-0.0344	-0.20	-0.21	-0.90	-0.92	-2.90	-7.61

Table 3.4: (Continued)

Panel C: Big Stocks												
	Slope						t-stats					
	1	2	3	4	5	All	1	2	3	4	5	All
$-B/M$	-0.0057	-0.0038	0.0005	0.0042	0.0027	0.0052	-1.04	-0.92	0.13	1.07	0.60	1.41
S	-0.0003	0.0036	0.0051	0.0043	0.0141	0.0104	-0.09	0.94	1.30	1.11	2.94	4.38
$-Mom$	-0.0041	-0.0066	-0.0054	-0.0043	-0.0219	-0.0228	-0.74	-1.67	-1.38	-1.00	-4.07	-3.74
$IdVol$	0.0065	0.0000	-0.0059	-0.0026	-0.0376	-0.0245	1.46	0.00	-1.68	-0.67	-8.34	-5.93
AG	0.0133	-0.0087	0.0006	-0.0018	-0.0127	0.0023	2.90	-2.17	0.15	-0.43	-2.82	0.68
CI	0.0056	0.0006	-0.0036	0.0000	-0.0146	-0.0003	1.25	0.15	-0.90	0.01	-3.34	-0.11
I/A	0.0061	-0.0081	0.0020	0.0029	-0.0118	0.0005	1.37	-1.96	0.44	0.68	-2.70	0.16
$-ROA$	-0.0049	-0.0082	-0.0028	0.0022	-0.0191	-0.0222	-1.01	-1.74	-0.60	0.45	-3.47	-5.00
Acc	0.0085	0.0032	0.0105	-0.0054	-0.0131	0.0030	1.48	0.56	1.86	-0.98	-2.17	0.82
NOA	0.0005	0.0064	-0.0036	0.0020	-0.0121	-0.0071	0.11	1.44	-0.78	0.42	-2.39	-2.12
NS	-0.0046	-0.0016	0.0024	-0.0103	-0.0078	-0.0103	-1.05	-0.36	0.49	-2.15	-1.49	-3.01
ι	0.0010	-0.0068	-0.0016	-0.0059	-0.0130	-0.0105	0.21	-1.65	-0.38	-1.40	-2.95	-2.92
O	-0.0078	-0.0037	0.0042	-0.0016	-0.0107	-0.0155	-1.55	-0.82	0.89	-0.30	-2.01	-3.44
D	-0.0061	-0.0033	-0.0009	-0.0029	-0.0146	-0.0259	-1.20	-0.63	-0.18	-0.57	-2.30	-4.19

Figure 3.1: Returns on Quintile Portfolios With and Without Stock Truncation

This figure plots average risk-adjusted returns on quintile portfolios formed on various characteristics. The solid line corresponds to returns on portfolios without truncation. The dashed line shows the change in returns on portfolio 5 when one stock with the lowest return is excluded from this portfolio every period. Similarly, the dashed-dotted line shows the change in returns on portfolio 1 when one stock with the highest return is excluded from this portfolio every period. To ensure that for all anomalies expected returns supposedly decrease with the characteristic, the signs of B/M, Mom, and ROA have been inverted.



Chapter 4

Conclusion and Summary

The analysis of asset pricing anomalies is an important step towards understanding the determinants and properties of the cross section of U.S. common stock returns. However, this analysis is complicated by the large variety of firm characteristics that appear to predict expected returns. In this dissertation we study both the time series and cross sectional properties of fourteen previously documented anomalies. We find that for most firm characteristics, their relations with future stock returns are similar in exhibiting short term time series persistence and in being sensitive to extreme observations in the cross section. We also uncover a common component from all characteristics capturing the information about future returns by applying a simple and powerful procedure. Overall, our findings suggest that characteristic-return predictability may be influenced by the same market forces and originate from common economic sources. Specifically, we offer some evidence that persistence may be attributed to flow-driven trading by mutual funds.

We study the time series performance persistence in strategies based on asset pricing anomalies in the first chapter. Based on prior annual strategy returns, we find significant continuation in the strategy performance for up to four subsequent months. The persistence of strategies can be isolated in new trading strategies, which earn on average 4.5% annually. To test the role of mutual fund trading in the strategy performance persistence, we compute a measure of expected price pressure based on the mutual fund prior performance and holdings. Then, we show that it significantly reduces the predictive power of past strategy returns. This finding implies that the flow-driven trading is at least partially responsible for the observed persistence in the returns of strategies. In addition, 13F institutions trade in the same direction as mutual funds and increase their holdings of strategies following their positive prior performance, possibly contributing to the persistence. Overall, these results suggest that the behavior of intermediaries has a similarly significant effect on the dynamics of many asset pricing anomalies.

An important question is whether some institutions exploit the vulnerability of funds to predictable flow shocks. Shive and Yun (2013) provide evidence of hedge funds front running mutual funds by predicting their flow-driven trades. In future research it would be interesting to study whether hedge funds are able to target specific mutual funds which follow a particular strategy.

We suggest a novel method to combine the return-related information contained in firm characteristics in chapter 2. This aggregation makes it possible to build new characteristics (filtered expected returns) whose sorts produce abnormal returns that exceed those produced by individual anomalies. This result implies that characteristics contain a common component related to future stock returns. The performance persistence of strategies based on this component may help explain the systematic persistence of other characteristics.

While we construct only two types of filtered expected returns, other types may be of interest. For example, using the HCF it is possible to construct a new characteristic that would encompass the information from several value/growth indicators such as the book-to-market ratio, the price-earnings ratio, the cash flows-to-price ratio, and the dividend-price ratio. Even though the book-to-market ratio tends to eliminate the statistical significance of other indicators in joint regressions (Fama and French, 1992), they still may be useful in our framework. In a recent paper, Gerakos and Linnainmaa (2013) argue that the pricing ability of the book-to-market ratio is due mostly to the changes in the market value of equity. They conclude that the five-year change in the equity value is a better measure of firm value. This new value signal can also be easily incorporated into our framework.

Although our framework and the HCF estimator are developed in the context of aggregating information about expected returns, they may have much broader applicability. Conceptually, we propose a general way to uncover cross-sectional attributes of multiple objects having a large number of signals which contain information about these attributes. For example, it may be interesting to aggregate various characteristics of mutual fund or hedge fund managers that are known to be related to their skill and may contain some information about their future performance. In accounting, our approach can be used for forecasting earnings by combining a large number of their predictors based on the fundamentals.

We explore the monotonicity of the cross sectional relation between firm characteristics and stock returns in the last chapter. We find that the nature of this relation is different for stocks with high and low characteristics. For stocks with presumably low returns, all anomalies except size are very robust and observed in various size groups. For stocks with presumably high returns, many anomalies are driven by individual influential stocks and the relation between the characteristic and returns changes its sign when the impact of such stocks is mitigated. This means that for the majority of stocks such anomalies are non-monotonic.

It should be emphasized that our analysis neither casts doubt on the existence of anomalies nor suggests that they cannot be exploited by practitioners. An arbitrager who buys an underpriced portfolio and sells an overpriced portfolio cares about the difference in expected returns, but not whether this difference is produced by all stocks in the portfolios or a few stocks with extremely high or low returns. Hence, while returns of persistence strategies and aggregate anomaly may be sensitive to extreme observations considered in previous chapters, they both represent relevant findings. The discovered non-monotonicity of many anomalies is mostly important from the theoretical point of view. It challenges the existing rational and behavioral explanations of anomalies predicting a monotonic relation between characteristics and returns and call for new theories that are able to explain the discovered sensitivity to extreme observations.

Appendix

The Appendix provides the definitions of all considered characteristics.

Size (S). Following Fama and French (2008), size is equal to the market value of equity $ME = PRC * SHROUT$, where CRSP PRC is the stock price, and CRSP $SHROUT$ is the number of shares outstanding.

Book-to-Market (B/M). Following Fama and French (2008),

$$B/M = \frac{BE}{ME} = \frac{AT - LT + TXDITC - PS}{PRC * SHROUT},$$

where BE is the book value of equity, and ME is the market value of equity. Compustat AT is the total assets, Compustat LT is the total liabilities, Compustat $TXDITC$ is deferred taxes and investment tax credit, and PS is the preferred stock value. Depending on the availability, PS is approximated by the liquidating value Compustat $PSTKL$, redemption value Compustat $PSTKRV$, or carrying value Compustat $PSTK$ in this order of priority. CRSP PRC is the stock price, and CRSP $SHROUT$ is the number of shares outstanding. ME is computed at the end of December of calendar year $t-1$ and together with BE is updated annually at the end of June of the current year t.

Momentum (Mom). Following Jegadeesh and Titman (1993),

$$Mom_t = \prod_{s=t-13}^{t-2} (1 + RET_s),$$

where CRSP RET_s is the stock return in month s. Month $t-1$ is skipped to control for the Jegadeesh (1990) and Lehmann (1990) short-term reversal.

Total Asset Growth (AG). Following Cooper, Gulen, and Schill (2008),

$$AG = \frac{AT_t - AT_{t-1}}{AT_{t-1}},$$

where Compustat AT is the total assets.

Abnormal Capital Investments (CI). Following Titman, Wei, and Xie (2004),

$$CI = \frac{CE_t}{(CE_{t-1} + CE_{t-2} + CE_{t-3})/3} - 1,$$

where $CE = \frac{CAPX}{SALE}$, Compustat $CAPX$ is the capital expenditures, and Compustat $SALE$ is sales.

Investments-to-Assets Ratio (I/A). Following Lyandres, Sun, and Zhang (2008),

$$I/A = \frac{INVT_t - INVT_{t-1} + PPEGT_t - PPEGT_{t-1}}{AT_{t-1}},$$

where Compustat $INVT$ is the inventories, Compustat $PPEGT$ is gross property, plant, and equipment, and Compustat AT is the total assets.

Net Stock Issues (NS). Following Fama and French (2008),

$$NS = \log\left(\frac{SASO_t}{SASO_{t-1}}\right),$$

where the split-adjusted shares outstanding $SASO = CSHO * AJEX$, Compustat $CSHO$ is the common shares outstanding, and Compustat $AJEX$ is the cumulative factor to adjust shares.

Composite Stock Issuance (ι). Following Daniel and Titman (2006),

$$\iota = \log\left(\frac{ME_t}{ME_{t-5}}\right) - r(t-5,t),$$

where the market equity $ME = PRC * SHROUT$ at the end of December of year t, CRSP PRC is the stock price, and CRSP $SHROUT$ is the number of shares outstanding. $r(t-5,t)$ is the cumulative log return over the previous five years.

Accruals (Acc). Following Sloan (1996),

$$Acc = \frac{(\Delta ACT_t - \Delta CHE_t) - (\Delta LCT_t - \Delta DLC_t - \Delta TXP_t) - DP_t}{AT_{t-1}},$$

where Compustat ACT is the total current assets, Compustat CHE is cash and short-term investments, Compustat LCT is the total current liabilities, Compustat DLC is debt in current liabilities, Compustat TXP is income taxes payable, Compustat DP is depreciation and amortization, and Compustat AT is the total assets. $\Delta X_t = X_t - X_{t-1}$.

Net Operating Assets (NOA). Following Hirshleifer, Hou, Teoh, and Zhang (2004),

$$NOA = \frac{\text{Operating Assets}_t - \text{Operating Liabilities}_t}{AT_{t-1}},$$

where

$$\text{Operating Assets}_t = AT_t - CHE_t,$$

$$\text{Operating Liabilities}_t = AT_t - DLC_t - DLTT_t - MIB_t - PSTK_t - CEQ_t.$$

Compustat AT is the total assets, Compustat CHE is cash and short-term investments, Compustat DLC is debt in current liabilities, Compustat $DLTT$ is the total long term debt, MIB is the minority interest, $PSTK$ is the total preferred stock, and CEQ is the total common equity.

Return on Assets (ROA). Following Wang and Yu (2012),

$$ROA = \frac{IBQ_t}{ATQ_{t-1}},$$

where Compustat IBQ is income before extraordinary items, and Compustat ATQ is the total assets.

Idiosyncratic Volatility ($IdVol$). Following Ang, Hodrick, Xing, and Zhang (2006), $IdVol$ is the standard deviation of the residual ϵ_t^d from the daily time-series regression in month t

$$RET_t^d - RF_t^d = \beta_t^{MKTRF} MKTRF_t^d + \beta_t^{SMB} SMB_t^d + \beta_t^{HML} HML_t^d + \beta_t^{UMD} UMD_t^d + \epsilon_t^d,$$

where RET_t^d and RF_t^d are the daily stock return and risk-free rate, respectively. $MKTRF_t^d$, SMB_t^d, and HML_t^d are daily Fama and French (1993) factors, and UMD_t^d is the daily Carhart (1997) momentum factor.

Ohlson's O-score (O). Following Ohlson (1980)

$$\begin{aligned} O\text{-}Score_t &= -1.32 - 0.407 \log(Size_t) + 6.03\, TLTA_t - 1.43\, WCTA_t + 0.076\, CLCA_t \\ &- 1.72\, OENEG_t - 2.37\, NITA_t - 1.83\, FUTL_t + 0.285\, INTWO_t - 0.521\, CHIN_t, \end{aligned}$$

where $Size_t = ATQ_t/CPI_t$ is total assets adjusted for inflation, where Compustat ATQ_t is the total assets, and CPI_t is the consumer price index from the U.S. Bureau of Labor Statistics. $TLTA_t = (DLCQ_t + DLTTQ_t)/ATQ_{t-1}$ is the total liabilities divided by lagged total assets, where Compustat $DLCQ_t$ is debt in current liabilities, Compustat $DLTTQ_t$ is total long term debt, and Compustat ATQ_t is total assets. $WCTA_t = (ACTQ_t - LCTQ_t)/ATQ_{t-1}$ is working capital divided by lagged total assets, where Compustat $ACTQ_t$ is current assets, Compustat $LCTQ_t$ is current liabilities, Compustat ATQ_t is total assets. $CLCA_t = LCTQ_t/ACTQ_t$ is current liabilities divided by current assets, where Compustat $LCTQ_t$ is current liabilities, and Compustat $ACTQ_t$ is current assets. $OENEG_t$ is one if total liabilities exceeds total assets and zero otherwise, where Compustat LTQ_t is total liabilities, and Compustat ATQ_t is total assets. $NITA_t = NIQ_t/ATQ_{t-1}$ is net income divided by lagged total assets, where Compustat NIQ_t is net income, and Compustat ATQ_t is total assets. $FULT_t = PIQ_t/LTQ_{t-1}$ is funds provided by operations divided by lagged total liabilities, where Compustat PIQ_t is pretax income, and Compustat LTQ_t is total liabilities. $INTOWO_t$ is one if net income was negative for the last two years and zero otherwise, where Compustat NIQ_t is net income. $CHIN_t = (NIQ_t - NIQ_{t-1})/(|NIQ_t| + |NIQ_{t-1}|)$ is level adjusted change in net income, where Compustat NIQ_t is net income.

Dispersion in Analysts' Earnings Forecasts (D). Following Diether, Malloy, and Scherbina (2002),

$$D = \frac{\sigma(e_t)}{\overline{e_t}},$$

where $\overline{e_t}$ and $\sigma(e_t)$ are the average and standard deviation of I/B/E/S next quarter analysts' earnings forecast, respectively.

Bibliography

Abarbanell, Jeffery S., and Brian J. Bushee, 1998, Abnormal returns to a fundamental analysis strategy, *The Accounting Review* 73, 19–45.

Adrian, Tobias, and Francesco Franzoni, 2009, Learning about beta: Time-varying factor loadings, expected returns, and the conditional CAPM, *Journal of Empirical Finance* 16, 537–556.

Ahn, Dong-Hyun, Jennifer Conrad, and Robert F. Dittmar, 2009, Basis assets, *Review of Financial Studies* 22, 5133–5174.

Ali, Ashiq, Lee-Seok Hwang, and Mark A. Trombley, 2003, Arbitrage risk and the book-to-market anomaly, *Journal of Financial Economics* 69, 355–373.

Anderson, Christopher W., and Luis Garcia-Feijóo, 2006, Empirical evidence on capital investment, growth options, and security returns, *Journal of Finance* 61, 171–194.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Ang, Andrew, and Dennis Kristensen, 2012, Testing conditional factor models, *Journal of Financial Economics* 106, 132–156.

Ang, Andrew, Jun Liu, and Krista Schwarz, 2008, Using stocks or portfolios in tests of factor models, Unpublished manuscript.

Armstrong, Christopher S., Snehal Banerjee, and Carlos Corona, 2013, Factor-loading uncertainty and expected returns, *Review of Financial Studies* 26, 158–207.

Avramov, Doron, Scott Cederburg, and Satadru Hore, 2010, Cross-sectional asset pricing puzzles: An equilibrium perspective, Unpublished manuscript.

Avramov, Doron, and Tarun Chordia, 2006, Asset pricing models and financial market anomalies, *Review of Financial Studies* 19, 1001–1040.

——— , Gergana Jostova, and Alexander Philipov, 2010, Anomalies and financial distress, Unpublished manuscript.

Babenko, Ilona, Oliver Boguth, and Yuri Tserlukevich, 2013, Can idiosyncratic cash flow shocks explain asset pricing anomalies?, Working Paper, Arizona State University.

Bai, Jushan, 2003, Inferential theory for factor models of large dimensions, *Econometrica* 71, 135–171.

Bali, Turan G., and Nusret Cakici, 2008, Idiosyncratic volatility and the cross-section of expected returns, *Journal of Financial and Quantitative Analysis* 43, 29–58.

Balke, Nathan S., and Mark E. Wohar, 2002, Low-frequency movements in stock prices: A state-space decomposition, *Review of Economics and Statistics* 84, 649–667.

Banz, Ralf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3–18.

Belloni, Alexandre, Victor Chernozhukov, and Chris Hansen, 2011, Inference for high-dimensional sparse econometric models, *10th World Congress of Econometric Society, Advances in Economics and Econometrics* pp. 245–295.

Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1607.

Black, Fischer, Michael C. Jensen, and Myron Scholes, 1972, The capital asset pricing model: Some empirical tests, in Michael C. Jensen, ed.: *Studies in the Theory of Capital Markets* (Praeger Publishers Inc.: New York).

Brandt, Michael W., and Qiang Kang, 2004, On the relationship between the conditional mean and volatility of stock returns: A latent VAR approach, *Journal of Financial Economics* 72, 217–257.

Brandt, Michael W., Pedro Santa-Clara, and Rossen Valkanov, 2009, Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns, *Review of Financial Studies* 22, 3411–3447.

Brennan, Michael J., Tarun Chordia, and Avanidhar Subrahmanyam, 1998, Alternative factor specifications, security characteristics, and the cross-section of expected stock returns, *Journal of Financial Economics* 49, 345–373.

Cao, Jie, and Bing Han, 2013, Idiosyncratic risk, costly arbitrage, and the cross-section of stock returns, Working Paper, UT Austin.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577–2603.

Chan, Louis K. C., Stephen G. Dimmock, and Josef Lakonishok, 2009, Benchmarking money manager performance: Issues and evidence, *Review of Financial Studies* 22, 4553–4599.

Chen, Hsiu-Lang, and Werner De Bondt, 2004, Style momentum within the S&P-500 index, *Journal of Empirical Finance* 11, 483 – 507.

Chen, Long, Robert Novy-Marx, and Lu Zhang, 2010, An alternative three-factor model, Unpublished manuscript.

Cheng, CS Agnes, and Wayne B Thomas, 2006, Evidence of the abnormal accrual anomaly incremental to operating cash flows, *The Accounting Review* 81, 1151–1167.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, pp. 1167–1200.

Chordia, Tarun, Avanidhar Subrahmanyam, and Qing Tong, 2013, Trends in the cross-section of expected stock returns, Working Paper.

Cochrane, John H., 1996, A cross-sectional test of an investment-based asset pricing model, *Journal of Political Economy* 104, 572–621.

——— , 2005, *Asset pricing* (Princeton University Press: Princeton, NJ).

——— , 2011, Presidential address: Discount rates, *Journal of Finance* 66, 1047–1108.

Conrad, Jennifer, and Gautam Kaul, 1988, Time-variation in expected returns, *Journal of Business* 61, 409–425.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609–1651.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479 – 512.

Cremers, Martijn, and Ankur Pareek, 2010, Institutional investors' investment durations and stock return anomalies: Momentum, reversal, accruals, share issuance and r&d increases, Unpublished manuscript.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *The Journal of Finance* 52, 1035–1058.

Daniel, Kent, and Sheridan Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, *Journal of Finance* 52, 1–33.

———, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605–1643.

Desai, Hemang, Shivaram Rajgopal, and Mohan Venkatachalam, 2004, Value-glamour and accruals mispricing: One anomaly or two?, *The Accounting Review* 79, 355–385.

Dichev, Ilia D., 1998, Is the risk of bankruptcy a systematic risk?, *The Journal of Finance* 53, 1131–1147.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113–2141.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

———, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

———, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

———, 2006, Profitability, investment and average returns, *Journal of Financial Economics* 82, 491–518.

———, 2007, Migration, *Financial Analysts Journal* 63, 48–58.

———, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653–1678.

——— , 2012, Size, value, and momentum in international stock returns, *Journal of Financial Economics* 105, 457–472.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Ferson, Wayne E., 1990, Are the latent variables in time-varying expected returns compensation for consumption risk?, *Journal of Finance* 45, 397–429.

——— , Stephen R. Foerster, and Donald B. Keim, 1993, General tests of latent variable models and mean-variance spanning, *Journal of Finance* 48, 131–156.

Ferson, Wayne E., and Campbell R. Harvey, 1991, The variation of economic risk premiums, *Journal of Political Economy* 99, 385–415.

Frazzini, Andrea, and Owen A. Lamont, 2008, Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics* 88, 299 – 322.

Fu, Fangjian, and Wei Yang, 2011, Size and return: A new perspective, Unpublished manuscript.

Gerakos, Joseph, and Juhani T. Linnainmaa, 2013, The unpriced side of value, Working Paper, University of Chicago.

Gibbons, Michael R., and Wayne Ferson, 1985, Testing asset pricing models with changing expectations and an unobservable market portfolio, *Journal of Financial Economics* 14, 217–236.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121–1152.

Gomes, Joao, Leonid Kogan, and Lu Zhang, 2003, Equilibrium cross section of returns, *Journal of Political Economy* 111, 693–732.

Green, Jeremiah, John RM Hand, and Mark T Soliman, 2011, Going, going, gone? The apparent demise of the accruals anomaly, *Management Science* 57, 797–816.

Green, Jeremiah, John R. M. Hand, and X. Frank Zhang, 2013, The supraview of return predictive signals, *Review of Accounting Studies* 18, 692–730.

——— , 2014, The remarkable multidimensionality in the cross-section of expected U.S. stock returns, Working Paper.

Griffin, John M., and Michael L. Lemmon, 2002, Book–to–market equity, distress risk, and stock returns, *Journal of Finance* 57, 2317–2336.

Hájek, Jaroslav, Zbynek Šidák, and Pranab K. Sen, 1999, *Theory of rank tests* (Academic Press: New York, NY).

Hamilton, James D., 1985, Uncovering financial market expectations of inflation, *Journal of Political Economy* 93, 1224–1241.

Hand, John, Jeremiah Green, and X. Frank Zhang, 2012, The supraview of return predictive signals, *Working Paper.*

Hanna, J. Douglas, and Mark J. Ready, 2005, Profitable predictability in the cross section of stock returns, *Journal of Financial Economics* 78, 463–505.

Hansen, Lars Peter, and Scott F. Richard, 1987, The role of conditioning information in deducing testable restrictions implied by dynamic asset pricing models, *Econometrica* 55, 587–613.

Harvey, Campbell R., 1989, Time-varying conditional covariances in tests of asset pricing models, *Journal of Financial Economics* 24, 289–317.

——— , Yan Liu, and Heqing Zhu, 2013, . . . and the cross-section of expected returns, Working Paper.

Haugen, Robert A., and Nardin L. Baker, 1996, Commonality in the determinants of expected stock returns, *Journal of Financial Economics* 41, 401 – 439.

Hirshleifer, David, Kewei Hou, Siew Hong Teoh, and Yinglei Zhang, 2004, Do investors overvalue firms with bloated balance sheets?, *Journal of Accounting and Economics* 38, 297–331.

Hogg, Robert V., 1979, Statistical robustness: One view of its use in applications today, *American Statistician* 33, 108–115.

Holland, Paul W., and Roy E. Welsch, 1977, Robust regression using iteratively reweighted least-squares, *Communications in Statistics: Theory and Methods* 6, 813–827.

Horowitz, Joel L., Tim Loughran, and N.E. Savin, 2000, Three analyses of the firm size premium, *Journal of Empirical Finance* 7, 143–153.

Hou, Kewei, Chen Xue, and Lu Zhang, 2012, Digesting anomalies: An investment approach, Working Paper.

Huang, Jian, Joel L Horowitz, and Shuangge Ma, 2008, Asymptotic properties of bridge estimators in sparse high-dimensional regression models, *Annals of Statistics* 36, 587–613.

Huber, Peter J., 1981, *Robust statistics* (John Wiley & Sons, Inc.: New York).

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *The Journal of Finance* 45, 881–898.

———, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Jiang, Hao, 2010, Institutional investors, intangible information, and the book-to-market effect, *Journal of Financial Economics* 96, 98–126.

Johnson, Timothy C., 2004, Forecast dispersion and the cross section of expected returns, *Journal of Finance* 59, 1957–1978.

Keim, Donald B., 1983, Size-related anomalies and stock return seasonality, *Journal of Financial Economics* 12, 13–32.

Kelly, Bryan, and Seth Pruitt, 2012a, Market expectations in the cross section of present values, *Journal of Finance* 68, 1721–1756.

———, 2012b, The three-pass regression filter: A new approach to forecasting using many predictors, Working Paper, University of Chicago.

Keloharju, Matti, Juhani T. Linnainmaa, and Peter Nyberg, 2013, Common factors in stock market seasonalities, Working Paper, University of Chicago.

Knez, Peter J., and Mark J. Ready, 1997, On the robustness of size and book-to-market in cross-sectional regressions, *Journal of Finance* 52, 1355–1382.

Kogan, Leonid, and Mary Tian, 2012, Firm characteristics and empirical factor models: A data-mining experiment, Working Paper, Board of Governors of the Federal Reserve System.

Kraft, Arthur, Andrew J. Leone, and Charles Wasley, 2006, An analysis of the theories and explanations offered for the mispricing of accruals and accrual components, *Journal of Accounting Research* 44, 297–339.

Lam, F.Y. Eric C., and K.C. John Wei, 2011, Limits-to-arbitrage, investment frictions, and the asset growth anomaly, *Journal of Financial Economics* 102, 127–149.

Lehmann, Bruce N., 1990, Fads, martingales, and market efficiency, *The Quarterly Journal of Economics* 105, 1–28.

Lewellen, Jonathan, 2002, Momentum and autocorrelation in stock returns, *Review of Financial Studies* 15, 533–564.

——— , 2013, The cross section of expected stock returns, Working Paper, Dartmouth College.

——— , and Stefan Nagel, 2006, The conditional CAPM does not explain asset-pricing anomalies, *Journal of Financial Economics* 82, 289–314.

Li, Dongmei, and Lu Zhang, 2010, Does q-theory with investment frictions explain anomalies in the cross section of returns?, *Journal of Financial Economics* 98, 297–314.

Li, Erica X. N., Dmitry Livdan, and Lu Zhang, 2009, Anomalies, *Review of Financial Studies* 22, 4301–4334.

Li, Ker-Chau, 1991, Sliced inverse regression for dimension reduction, *Journal of the American Statistical Association* 86, 316–327.

Li, Yan, and Liyan Yang, 2011, Testing conditional factor models: A nonparametric approach, *Journal of Empirical Finance* 18, 972–992.

Lin, Xiaoji, and Lu Zhang, 2012, The investment manifesto, *Journal of Monetary Economics* 60, 351–366.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *The Review of Economics and Statistics* 47, 13–37.

Lipson, Marc L., Sandra Mortal, and Michael J. Schill, 2012, On the scope and drivers of the asset growth effect, *Journal of Financial and Quantitative Analysis* 46, 1651–1682.

Livdan, Dmitry, Horacio Sapriza, and Lu Zhang, 2009, Financially constrained stock returns, *Journal of Finance* 64, 1827–1862.

Lou, Dong, 2012, A flow-based explanation for return predictability, *Review of Financial Studies* 25, 3457–3489.

Lyandres, Evgeny, Le Sun, and Lu Zhang, 2008, The new issues puzzle: Testing the investment-based explanation, *Review of Financial Studies* 21, 2825–2855.

Mashruwala, Christina, Shivaram Rajgopal, and Terry Shevlin, 2006, Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs, *Journal of Accounting and Economics* 42, 3–33.

McLean, R. David, and Jeffrey Pontiff, 2013, Does academic research destroy stock return predictability?, *Unpublished working paper. Boston College.*

Mohanram, Partha S., 2005, Separating winners from losers among low book-to-market stocks using financial statement analysis, *Review of Accounting Studies* 10, 133–170.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum?, *The Journal of Finance* 54, 1249–1290.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Ohlson, James A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* 18, 109–131.

Ou, Jane A., and Stephen H. Penman, 1989, Financial statement analysis and the prediction of stock returns, *Journal of Accounting and Economics* 11, 295–329.

Pástor, Ľubos, and Robert F. Stambaugh, 2009, Predictive systems: Living with imperfect predictors, *Journal of Finance* 64, 1583–1628.

Patton, Andrew J., and Allan Timmermann, 2010, Monotonicity in asset returns: New tests with applications to the term structure, the CAPM, and portfolio sorts, *Journal of Financial Economics* 98, 605–625.

Petersen, Mitchell A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *Review of Financial Studies* 22, 435–480.

Piatti, Ilaria, and Fabio Trojani, 2012, Predictable risks and predictive regression in present-value models, Working Paper.

Piotroski, Joseph D., 2000, Value investing: The use of historical financial statement information to separate winners from losers, *Journal of Accounting Research* 38, 1–41.

Pontiff, Jeffrey, 1996, Costly arbitrage: Evidence from closed-end funds, *Quarterly Journal of Economics* 111, 1135–1151.

——— , 2006, Costly arbitrage and the myth of idiosyncratic risk, *Journal of Accounting and Economics* 42, 35–52.

———, and Artemiza Woodgate, 2008, Share issuance and cross-sectional returns, *Journal of Finance* 63, 921–945.

Reinganum, Marc R., 1981, Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values, *Journal of Financial Economics* 9, 19–46.

———, 1983, The anomalous stock market behavior of small firms in january: Empirical tests for tax-loss selling effects, *Journal of Financial Economics* 12, 89 – 104.

Roll, Richard, 1977, A critique of the asset pricing theory's tests. Part I: On past and potential testability of the theory, *Journal of Financial Economics* 4, 129–176.

Romero, Alberto, 2012, Sharpe ratio volatility: Is it a puzzle?, Working Paper.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985, Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9–16.

Rousseeuw, Peter J., and Annick M. LeRoy, 1987, *Robust regression and outlier detection* (Wiley: New York).

Rytchkov, Oleg, 2010, Expected returns on value, growth, and HML, *Journal of Empirical Finance* 17, 552–565.

———, 2012, Filtering out expected dividends and expected returns, *Quarterly Journal of Finance* 2.

Schwert, G William, 2003, Anomalies and market efficiency, in G. Constantinides, M. Harris, and R. M. Stulz, ed.: *Handbook of the Economics of Finance* . pp. 939–974 (North-Holland: Amsterdam, Netherlands).

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *The Journal of Finance* 19, 425–442.

Shive, Sophie, and Hayong Yun, 2013, Are mutual funds sitting ducks?, *Journal of Financial Economics* 107, 220 – 237.

Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *The Journal of Finance* 53, 1589–1622.

Sloan, R., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *The Accounting Review* 71, 289–315.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288 – 302.

——— , 2013, Arbitrage asymmetry and the idiosyncratic volatility puzzle, Working Paper.

Stock, James H., and Mark W. Watson, 2006, Forecasting with many predictors, in Graham Elliot, Clive W.J. Granger, and Allan Timmermann, ed.: *Handbook of economic forecasting* vol. 1 . chap. 10, pp. 515–554 (Elsevier).

Street, James O., Raymond J. Carroll, and David Ruppert, 1988, A note on computing robust regression estimates via iteratively reweighted least squares, *American Statistician* 42, 152–154.

Subrahmanyam, Avanidhar, 2010, The cross-section of expected stock returns: What have we learnt from the past twenty-five years of research?, *European Financial Management* 16, 27–42.

Titman, Sheridan, K. C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of Financial and Quantitative Analysis* 39, 677–700.

van Binsbergen, Jules H., and Ralph S. J. Koijen, 2010, Predictive regressions: A present-value approach, *Journal of Finance* 65, 1439–1471.

Vassalou, Maria, and Yuhang Xing, 2004, Default risk in equity returns, *Journal of Finance* 59, 831–868.

Vinzi, Vincenzo Esposito, Wynne W. Chin, Jörg Henseler, and Huiwen Wang, 2010, *Handbook of Partial Least Squares: Concepts, Methods and Applications* (Springer).

Wahal, Sunil, and M. Deniz Yavuz, 2013, Style investing, comovement and return predictability, *Journal of Financial Economics* 107, 136 – 154.

Wang, Huijun, and Jianfeng Yu, 2012, Dissecting the profitability premium, Unpublished manuscript.

Wermers, Russ, 2004, Is money really smart? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence, *Unpublished manuscript*.

Wu, Jin Ginger, Lu Zhang, and X. Frank Zhang, 2010, The q-theory approach to understanding the accrual anomaly, *Journal of Accounting Research* 48, 177–223.

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.