Essays in Empirical Finance

by

Kin Wai Chan

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Author ....
Sloan School of Management
May 18, 2004

Certified by ....
Jiang Wang
Nanyang Technological University Professor of Finance
Thesis Supervisor

Accepted by ....
Birger Wernerfelt
J. C. Penny Professor of Management Science
Chair of PhD Committee

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Abstract

This thesis consists of three essays on various topics in empirical financial studies.

In Chapter 1, I study the profitability of momentum trading from evidence in mutual fund performance. I find that mutual funds that exhibit a strong momentum trading pattern earn significant risk-adjusted returns relative to Fama-French 3-Factor model, and tend to outperform other funds that do not momentum trade as much. The superior performance of these funds persists across different investment objectives as well as after controlling for fund size or fund flow. The robustness of my results suggests that momentum profits are real and momentum trading has the potential to improve a funds return. However, I also find relatively weak evidence of persistence in mutual funds trading styles. In particular, most funds do not seem to maintain their aggressiveness in momentum trading from one year to another. The findings indicate that momentum trading patterns observed in these mutual funds are more likely to be caused by random chances than the managers intention to capture momentum profits. Results in this paper also favor the under-reaction hypothesis as explanation for momentum in stock returns.

Chapter 2 is a joint work with Charles Chang and Albert Wang. We explore how financial firms trade on in-house, US equity recommendations. We match the quarterly trades of financial firms with their own recommendations and document their trading patterns before, in the same quarter as, and after issuing recommendations. We find that net trade is more positive around upgrades than downgrades for all periods, and these relations are particularly significant in the quarter of and quarter immediately after the recommendation change. These empirical relations suggest that by and large, financial firms actually do "put their money where their mouths are".

Previous studies have found that the execution costs and volatilities of the securities traded in the auction market are generally lower than those of the comparable securities traded in the dealer market. However, due to the difficulty of identifying perfectly matched pairs of stocks, the conclusions drawn from those studies are always subject to the criticism of inadequate control for individual stock characteristics. In Chapter 3, I repeat previous studies of execution costs and volatilities using a sample of stocks that is chosen specifically to address this criticism. The sample is made up of stocks that are listed on both the NASDAQ and AMEX in 2003. Consistent with existing literature, I find that the volatilities are generally higher on the NASDAQ than on the AMEX. On the other hand, the transaction costs are higher on the AMEX, which is at odds with previous empirical studies. The difference in execution costs and volatilities can be partially explained by their different sensitivities to various stock characteristics in the two different markets.

Thesis Supervisor: Jiang Wang
Title: Nanyang Technological University Professor of Finance

Thesis Committee: S. P. Kothari
Title: Gordon Y Billard Professor of Management

Thesis Committee: Andrew Lo
Title: Harris and Harris Group Professor of Finance

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As anyone who has undertaken a Ph.D. understands, there seems an eternity of stressful time spent studying for generals and searching for research ideas. The company of friends and classmates made this time bearable, and even enjoyable. I especially thank Albert Wang, Ioanid Rosu, Joon Chae, Sergey Iskov, Calvin Yuen, Fai Tong Chung, Sean Kwok, Teresa Tam, and the basketball team I play with every Thursday and Sunday.

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I dedicate this thesis to my brother, Kin Hung Chan, who is probably still hung over with joy from the news that I will finally complete my degree.

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Chapter 1

On Profitability of Momentum Trading: Evidence from Mutual Fund Performance

1.1 Introduction

It has been well-documented in the finance literature that stock returns follow a momentum pattern.[1] But can the investment community benefit from this predictable pattern? The answer to this question is not straightforward as there are numerous reasons to believe momentum trading may not be a feasible investment strategy in

[1]Jegadeesh and Titman [1993] find that past winner that have performed well over the last three to twelve months continue to outperform past loser stocks in the following year. Such momentum patterns in stock returns remain strong and significant under different models of risk-adjustment and are able to survive out-of-sample tests [Jegadeesh and Titman, 2001]. Lewellen [2002] observes momentum profits in portfolios constructed on size and book-to-market while Moskowitz and Grinblatt [1999] find a strong and prevalent momentum effect in industry portfolios. Rouwenhorst [1998] studies international stock returns and discovers similar pattern of return continuation. Findings in other studies also show that momentum effect is robust and ubiquitous. Chui, Titman, and Wei [2000] document that, with the notable exception of Japan and Korea, momentum profits are also observed in Asian countries. Rouwenhorst [1999] find that momentum strategies earn significant profits on average in a sample of 20 emerging markets. Asness, Liew, and Stevens [1997] study momentum in country returns and report similar profitability. Other momentum literatures explore the relation between momentum profits and financial variables. Chan, Jegadeesh, and Lakonishok [1996] examine the relation between earnings and return momentum. Asness [1997], Lee and Swaminathan [2000], and Hong, Lim, and Stein [2000] study the interaction of momentum with book-to-market ratios, trading volume and analyst coverage respectively.

practice. Some recent studies argue that trading costs are substantial in implementing the momentum strategy. Lesmond, Schill, and Zhou [2004] find that the strategy requires large transaction costs and the momentum profits quickly diminish after taking those friction effects into account. Chen, Stanzl, and Watanabe [2002] use a non-linear price-impact function to assess the magnitude of trading costs and find that the fund sizes need to be impractically small in order for the momentum anomaly to remain profitable. Keim [2003] studies the trading costs conditional on prior stock price movements and reaches similar conclusion. However, there are also articles in support of profitability of momentum trading. Bushee and Raedy [2003] and Korajczyk and Sadka [2004] find that momentum strategies continue to generate positive abnormal returns even in the presence of price impact and other constraints.

Besides execution issues, source of momentum profits is another reason why momentum trading may not be profitable. Some researchers attribute the source of momentum profits to overzealous investors over-reacting and driving the stock prices beyond the fundamental values. The positive-feedback-trader model proposed by De Long, Shleifer, Summers, and Waldmann [1990] is along this vein, so is the overconfidence model suggested by Daniel, Hirshleifer, and Subrahmanyam [1998]. Others propose that momentum is a consequence of market under-reaction in which prices adjust too slowly to news. The representative investor who suffers from conservatism bias in Barberis, Shleifer, and Vishny [1998] or the gradual diffusion of firm-specific information assumption in Hong and Stein [1999] are examples of possible factors that can cause under-reaction and generate positive autocorrelations in stock returns. These two mainstream behavioral candidates for explanation of momentum profits have different implications on profitability of momentum trading.[2] The over-reaction

[2]There are other literatures suggesting potential links between momentum and risk factors but an accepted explanation has not yet emerged. Conrad and Kaul [1998] argue that the differences in unconditional drifts across stocks explain momentum profits. Harvey and Siddique [2000] find relation between momentum effect and systematic skewness. Berk, Green, and Naik [1999] and Sagi and Seasholes [2001] study models that link momentum profits to time-varying expected returns. Their model predictions are consistent with the empirical findings by Chordia and Shivakumar [2002]. Johnson [2002] suggests that a single-firm model with a standard pricing kernel can produce momentum effects when expected dividend growth rates vary over time. Ang, Chen, and Xing [2002] find that some of the momentum profits can be explained as compensation for bearing high exposure to downside risk.

model predicts that momentum traders on average lose money to their counterparty whereas the under-reaction model allows profit opportunities.

Given the controversy behind the issues about implementing momentum strategy, it should be interesting to see if momentum trading can actually contribute to fund performance. In this paper I intend to address the question of whether momentum trading is a viable investment strategy in practice by studying the profitability of mutual funds that employ different degrees of feedback trading. I follow in Wermers's [2000] footsteps and combine the CRSP mutual fund database and the CDA/Spectrum mutual fund holdings database for this study. The new merged database allows a more accurate analysis of the relation between performance and trading behavior of mutual funds. In particular, I can directly identify mutual funds that engage in the most active momentum trading by examining their change of security holdings and compare the net returns and characteristics of those funds with the others. Not only my results can address the issue about the profitability of momentum trading in practice, they also provide valuable insights into the source of momentum profits. Since under-reaction and over-reaction have different implications on profitability of momentum trading, studying the trading behavior and performance of mutual funds can help answer the question which behavioral model is a more promising candidate to explain momentum profits.

Several prior studies have investigated similar matters. Carhart [1997] uses the loadings on momentum factor to identify mutual funds that follow momentum strategy and finds that momentum funds do not earn substantially higher returns than contrarian funds. However Carhart's methodology fails to distinguish between active and passive momentum trading. Mutual funds that accidentally hold stocks that experience high momentum profits during the sample period can also exhibit significant momentum loadings and those funds do not necessarily have to be engaged in any active trading. Therefore the verdict of whether momentum trading is practically profitable or not is still unclear since momentum factor loading cannot be synonymously related to actual momentum trading.

Grinblatt, Titman, and Wermers [1995] find opposite evidence to Carhart's study.

They examine the quarterly portfolio holdings of 155 surviving mutual funds from 1975 to 1984 and categorize those funds into either momentum or contrarian based on how they tilt their portfolio composition in response to previous stock returns. Grinblatt et al. find that momentum funds in general have better gross performance than contrarian funds. However, since the authors only study the mutual fund gross returns, their results have ignored any possible difference in trading costs and administrative expenses associated with the two investment styles. Furthermore, their estimation of gross return is based on the assumption that trade orders are executed primarily around the ends of quarters at the closing price. Some important execution issues such as price impact or timings of trades are neglected and this may potentially introduce significant errors to the estimation of fund performance. In my study I am able to bypass those issues by directly examining the net returns of mutual funds.

Another important distinction between my work and prior studies is that I reconstruct my mutual fund portfolios on an annual basis to separate momentum funds from contrarian funds instead of categorizing those funds based on how they trade on average over the entire sample period. Such distinction turns out to be crucial as I find that some mutual funds may alter their trading style through time. My approach also allows a more conclusive and information inference to be drawn about the link between profitability and momentum trading as it emphasizes more on the contemporaneous relation between average trading style and profitability.

The remainder of the paper is organized as follows. Section 1.2 provides a brief description of the CRSP mutual fund database and the CDA/Spectrum mutual fund holdings database. Section 1.3 describes the momentum measure, methodology and different performance measurement models employed in the paper. Section 1.4 reports and discusses the major results. Section 1.5 comments on the implications of my findings on competing behavioral models that explain momentum profits and Section 1.6 concludes.

1.2 Description of Data

I use two databases to obtain the empirical results in my paper. Equity returns and mutual fund returns and characteristics are taken from the Center for Research in Security Prices (CRSP). Data for mutual fund holdings are obtained from the CDA/Spectrum Mutual Fund Holdings database. The two databases are provided by Wharton Research Data Services (WRDS).

The main source of the CDA/Spectrum Mutual Fund Holdings database is the mandatory reports filed with the Securities and Exchange Commission (SEC) by mutual funds. Prior to 1985, Section 30 of the Investment Company Act of 1940 required individual funds to report portfolio information at the end of each fiscal quarter. Starting 1985, the SEC required individual mutual funds to file the report only twice per year, although some funds may still voluntarily file their reports quarterly. The semiannual reporting dates are determined by the fiscal year chosen by a given mutual fund and therefore are not necessarily aligned with the calendar quarter end. This also implies that mutual fund holdings in the database are not synchronized in terms of reporting dates for different funds. Such inconsistent format may raise some issues on the calculation of momentum measure which I will discuss in greater details in the methodology section. For a more comprehensive overview of this mutual fund holdings database, interested readers are referred to Wermers [1999]

Mutual fund holdings data are available to my study from the first quarter of 1980 to the last quarter of 2002. I include all mutual funds with a self-declared investment objective of aggressive growth, growth, growth and income, and balanced. Since I intend to study the domestic equity trading behavior of the US mutual funds, I eliminate index funds, funds that invest less than 50% of their total net asset value in the US equities as well as funds of which the country of registration is not the United States. Finally I also remove funds that do not file their holdings reports in a timely fashion, i.e., any fund with more than 200 days in between reporting dates.

Fund performance and other mutual fund characteristics are obtained from the CRSP mutual fund database used by Carhart [1997]. I eliminate all funds of which the Wiesenberger fund type code or ICDI's fund objective code does not indicate US equities as major investment instruments.[3] Again, in similar fashion to the filters applied to the mutual fund holdings database, I eliminate index funds and funds that invest less than 50% of their assets in equities. To relate mutual fund trading behavior to performance and portfolio characteristics I follow Wermers [2000] and merge the CDA/Spectrum database with the CRSP mutual fund database. Since there are no other effective identifiers provided by the data vendor to combine the two datasets, funds are in general matched between the two databases by matching their fund names. Other fund characteristics such as investment objective, age and stock holdings are occasionally used to facilitate the accuracy of the matching process.

In the last decade, mutual fund companies have begun to offer different classes of shares under the same mutual fund name to appeal to different investor clienteles. For example, different share classes are offered to institutional investors or individual investors of different account sizes. Unfortunately the databases I use are not robust enough to accommodate this ongoing trend. Indeed, the CDA/Spectrum database lists only the underlying mutual funds whereas the CRSP database lists each share class separately. If a mutual fund has more than one share class, characteristics of the different share classes of that fund are value-weighted to create a set of composite measures.[4]

Table 1.1 briefly describes the mutual fund sample used in my study. Panel A reports the number of funds available in the CDA/Spectrum database by year. Qualified funds are funds that fulfill my filtering criteria discussed earlier. On average, around 73% of qualified funds are successfully matched to the CRSP funds. Panel B reports the number of share classes available in the CRSP database. The rate of

[3]Specifically, I remove funds of which the ICDI objective code belongs to one of the followings: BQ, BY, GB, GE, GM, GS, IE, MF, MG, MQ, MS, MT, MY or PM. I also remove funds of which the Wiesenberger fund type code is one of the followings: CBD, CHY, GOV, GPM, IBD, IFL, INT, LTG, MBD, MHY, MMF, MSS, MTG, TFM or TMM.

[4]I also compute another set of composite measures by equally weighting the different share classes of the same mutual fund. This method basically gives identical results to the one using value-weighting. Since mutual funds with multiple share classes are usually dominated by one or two more prominent share classes, I use the value-weighting approach as it is more representative of the dominating share class.

successful matching in this panel is slightly lower, at around 70%, partly because CRSP usually introduces new fund data more promptly than CDA/Spectrum. Most of the unmatched funds are of smaller sizes and therefore the possibility of sample bias should be minimal as my results are robust to both equal-weighting and value-weighting methods when aggregating mutual funds into portfolios. The fourth column of Panels A and B shows the share of the matched funds with respect to the total market value of the qualified funds for the CDA/Spectrum database and CRSP database respectively. The matched funds in the CDA/Spectrum database constitute for more than 70% of the total market value of the qualified funds and the matched funds in the CRSP database account for more than 90%. Given the substantial market share accounted by my merged database, my results should represent the majority of the mutual fund industry. Finally, Panel C shows the number of matched funds by year under each CDA/Spectrum investment objective. Since the methodology I use to compare mutual fund performance, which I will discuss in detail in the next section, involves forming quintile portfolios, it is important to verify that there are enough funds available each year under each investment objective, in order to eliminate noise associated with individual fund behavior. The size of my sub-samples, except in the earlier years of the balanced category, is always large enough to ensure that the results are driven by common characteristics of funds within the same portfolio instead of by individual idiosyncrasies.

1.3 Methodology

In this section, I will describe the momentum measure I use to assess the degree of feedback trading by mutual funds. I will also outline the methodology of testing mutual funds' profitability and discuss the various models of performance measurement employed in this paper.

1.3.1 Momentum Measure

The momentum measure that I use to distinguish momentum trading mutual funds from the rest is the sum of the cross-products of mutual fund trades with returns. It can be considered as a modified version of the one used by Grinblatt et al. [1995] or Badrinath and Wahal [2002]. Specifically, the momentum measure[5] for a mutual fund is defined as:

$$M_t(l,k) = \sum_{i=1}^{n} T_{i,t,l} \cdot R_{i,t-l,k}$$

where $T_{i,t,l}$ is the change of portfolio weight for security i from date $t-l$ to date t, $R_{i,t-l,k}$ is the return of security i from date $t-l-k$ to date $t-l$, and l is the time period between reporting dates, which varies depending on each mutual fund's filing cycle. The momentum measure is then estimated for every reporting cycle and is averaged for every year to obtain an annual average measure for each mutual fund.

The statistic is designed to estimate the degree to which a fund manager tilts his portfolio composition in the direction of stocks that have experienced high returns and away from stocks that have experienced low returns. Interpretation of the statistic is straightforward. A positive value indicates momentum trading whereas negative implies contrarian. Since most literature focus on momentum strategy based on stock returns in the past six months, the k chosen for all my empirical tests is also six.[6]

Unfortunately, several complexities arise from applying this measure on the actual data. First of all, portfolio weight can change over successive periods due to either a change in holdings or a change in the price of security. Some mutual funds may end up having a high momentum measure just because they happen to hold securities that experience high returns between the mandated security filing dates. Grinblatt

[5]This momentum measure can be loosely interpreted as the covariance between institutional trades and previous stock returns. I also repeat my tests using the correlation version, which is my momentum measure divided by the standard deviation of the institutional trades and the standard deviation of previous stock returns. I thank Mark Carhart and Andrew Lo for making the suggestions. The results in this paper remain intact after the modifications. I do not report the results but they are available upon request.

[6]I also repeat all tests in this paper using alternative definitions of momentum measure, such as momentum measure using previous three-, nine-, or twelve-month returns, or momentum measure using previous returns measured from the end of trade instead of from the beginning of trade. All inferences from the tests remain unchanged and are essentially qualitatively identical. These results are available from the author upon request.

et al. [1995] refer this as passive momentum. To ensure that only mutual funds of active momentum trading are picked up in the study, I use the dollar value of mutual fund trades as a percentage of the total portfolio value to replace change of portfolio weights.[7]

Another potential issue is caused by the limited frequency of the trading data. Since the data for mutual fund trading are available for at most frequent quarterly, the exact time and prices at which the mutual funds actually execute their trades are unknown. Assuming all trades predominantly happen exactly at the filing date and using the filing-date equity data may introduce some undesirable bias into the estimation of the change of portfolio weights. To alleviate such a problem, average prices and portfolio values are used.[8] Specifically, the change of portfolio weight that I use in the calculation of momentum measure is defined as:

$$T_{i,t,l} = \frac{(H_{i,t+l} - H_{i,t}) \cdot P_{i,t,l}}{A_{t,l}}$$

where $H_{i,t+l}H_{i,t}$ is the change of holdings of security i between time $t-l$ and time t, $P_{i,t,l}$ is the average of security i price at time $t-l$ and time t, and $A_{t,l}$ is the average of portfolio value at time $t-l$ and time t.

As already mentioned in the data section, mutual funds are only required to file their holdings twice a year, although some funds may voluntarily file their reports quarterly. Consequently the frequency of the observations of change of mutual fund holdings varies from quarterly to semi-annually. In other words, l can vary from three months to six months, depending on the customary filing routine of each mutual fund. To allow comparison of momentum measure of various trading frequencies I normalize the measure by dividing it by the number of days between filings and multiplying it by thirty. My final measure can be loosely interpreted as monthly mutual fund trade

[7]I also run my tests using the modification proposed by Grinblatt et al. [1995], who use the average of the beginning- and end-of-quarter share prices to calculate the portfolio weights. It does not affect any of my results.

[8]I also compute the momentum measure using security information right at the filing date and the results are similar. I choose to present the results using average prices and portfolio values simply because it is more plausible to believe that mutual funds tend not to execute all of their trades at the same time as their filing dates.

in response to previous stock returns.

1.3.2 Portfolio Formation

To compare performance of mutual funds of different degrees of momentum trading, I form portfolios of mutual funds on momentum measure and estimate performance on the resulting portfolios. This methodology is similar to the one used by Hendricks, Patel, and Zeckhauser [1993] or Carhart [1997], except that I use my momentum measure instead of return as sorting criterion. In the beginning of every year, I rank the mutual funds based on their momentum measure for that year and then form five equal-weighted mutual fund portfolios according to the ranking orders.[9] I hold the portfolios for one year and then re-organize them. This gives me a time series of monthly returns on each quintile portfolios from 1980 to 2002. Funds that disappear during the course of the year are still included in the equal-weighted average until they disappear, then the portfolio weights are re-adjusted accordingly.

Since the holdings filing dates are determined by the fiscal year chosen by the mutual funds and are not necessarily aligned with the calendar end of quarter or semester, some of the mutual fund trading period may span two calendar years. To deal with such exception, I treat the trading period as belong to the year in which most trading presumably takes place. For example, if the fiscal yearend of a mutual fund is November and its next reporting date is January 1990, I will treat the mutual fund trading as belong to the year 1989 since two thirds of the trading period is during 1989. Another similar issue is that a handful of mutual funds file their reports in mid month instead of month end. In those cases, the filing date is rounded to the nearest end of month.

Scrupulous readers may be skeptical about my ad hoc procedures that are used to deal with the inconsistent format in the database when calculating the momentum measure and question the potential impacts of those procedures on the reliability of

[9] I also calculate value-weighted portfolio returns and the major findings remain unchanged. Since there is a minor possibility that funds can be mismatched in the merged database, I choose to present the equal-weighted results to avoid the unlikely event of having a mismatched large fund dominating the inference.

the results. For example, one may suggest that since the mutual funds report their filings at different times in a year, their momentum measure may not be directly comparable as the discrepancy may reflect return differentials in different times of year instead of actual different trading styles. Normalizing mutual fund trading of different durations into monthly trading may be another potential base for criticism since mutual funds may not necessarily trade a constant amount of stocks throughout each month during the trading period. Nevertheless, I believe that the impacts from these ad hoc procedures on the final results are minimal since the measure is only used as a rudimentary pointer to classify mutual funds into portfolios of funds of different degrees of momentum trading, the purpose of which is to identify a group of funds that do more momentum trading than the others. These ad hoc procedures should only have impacts on marginal mutual funds between portfolios and any possible idiosyncrasies should be diversified away by such portfolio aggregation approach. In other words, although imprecision and errors are inevitable because of the various special treatments when applying the momentum measure on the mutual fund holdings database, their effects on the inference from the major results should be negligible since only a small portion of the aggregate portfolio is affected.

1.3.3 Performance Measurement Models

To compare performance of mutual funds, I employ three different models of performance measurement: the Capital Asset Pricing Model (CAPM) described in Sharpe [1964] and Lintner [1965], the Fama and French [1993] 3-factor model and the Carhart [1997] 4-factor model. The risk-adjusted returns of any portfolio of mutual funds are estimated as the intercepts from each of the following market model regressions:

$$
\begin{aligned}
r_{i,t} &= \alpha_i + \beta_{i,1}\mathrm{RMRF}_t + \epsilon_{i,t} \\
r_{i,t} &= \alpha_i + \beta_{i,1}\mathrm{RMRF}_t + \beta_{i,2}\mathrm{SMB}_t + \beta_{i,3}\mathrm{HML}_t + \epsilon_{i,t} \\
r_{i,t} &= \alpha_i + \beta_{i,1}\mathrm{RMRF}_t + \beta_{i,2}\mathrm{SMB}_t + \beta_{i,3}\mathrm{HML}_t + \beta_{i,4}\mathrm{UMD}_t + \epsilon_{i,t}
\end{aligned}
$$

The first, second and third equations correspond respectively to CAPM, Fama-French 3-factor model and Carhart 4-factor model.[10] r_i is the excess return on portfolio i, RMRF is the excess return on market proxy, and SMB, HML, and UMD are factor-mimicking portfolios for size, book-to-market equity and momentum.[11] Specifically, the four factors are constructed as follows.[12] RMRF is the value-weighted return on all stocks traded in NYSE, AMEX and NASDAQ minus one month Treasury bill rate. The HML and SMB factors are constructed using six value-weighted portfolios formed on size and book-to-market. Those six portfolios are the intersections of two portfolios formed on size and three portfolios formed on the ratio of book equity to market equity. HML is the average return on the two value portfolios minus the average return on the two growth portfolios. SMB is the average return on the three small portfolios minus the average return on the three big portfolios. Similarly, the UMD factor is constructed using six value-weighted portfolios formed on size and prior returns. The six portfolios are the intersection of two portfolios formed on size and three portfolios formed on last eleven-month returns lagged one month. UMD is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. The size breakpoint is the median NYSE market equity and the prior return breakpoints are the 30th and 70th NYSE percentiles.

Table 1.2 presents the summary statistics for the factors. Autocorrelation within each factor is quite low, with the exception of the HML factor which has a relatively high coefficient of 0.12. The low correlations among the factors imply that multi-collinearity should not substantially affect the coefficient estimates of the models. During the period from January 1980 to December 2002, the average market risk premium is around 0.55% per month and 1.97 standard errors from 0. The HML and

[10]In fact, my Carhart 4-factor model is slightly different from the one used by Carhart [1997]. Carhart uses PR1YR as the factor-mimicking portfolio for momentum. He constructs PR1YR as the equal-weight average of firms with the highest 30 percent eleven-month returns lagged one month minus the equal-weight average of firms with the lowest 30 percent eleven-month returns lagged one month. Both PR1YR and UMD are designed to replicate risks and returns in momentum factor and therefore closely resemble each other.

[11]I thank Ken French for providing the factor returns.

[12]For a detailed description on the construction of the four factors, please refer to Ken French's personal webpage http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

UMD factor portfolios also show strong performance. Their average monthly returns are 0.41% and 0.96% respectively, both of which are significant at the 95% confidence level. Comparatively, the return on the SMB factor is much weaker, with only 4 basis points per month during the sample period and is statistically insignificant from zero.

1.4 Results

In this section, I will report and discuss the major results in this paper. I will go over the characteristics and performance of momentum trading mutual funds as well as run through several robustness tests to confirm my findings.

1.4.1 Characteristics of Mutual Fund Portfolios Formed on Momentum Trading

Table 1.3 shows the characteristics of mutual fund portfolios formed on momentum trading. Cross-sectional average of excess returns, momentum measures and portfolio attributes are calculated every year among the mutual funds within the same momentum-trade quintile group. The table reports the time-series average of the characteristics of each quintile portfolio.

The first row displays the excess returns of mutual fund portfolios over the risk-free rate. On average, mutual funds earn around 0.50% per month, which is lower than the 0.55% earned by the market proxy as shown in Table 1.2. Such results are consistent with the existing literature that documents underperformance of actively managed funds [Gruber, 1996]. There is a weak pattern of increasing excess return with the momentum trading intensity. The excess returns of the mutual fund portfolios increase gradually from 0.40% in the first momentum-trade quintile to 0.48% in the fourth quintile, all of which are marginally significant. The average excess return then suddenly jumps to 0.72% in the last quintile, in which the mutual funds engage in the most aggressive momentum trading. The figure is also significant, with more than two standard errors from zero.

Momentum measure for each group of mutual funds is shown in the third row. My momentum measure for the universe of mutual funds is 0.65% and is highly significant (t-statistic is 6.60). The significant value indicates that the majority of mutual funds engage in momentum trading. The first two momentum-trade quintiles have negative signs in their momentum measures, which suggest that mutual funds belonging to those two quintiles are mostly contrarian investors. These results are similar to those documented in Grinblatt et al. [1995], in which the authors report around 70% of mutual funds in their study are momentum traders. The significance of momentum trading practice among the mutual funds should not come as too surprising as mutual funds have various reasons to positive-feedback trade. Other than profiting from momentum, mutual funds sometimes window-dress their portfolio holdings [Lakonishok, Shleifer, Thaler, and Vishny, 1991]. Money managers may get rid of past loser stocks and purchase past winner stocks to create an illusion of making the correct investment decision to their investors. Effectively, the trades associated with window dressing are identical to trade executions from momentum investing strategy and my momentum measure will pick up a positive sign for either case.

The next two items after momentum measure on the table report the expense ratio and turnover of the mutual funds. Expense ratio is the percentage of the total investment that shareholders pay for the mutual funds' operating expenses which include management, administrative and marketing expenses. Turnover is the minimum of aggregate purchases of securities or aggregate sales of securities divided by the average total net assets of the fund. The expense ratio and turnover for the mutual funds with the strongest momentum trading are 1.37% and 141.6% respectively. Those values are much higher than the expense ratio and turnover of the rest of the funds. These observations are consistent with the conventional intuition that momentum trading strategy requires high turnover and therefore high trading costs and high expenses. The two mutual fund attributes monotonically decrease with the momentum measure except in the first quintile, where a moderate reversal pattern is noted. Specifically, the value of turnover decreases from 141.6% in the momentum-trade quintile 5 to 57.6% in quintile 2 and rises up again to 80.5% in quintile 1. A similar pattern is also observed for expense ratio. The ratio decreases from 1.37% to 1.12% and finally rises up to 1.27% along the decreasing order of momentum measure. The slightly higher expense ratio and turnover in the first quintile seem to suggest that mutual funds belonging to that group are probably adopting some sorts of active contrarian trading strategy that is burdened with high turnover and trading costs.

The last row of the table shows the average total net asset value (TNA) among each group. The observed pattern is that more actively trading mutual funds are in general smaller than the ones that are more passive. The average TNA for each of the two strongest momentum trading portfolios (momentum-trade quintile 4 and 5) and the strongest contrarian trading portfolio (momentum-trade quintile 1) is less than \$520 million whereas the average TNA for the other two portfolios are at least over \$580 million. The average fund size of mutual funds in quintile two (\$713.6 million) is more than double the average fund size of mutual funds in quintile five (\$332.3 million). It seems from the evidence that there is a potential relation between fund size and trading activity.

1.4.2 Performance of Mutual Fund Portfolios Formed on Momentum Trading

Panel A in Table 1.4 shows the risk-adjusted performance of mutual fund portfolios of different degrees of momentum trading under CAPM. Mutual funds in my sample on average earn a negative risk-adjusted alpha of 2 basis points per month. The figure is not significant, with t-statistics equal to -0.50. After breaking down the universe of mutual funds into quintile portfolios based on intensity of momentum trading, I find that the mutual fund portfolio with the strongest momentum measure (momentum-trade quintile 5) has a positive yet insignificant alpha of 14 basis points. The alphas for rest of the funds are all negative, ranging from -3 basis points to -11 basis points per month.

The spread section compares the performance of the strongest momentum trading mutual funds with the performance of other funds. The evidence indicates that mutual funds in momentum-trade quintile 5 in general outperform other mutual funds by at least 17 basis points per month. Some of the t-statistics are even significant at the 95% level. Looking at the R-squares from the regressions, it can be observed that variations in market returns can explain at least 86% of variations in the returns of mutual fund portfolios. The major reason for the strong explanatory power of CAPM is that most of these mutual funds are using some kinds of market proxy as benchmark. In aggregate, these mutual fund portfolios have a strong exposure to market returns and thus most of their variations can be explained by a simple CAPM market proxy. In contrast, CAPM fails to explain relative returns between portfolios. Although some of the differences in portfolio returns can be attributed to the different market risks, the relatively low R-squares in the spread section, ranging from 0.07 to 0.15, suggests that CAPM may not be adequate to explain variations in portfolio spread. In order to gain better insights into contributions of different risk factors to the return differentials between different mutual fund portfolios, multi-factor models such as Fama-French 3-factor model and Carhart 4-factor model are used to evaluate mutual fund performance.

Panel B reports the loadings on the three Fama-French risk factors and the risk-adjusted alphas, and their t-statistics for each of the momentum-trade quintile portfolios. The loadings on SMB demonstrate a U-shaped pattern along the increasing momentum measure. The coefficient of SMB decreases from 0.15 in momentum-trade quintile 1 to 0.04 in quintile 2 and rises to 0.39 in quintile 5. The high SMB loadings in the two extreme portfolios suggest that mutual funds with more active contrarian or momentum trading usually invest in stocks of smaller market capitalizations. There also seems to be a pattern of decreasing loadings on HML with momentum measure, especially evidential in the last two portfolios (momentum-trade quintile 4 and 5) where the coefficients are negative. The reason for the pattern in HML loadings is intuitive. When mutual funds invest in momentum, they tend to buy stocks that experience high returns and sell stocks with low returns in the previous periods. If the fundamentals do not keep up closely with price changes, those stocks with high (low) returns tend to exhibit lower (higher) book-to-price ratio. As a result, the strongest momentum trading mutual funds should also show weak loadings on HML which is exactly what is observed in my findings.

The risk-adjusted alphas from the Fama-French 3-factor model provide strong evidence in support of profitability in momentum trading for mutual funds. The alpha increases monotonously from -0.17% to 0.29% per month along the increasing order of momentum trading. The alpha of the strongest momentum trading portfolio (momentum-trade quintile 5) is highly significant, with more than 3 standard errors from 0, while all other mutual fund portfolios have negative alphas. The superior performance of momentum trading mutual funds can also be observed from the spread section in which the abnormal return differentials between quintile 5 and rest of the quintile portfolios are shown. Momentum trading mutual funds, on average, outperform other funds by at least 32 basis points after adjusted for the Fama-French risk factors and the differences are all significant at more than 95% level.

The R-squares from the regressions of quintile portfolio returns on the Fama-French factors do not improve much from those from the CAPM regressions as most of the variations in the mutual fund portfolios are dominated by the market returns. On the other hand, the Fama-French factors are extremely useful in explaining the variations in the return differentials between portfolios as shown by the much higher R-squares in those regressions. Since mutual funds of different degrees of momentum trading have different exposures to the Fama-French factors, the results from Fama-French 3-Factor model should be more informative than those from CAPM as the Fama-French model can also explain the return premiums that are associated with other risk characteristics besides the basic market risk in these mutual fund portfolios.

Finally, I look at performance measurement under the Carhart 4-Factor model to see if the momentum factor can explain away the superior performance of momentum trading mutual funds. The results are shown in Panel C. The addition of momentum factor (UMD) helps explain the variations in the spread portfolios. The R-squares have increased by more than 0.1 compared to those from the Fama-French 3-factor regressions for almost every portfolio in the spread section. The loading on UMD increases with the intensity of momentum trading. This observation confirms the relation between my momentum measure and the return premium associated with the momentum factor and can be interpreted as further evidence in support of the benefits of momentum trading. If price impacts and transaction costs are substantial and pivotal for the profitability of momentum trading strategy, as some literature suggest [e.g. Lesmond et al., 2004], the mutual funds that implement momentum trading may not be able to experience the return premium that the strategy promises and should therefore have a weak exposure to the momentum factor. My findings show the contrary, which suggests mutual funds that trade on momentum are actually able to capture the corresponding profits. One caveat from the results in Panel C is that the superior performance of momentum trading mutual funds persists even after adjusted for the momentum factor. The alpha of the strongest momentum trading mutual funds is positive and highly significant (t-statistic is 1.94). It is also significantly higher than the alphas of other mutual fund portfolios, which are all negative.

The evidence so far suggests that mutual funds can improve their performance by aggressively engaging in momentum trading and the benefits of momentum trading outweigh the potential costs from the higher turnover and trading expenses. The following subsections will investigate the robustness of my results under different scenarios.

1.4.3 Mutual fund Portfolios Formed on Momentum Trading by Investment Objective

This subsection analyzes the characteristics and performance of momentum trading mutual funds under different investment objectives. Mutual funds in my sample are classified into four categories, according to their investment objective code specified by the CDA/Spectrum mutual fund holdings database. The four categories are aggressive growth, growth, growth and income, and balanced. Table 1.5 reports the portfolio attributes. Mutual funds of aggressive growth on average have the highest excess return, momentum measure and expense ratio, followed by growth funds and then growth and income funds. The last in the order are balanced funds, which have the lowest values in all three portfolio characteristics. Such pattern corroborates with the conventional wisdom that aggressive funds usually employ a more active and aggressive approach toward investment and trading. Also consistent with the intuition, growth and income funds have the largest average TNA but the lowest turnover compared to funds of other investment objectives, since conservative funds usually do not trade as much and their lower turnover is thus less restraining on fund size.

The relation between portfolio characteristics and momentum trading found in Table 1.3 can also be observed in Table 1.5 for mutual funds of different investment objectives. In particular, the monotonous increasing pattern in excess return and momentum measure, the U-shaped pattern in expense ratio and turnover and finally the inverted U-shaped pattern in TNA all persist after the mutual funds are separated into four different categories.

The results of risk-adjusted mutual fund performance under different investment objectives displayed in Table 1.6 are also similar to those shown in Table 1.4. The superior performance of momentum trading mutual funds is most notable among the aggressive growth and growth funds. The alphas and relative outperformance of momentum trading mutual funds in those two categories are significant under the Fama-Frech 3-Factor model. After adjusted for the momentum factor (UMD), those strongest momentum trading mutual funds still demonstrate signs of better profitability. On the other hand, the evidence of superior performance in growth and income and balanced funds are slightly weaker. Although the pattern still persists, much of the significance has disappeared. One of the possible explanations for the less robust results in those funds is that funds belonging to those two categories are in general more conservative and do not trade aggressively on momentum, as evidenced by their momentum measures which are almost half of the growth funds'. Therefore it is likely that the performance of growth and income and balanced funds suffers accordingly because of their lesser intensity in momentum trading.

1.4.4 Size-Neutral Mutual Fund Portfolios Formed on Momentum Trading

Chen, Hong, Huang, and Kubik [2003] study the effect of scale on performance in the active money management industry and find that fund returns decline with lagged fund size even after adjusting for various performance benchmarks. Their arguments seem to coincide with the evidence presented in Table 1.3 in which funds with smaller total net asset value (momentum-trade quintile 5) experience higher excess returns than funds of larger size (momentum-trade quintile 2 and 3). It is quite possible that the superior performance of momentum trading mutual funds documented earlier is related to their fund size instead of the trading mechanics. This subsection investigates into this issue and compares performance of mutual funds of different degrees of momentum trading after controlling for fund size.

Mutual funds are sorted at the beginning of each year from 1980 to 2002 into quintile portfolios based on their total net assets at that time. The mutual funds in each TNA quintile are then further sorted into 5 portfolios based on their momentum measure during the same year. A total of 25 TNA-momentum-trade-sorted portfolios are formed. Those portfolios are then re-aggregated based on their momentum measure quintile rank into 5 TNA stratified, momentum trading portfolios. In particular, mutual funds in the stratified portfolios with the highest momentum trading are made up of mutual funds in momentum-trade quintile 5 (highest momentum measure) of TNA quintile 1, mutual funds in momentum-trade quintile 5 of TNA quintile 2 etc., all the way to TNA quintile 5. The other stratified portfolios are formed similarly. The purpose of this methodology is to control for the total net assets of mutual funds and to ensure that the average sizes of mutual funds across different stratified portfolios do not differ too much.

Table 1.7 reports the characteristics of the size-neutral mutual fund portfolios of different degrees of feedback trading. The general results are almost identical to those in Table 1.3. Excess return is highest for mutual funds with the strongest momentum trading and gradually decreases from portfolio 5 to portfolio 1. The familiar U-shaped pattern is observed for turnover and expense ratio across the five quintile portfolios. The only difference is in the TNA characteristic. Variations in TNA among the portfolios are much attenuated. Average size of mutual funds within each quintile portfolio now ranges from $416.9 million to $572.6 million in contrast to the range from $332.3 million to $713.6 million as discussed earlier when the size effect of mutual funds is not adjusted.

Table 1.8 shows the performance of size-neutral mutual fund portfolios formed on momentum trading. Again the pattern displayed in the table is almost identical to that in Table 1.4. The evidence that momentum trading mutual funds tend to do better than other funds is robust under different models of performance measurement and after controlling for fund size. The results suggest that the superior performance associated with momentum trading cannot be attributed merely to the effect of scale on performance documented by Chen et al. [2003].

1.4.5 Momentum Measure and Fund Flow

One of the major drawbacks from my momentum measure is that there is no way to distinguish whether the dollar trade recorded in the CDA/Spectrum database is initiated from the portfolio strategy executed by the mutual funds or from the new fund flows experienced by the better-performing funds. If it is the latter case, my previous results may be biased because of the potential link between mutual fund performance and fund flow. Indeed, a simple univariate regression of fund flow on risk-adjusted fund performance has revealed that fund flow and performance are strongly related, as shown by the significant regression coefficient.

Since mutual funds on average momentum trade, when they receive new money from the investors, they may invest the money in stocks that did well in the past. If my momentum measure captures momentum trade from trading strategy as well as momentum trade from new fund flows, my tests may produce results with a strong upward bias on the risk-adjusted alpha as my mutual fund portfolio with the strongest momentum measure is likely to have the highest fund flow as well, and the strong performance observed may therefore be misleading because of the correlation between fund flow and performance. Unfortunately such bias is not negligible as the regression of momentum measure on fund flow has shown that the relationship is quite significant. Although the causality in the relation between fund flow and momentum measure is not clear, since it is both possible that momentum trading generates performance and then attracts new fund flows, and that my momentum measure captures funds with high fund flow and therefore biases my findings to favor conclusion of superior performance, it is still important to isolate the potential impact from the link between fund flow and momentum measure to avoid spurious inference.

To achieve this, I apply the methodology used in Subsection 1.4.4, but instead of forming quintile portfolios based on the total net asset value, I form portfolios according to the fund flow received by each mutual fund. Table 1.9 reports the performance of these fund-flow-stratified, momentum trading portfolios. The results in the table confirm the validity of the concern that my findings may be contaminated by the link between momentum measure and fund flow and thus fund performance. The value and significance of the Fama-French adjusted alpha has decreased considerably. The risk-adjusted alpha for the quintile portfolio with the strongest momentum measure is now 0.15%, with t-statistics of 2.40, compared to the original estimate of 0.25% and t-statistics of 3.37 observed in Table 1.4. The loading on the UMD factor still shows an increasing pattern with momentum trading, but the Carhart adjusted alpha is now indistinguishable from zero. However, despite the negative impact of controlling fund flow on fund performance, the major conclusion in the paper stays unchanged. In other words, mutual funds that engage in momentum trading in general have better performance than funds that do not.

1.4.6 Persistence of Momentum Trading and Performance

My previous results show that there is a strong relation between momentum trading and mutual fund performance. The logical question to ask then is whether or not a mutual fund investor can benefit from this knowledge by identifying and investing in mutual funds that practice momentum trading. The results in Table 1.10 intend to address this question. At the beginning of every year, I rank the mutual funds based on their past-year momentum measure instead of current-year momentum measure as done in Subsection 1.4.2. Quintile portfolios are formed and their characteristics and performance are presented in Table 1.10. Panel A shows the portfolio attributes. The patterns in expense ratio, turnover and TNA closely resemble those in Table 1.3. If not for the omission of the year 2002 data point, the average past-year momentum measure in Table 1.10 should be identical to the average momentum measure in Table 1.3. My figures show only a trivial difference, which is precisely what should have happened.

Although the quintile portfolios still show an increasing order of current-year momentum measure with previous-year momentum trading, which suggests some persistence in momentum investment style, there are a few notable oddities in Table 1.10. Firstly, some of the past-year contrarian funds have changed their style to momentum investing, as reflected by their positive current-year momentum measure. Secondly, the strongest past-year momentum trading mutual funds seems to have moderated their aggressiveness significantly in the following year. Their average current-year momentum measure (1.55) is only half of their average past-year counterpart (2.87). Finally, the increasing order of excess return with momentum trading observed in Table 1.3 is completely disentangled. Last-year contrarian funds (past-year-momentum-trade quintile 1) actually have the best unadjusted performance. The t-statistic of excess return for last-year momentum funds (past-year-momentum-trade quintile 5), on the other hand, is the least significant compared to others.

Panels B, C, and D report the performance evaluation of mutual fund portfolios formed on past-year momentum-trading under CAPM, Fama-French 3-Factor model and Carhart 4-Factor model respectively. The evidence that momentum trading mutual funds command better performance than the rest has almost disappeared. Under CAPM, momentum trading funds (formed on previous-year momentum measure) actually do worse than the others. Although the superior performance still persists under either Fama-French 3-Factor model or Carhart 4-Factor model, the statistical significance is much weaker. For example, the Fama-French risk-adjusted alpha for the strongest past-year momentum trading mutual funds is only 7 basis points, compared to the 29 basis points observed in Table 1.4, not to mention the figure is no longer significant at a respectable level.

As much as I want to believe in the skills of mutual fund managers to profit from momentum trading, my results indicate the contrary. Mutual funds that traded on momentum aggressively in a previous period experienced better performance than the others during that period as implied by the evidence presented in previous tables. Such better performance can be a result of implementation of momentum trading or a result of private information possessed by those mutual funds of which the trade executions are effectively identical to momentum trading. Whatever the cause of the superior performance is, it seems that those funds fail to apply consistently their profitability in the next period. The evidence suggests that the funds either fail to acquire profitable private information consistently or decide to alter their trading style from aggressive momentum trading. Although my earlier findings show that momentum trading is profitable for mutual funds, my results in Table 1.10 suggests that such trading practice among those funds are more likely to be manifestations of serendipity instead of consequences of consistent trading style or information advantage.

The following regression provides further evidence that persistence in momentum trading by mutual funds is relatively weak. I estimate the following cross-sectional regression every year across each stock:

$$\text{mom}_{i,t} = \theta_t \cdot \text{mom}_{i,t-1} + \epsilon_t$$

where $\text{mom}_{i,t}$ is the momentum measure of stock i at time t. To allow fair comparison between the measure this year and measure of last year, I standardize the momentum measure of each stock by subtracting the same-period cross-sectional mean and dividing the difference by the same-period cross-sectional standard deviation. As in Fama and MacBeth [1973], I obtain my final estimate θ by averaging the regression coefficient calculated in each year across the entire sample period. The t-statistic is simply the standard deviation of the time series of each-year regression estimate. I find that θ is significantly different from zero, with a t-statistic of 10.28. The result is consistent with the positive relation between current-year momentum measure and last-year momentum measure observed in Table 1.10. I also find that θ is significantly less than 0.36 at more than 95% confidence level. This finding suggests that most mutual funds do not maintain the same level of momentum trading as they did in previous year and they moderate their intensity of momentum trading by more than half. In short, the regression analysis confirms the observations in Table 1.10 that momentum trading style is not a predominant strategy of most mutual funds.

1.4.7 Regression Tests of Mutual Fund Performance

In this subsection, I perform regression test on the relation between mutual fund performance and momentum measure. Results are presented in Table 1.11. The table reports the time-series average of slope coefficients estimated from annual Fama-MacBeth regressions of the following model:

$$\alpha_{i,t} = a + b_1 \text{mom}_{i,t} + b_2 \text{mom}_{i,t-1} + b_3 \text{turn}_{i,t} + b_4 \text{exp}_{i,t} + b_5 \text{flow}_{i,t} + b_6 \text{TNA}_{i,t} + \epsilon_{i,t}$$

where $\text{mom}_{i,t}$ is the momentum measure, $\text{turn}_{i,t}$ is the turnover, $\text{exp}_{i,t}$ is the expense ratio, $\text{flow}_{i,t}$ is the fund flow, and $\text{TNA}_{i,t}$ is the natural logarithm of total net asset value, and the subscripts i and t in these variables denote observation for mutual fund i at time t. The performance estimate, $\alpha_{i,t}$, is the average monthly abnormal return from either the Fama-French 3-factor model or the Carhart 4-factor model during year t, which are defined as follows:

$$\begin{aligned} \alpha_{i,t}^{\text{FF}} &\equiv r_{i,t} - r_{f,t} - \hat{b}_{i,t} r_{m,t} - \hat{s}_{i,t} r_{\text{SMB},t} - \hat{h}_{i,t} r_{\text{HML},t} \\ \alpha_{i,t}^{\text{Carhart}} &\equiv r_{i,t} - r_{f,t} - \hat{b}_{i,t} r_{m,t} - \hat{s}_{i,t} r_{\text{SMB},t} - \hat{h}_{i,t} r_{\text{HML},t} - \hat{u}_{i,t} r_{\text{UMD},t} \end{aligned}$$

where $r_{i,t}$ is the return on mutual fund i, $r_{f,t}$ is the return on risk-free asset, and $r_{m,t}$, $r_{\text{SMB},t}$, $r_{\text{HML},t}$ and $r_{\text{UMD},t}$ are the premium on market, SMB factor, HML factor and UMD factor respectively. The factor loadings are estimated over the three-year window around time t with at least thirty observations.[13] The cross-sectional regression is run each year using all mutual funds available during that year and the standard error of the coefficients is the time-series standard deviation of the regression estimates across the entire sample period.

The results in Table 1.11 indicate a strong relation between performance and momentum measure, fund flow and expense ratio. The coefficient on fund flow is significant at more than the 95% confidence level (t-statistic is more than 3.0 in either regression using Fama-French alpha or Carhart alpha as the dependent variable). The coefficient on expense ratio is negative and significant in both regressions. The result is consistent with the evidence presented by Carhart [1997] that expenses reduce performance and that most mutual funds fail to recoup their investment costs through higher returns. The positive relation between performance and turnover is in contrast to the observations documented by Carhart [1997] but the relation is not statistically significant. I also find that total net asset is negatively related to performance, which may be explained by the negative economy of scale in the money management business suggested by Chen et al. [2003]. Last-year momentum measure has no discernible effect on the fund risk-adjusted performance. The most important result from the regression is that the coefficient of momentum measure in the regression using Fama-French alpha as the dependent variable is highly significant (t-statistics is 3.13) and becomes statistically indistinguishable from zero when the dependent variable is Carhart alpha. This assures my earlier assertion that momentum trading can contribute significantly to a fund performance.

1.4.8 Are Price Impacts and Transaction Costs Fully Accounted in the Mutual Fund Net Returns?

One of the potential issues about using net return to evaluate mutual fund performance is that the net return may not be able to completely reflect the round-trip

[13] I also run the regression tests using loadings estimated over the prior three years to avoid the potential look-ahead bias. The conclusion from the regression results remains unchanged. I decide to present results using loadings estimated over the three-year window around time t because it should more accurately reflect the most recent factor loadings of the mutual funds.

transaction costs and market impacts of a trading strategy. For example, if a momentum trading mutual fund rebalances its portfolio only once a year it will incur some transaction and market impact costs when it enters its trade but the round-trip costs will not be fully incorporated in its current-year net return. Part of those trading costs is only realized in the year after the mutual fund rebalances its portfolio. As I reconstruct my momentum-trade portfolios every year, my methodology may neglect the second leg of the round-trip trading costs and therefore overestimate the mutual fund performance. This issue is especially noticeable for momentum trading strategy because the execution of the strategy has the potential to create a substantial market impact and most of those trading costs may not be realized unless the mutual funds rebalance their portfolios again during the same year as the year when their net returns are reported.

To mitigate this problem I focus exclusively on mutual funds that consistently trade on momentum to ensure that the round-trip trading costs will be fully incorporated in their net returns. I sort the mutual funds into five groups every year according to their rankings in momentum measure. I only select the mutual funds that belong to the strongest momentum-trade quintile group in both the current and previous year. In this way I can ensure that the potential market impact from momentum trading is reflected in the net returns of these mutual funds. Table 1.12 shows the number of mutual funds that consistently trade on momentum in each year of the sample period. It can be observed that those numbers are fewer than the numbers in the third column which show the number of funds in the original strongest momentum-trade quintile portfolio. So, this table can also be interpreted as evidence that only a few funds are able to trade on momentum consistently.

Table 1.13 shows the performance of this special group of momentum trading mutual funds. Unexpectedly, the Fama-French alpha of these funds does not decline but actually improves to an amazing 0.37%, with a t-statistic of 3.69. The loading on the Carhart factor is also strong and significant. The results suggest that the aforementioned round-trip trading costs may have already been well-accounted for in my previous tests. Instead of cornering the second leg of the round-trip transaction costs, I may have selected mutual funds that are committed to momentum trading and therefore observe even better performance among them.

1.5 Relation to Behavioral Models

What other inference can be drawn from my findings other than profitability of momentum trading at the mutual fund level? In this section, I will discuss the implications of my results on competing behavioral models. Conventional asset pricing models have difficulties explaining the momentum pattern in stock returns. This has prompted some researchers to seek potential explanations by exploring the limited rationality in human behavior. In general there are two major schools of thoughts in behavioral finance that propose to explain momentum profits. They basically revolve around whether the source of momentum comes from under-reaction or delayed over-reaction. Proponents of the under-reaction hypothesis include Barberis et al. [1998] and Hong and Stein [1999]. Barberis et al. describe a model in which investors exhibit conservatism bias and react too little to public earnings announcements. Hong and Stein develop a model in which information diffuses gradually and market participants can only process a subset of public information and trade accordingly. The common theme in either model is that the market fails to fully incorporate information efficiently into asset prices therefore resulting in positive autocorrelation in stock returns in the short run. An alternative candidate for source of momentum profits to under-reaction is the hypothesis of over-reaction advocated by Daniel et al. [1998] and De Long et al. [1990]. Daniel et al. develop a theory based on investor overconfidence and biased self-attribution and study the evolution of market prices as a result of these two well-known psychological biases. De Long et al. describe a scenario in which rational speculators intentionally destabilize market prices to take advantage of the predictable trading pattern of positive-feedback traders. Both models suggest that return continuation can be caused by investors driving security prices beyond fundamental values.

Only a few empirical literatures explicitly test these behavioral explanations for momentum against each other. Lee and Swaminathan [2000] and Jegadeesh and Titman [2001] take a step in this direction by examining long-horizon returns of momentum strategies. Although their discovery of long-run momentum return reversals favors the delayed over-reaction models, their results still fail to refute the under-reaction hypothesis. Their findings only suggest that delayed over-reaction plays a significant role in the evolution of momentum profits but lend little insights into what fuels the momentum price pattern in the first place. Indeed the under-reaction models proposed by Hong and Stein [1999] and Barberis et al. [1998] also predict some sorts of reversal pattern which is therefore still consistent with the empirical findings of long-term momentum reversal. So, study of long-horizon momentum return can hardly be considered as a useful empirical indicator of what causes the momentum profits.

Nagel [2002] also tries to address this issue by studying alternative variables that have potentials to distinguish between under-reaction and delayed over-reaction hypothesis. In particular he examines breath of ownership and change in the share of outstanding equity held by institutions and conjecture that the two competing hypotheses have different implications on the value of those two variables. Based on his findings Nagel concludes in his paper that under-reaction is the more promising behavioral explanation for momentum effects.

My paper adds to the existing empirical literature and hopefully sheds some lights on resolving the controversy by examining the direct implications of the opposing behavioral models on profitability of momentum trading. One of the major predictions of Hong and Stein's [1999] model is that momentum traders are able to earn positive profits on average from exploring the inefficiency of price incorporation of information. On the other hand, overzealous investors in both De Long et al. [1990] and Daniel et al. [1998] models are being traded against by smart investors and lose money on average. This important distinction in profitability may help determining which type of market reaction is behind the momentum force. My findings of superior performance of momentum trading mutual funds strengthen the credibility of arguments that stock momentum is more likely to be caused by under-reaction.

1.6 Conclusion

The abnormal profits generated from buying past winner stocks and selling past loser stocks are well documented and rather indisputable. However, whether or not this momentum trading strategy is profitable in practice for mutual funds is not so clear. Price impacts and transactions costs have the potentials to eliminate the profit margins documented in the literature. Stocks that exhibit the strongest momentum profits may not be the types that the mutual funds prefer to hold. Moreover the theoretical literature in support of over-reaction hypothesis as an explanation for momentum profits predict that momentum investors on average lose money to smart traders who trade against them. This paper studies the trading behavior of mutual funds and compares performance of funds with different degrees of momentum trading. I find that despite the higher expense ratio and turnover, as well as the above arguments against momentum trading, mutual funds that momentum trade most aggressively tend to outperform other funds. This conclusion stands even after subjecting the results to various robustness tests. My findings suggest that mutual funds can potentially enhance their performance through implementing the momentum trading strategy.

My results also complement the existing empirical literature that argues in favor of under-reaction over over-reaction as a more promising behavioral candidate to explain momentum profits. Since over-reaction models predict losses for momentum traders, my evidence of profitability in momentum trading essentially counters any hypothesis along this vein.

Another interesting finding in my paper is the relative lack of persistence in trading style. Although mutual funds show better performance when they momentum trade, they seldom maintain their aggressiveness in momentum trading. The evidence suggests that the strong momentum measure of the better performing funds is more likely to be a manifestation of luck rather than a consequence of intention to capture the momentum profits. Therefore, funds that do well in one period may fail to achieve respectable returns in other periods. My results essentially uncover a potential market anomaly – why don't money managers trade consistently on momentum to improve their fund performance?

Table 1.1: Sample Size of Mutual Fund Databases

This table presents the sample size of the mutual fund databases. Panel A reports the sample size of the CDA/Spectrum Mutual Fund Holdings database by year. The first column shows the total number of funds available in the sample. The second column reports the number of qualified funds, which are defined as funds that are not index funds, funds that invest more than 50% in US equities, funds of which the country of registration is the United States and funds that file reports in a timely manner. The third column reports the number of qualified funds that can be matched to funds in the CRSP database. The fourth column shows the percentage of market share of the matched funds compared to the total market value of all qualified funds in the CDA/Spectrum database. Panel B reports the sample size of the CRSP mutual fund database by year. Similar to Panel A, the first column shows the total number of share classes in the sample. The second column reports the number of qualified share classes, which are defined as share classes of funds that invest more than 50% of assets in equities, share classes of funds that are not index funds and share classes of funds of which the objective indicates US equities as major investment instruments. See footnote 3 of Chapter 1 for the list of objective codes of eliminated funds. The third column reports the number of qualified share classes that can be matched to funds in the CDA/Spectrum database. The fourth column shows the percentage of market share of the matched funds compared to the total market value of all qualified funds in the CRSP database. Panel C reports the number of funds by year in the merged database under the four different CDA/Spectrum investment objective categories.

	Panel A: CDA/Spectrum				Panel B: CRSP				Panel C: Merged Database			
Year	Total	Qualified Funds	Matched Funds	Market Share	Total	Qualified Share Classes	Matched Share Classes	Market Share	Aggressive Growth	Growth	Growth and Income	Balanced
1980	553	413	241	68.3%	728	242	221	97.7%	62	74	66	15
1981	572	428	251	67.6%	830	260	240	98.2%	63	90	75	19
1982	855	406	245	70.3%	987	267	251	98.5%	51	97	67	22
1983	925	433	271	72.5%	1171	281	264	98.8%	57	108	71	28
1984	975	452	280	73.7%	1384	313	291	98.2%	65	117	81	25
1985	1080	471	292	72.7%	1712	375	346	95.9%	69	122	80	40
1986	1145	532	336	72.8%	2149	440	408	93.2%	78	158	99	38
1987	1151	597	382	72.5%	2690	525	483	93.6%	84	193	94	41
1988	1243	649	415	73.3%	3140	585	529	94.7%	96	204	90	45
1989	1347	712	464	59.2%	3388	628	567	95.8%	111	218	102	55
1990	1745	780	510	74.2%	3793	698	622	96.0%	121	230	124	57
1991	2081	903	614	75.2%	4216	818	725	96.6%	145	263	140	65
1992	2146	1042	747	76.3%	5131	1114	984	96.6%	152	358	168	77
1993	3001	1479	1090	77.7%	6702	1598	1419	97.0%	184	608	218	104
1994	5912	1678	1280	79.9%	9278	2369	2096	97.1%	191	749	237	114
1995	7210	1832	1405	78.7%	10214	2751	2441	97.7%	181	785	375	159
1996	8879	2103	1650	81.7%	11394	3367	2995	97.5%	174	943	362	166
1997	8472	2294	1815	80.9%	13040	4213	3538	96.9%	183	1093	369	167
1998	10165	2256	1833	84.9%	14551	5014	3772	96.3%	178	1122	361	162
1999	12866	2063	1745	87.4%	15585	5691	3898	94.1%	170	1062	346	156
2000	16303	1990	1685	87.2%	16793	6512	3915	90.9%	164	1021	335	143
2001	17951	1889	1600	87.7%	17192	6887	3866	87.5%	162	957	319	134
2002	14555	1799	1527	90.4%	17336	7188	3768	85.2%	158	916	301	125

Table 1.2: Performance Measurement Model Summary Statistics, January 1980 to December 2002

This table presents summary statistics for the factors used in the various performance measurement models. Monthly return and standard deviation are reported in percentage. RMRF is the value-weighted return on all stocks traded in NYSE, AMEX and NASDAQ minus one month Treasury bill rate. The HML and SMB factors are constructed using the six value-weighted portfolios formed on size and book-to-market. Those six portfolios are the intersections of two portfolios formed on size and three portfolios formed on the ratio of book equity to market equity. HML is the average return on the two value portfolios minus the average return on the two growth portfolios. SMB is the average return on the three small portfolios minus the average return on the three big portfolios. The UMD factor is constructed using six value-weighted portfolios formed on size and prior returns. The six portfolios are the intersection of two portfolios formed on size and three portfolios formed on last eleven-month returns lagged one month. UMD is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. The size breakpoint is the median NYSE market equity and the prior return breakpoints are the 30th and 70th NYSE percentiles. RMRF can be interpreted as the excess return on market proxy whereas SMB, HML and UMD are specifically constructed to mimic size, book-to-market and momentum factors respectively. The sample period is from January 1980 to December 2002.

					Correlation			
Factors	Monthly Return	Standard Deviation	t-statistic	Autocorrelation	RMRF	SMB	HML	UMD
RMRF	0.55	4.64	1.97	0.05	1.00			
SMB	0.04	3.36	0.19	-0.01	0.18	1.00		
HML	0.41	3.36	2.01	0.13	-0.54	-0.41	1.00	
UMD	0.97	4.49	3.59	-0.04	-0.01	0.11	-0.13	1.00

Table 1.3: Characteristics of Momentum Trading Mutual Fund Portfolios
The table presents the average annual attributes of mutual fund portfolios of different degrees of positive-feedback trading. Mutual funds are sorted in the beginning of each year from 1980 to 2002 into equally-weighted quintile portfolios based on their momentum measure during that year, which is defined as

$$M_t(l,k) = \sum_{i=1}^{n} T_{i,t,l} \cdot R_{i,t-l,k}$$

where $T_{i,t,l}$ is the number of shares of security i traded between time $t-l$ and time t, multiplied by the average of security i price at time $t-l$ and time t and divided by the average of portfolio value at time $t-l$ and time t and $R_{i,t-l,k}$ is the return of security i from date $t-l-k$ to date $t-l$. l varies depending on the security holdings filing cycle of the mutual funds. k is chosen to be six to capture how mutual funds trade in response to previous six-month stock returns. The column labeled Universe shows the average annual portfolio attributes of all mutual funds in the merged database. Funds with the highest momentum measure comprise quintile 5 and funds with the lowest comprise quintile 1. TNA is total net assets. Expense ratio is the percentage of the total investment that shareholders pay for the mutual funds operating expenses, which include management, administrative and 12b-1 expenses. Turnover is the minimum of aggregate purchases of securities or aggregate sales of securities, divided by the average total net assets of the fund. Excess return, expense ratio, turnover and momentum measure are reported in percentages. The t-statistics are shown in parentheses.

Average Annual Portfolio Attributes						
		Positive Feedback Trading				
		Lowest				Highest
	Universe	1	2	3	4	5
Excess Return (%)	0.50	0.40	0.45	0.44	0.48	0.72
	(1.86)	(1.50)	(1.81)	(1.77)	(1.73)	(2.26)
Momentum Measure (%)	0.65	-0.73	-0.02	0.30	0.85	2.87
	(6.60)	(-6.33)	(-0.72)	(5.03)	(7.43)	(8.49)
Expense Ratio (%)	1.22	1.27	1.12	1.16	1.21	1.37
Turnover (%)	87.8	80.5	57.6	71.1	94.3	141.6
TNA ($ million)	520.5	511.5	713.6	581.4	454.2	332.3

Table 1.4: Performance of Momentum Trading Mutual Fund Portfolios

The table presents performance of mutual fund portfolios of different degrees of positive-feedback trading under different models of performance measurement. Mutual funds are sorted in the beginning of each year from 1980 to 2002 into equally-weighted quintile portfolios based on their momentum measure during that year, which is defined as

$$M_t(l,k) = \sum_{i=1}^{n} T_{i,t,l} \cdot R_{i,t-l,k}$$

where $T_{i,t,l}$ is the number of shares of security i traded between time $t-l$ and time t, multiplied by the average of security i price at time $t-l$ and time t and divided by the average of portfolio value at time $t-l$ and time t, and $R_{i,t-l,k}$ is the return of security i from date $t-l-k$ to date $t-l$. l varies depending on the security holdings filing cycle of the mutual funds. k is chosen to be six to capture how mutual funds trade in response to previous six-month stock returns. The column labeled universe shows the average performance of all mutual funds in the merged database. Funds with the highest momentum measure comprise quintile 5 and funds with the lowest comprise quintile 1. Panel A, B and C present performance evaluation under CAPM, Fama-French 3-Factor model and Carhart 4-Factor models respectively. The Spread section presents the performance difference between mutual fund portfolios of the highest momentum measure and the rest of mutual funds. RMRF is the excess return on market proxy. SMB, HML and UMD are factor-mimicking portfolios for size, book-to-market equity and momentum. Alpha is the intercept of the model. The t-statistics to test whether the statistics are reliably different from zero are reported in parentheses.

Panel A: CAPM

		Positive Feedback Trading					Spread			
		Lowest				Highest				
	Universe	1	2	3	4	5	5-1	5-2	5-3	5-4
RMRF	0.94	0.94	0.86	0.88	0.97	1.06	0.12	0.20	0.18	0.09
	(93.42)	(67.86)	(73.72)	(103.00)	(85.44)	(40.57)	(4.55)	(6.37)	(7.10)	(4.70)
Alpha (%)	-0.02	-0.11	-0.03	-0.04	-0.06	0.14	0.25	0.17	0.18	0.20
	(-0.50)	(-1.77)	(-0.51)	(-1.12)	(-1.11)	(1.14)	(1.99)	(1.16)	(1.52)	(2.28)
Adj. R-Square	0.97	0.94	0.95	0.97	0.96	0.86	0.07	0.13	0.15	0.07

Table 1.4: continued

Panel B: Fama-French 3-Factor Model										
		Positive Feedback Trading					Spread			
		Lowest				Highest				
	Universe	1	2	3	4	5	5-1	5-2	5-3	5-4
RMRF	0.93	0.95	0.91	0.90	0.94	0.93	-0.03	0.01	0.03	-0.01
	(104.11)	(64.72)	(71.50)	(93.94)	(93.77)	(50.29)	(-1.17)	(0.52)	(1.56)	(-0.77)
SMB	0.16	0.15	0.04	0.06	0.17	0.39	0.24	0.35	0.33	0.23
	(14.27)	(8.11)	(2.49)	(5.09)	(12.98)	(16.64)	(7.64)	(11.30)	(13.61)	(11.60)
HML	0.01	0.10	0.14	0.07	-0.04	-0.22	-0.31	-0.36	-0.29	-0.18
	(0.94)	(4.37)	(7.36)	(4.96)	(-2.44)	(-7.87)	(-8.56)	(-9.83)	(-10.14)	(-7.91)
Alpha (%)	-0.03	-0.17	-0.11	-0.09	-0.03	0.29	0.46	0.40	0.37	0.32
	(-0.72)	(-2.84)	(-2.21)	(-2.25)	(-0.76)	(3.87)	(4.62)	(4.09)	(4.89)	(5.18)
Adj. R-Square	0.98	0.95	0.96	0.98	0.98	0.95	0.47	0.62	0.68	0.56

Panel C: Carhart 4-Factor Model										
		Positive Feedback Trading					Spread			
		Lowest				Highest				
	Universe	1	2	3	4	5	5-1	5-2	5-3	5-4
RMRF	0.93	0.95	0.91	0.89	0.94	0.94	0.00	0.03	0.05	0.00
	(103.53)	(69.35)	(75.63)	(94.80)	(98.28)	(60.72)	(-0.27)	(1.78)	(3.19)	(-0.09)
SMB	0.16	0.16	0.05	0.06	0.16	0.38	0.22	0.33	0.31	0.22
	(14.20)	(9.23)	(3.05)	(5.36)	(13.24)	(19.15)	(9.13)	(13.36)	(16.57)	(12.51)
HML	0.01	0.08	0.13	0.06	-0.03	-0.18	-0.26	-0.31	-0.25	-0.16
	(0.96)	(3.82)	(7.02)	(4.60)	(-1.88)	(-7.96)	(-9.38)	(-10.65)	(-11.22)	(-7.76)
UMD	0.00	-0.08	-0.07	-0.03	0.04	0.15	0.23	0.21	0.17	0.10
	(0.25)	(-7.04)	(-6.37)	(-3.16)	(5.23)	(10.78)	(14.06)	(12.49)	(13.24)	(8.61)
Alpha (%)	-0.03	-0.07	-0.04	-0.06	-0.08	0.12	0.20	0.16	0.18	0.20
	(-0.76)	(-1.33)	(-0.80)	(-1.48)	(-2.01)	(1.94)	(2.57)	(2.03)	(2.96)	(3.63)
Adj. R-Square	0.98	0.96	0.96	0.98	0.98	0.96	0.69	0.76	0.81	0.66

Table 1.5: Characteristics of Mutual Fund Portfolios Formed on Momentum Trading, by Investment Objective

The table presents the average annual attributes of mutual fund portfolios of different degrees of positive-feedback trading, categorized by the mutual fund investment objective. Panel A, B, C and D report the attribute statistics for mutual funds of investment objective of aggressive growth, growth, growth and income and balanced respectively. See Table 1.3 for definition of mutual fund characteristic and description of portfolio formation. Excess return, expense ratio, turnover and momentum measure are reported in percentages. The t-statistics are shown in parentheses.

Panel A: Aggressive Growth

		Positive Feedback Trading		
		Lowest		Highest
	All	1	3	5
Excess Return (%)	0.56	0.33	0.52	0.89
	(1.56)	(0.92)	(1.49)	(2.26)
Momentum Measure (%)	1.01	-0.81	0.64	3.72
	(6.66)	(-7.97)	(5.87)	(8.43)
Expense Ratio (%)	1.43	1.56	1.38	1.46
Turnover (%)	113.4	110.0	96.4	158.0
TNA ($ million)	572.5	404.8	749.8	434.4

Panel C: Growth and Income

		Positive Feedback Trading		
		Lowest		Highest
	All	1	3	5
Excess Return (%)	0.45	0.46	0.41	0.48
	(2.02)	(2.02)	(1.88)	(2.02)
Momentum Measure (%)	0.39	-0.52	0.18	1.84
	(5.18)	(-10.05)	(3.59)	(8.69)
Expense Ratio (%)	1.07	1.06	1.05	1.17
Turnover (%)	68.5	63.0	60.3	111.9
TNA ($ million)	959.1	1047.2	1067.6	471.4

Panel B: Growth

		Positive Feedback Trading		
		Lowest		Highest
	All	1	3	5
Excess Return (%)	0.50	0.40	0.48	0.75
	(1.77)	(1.41)	(1.77)	(2.29)
Momentum Measure (%)	0.72	-0.67	0.34	3.03
	(6.43)	(-8.50)	(5.76)	(7.65)
Expense Ratio (%)	1.26	1.34	1.20	1.43
Turnover (%)	89.6	75.9	72.0	143.0
TNA ($ million)	330.0	313.3	400.5	248.2

Panel D: Balanced

		Positive Feedback Trading		
		Lowest		Highest
	All	1	3	5
Excess Return (%)	0.39	0.39	0.39	0.45
	(2.22)	(2.28)	(2.17)	(2.43)
Momentum Measure (%)	0.28	-1.37	0.20	1.98
	(1.53)	(-1.67)	(3.60)	(8.69)
Expense Ratio (%)	1.07	1.11	1.00	1.16
Turnover (%)	84.9	87.3	71.1	119.7
TNA ($ million)	490.1	491.6	686.4	272.0

Table 1.6: Performance of Mutual Fund Portfolios Formed on Momentum Trading, by Investment Objective

The table presents performance of mutual fund portfolios of different degrees of positive-feedback trading under different models of performance measurement, categorized by the mutual fund investment objective. Panel A, B, C and D report the regression results for mutual funds of investment objective of aggressive growth, growth, growth and income, and balanced respectively. See Table 1.4 for description of portfolio formation. The row labeled All shows the average performance of mutual funds with the same investment objective. Funds with the highest momentum measure comprise portfolio 5 and funds with the lowest comprise portfolio 1. RMRF is the excess return on market proxy. SMB, HML and UMD are factor-mimicking portfolios for size, book-to-market equity and momentum. Alpha is the intercept of the model. The t-statistics to test whether the statistics are reliably different from zero are reported in parentheses.

	Panel A: Aggressive Growth														
	CAPM			Fama-French 3-Factor Model					Carhart 4-Factor Model						
All	RMRF	Alpha	Adj. R-Sqr	RMRF	SMB	HML	Alpha	Adj. R-Sqr	RMRF	SMB	HML	UMD	Alpha	Adj. R-Sqr
	1.20	-0.10	0.87	1.06	0.45	-0.21	0.04	0.96	1.07	0.44	-0.20	0.05	-0.01	0.96
	(42.59)	(-0.77)		(55.20)	(18.16)	(-7.22)	(0.54)		(56.02)	(18.20)	(-6.89)	(2.95)	(-0.16)	
1 (Low)	1.17	-0.32	0.85	1.05	0.47	-0.15	-0.21	0.94	1.05	0.47	-0.15	-0.02	-0.19	0.94
	(38.93)	(-2.28)		(45.14)	(15.86)	(-4.29)	(-2.26)		(44.86)	(15.89)	(-4.37)	(-0.93)	(-1.98)	
3	1.19	-0.13	0.88	1.06	0.38	-0.19	0.00	0.95	1.07	0.38	-0.18	0.06	-0.07	0.95
	(45.02)	(-1.06)		(52.58)	(14.89)	(-6.32)	(0.01)		(53.91)	(14.98)	(-5.95)	(3.70)	(-0.86)	
5 (High)	1.25	0.21	0.78	1.04	0.57	-0.34	0.44	0.91	1.05	0.56	-0.31	0.16	0.26	0.92
	(30.77)	(1.09)		(34.44)	(14.94)	(-7.67)	(3.62)		(37.31)	(15.57)	(-7.34)	(6.40)	(2.26)	
5-1 Spread	0.08	0.53	0.03	-0.01	0.10	-0.20	0.65	0.17	0.01	0.09	-0.16	0.18	0.45	0.32
	(2.98)	(4.37)		(-0.45)	(2.83)	(-4.59)	(5.67)		(0.21)	(2.63)	(-4.05)	(7.80)	(4.24)	
5-3 Spread	0.06	0.34	0.02	-0.02	0.19	-0.15	0.44	0.23	-0.01	0.18	-0.13	0.09	0.33	0.28
	(2.48)	(2.90)		(-0.90)	(5.69)	(-3.94)	(4.15)		(-0.54)	(5.59)	(-3.50)	(4.19)	(3.16)	

Table 1.6: continued

Panel B: Growth	CAPM			Fama-French 3-Factor Model					Carhart 4-Factor Model					
	RMRF	Alpha	Adj. R-Sqr	RMRF	SMB	HML	Alpha	Adj. R-Sqr	RMRF	SMB	HML	UMD	Alpha	Adj. R-Sqr
All	1.00	-0.05	0.96	0.96	0.21	-0.01	-0.03	0.98	0.96	0.21	-0.01	0.01	-0.04	0.98
	(80.58)	(-0.81)		(97.77)	(16.65)	(-0.93)	(-0.78)		(97.41)	(16.56)	(-0.81)	(0.88)	(-0.97)	
1(Low)	0.99	-0.14	0.93	1.00	0.20	0.08	-0.19	0.95	0.99	0.20	0.06	-0.09	-0.09	0.95
	(60.19)	(-1.86)		(57.68)	(8.91)	(3.18)	(-2.69)		(60.57)	(9.84)	(2.60)	(-6.07)	(-1.35)	
3	0.96	-0.05	0.97	0.96	0.14	0.05	-0.07	0.98	0.96	0.14	0.04	-0.02	-0.04	0.98
	(89.09)	(-0.91)		(86.49)	(9.57)	(3.04)	(-1.62)		(86.79)	(9.81)	(2.72)	(-2.58)	(-0.98)	
5 (High)	1.07	0.16	0.83	0.93	0.43	-0.23	0.31	0.94	0.94	0.41	-0.19	0.16	0.13	0.95
	(36.91)	(1.18)		(43.28)	(15.59)	(-7.10)	(3.66)		(51.53)	(17.63)	(-6.99)	(10.20)	(1.76)	
5-1 Spread	0.08	0.30	0.02	-0.07	0.23	-0.31	0.50	0.35	-0.05	0.21	-0.25	0.25	0.22	0.57
	(2.56)	(2.14)		(-2.46)	(6.07)	(-7.01)	(4.23)		(-1.94)	(6.71)	(-7.07)	(11.85)	(2.25)	
5-3 Spread	0.11	0.21	0.06	-0.03	0.29	-0.28	0.39	0.52	-0.01	0.27	-0.24	0.19	0.18	0.67
	(4.20)	(1.63)		(-1.42)	(9.87)	(-8.06)	(4.17)		(-0.70)	(11.20)	(-8.24)	(11.22)	(2.24)	

Panel C: Growth and Income	CAPM			Fama-French 3-Factor Model					Carhart 4-Factor Model					
	RMRF	Alpha	Adj. R-Sqr	RMRF	SMB	HML	Alpha	Adj. R-Sqr	RMRF	SMB	HML	UMD	Alpha	Adj. R-Sqr
All	0.79	0.02	0.95	0.86	-0.06	0.17	-0.09	0.98	0.86	-0.05	0.16	-0.03	-0.05	0.98
	(74.41)	(0.40)		(97.64)	(-5.05)	(13.02)	(-2.49)		(100.45)	(-4.94)	(12.81)	(-4.66)	(-1.41)	
1(Low)	0.78	0.03	0.92	0.88	-0.03	0.23	-0.11	0.95	0.87	-0.03	0.22	-0.05	-0.05	0.96
	(56.50)	(0.45)		(69.89)	(-1.89)	(12.30)	(-2.27)		(72.31)	(-1.65)	(12.11)	(-5.13)	(-1.10)	
3	0.76	0.00	0.92	0.84	-0.08	0.18	-0.12	0.96	0.84	-0.08	0.17	-0.05	-0.07	0.96
	(57.98)	(-0.07)		(72.83)	(-5.69)	(10.70)	(-2.62)		(75.13)	(-5.61)	(10.45)	(-4.93)	(-1.48)	
5 (High)	0.83	0.02	0.97	0.85	0.01	0.05	-0.01	0.97	0.85	0.01	0.06	0.03	-0.05	0.97
	(90.75)	(0.45)		(79.46)	(0.74)	(3.37)	(-0.32)		(80.93)	(0.55)	(3.83)	(3.37)	(-1.11)	
5-1 Spread	0.05	-0.01	0.03	-0.03	0.04	-0.18	0.10	0.26	-0.02	0.03	-0.16	0.09	0.01	0.37
	(3.11)	(-0.14)		(-1.76)	(2.02)	(-7.56)	(1.61)		(-1.28)	(1.76)	(-7.24)	(6.67)	(0.10)	
5-3 Spread	0.07	0.02	0.09	0.01	0.09	-0.13	0.11	0.37	0.01	0.09	-0.11	0.08	0.02	0.48
	(5.29)	(0.38)		(0.51)	(5.59)	(-6.66)	(2.04)		(1.24)	(5.65)	(-6.31)	(7.49)	(0.40)	

Table 1.6: continued

Panel D: Growth	CAPM			Fama-French 3-Factor Model					Carhart 4-Factor Model					
	RMRF	Alpha	Adj. R-Sqr	RMRF	SMB	HML	Alpha	Adj. R-Sqr	RMRF	SMB	HML	UMD	Alpha	Adj. R-Sqr
All	0.61	0.06	0.94	0.65	-0.03	0.09	0.00	0.95	0.65	-0.03	0.09	0.00	0.00	0.95
	(63.07)	(1.22)		(62.19)	(-2.51)	(5.84)	(-0.06)		(61.80)	(-2.48)	(5.74)	(-0.37)	(0.02)	
1(Low)	0.58	0.07	0.89	0.63	-0.05	0.12	0.00	0.91	0.63	-0.05	0.11	-0.04	0.05	0.91
	(46.24)	(1.24)		(47.48)	(-3.13)	(6.02)	(-0.07)		(48.16)	(-2.96)	(5.64)	(-3.90)	(0.85)	
3	0.62	0.05	0.92	0.66	-0.04	0.11	-0.02	0.93	0.66	-0.04	0.11	0.00	-0.02	0.93
	(55.18)	(0.96)		(55.56)	(-2.55)	(6.19)	(-0.41)		(55.21)	(-2.53)	(6.10)	(-0.21)	(-0.35)	
5 (High)	0.63	0.10	0.90	0.63	0.01	0.01	0.10	0.90	0.64	0.01	0.02	0.05	0.04	0.91
	(50.83)	(1.77)		(42.69)	(0.77)	(0.34)	(1.65)		(44.21)	(0.53)	(0.88)	(4.23)	(0.66)	
5-1 Spread	0.05	0.03	0.05	0.00	0.07	-0.11	0.10	0.24	0.01	0.06	-0.09	0.10	-0.01	0.42
	(3.80)	(0.50)		(-0.23)	(3.84)	(-5.43)	(1.83)		(0.57)	(3.81)	(-5.01)	(9.19)	(-0.14)	
5-3 Spread	0.01	0.05	0.00	-0.03	0.05	-0.10	0.12	0.15	-0.03	0.05	-0.09	0.06	0.06	0.21
	(1.09)	(0.86)		(-2.25)	(2.89)	(-4.75)	(2.03)		(-1.92)	(2.71)	(-4.31)	(4.51)	(0.97)	

Table 1.7: Characteristics of Size-Neutral Mutual Fund Portfolios Formed on Momentum Trading

The table presents the average annual attributes of size neutral mutual fund portfolios of different degrees of positive-feedback trading. At the beginning of each year from 1980 to 2002 the mutual fund portfolios have been sorted into quintiles based on their total net assets. The mutual funds in each TNA quintile are then further sorted into 5 portfolios based on their momentum measure during the same year. A total of 25 TNA-momentum-trade-sorted portfolios are formed. Those portfolios are then re-aggregated based on their momentum measure quintile rank, resulting in 5 TNA stratified, momentum trading portfolios. See Table 1.3 for definition of momentum measure and description of each portfolio attribute. Excess return, expense ratio, turnover and momentum measure are reported in percentages. The t-statistics are shown in parentheses.

Average Annual Portfolio Attributes					
	Positive Feedback Trading				
	Lowest				Highest
	1	2	3	4	5
Excess Return (%)	0.42	0.43	0.46	0.47	0.71
	(1.57)	(1.73)	(1.78)	(1.74)	(2.23)
Momentum Measure (%)	-0.76	-0.05	0.28	0.84	2.83
	(-6.43)	(-1.52)	(5.29)	(7.30)	(8.14)
Expense Ratio (%)	1.23	1.15	1.18	1.21	1.34
Turnover (%)	80.7	58.9	69.5	93.5	136.0
TNA ($ million)	570.9	572.6	556.7	485.5	416.9

Table 1.8: Performance of Size-Neutral Mutual Fund Portfolios Formed on Momentum Trading

The table presents performance of size neutral mutual fund portfolios of different degrees of positive-feedback trading under different models of performance measurement. At the beginning of each year from 1980 to 2002 the mutual fund portfolios have been sorted into quintiles based on their total net assets. The mutual funds in each TNA quintile are then further sorted into 5 portfolios based on their momentum measure during the same year. A total of 25 TNA-momentum-trade-sorted portfolios are formed. Those portfolios are then re-aggregated based on their momentum measure quintile rank, resulting in 5 TNA stratified, momentum trading portfolios. See Table 1.4 for definition of momentum measure. The column labeled Universe shows the average performance of all mutual funds in the merged database. Funds with the highest momentum measure comprise quintile 5 and funds with the lowest comprise quintile 1. Panel A, B and C present performance evaluation under CAPM, Fama-French 3-Factor model and Carhart 4-Factor models respectively. The Spread section presents the performance difference between mutual fund portfolios of the highest momentum measure and the rest of mutual funds. RMRF is the excess return on market proxy. SMB, HML and UMD are factor-mimicking portfolios for size, book-to-market equity and momentum. Alpha is the intercept of the model. The t-statistics to test whether the statistics are reliably different from zero are reported in parentheses.

Panel A: CAPM

	Positive Feedback Trading					Spread			
	Lowest 1	2	3	4	Highest 5	5-1	5-2	5-3	5-4
RMRF	0.94	0.86	0.90	0.94	1.06	0.13	0.20	0.16	0.12
	(66.83)	(77.91)	(99.40)	(88.22)	(41.13)	(4.58)	(6.59)	(6.13)	(6.43)
Alpha (%)	-0.09	-0.05	-0.04	-0.05	0.13	0.22	0.18	0.17	0.18
	(-1.44)	(-0.98)	(-1.01)	(-1.07)	(1.05)	(1.71)	(1.26)	(1.40)	(2.09)
Adj. R-Square	0.94	0.96	0.97	0.97	0.86	0.07	0.13	0.12	0.13

Table 1.8: continued

Panel B: Fama-French 3-Factor Model

	Positive Feedback Trading					Spread			
	Lowest				Highest				
	1	2	3	4	5	5-1	5-2	5-3	5-4
RMRF	0.95	0.91	0.92	0.91	0.93	-0.03	0.02	0.01	0.01
	(62.66)	(76.09)	(90.79)	(97.60)	(51.16)	(-1.08)	(0.64)	(0.30)	(0.85)
SMB	0.14	0.05	0.07	0.16	0.38	0.24	0.33	0.31	0.22
	(7.33)	(3.36)	(5.69)	(13.49)	(16.56)	(7.53)	(11.05)	(12.16)	(12.13)
HML	0.09	0.14	0.07	-0.02	-0.22	-0.31	-0.36	-0.29	-0.20
	(4.15)	(7.75)	(4.58)	(-1.57)	(-8.16)	(-8.43)	(-10.24)	(-9.76)	(-9.30)
Alpha (%)	-0.15	-0.13	-0.08	-0.03	0.28	0.42	0.41	0.36	0.31
	(-2.42)	(-2.80)	(-2.04)	(-0.91)	(3.79)	(4.22)	(4.35)	(4.49)	(5.39)
Adj. R-Square	0.95	0.96	0.98	0.98	0.95	0.46	0.63	0.63	0.63

Panel C: Carhart 4-Factor Model

	Positive Feedback Trading					Spread			
	Lowest				Highest				
	1	2	3	4	5	5-1	5-2	5-3	5-4
RMRF	0.94	0.90	0.92	0.92	0.94	0.00	0.04	0.02	0.02
	(66.93)	(81.37)	(90.94)	(100.51)	(62.73)	(-0.15)	(2.04)	(1.44)	(2.01)
SMB	0.15	0.06	0.08	0.16	0.37	0.22	0.31	0.29	0.21
	(8.35)	(4.06)	(5.87)	(13.61)	(19.32)	(8.96)	(13.39)	(14.21)	(13.85)
HML	0.08	0.12	0.06	-0.01	-0.19	-0.26	-0.31	-0.25	-0.17
	(3.58)	(7.46)	(4.29)	(-1.08)	(-8.39)	(-9.18)	(-11.41)	(-10.43)	(-9.69)
UMD	-0.09	-0.07	-0.02	0.03	0.15	0.23	0.22	0.17	0.12
	(-6.91)	(-6.89)	(-2.32)	(4.20)	(11.31)	(13.91)	(13.47)	(11.90)	(10.98)
Alpha (%)	-0.05	-0.06	-0.06	-0.07	0.11	0.16	0.17	0.17	0.18
	(-0.91)	(-1.31)	(-1.45)	(-1.90)	(1.79)	(2.06)	(2.27)	(2.56)	(3.69)
Adj. R-Square	0.96	0.97	0.98	0.98	0.97	0.69	0.78	0.76	0.74

Table 1.9: Performance of Fund-Flow-Adjusted Mutual Fund Portfolios Formed on Momentum Trading

The table presents performance of fund-flow-adjusted mutual fund portfolios of different degrees of positive-feedback trading under different models of performance measurement. Mutual funds are sorted in the beginning of each year from 1980 to 2002 into quintile portfolios based on their fund flows during that year. The mutual funds in each fund-flow quintile are then further sorted into 5 portfolios based on their momentum measure during the same year. A total of 25 fund-flow-momentum-trade-sorted portfolios are formed. Those portfolios are then re-aggregated based on their momentum measure quintile rank, resulting in 5 fund-flow stratified, momentum trading portfolios. See Table 1.4 for definition of momentum measure. Funds with the highest momentum measure comprise quintile 5 and funds with the lowest comprise quintile 1. Panel A, B and C present performance evaluation under CAPM, Fama-French 3-Factor model and Carhart 4-Factor model respectively. The spread section presents the performance difference between mutual fund portfolios of the highest momentum measure and the rest of mutual funds. RMRF is the excess return on market proxy. SMB, HML and UMD are factor-mimicking portfolios for size, book-to-market equity and momentum. Alpha is the intercept of the model. The t-statistics to test whether the statistics are reliably different from zero are reported in parentheses.

Panel A: CAPM

	Positive Feedback Trading					Spread			
	Lowest 1	2	3	4	Highest 5	5-1	5-2	5-3	5-4
RMRF	0.94	0.86	0.90	0.96	1.05	0.11	0.19	0.15	0.09
	(67.79)	(87.65)	(101.75)	(85.12)	(47.03)	(4.80)	(7.73)	(7.07)	(6.74)
Alpha (%)	-0.07	-0.03	-0.05	-0.01	0.03	0.10	0.06	0.08	0.04
	(-1.06)	(-0.59)	(-1.18)	(-0.19)	(0.33)	(0.99)	(0.54)	(0.87)	(0.69)
Adj. R-Square	0.94	0.97	0.97	0.96	0.89	0.07	0.18	0.15	0.14

Table 1.9: continued

Panel B: Fama-French 3-Factor Model

	Positive Feedback Trading					Spread			
	Lowest				Highest				
	1	2	3	4	5	5-1	5-2	5-3	5-4
RMRF	0.96	0.90	0.92	0.92	0.94	-0.02	0.04	0.02	0.02
	(65.69)	(84.47)	(95.82)	(93.10)	(59.30)	(-0.92)	(2.07)	(1.35)	(1.75)
SMB	0.17	0.05	0.09	0.16	0.34	0.17	0.29	0.24	0.18
	(8.96)	(3.93)	(7.71)	(12.74)	(16.80)	(6.60)	(12.38)	(12.49)	(12.97)
HML	0.09	0.12	0.06	-0.04	-0.17	-0.26	-0.29	-0.24	-0.13
	(4.27)	(7.47)	(4.49)	(-2.81)	(-7.32)	(-8.68)	(-10.80)	(-10.32)	(-8.15)
Alpha (%)	-0.12	-0.10	-0.09	0.02	0.15	0.27	0.25	0.24	0.13
	(-2.06)	(-2.30)	(-2.22)	(0.53)	(2.40)	(3.32)	(3.46)	(3.86)	(3.04)
Adj. R-Square	0.96	0.97	0.98	0.98	0.96	0.45	0.68	0.66	0.63

Panel C: Carhart 4-Factor Model

	Positive Feedback Trading					Spread			
	Lowest				Highest				
	1	2	3	4	5	5-1	5-2	5-3	5-4
RMRF	0.95	0.89	0.92	0.92	0.95	0.00	0.05	0.03	0.03
	(70.35)	(89.19)	(95.48)	(98.19)	(68.46)	(0.09)	(3.89)	(2.62)	(2.62)
SMB	0.17	0.06	0.10	0.16	0.33	0.15	0.27	0.23	0.17
	(10.14)	(4.57)	(7.80)	(13.05)	(18.63)	(7.83)	(15.15)	(14.30)	(13.80)
HML	0.07	0.11	0.06	-0.03	-0.15	-0.22	-0.25	-0.21	-0.12
	(3.71)	(7.13)	(4.28)	(-2.24)	(-7.15)	(-9.60)	(-12.17)	(-10.93)	(-7.95)
UMD	-0.08	-0.05	-0.01	0.05	0.11	0.20	0.17	0.12	0.07
	(-7.01)	(-6.21)	(-1.42)	(5.56)	(9.26)	(14.34)	(13.60)	(11.07)	(7.74)
Alpha (%)	-0.03	-0.04	-0.07	-0.03	0.03	0.06	0.07	0.10	0.06
	(-0.51)	(-0.92)	(-1.83)	(-0.78)	(0.49)	(0.88)	(1.14)	(1.89)	(1.43)
Adj. R-Square	0.96	0.97	0.98	0.98	0.97	0.69	0.81	0.77	0.70

Table 1.10: Characteristics and Performance of Mutual Fund Portfolios Formed on Lagged 1-Year Momentum Trading

The table presents attributes and performance of mutual fund portfolios of different degree of past-year positive-feedback trading under different models of performance measurement. Mutual funds are sorted in the beginning of each year from 1980 to 2002 into equally-weighted quintile portfolios based on their momentum measure in previous year. Definition of momentum measure is described in Table 1.3. Funds with the highest past momentum measure comprise quintile 5 and funds with the lowest comprise quintile 1. Panel A reports the attributes of mutual fund portfolios. Momentum measure($t-1$) is the past-year momentum measure on which the ranking are based. Momentum measure(t) is the momentum measure during the year right after the portfolios are formed. See Table 1.3 for definitions of mutual fund attributes. Panel B, C and D report the performance evaluation under CAPM, Fama-French 3-Factor model and Carhart 4-Factor model respectively. The spread section presents the performance difference between mutual fund portfolios of the highest past momentum measure and the rest of the mutual funds. RMRF is the excess return on market proxy. SMB, HML and UMD are factor-mimicking portfolios for size, book-to-market equity and momentum. Alpha is the intercept of the model. The t-statistics to test whether the statistics are reliably different from zero are reported in parentheses.

Panel A: Portfolio Attributes

	Past-Year Positive Feedback Trading				
	Lowest				Highest
	1	2	3	4	5
Excess Return (%)	0.44	0.41	0.37	0.38	0.42
	(1.65)	(1.66)	(1.47)	(1.40)	(1.30)
Momentum Measure($t-1$) (%)	-0.73	-0.02	0.30	0.85	2.87
	(-6.33)	(-0.72)	(5.03)	(7.43)	(8.49)
Momentum Measure(t) (%)	0.20	0.23	0.33	0.64	1.55
	(2.00)	(4.16)	(5.10)	(6.21)	(6.37)
Expense Ratio (%)	1.28	1.13	1.18	1.23	1.38
Turnover (%)	81.5	57.4	72.6	97.0	138.3
TNA ($ million)	585.7	810.9	666.5	521.6	399.8

Table 1.10: continued

Panel B: CAPM

	Past-Year Positive Feedback Trading					Spread			
	Lowest				Highest				
	1	2	3	4	5	5-1	5-2	5-3	5-4
RMRF	0.91	0.85	0.89	0.96	1.08	0.17	0.23	0.20	0.13
	(65.37)	(70.39)	(100.26)	(81.21)	(41.77)	(6.64)	(7.54)	(7.51)	(7.04)
Alpha (%)	-0.02	-0.02	-0.07	-0.09	-0.12	-0.10	-0.10	-0.05	-0.02
	(-0.30)	(-0.28)	(-1.75)	(-1.73)	(-0.99)	(-0.83)	(-0.71)	(-0.38)	(-0.29)
Adj. R-Square	0.94	0.95	0.97	0.96	0.87	0.14	0.17	0.17	0.16

Panel C: Fama-French 3-Factor Model

	Past-Year Positive Feedback Trading					Spread			
	Lowest				Highest				
	1	2	3	4	5	5-1	5-2	5-3	5-4
RMRF	0.94	0.91	0.91	0.92	0.95	0.01	0.03	0.04	0.02
	(66.75)	(71.76)	(89.72)	(84.82)	(51.20)	(0.29)	(1.53)	(1.99)	(1.75)
SMB	0.18	0.02	0.05	0.15	0.34	0.16	0.32	0.29	0.19
	(10.34)	(1.29)	(3.82)	(10.95)	(14.80)	(5.75)	(11.68)	(12.37)	(11.07)
HML	0.12	0.16	0.07	-0.05	-0.24	-0.37	-0.41	-0.31	-0.20
	(5.88)	(8.59)	(4.75)	(-2.83)	(-8.77)	(-11.01)	(-12.33)	(-11.08)	(-9.41)
Alpha (%)	-0.10	-0.13	-0.12	-0.06	0.07	0.17	0.20	0.19	0.12
	(-1.77)	(-2.57)	(-2.98)	(-1.29)	(0.91)	(1.87)	(2.25)	(2.47)	(2.20)
Adj. R-Square	0.96	0.96	0.98	0.98	0.95	0.56	0.71	0.70	0.64

Table 1.10: continued

Panel D: Carhart 4-Factor Model

	Past-Year Positive Feedback Trading					Spread			
	Lowest 1	2	3	4	Highest 5	5-1	5-2	5-3	5-4
RMRF	0.93	0.91	0.91	0.93	0.96	0.03	0.06	0.06	0.04
	(66.84)	(71.75)	(88.78)	(85.95)	(55.26)	(1.44)	(2.74)	(3.19)	(2.65)
SMB	0.19	0.02	0.05	0.15	0.33	0.15	0.31	0.28	0.19
	(10.73)	(1.51)	(3.92)	(10.92)	(15.44)	(5.87)	(12.34)	(13.05)	(11.33)
HML	0.11	0.16	0.07	-0.04	-0.22	-0.34	-0.38	-0.29	-0.18
	(5.52)	(8.27)	(4.53)	(-2.45)	(-8.53)	(-11.12)	(-12.51)	(-11.10)	(-9.16)
UMD	-0.04	-0.04	-0.01	0.03	0.10	0.14	0.13	0.11	0.07
	(-3.36)	(-3.16)	(-1.55)	(3.28)	(6.34)	(7.75)	(7.43)	(7.19)	(5.63)
Alpha (%)	-0.05	-0.09	-0.10	-0.09	-0.04	0.01	0.05	0.07	0.05
	(-0.96)	(-1.79)	(-2.53)	(-2.05)	(-0.56)	(0.18)	(0.64)	(0.92)	(0.93)
Adj. R-Square	0.96	0.96	0.98	0.98	0.96	0.64	0.76	0.75	0.68

Table 1.11: Regression Test of Mutual Fund Performance

The table reports the time-series average of slope coefficients estimated from annual Fama-MacBeth regressions of the following model:

$$\alpha_{i,t} = a + b_1 \text{mom}_{i,t} + b_2 \text{mom}_{i,t-1} + b_3 \text{turn}_{i,t} + b_4 \text{exp}_{i,t} + b_5 \text{flow}_{i,t} + b_6 \text{TNA}_{i,t} + \epsilon_{i,t}$$

where $\text{mom}_{i,t}$ is the momentum measure, $\text{turn}_{i,t}$ is the turnover, $\text{exp}_{i,t}$ is the expense ratio, $\text{flow}_{i,t}$ is the fund flow, and $\text{TNA}_{i,t}$ is the natural logarithm of total net asset value, and the subscripts i and t in these variables denote observation for mutual fund i at time t. The performance estimate, $\alpha_{i,t}$, is the average monthly abnormal return from either the Fama-French 3-factor model or the Carhart 4-factor model during year t, which are defined as follows:

$$\begin{aligned} \alpha_{i,t}^{\text{FF}} &\equiv r_{i,t} - r_{f,t} - \hat{b}_{i,t} r_{m,t} - \hat{s}_{i,t} r_{\text{SMB},t} - \hat{h}_{i,t} r_{\text{HML},t} \\ \alpha_{i,t}^{\text{Carhart}} &\equiv r_{i,t} - r_{f,t} - \hat{b}_{i,t} r_{m,t} - \hat{s}_{i,t} r_{\text{SMB},t} - \hat{h}_{i,t} r_{\text{HML},t} - \hat{u}_{i,t} r_{\text{UMD},t} \end{aligned}$$

where $r_{i,t}$ is the return on mutual fund i, $r_{f,t}$ is the return on risk-free asset, and $r_{m,t}$, $r_{\text{SMB},t}$, $r_{\text{HML},t}$, and $r_{\text{UMD},t}$ are the premium on market, SMB factor, HML factor and UMD factor respectively. The factor loadings are estimated over the three-year window around time t with at least thirty observations. The cross-sectional regression is run each year using all mutual funds available during that year and the standard error of the coefficients is the time-series standard deviation of the regression estimates across the entire sample period. The t-statistics are shown in parenthiesis.

	Dependent Variable	
Independent Variables	Fama-French Alpha	Carhart Alpha
Momentum Measure(t)	0.046	0.015
	(3.13)	(1.00)
Momentum Measure($t-1$)	0.013	-0.001
	(0.88)	(-0.07)
Fund Flow(t) $\times$ 100	0.144	0.146
	(3.02)	(3.36)
Turnover(t) $\times$ 100	0.038	0.025
	(1.27)	(0.97)
Expense Ratio(t)	-0.118	-0.115
	(-2.79)	(-3.41)
Ln TNA(t) $\times$ 100	-0.016	-0.017
	(-1.17)	(-1.69)

Table 1.12: Momentum Trading Mutual Funds

This table presents the number of mutual funds that implement aggressive momentum trading strategy in each year during the sample period. The second column shows the number of funds that engage in aggressive momentum trading for at least two years in a row. In other words, the mutual funds counted in this column are mutual funds that are found in the strongest momentum-trade quintile portfolio in both current and previous year. See Table 1.4 for definition of momentum measure and details on how to create momentum-trade quintile portfolios. The third column reports the number of funds found in the strongest momentum-trade quintile portfolio in each year. The fourth column reports the percentage of funds that are consistently found to have the strongest momentum measure.

	Number of Funds		
	Mutual funds that trade on momentum consistently	Mutual funds that belong to the strongest momentum-trade quintile portfolio	Percentage
1981	24	44	54.5%
1982	20	41	48.8%
1983	21	46	45.7%
1984	19	50	38.0%
1985	20	56	35.7%
1986	27	63	42.9%
1987	26	71	36.6%
1988	19	77	24.7%
1989	24	88	27.3%
1990	39	94	41.5%
1991	38	115	33.0%
1992	58	128	45.3%
1993	52	173	30.1%
1994	70	217	32.3%
1995	82	258	31.8%
1996	94	286	32.9%
1997	87	336	25.9%
1998	117	350	33.4%
1999	133	330	40.3%
2000	162	306	52.9%
2001	98	299	32.8%
2002	118	291	40.5%

Table 1.13: Performance of Momentum Trading Mutual Funds

This table reports the performance of portfolios of mutual funds that are found in the strongest momentum-trade quintile portfolio in both current and previous year. See Table 1.4 for the construction of momentum-trade quintile portfolios and the definition of momentum measure. RMRF is the excess return on market proxy. SMB, HML, and UMD are factor-mimicking portfolios for size, book-to-market equity and momentum. Alpha is the intercept of the model. The t-statistics to test whether the statistics are reliably different from zero are reported in parentheses.

	Estimate	t-statistic
Panel A: CAPM		
RMRF	1.13	(32.74)
Alpha (%)	0.12	(0.78)
Adj. R-Square	0.80	
Panel B: Fama-French 3-Factor Model		
RMRF	0.95	(37.31)
SMB	0.44	(13.83)
HML	-0.33	(-8.67)
Alpha (%)	0.37	(3.69)
Adj. R-Square	0.93	
Panel C: Carhart 4-Factor Model		
RMRF	0.98	(45.18)
SMB	0.42	(15.69)
HML	-0.29	(-8.88)
UMD	0.20	(10.26)
Alpha (%)	0.16	(1.81)
Adj. R-Square	0.95	

Chapter 2

Put Your Money Where Your Mouth Is: Do Financial Firms Follow Their Own Recommendations?

2.1 Introduction

Recent controversy and media attention about the credibility and accuracy of US financial analysts has raised significant questions about their stock recommendations. On one hand, there is the notion that the primary function of analyst recommendations is to reveal information that has been discovered through fundamental and technical research. Presumably, clients of financial firms with (early) access to recommendations may gain from trading on this information, and if the recommendations are accurate then the firm will gain credibility, reputation, and more clients. On the other hand, there are many alternative reasons firms might issue stock recommendations. Some examples of these alternatives include relationship management (upgrading firms that have banking relationships), generating order flow for the brokerage arm of the firm, and possibly even manipulating the market for the purpose of improving transaction prices or end-of-day marking. In light of the recent scandals surrounding financial firms, would it be a surprise if financial firms traded against their own recommendations to manipulate the market or for other nefarious motives?

To better understand what information and motives are truly behind analyst recommendations, it is both obvious and critical to understand how firms trade on their own recommendations.[1] For example, following trading strategies that are consistent with their own recommendations is evidence that there might be credible information in the analyst reports that is yet to have been incorporated into market prices. Trading against own-firm recommendations is evidence contrary to there being any new information revealed through recommendations. Furthermore, both trading with and against own-firm recommendations also suggests a host of alternative possibilities, and clarifying which are true will help us understand the role and information content of analyst recommendations.

To this end, the primary objective of this paper is to document how financial firms in the US trade on their own US equity recommendations. In particular, we measure the relation between stock trades of financial firms and the change in their own analyst recommendations. Perhaps surprisingly, we find that financial firms actually trade with their own recommendations before, during, and after they are issued. These results are particularly strong during and after recommendations are issued, and they are robust to time sub-periods, different definitions of trade and recommendation measurement, and return control variables.

In the past decade or so, there has been a significant increase in academic interest in the investment value of analyst recommendations. Womack [1996] documented that new buy and sell recommendations have return-predicting power, particularly sell recommendations. He concludes that analysts have material stock-picking and market-timing abilities. Barber, Lehavy, McNichols, and Trueman [2001] further show that trading strategies based on consensus recommendations, in conjunction with daily rebalancing, yield annual abnormal gross returns greater than four per-

[1] To clarify the exposition in this paper, we use firm to denote a financial firm which issues recommendations, whereas company and stock both denote the target of an analyst stock recommendation.

cent. However, these returns would likely disappear after considering reasonable trading costs.[2] These and other studies show that US analyst recommendations do have predictive power and possibly reveal information that has yet to be incorporated into market prices. Thus, low-cost traders might be able to profit from early access to recommendations.

More recently, several researchers have shown evidence of strategic trading based on analyst recommendations. Chen and Cheng [2002] show that quarterly institutional trades are correlated with consensus stock recommendations, but they do not match institutions with their own recommendations. Finally, Heidle and Li [2003] find that NASDAQ market makers affiliated with analysts trade more aggressively before analyst recommendations. Their results are most striking on about an hourly basis (1.5 hours before for upgrades and 3.0 hours before for downgrades). This is evidence that the market making division of financial firms do trade strategically on recommendations for NASDAQ stocks within hours before recommendations are publicly released. In summary, these papers show that financial institutions follow trading strategies based on analyst recommendations. However, only Heidle and Li match financial firms with their own trades, and they do so only on an hourly basis and for companies listed on the NASDAQ.

Our main contribution is documenting the quarterly trading of US financial institutions with respect to their own analyst recommendations. Section 2.2 describes the dataset and market in detail, Section 2.3 describes the empirical methods and results, and Section 2.4 concludes with a brief summary and discussion of some potential hypotheses supporting our findings.

[2]An early study by Bjerring, Lakonishok, and Vermaelen [1983] show that investors in the Canadian stock market following Canadian brokerage house analyst recommendations would have profited, even after accounting for transaction costs.

2.2 Data and Markets

2.2.1 Data

We use the CDA Spectrum institutional holdings database, the I/B/E/S analyst recommendation database (provided by Thomson Financial[3]), and the CRSP database, all of which are accessed through Wharton's WRDS system. We focus exclusively on firms that trade and issue recommendations on US stocks. The CDA Spectrum database reports quarterly discretionary holdings of all institutions with discretionary investments of $100 million or more, as reported in SEC 13F filings. We use only firms which have operations based in the US (including wholly or majority-foreign-owned subsidiaries of foreign firms with a base in the US). We test using the reported holdings changes, but we also re-check all results with the implied period-over-period level changes and find no qualitative differences.[4] The I/B/E/S database contains analyst recommendations levels converted from each firm's proprietary levels to a standardized ranking from 1 (strongest) to 5.[5] We focus on inference from recommendation changes instead of levels, since the conversion of each financial institutions recommendation jargon to five-level ratings implies that the I/B/E/S recommendation levels for different firms may not coincide with identical true recommendation levels. In addition, many firms have more than five levels of recommendations, which clearly do not map perfectly into a five-level system.

Both datasets include data from at least October 1993 to December 2002. Over this period, the CDA Spectrum database includes 3,529 firms trading 38,452 US stocks, and the I/B/E/S database includes 624 firms making recommendations on 12,653 stocks. See Table 2.1 for more complete summary information of the CDA Spectrum and I/B/E/S Databases over this period.

[3]In accordance with contractual agreements with Thomson Financial, we cannot disclose any individual financial firm identities.

[4]As documented previously in Badrinath and Wahal [2002] and others, there is a slight discrepancy between the CDA Spectrum holdings change field and implied changes (using quarter over quarter differences in levels).

[5]1 = Strong Buy, 2 = Buy, 3 = Hold, 4 = UnderPerform, 5 = Sell

2.2.2 Merging Databases and Matching Trades with Analyst Recommendations

To look at the trading patterns of financial firms with respect to their own recommendations, we must first match firm recommendations recorded in the I/B/E/S dataset with their own trades recorded in the CDA Spectrum database. Since there is no common CUSIP or key to merge by (and the names of firms are written with non-standard abbreviations), we do a manual merging. In some cases, we simply do a one-to-one mapping of CDA Spectrum to I/B/E/S names. However, there are also several conglomerate firms which we match. For each conglomerate, we first identify all US subsidiaries. CDA Spectrum generally reports conglomerate holdings, while I/B/E/S generally reports subsidiary-issued recommendations. Thus, we do a one-to-many mapping of CDA Spectrum conglomerates with each subsidiary in the I/B/E/S database.

The following representative examples are purely for illustrative purposes, and may or may not be included in our dataset. In the case of conglomerate firms with multiple subsidiary firms, we associate all subsidiary recommendations with the conglomerate holdings. For example, Citigroup currently owns both Salomon Brothers and Smith Barney. Both Salomon and Smith Barney have separate analysts issuing recommendations. Therefore, we match both Salomon Brothers and Smith Barney recommendations to Citigroup trades. Before Citigroup acquired Travelers on October 8, 1998, Citigroup did not have any equity analysts associated with it, so we did not match any recommendations to it.

In the case of firm mergers, we research the exact dates when mergers occur. Continuing on the previous example, Salomon Brothers and Smith Barney merged on November 26, 1997. Before that date, each firm had a separate matched pair from the I/B/E/S and CDA Spectrum databases. After that date, recommendations continued to be issued separately by both Salomon Brothers and Smith Barney, so we associated recommendations from both to the financial holdings of Travelers Group (which owned the merged entity, Salomon Smith Barney).

After our merging procedure and before applying any data filters, we matched 77 financial firms (where conglomerates count as one) which trade and recommend 8,966 stocks. There are 123,757 total data points (i.e. recommendation changes).

2.2.3 Data Filters

We employ several filters to target the most relevant data. Our first filter is to discard any recommendations for which there are multiple recommendation changes within a single quarter. Since we have quarterly firm trading data, we cannot differentiate the inference from such recommendations. After applying this filter, we have 77 firms, 8,850 stocks, and 98,654 data points.

Our second filter is to exclude any recommendation changes which took over 2 years to update. Anecdotally, in many of these cases the recommendation change actually indicates re-initiation of analyst coverage rather than a timely change in the stock recommendation.[6] After this filter we have 77 firms, 8,760 stocks and 88,761 data points. See Figure 2-1 for the distribution of the number of days between recommendations.

Our third and final filter is to accommodate the return control variables and merge with the CRSP database. After including contemporaneous and past returns as controls, our dataset is diminished due to lack of lagged return data on IPO stocks and CRSP stock mismatching. This leaves us with a final sample of 77 firms, 6,479 stocks, and 65,414 data points.[7] See Table 2.2 for our summary of the filtered data and a recommendation transition matrix of the filtered sample of recommendations.

In Table 2.3, we report end-of-year summaries of the stocks in the final, filtered sample. These are stocks for which we have matched at least one financial firm trade and recommendation. We can see that the number of stocks ranges from 3,648 to 5,238, average stock price ranges from 27.72 to 39.13, average market capitalization ranges from \$1.152 billion to \$3.423 billion, and monthly turnover ranges from 9.95%

[6]Our results do not change qualitatively whether or not we include the time between recommendations, as shown in our preliminary filters of 6 months, 1 year, and 2 years.

[7]We also run preliminary tests without the third CRSP-matching filter or return control variables, and the qualitative inference is unchanged.

to 17.67% (of shares outstanding). These figures all peak during the internet boom, around 1999 or 2000. Monthly share volume increases steadily throughout the sample, from 2.786 million to 16.397 million shares.

2.3 Empirical Methods and Results

2.3.1 Methodology

For each of the tests, we generally use three regression procedures: pooled OLS, weighted Fama and MacBeth [1973] style (FM), and ordered probit regressions. For the pooled OLS regressions, we pool all firms and stocks together. For the FM regressions, we run OLS regressions within each quarter and calculate standard errors using the time-series estimates of cross-sectional (quarterly) coefficients. Then, we use the degrees of freedom in each quarterly regression to weight our time-series estimates to calculate weighted-average coefficients and standard errors. For the ordered probit, we again pool all firms and stocks. Our tables report results from each procedure, except in cases where there are too few quarterly observations to run the FM regressions.

Our general method is to regress firm trade on recommendation changes and control variables. We test for trades occurring from $i = t - 3$ to $t + 3$, where we define i as the period in which trade occurs and t as the period in which there is a recommendation change. We test contemporaneous firm trade by matching recommendations issued any time within a quarter to the change in holdings during that quarter.[8] We also match trades to recommendations from three quarters before up to three quarters after the trade. Exploring the trading before, during, and after recommendation changes helps us gain a complete picture of firm trading patterns.

For each of the tests, we include dummy variables to control for the recommendation level before the recommendation change at time t. These controls are particularly important in the cases of previous strong buys and sells (I/B/E/S levels 1 and 5),

[8]Although the recommendation may come at any time within the quarter, the holdings change reporting always occurs at the end of March, June, September, or December.

since the recommendation change associated with these will always be a downgrade or upgrade, respectively. Given the empirical asymmetry in recommendation levels indicated in the transition matrix shown in Panel B of Table 2.2 (we observe many more strong buys than sells), excluding these level controls would severely bias our results and distort our inference.

$$\text{Trade}(i) = \beta_{\text{Upgrade(t)}} D_{\text{Upgrade(t)}} + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \epsilon$$

The OLS and FM regression specifications are both given by the above equation. Trade(i) is defined as the firms net trade in a given stock divided by the shares outstanding. $D_{\text{Upgrade(t)}}$ is a dummy variable which takes a value of one if the recommendation change is an upgrade and zero if it is a downgrade. $\beta_{\text{Upgrade(t)}}$ is the difference in average net trade around an upgrade relative to around a downgrade, holding fixed the previous recommendation level. Each of D_1 to D_5 is a dummy variable which takes a value of one if the prior I/B/E/S recommendation level is matched and zero otherwise. β_1, β_2, β_3, β_4, and β_5 represent the mean trade given prior recommendation levels of Strong Buy, Buy, Hold, Underperform, and Sell, respectively, when the time t recommendation change is downgrade.

$$\begin{aligned}
p_1 &= \Phi(\alpha_1 + \beta' x) \\
p_2 &= \Phi(\alpha_2 + \beta' x) - \Phi(\alpha_1 + \beta' x) \\
p_3 &= 1 - \Phi(\alpha_2 + \beta' x) \\
\beta' x &= \beta_{\text{Upgrade(t)}} D_{\text{Upgrade(t)}} + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \epsilon
\end{aligned}$$

The probit specification is given above. In this case, we use an ordered trade variable to denote firm actions of buying (1), no trade (2), and selling (3), where all other variables remain the same as in the OLS/FM specification. Φ is the cumulative standard normal distribution function. As such, a significantly positive (negative) value for the coefficient on $D_{\text{Upgrade(t)}}$ would indicate that an upgrade would increase (decrease) the probability, or z-score, of a firm buying and decrease (increase) the probability of a firm selling. The effect on the probability of a firm not trading is dependent on the net effects on buying and selling combined. The magnitude of these effects would vary depending on the natural response levels, which essentially correspond to a location on the cumulative normal distribution function. For example, if the natural probability of firm buying is very high, then even a statistically significant positive coefficient on $D_{\text{Upgrade(t)}}$ would indicate only a small increase in the probability of buying associated with an upgrade.

2.3.2 Preliminary Results: Percentage of Firm Buys and Sells around Recommendations

Panels A and B of Table 2.4 report the percentage of recommendation changes around which institutions buy and sell. For example, in the column where $i = t$, when the previous recommendation level is Hold and the recommendation change at t is an upgrade, we find that institutions buy 26.9% (from Panel A) of the time and sell 19.4% (from Panel B) of the time. As indicated, institutions do not trade during the quarter of their recommendation in the remaining 53.7% (100% − 26.9% − 19.4%) of the observations. This may be because of regulatory restrictions or simply the lack of institutional need or desire to trade. Panel C reports the buy percentage, excluding the cases in which the institutions do not trade. The analogous entry in Panel C for the above example is 58.1%, or simply the buy percentage (26.9%) divided by the sum of the buy and sell percentages (26.9% + 19.4%). Note that there cannot be an upgrade (downgrade) following a prior recommendation level of Strong Buy (Sell).

2.3.3 Main Results: Trading before Upgrades versus Downgrades

Our main results are shown below in Table 2.5. Firm net trade is significantly higher after upgrades than downgrades, particularly for $i = t$ and $t + 1$. In all panels, the coefficients on the Upgrade Dummy for trade in periods t and $t + 1$ is statistically positive and significant. The period t coefficient of 0.121 (t-statistic 2.46) in Panel B suggests that on average, each firm in our sample buys 1.29 basis points (of shares outstanding) more after upgrades than after downgrades. This is economically significant as well, considering the average capitalization of firms in our sample (from $1.152 billion to $3.423 billion depending on the year). The analogous coefficient in Panel C is 0.197 (t-statistic of 18.39), indicating that the z-score of the likelihood of firm buying is 0.197 higher if the recommendation is an upgrade rather than a downgrade.

The coefficients for trade during period $t-1$ is positive in all three panels and significantly positive in the probit specification. This is evidence, either that there is leakage of analyst recommendations in the quarter prior to issuance, or that firms tend to discover information and trade before issuing recommendations reflecting that information.

One simple robustness check for the contemporaneous trade and recommendation relationship can be seen in the $t-3$ to $t-1$ coefficients on the prior recommendation dummy variables. In Panels A and B, we see that the firm trade before t is almost monotonically related to the recommendation level before t (both coefficients and t-statistics). As indicated in our methodology section, these coefficients are the average net trade before downgrades for each prior recommendation level. The coefficients before t are significantly positive when the previous recommendation is Strong Buy or Buy. In other words, firms seem to be buying based on their prior recommendations in prior periods. Note that we include the prior recommendation dummy variables in the probit; we do not report the results, but they are available on request.

In Table 2.6, we report results from regressing firm trade on only upgrade and downgrade dummy variables. The coefficients now represent the mean absolute trade given upgrades and downgrades. For example, in Panel B where $i = t$, we see that the net trade in the quarter of an upgrade is 1.01 basis points, while in the quarter of a downgrade it is -0.05 basis points. Generally, firm trade is positive and statistically significant before downgrades and statistically zero after downgrades; firm trade is consistently positive and significant before, during, and after upgrades. As for the relative comparison, we find that net trade is higher before downgrades and higher during/after upgrades.[9] This seems to indicate that upgrades contain marginal if any information, while downgrades contain significant, material information.

We continue to control for prior recommendation levels in each of the robustness tests shown below. We do not report the coefficients, since they are qualitatively similar to the main tables and do not affect the inference on the main independent variable, recommendation change.

2.3.4 Robustness Test 1: Firm Trade Defined as Change in Portfolio Weight

In Table 2.7, we perform identical tests to those in the main results, except that we define Trade(i) as the change in portfolio weight of the stock for the institution instead of [shares traded / shares outstanding]. We use the CDA Spectrum overall firm holdings to determine the total value of the portfolio for each firm at each quarter. Then, we calculate what percentage of the firms portfolio each stock represents, and Trade(i) represents the change in that percentage period over period.

This definition of trade accounts for differing sizes of financial institutions as well as variation in stock size. While smaller institutions may trade a smaller percentage of the shares outstanding, this test reflects that changes in overall portfolio weighting for small firms is as important as for larger firms. In addition, this definition gives less weight to smaller-capitalization stocks since it is unlikely that they will comprise a large proportion of the total holdings of any firm. Inference from this test is very similar to the main result, except that firm trade begins to be significant at $i = t - 2$. Apparently, this change reflects that smaller financial firms tend to start trading significantly on their recommendation changes even two quarters before issuance.

[9]Note that the results here are not conditional on prior recommendation level; hence we do not find that firm trade is consistently higher before, during, and after upgrades as in Table 2.5.

2.3.5 Robustness Test 2: Size Quartiles

The second robustness test shows explicitly the difference in trading across stock size quartiles. For this and subsequent tests, we return to the original definition of trade as [shares traded / shares outstanding]. We run the main tests again, splitting the sample by size quartiles. We define the size break points with New York Stock Exchange (NYSE) quartiles at the beginning of each quarter and apply these break points to all stocks in that quarter.

Much of the inference from the main results remains the same for each quartile in Table 2.8, in particular that generally trading around upgrades is greater than around downgrades. Although there are some variations in statistical significance (particularly for the Fama and MacBeth [1973] style regressions), there is no discernable pattern across stock size. For the most part, we find evidence that firms buy significantly more at $i = t - 1$ to $t + 1$, with slight variations across stock size.

2.3.6 Robustness Test 3: Consensus Control Variable

It is well-documented that analysts tend to herd, so it might be the case that firms trade based on the consensus rather than on their own analysts. To account for this, our third robustness test includes a control variable for consensus recommendation change. For each stock in each quarter, we assign a value of $+1$ to each upgrade -1 to each downgrade by financial firms. We define the summation of these values across all firms in the quarter as our consensus recommendation change variable.

From Table 2.9, we do not find strong evidence that firm trade is related to consensus recommendation changes as defined.[10] Furthermore, the inference on trades relative to own-firm analyst recommendations remains almost identical to the main results.

[10] We tried several alternative definitions of consensus recommendation changes with similar results.

2.3.7 Robustness Test 4: Return Control Variables

It is also documented that financial firms trade in response to current and past stock returns, possibly following momentum or contrarian trading strategies. In Table 2.10, we show the results from tests including control variables for contemporaneous and past stock returns. The equation below shows the OLS and FM specifications, and the probit specification is identical to the one defined in the methodology subsection, except that $\beta' x$ is now given by the right-hand-side of the following equation. $r(i)$, $r(i-1)$, $r(i-2)$, and $r(i-3)$ are quarterly stock returns relative to period i.

$$\begin{aligned}\text{Trade}(i) &= \beta_{\text{Upgrade(t)}} D_{\text{Upgrade(t)}} + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 \\ &\quad + \beta_{r(i)} r(i) + \beta_{r(i-1)} r(i-1) + \beta_{r(i-2)} r(i-2) + \beta_{r(i-3)} r(i-3) + \epsilon\end{aligned}$$

The inference on the recommendation change (upgrade dummy) remains unchanged from the main results in each of the OLS, FM, and probit specifications. We see that firm trade may depend in a positive way on contemporaneous and last quarter stock return, re-confirming other studies that find such momentum trading strategies. These effects are statistically significant in the OLS and probit regressions, but less so in the FM regression.

2.3.8 Robustness Test 5: Recommendation Changes instead of Upgrade Dummy

It may be reasonable to expect that larger changes in recommendations lead to more obvious strategic trading by firms. This test accommodates this expectation assuming a linear relationship between the changes in recommendation levels recorded by I/B/E/S. Though such a linear relationship is likely not exact, there is clearly a monotonic difference in magnitude of different levels of recommendation change.

$$\text{Trade}(i) = \beta_{\text{recChange}} D_{\text{recChange}} + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \epsilon$$

The above equation is the OLS and FM specification with recommendation change represented by the difference in the I/B/E/S recommendation levels. RecChange represents the actual difference in I/B/E/S recommendation level, from the previous to current recommendation. In Table 2.11, we see no qualitative the statistical significance of $\beta_{\text{RecChange}}$, though the magnitude of the coefficient is lower since it represents the difference in mean trade for each level of recommendation change.

2.3.9 Robustness Test 6: Sub-periods

In Table 2.12, we show that our main result in sub-periods. We split our sample in half chronologically, and we also split into "internet boom" and "excluding internet boom" periods. We find that the results are slightly weaker during the internet boom period, but once again the qualitative results are quite similar to the main results in each sub-period.

2.3.10 Robustness Test 7: Individual Firm Results

In our final robustness test, we run the main test for each of the 77 matched firms. In Table 2.13, we report the mean and median t-statistics as well as the percentage of positive t-statistics for each coefficient.

Panel A displays results from the OLS regressions, and we see that 66.7% of firms buy more during upgrades during the period of the recommendation. 75.9% buy more during upgrades during the period after the recommendation. The results from the probit regressions in Panel B show similar results; there are to few cross-sectional observations per firm to run FM regressions. The results in Table 2.13 indicate that a majority of firms follow the trading patterns found in the main results, but there are some firms that do not.

2.4 Conclusion

We have documented that firm net trade is higher around upgrades than downgrades, with strong statistical significance in the same quarter as and subsequent quarter to recommendation changes. These general results are robust to many different data cross sections. Furthermore, we find that firm trade drops significantly in response to downgrades, though it does not jump in response to upgrades. This indicates that the main result may be driven by the new information reflected in downgrades.

2.4.1 Potential Explanations

Our results imply that firm trading and recommendation changes are consistent. This consistency may be somewhat surprising given the recent negative publicity around financial firms. However, we can identify and explore some potential hypotheses for our observed patterns between firm trading and their own recommendations.

First, if analyst recommendation changes reflect new information and that is recognized by the firm, then we would expect to see that the firms trade on that information before issuing it publicly. Since we cannot differentiate intra-quarter trading, we would also expect to see a positive relation during the same quarter as recommendations. However, assuming even weak-form market efficiency, we would not expect to see a positive relation in quarters after recommendations. Thus, the hypothesis of recommendations containing material information might explain the trading before and during recommendations, but not after.

Second, firms supporting their analysts may explain trading after recommendation changes. We find that firms continue to trade on their recommendations even in the quarter after public issuance. This might indicate that firms do not believe in market efficiency and continue to trade on the information in the recommendations even after it is publicly available. However, it may also reflect a public show of solidarity by firms for their analysts. To the extent that analyst recommendations bring in investment banking, investment management, or financial consulting revenue, firms depend on analyst recommendations. Trading in support of recommendations may indicate support of analysts rather than the belief that there is information in the recommendation that is priced "slowly".

Finally, downgrades may reflect material information more so than upgrades. There is a significant in drop in firm net trade after downgrades, but not a corresponding increase in net trade after upgrades. This indicates that there may be an asymmetry in the motives for upgrades and downgrades. While it seems clear that downgrades reflect material negative information about stocks, upgrades do not reflect enough positive information to warrant a significant increase in trading after issuance.

Table 2.1: CDA Spectrum and I/B/E/S Database Summary Information The table reports summary information about the CDA Spectrum and I/B/ES databases through sample period from 1993 to 2002. Panel A reports the number of firms in the CDA Spectrum database (i.e. those with discretionary investment holdings of \$100 million or more) and the number of stocks held by those firms. Panel B reports the number of firms in the I/B/E/S analyst recommendation database, along with the number of stocks covered and the number of individual analyst recommendations.

Panel A: CDA Spectrum Institutional Holdings Database	
Number of Firms	3,529
Number of US Stocks Traded	38,452

Panel B: I/B/E/S Database	
Number of Recommending Firms	1,347
Number of Analyst Recommendations	1,062,857
Number of Stocks Covered	34,992
Number of Recommending Firms Covering only US Stocks	624
Number of Analyst Recommendations	341,438
Number of Stocks Covered	12,653

Table 2.2: Merged Dataset Summary and Analyst Recommendation Transition Matrix

The table reports summary information of our merged I/B/E/S and CDA Spectrum database in Panel A, and a recommendation transition matrix of the final filtered sample in Panel B. The unfiltered sample matches each data point with a single firm from both databases.

Panel A: Summary Statistics of Merged Database	
Unfiltered	
Number of Firms	77
Number of Stocks	8,966
Number of Recommendation Changes	123,757
First filter: One Recommendation Change Per Stock Per Quarter Per Firm	
Number of Firms	77
Number of Stocks	8,850
Number of Recommendation Changes	98,654
Second Filter: Less than Two Years between Recommendations	
Number of Firms	77
Number of Stocks	8,760
Number of Recommendation Changes	88,761
Days between recommendations	
Maximum	729
Minimum	1
Average	236
Third Filter: Return Control Variables and CRSP Merging	
Number of Firms	77
Number of Stocks	6,479
Number of Recommendation Changes	65,414

Panel B: Transition Matrix of Analyst Recommendations

			To		
From	Strong Buy	Buy	Hold	Underperform	Sell
Strong Buy		13,133	11,881	257	267
Buy	12,219		21,492	740	258
Hold	6,978	13,547		3,173	1,246
Underperform	104	345	1,725		92
Sell	135	159	958	52	

Table 2.3: Stock Summary Statistics

This table reports summary statistics for the stocks included in our final, filtered sample. At the end of each calendar year of our dataset, we calculate the number of stocks in the sample for that year. Stock price and market capitalization (in millions of dollars) are taken at the end of each year, while monthly volume (in thousands of shares) and turnover (in percent of shares outstanding) are calculated as monthly averages for each year.

End of Year	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Number of Stocks	3,648	4,114	4,492	4,968	5,221	5,208	5,238	5,072	4,686	4,285
Stock Price ($)										
Average	28	25	31	31	35	38	39	36	38	35
Maximum	16,325	20,400	32,100	34,100	46,000	70,000	56,100	71,000	75,600	72,750
Minimum	1	0	0	0	0	0	0	0	0	0
Median	19	17	19	20	21	17	18	15	17	14
Market Capitalization ($ 1,000,000s)										
Average	1,281	1,152	1,467	1,645	2,092	2,618	3,423	3,294	3,096	2,566
Maximum	89,452	87,193	120,260	162,790	240,136	342,558	602,433	475,003	398,105	276,631
Minimum	1	1	1	0	0	0	0	0	1	0
Median	227	200	246	269	316	295	374	306	379	323
Monthly Volume (share 1,000s)										
Average	2,786	2,724	3,327	3,793	4,561	5,754	7,716	11,153	13,957	16,397
Maximum	87,973	99,406	176,962	197,017	323,885	366,786	545,702	1,048,066	1,774,642	3,137,673
Minimum	1	-	0	0	2	5	3	2	1	3
Median	1,164	987	1,258	1,451	1,524	1,726	2,140	2,911	2,669	2,868
Monthly Turnover (%)										
Average	11.39	9.95	12.18	13.14	13.25	13.73	16.75	17.67	14.90	14.51
Maximum	186.23	130.07	189.84	662.50	558.69	704.22	684.83	2551.00	604.01	787.71
Minimum	0.01	0.00	0.01	0.00	0.02	0.04	0.08	0.08	0.02	0.06
Median	7.22	6.54	7.65	8.67	8.72	8.71	9.17	10.53	9.01	9.16

Table 2.4: Percentage of Firm Buys versus Firm Sells around Recommendation Changes

The table reports the percentage of recommendation changes around which institutions buy (sell) the stock in Panel A (Panel B). Since there are many observations around which institutions do not trade, Panel C reports the percentage of recommendation changes around which institutions buy, excluding the cases in which the institutions do not trade. The percentages are those associated with our merged sample; each firm recommendation is matched with trading of the same firm. Recommendations occur in period t, and trades occur in period i (from $t-3$ to $t+3$). Prior Rec. is the previous recommendation level before the recommendation change, and RecChange(t) is the recommendation change at time t.

					i			
Prior Rec.	RecChange(t)	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: Percentage of Institutional Buy								
Strong Buy (1)	Downgrade	26.3%	27.2%	27.6%	24.4%	22.7%	21.8%	21.5%
	Upgrade	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Buy (2)	Downgrade	23.9%	24.5%	24.0%	21.1%	20.9%	19.5%	19.5%
	Upgrade	23.4%	25.1%	27.6%	30.4%	28.4%	26.7%	25.1%
Hold (3)	Downgrade	27.1%	24.8%	23.8%	21.5%	16.2%	15.0%	13.4%
	Upgrade	22.8%	22.9%	23.5%	26.9%	25.6%	24.2%	23.8%
UnderPerform (4)	Downgrade	23.9%	16.3%	20.7%	25.4%	23.5%	8.3%	17.4%
	Upgrade	22.0%	21.9%	20.6%	20.1%	19.5%	17.5%	18.7%
Sell (5)	Downgrade	n/a	n/a	n/a	n/a	n/a	n/a	n/a
	Upgrade	14.5%	12.2%	12.3%	13.8%	14.7%	13.2%	14.1%
Panel B: Percentage of Institutional Sell								
Strong Buy (1)	Downgrade	19.2%	20.8%	21.9%	24.5%	22.7%	21.5%	20.0%
	Upgrade	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Buy (2)	Downgrade	18.4%	19.7%	20.8%	22.4%	19.5%	18.4%	17.2%
	Upgrade	18.3%	19.4%	20.4%	19.4%	21.6%	22.4%	22.4%
Hold (3)	Downgrade	23.3%	26.1%	26.0%	25.3%	19.4%	13.9%	12.9%
	Upgrade	20.2%	20.9%	21.1%	19.4%	20.1%	20.9%	20.3%
UnderPerform (4)	Downgrade	28.3%	37.0%	29.9%	23.9%	29.4%	16.7%	8.7%
	Upgrade	22.4%	22.3%	22.3%	19.6%	17.5%	17.1%	14.8%
Sell (5)	Downgrade	n/a	n/a	n/a	n/a	n/a	n/a	n/a
	Upgrade	12.9%	14.8%	13.3%	10.8%	10.4%	10.1%	8.9%
Panel C: Percentage of Institutional Buy (excluding zero trades)								
Strong Buy (1)	Downgrade	57.8%	56.7%	55.8%	49.8%	49.9%	50.3%	51.9%
	Upgrade	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Buy (2)	Downgrade	56.4%	55.5%	53.5%	48.5%	51.8%	51.5%	53.1%
	Upgrade	56.2%	56.4%	57.5%	61.1%	56.8%	54.4%	52.9%
Hold (3)	Downgrade	53.8%	48.7%	47.8%	45.9%	45.5%	51.9%	50.9%
	Upgrade	53.1%	52.3%	52.7%	58.1%	56.0%	53.7%	54.0%
UnderPerform (4)	Downgrade	45.8%	30.6%	40.9%	51.4%	44.4%	33.3%	66.7%
	Upgrade	49.5%	49.5%	48.0%	50.6%	52.7%	50.5%	55.9%
Sell (5)	Downgrade	n/a	n/a	n/a	n/a	n/a	n/a	n/a
	Upgrade	52.8%	45.2%	48.0%	56.3%	58.6%	56.8%	61.3%

Table 2.5: Main Result: Firm Trades before Upgrades Relative to Downgrades

This table reports estimated regression coefficients from regressing firm trades on recommendations and control variables.

$$\text{Trade}(i) = \beta_{\text{Upgrade}(t)} \cdot D_{\text{Upgrade}(t)} + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \epsilon$$

The OLS and Fama and MacBeth [1973] style regression specifications are both given by the above equation, with results reported in Panels A and B. Trade(i) is defined as the firms net trade in a given stock divided by the shares outstanding. $D_{\text{Upgrade}(t)}$ is a dummy variable which takes a value of one if the recommendation change is an upgrade and zero if it is a downgrade. $\beta_{\text{Upgrade}(t)}$ is the difference in average net trade around an upgrade relative to around a downgrade, holding fixed the previous recommendation level. Each of D_1 to D_5 is a dummy variable which takes a value of one if the prior I/B/E/S recommendation level is matched and zero otherwise. β_1, β_2, β_3, β_4, and β_5 represent the mean trade given prior recommendation levels of Strong Buy, Buy, Hold, Underperform, and Sell, respectively, when the time t recommendation change is downgrade. Recommendations occur in period t, and trades occur in period i (from $t-3$ to $t+3$).

i	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: OLS Regression							
Upgrade Dummy	0.038	0.066	0.079	0.138	0.136	0.040	0.005
	(1.05)	(1.71)	(1.92)	(3.86)	(3.98)	(1.19)	(0.15)
Strong Buy (1) Dummy	0.202	0.211	0.134	-0.017	-0.008	-0.020	0.007
	(8.36)	(8.15)	(4.85)	(-0.69)	(-0.35)	(-0.92)	(0.32)
Buy (2) Dummy	0.106	0.112	0.091	0.006	-0.018	0.039	0.028
	(4.37)	(4.32)	(3.27)	(0.26)	(-0.76)	(1.75)	(1.22)
Hold (3) Dummy	0.023	-0.026	-0.074	-0.031	-0.042	0.030	0.098
	(0.60)	(-0.62)	(-1.68)	(-0.79)	(-1.13)	(0.79)	(2.53)
UnderPerform (4) Dummy	0.114	-0.057	-0.083	-0.169	-0.108	-0.020	0.003
	(1.30)	(-0.61)	(-0.80)	(-1.79)	(-1.19)	(-0.23)	(0.03)
Sell (5) Dummy	0.027	-0.022	0.010	-0.076	-0.011	0.054	0.152
	(0.24)	(-0.18)	(0.08)	(-0.67)	(-0.11)	(0.53)	(1.45)
Panel B: Fama MacBeth Regression							
Upgrade Dummy	0.025	0.039	0.060	0.121	0.128	0.046	0.006
	(0.68)	(0.81)	(1.16)	(2.46)	(3.41)	(1.49)	(0.17)
Strong Buy (1) Dummy	0.195	0.207	0.137	-0.021	-0.006	-0.022	0.005
	(5.73)	(5.30)	(4.42)	(-0.63)	(-0.17)	(-0.83)	(0.17)
Buy (2) Dummy	0.105	0.113	0.102	0.018	-0.005	0.036	0.033
	(4.65)	(4.89)	(3.82)	(0.79)	(-0.21)	(1.37)	(1.34)
Hold (3) Dummy	0.027	0.002	-0.072	-0.019	-0.041	0.019	0.090
	(0.86)	(0.03)	(-1.35)	(-0.53)	(-1.04)	(0.48)	(2.33)
UnderPerform (4) Dummy	0.071	-0.031	-0.070	-0.170	-0.070	0.001	0.004
	(1.48)	(-0.36)	(-1.07)	(-2.37)	(-1.13)	(0.01)	(0.08)
Sell (5) Dummy	0.045	-0.083	-0.008	-0.007	0.252	0.074	0.261
	(0.77)	(-0.98)	(-0.09)	(-0.09)	(0.87)	(1.15)	(2.24)

Table 2.5: continued

Panel C reports results from the ordered probit specification as shown below:

$$\begin{aligned}
p_1 &= \Phi(\alpha_1 + \beta' x) \\
p_2 &= \Phi(\alpha_2 + \beta' x) - \Phi(\alpha_1 + \beta' x) \\
p_3 &= 1 - \Phi(\alpha_2 + \beta' x) \\
\beta' x &= \beta_{\text{Upgrade}(t)} D_{\text{Upgrade}(t)} + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \epsilon
\end{aligned}$$

We use an ordered trade variable to denote firm actions of buying (1), no trade (2), and selling (3), where all other variables remain the same as in the OLS and FM specification. Φ is the cumulative standard normal distribution function. A significantly positive (negative) value of $\beta_{\text{Upgrade}(t)}$ would indicate that an upgrade would increase (decrease) the probability, or z-score, of a firm buying and decrease (increase) the probability of a firm selling. The effect on the probability of a firm not trading is dependent on the net effects on buying and selling combined. The magnitude of these effects would vary depending on the natural response levels, which essentially correspond to a location on the cumulative normal distribution function. β_1 to β_5 represent z-scores given prior recommendation levels of 1 through 5, and are not reported (available upon request).

i	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel C: Probit Regression							
Upgrade Dummy	-0.009	0.029	0.069	0.197	0.106	0.051	0.018
	(-0.88)	(2.82)	(6.60)	(18.39)	(9.54)	(4.32)	(1.48)

Table 2.6: Mean Firm Trades given Upgrades and Downgrades
This table reports estimated regression coefficients from regressing firm trades on upgrade and downgrade dummy variables, as shown below:

$$\text{Trade}(i) = \beta_{\text{Upgrade}(t)} D_{\text{Upgrade}(t)} + \beta_{\text{Downgrade}(t)} D_{\text{Downgrade}(t)} + \epsilon$$

The OLS and Fama and MacBeth [1973] style regression coefficients are reported in Panels A and B. Trade(i) is defined as the firms net trade in a given stock divided by the shares outstanding. $D_{\text{Upgrade}(t)}$ ($D_{\text{Downgrade}(t)}$) is a dummy variable which takes a value of one if the recommendation change is an upgrade (downgrade) and zero if it is a downgrade (upgrade). $\beta_{\text{Upgrade}(t)}$ and $\beta_{\text{Downgrade}(t)}$ represent the mean net trade given upgrades and downgrades, respectively. Recommendations occur in period t, and trades occur in period i (from $t-3$ to $t+3$). Given that the recommendation transition matrix is not uniform, this table reflects some of the biases reflected there and is meant to be used for reference rather than for inference.

i	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: OLS Regression							
Upgrade Dummy	0.094	0.085	0.064	0.112	0.101	0.072	0.076
	(4.64)	(3.91)	(2.77)	(5.55)	(5.33)	(4.01)	(4.16)
Downgrade Dummy	0.146	0.148	0.098	-0.008	-0.014	0.008	0.021
	(8.64)	(8.22)	(5.11)	(-0.48)	(-0.90)	(0.54)	(1.31)
Panel B: Fama MacBeth Regression							
Upgrade Dummy	0.091	0.081	0.054	0.101	0.095	0.068	0.074
	(3.71)	(3.43)	(2.20)	(2.62)	(3.10)	(2.37)	(2.82)
Downgrade Dummy	0.146	0.148	0.100	-0.005	-0.014	0.007	0.020
	(6.69)	(6.11)	(4.46)	(-0.27)	(-0.69)	(0.40)	(0.92)

Table 2.7: Change in Portfolio Weight Tests

This table reports estimated regression coefficients from the main test (identical to Table 2.5, Panels A and B), except that the dependent variable Trade(i) now represents the change in institutional portfolio weight instead of the percentage of shares outstanding.

$$\text{Trade}(i) = \beta_{\text{Upgrade}(t)} \cdot D_{\text{Upgrade}(t)} + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \epsilon$$

OLS and Fama and MacBeth [1973] style regression specifications are both given by the above equation, with results reported in Panels A and B. Dummy variables for previous recommendation level (D_1 to D_5) are included, but these dummy coefficients are not reported (available on request). Recommendations occur in period t, and trades occur in period i (from $t-3$ to $t+3$).

i	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: OLS Regression							
Upgrade Dummy	0.022	0.051	0.055	0.055	0.106	-0.030	0.026
	(1.25)	(2.67)	(2.24)	(2.36)	(4.52)	(-1.16)	(1.44)
Panel B: Fama MacBeth Regression							
Upgrade Dummy	0.028	0.046	0.056	0.062	0.107	-0.022	0.028
	(1.34)	(2.35)	(1.69)	(1.72)	(2.72)	(-0.68)	(1.44)

Table 2.8: Main Result: Size Quartiles

This table reports estimated regression coefficient of the upgrade dummy variable from the main test (identical to Table 2.5) by stock size quartile. NYSE stock size quartiles are applied to the entire sample. OLS, Fama and MacBeth [1973] style, and ordered probit results are shown in Panels A, B, and C, respectively. Recommendations occur in period t, and trades occur in period i (from $t-3$ to $t+3$). Dummy variables for previous recommendation level (D_1 to D_5) are included, but these dummy coefficients are not reported (available on request).

i	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: Size Quartile 1 (Smallest)							
OLS	-0.013	0.040	0.084	0.395	0.024	0.151	-0.093
	(-0.09)	(-0.21)	(-0.44)	(-3.00)	(-0.20)	(-1.36)	(-0.88)
Fama MacBeth	-0.014	0.092	0.068	0.376	0.068	0.155	-0.113
	(-0.12)	(-0.95)	(-0.57)	(-2.56)	(-0.75)	(-1.35)	(-1.05)
Probit	-0.045	0.015	0.042	0.246	0.072	0.085	0.049
	(-1.24)	(-0.42)	(-1.13)	(-6.39)	(-1.75)	(-1.85)	(-1.02)
Number of Observations	9439	9439	9080	8627	8210	7615	7421
Panel B: Size Quartile 2							
OLS	0.051	0.023	0.232	0.258	0.270	0.113	0.072
	(-0.58)	(-0.23)	(-2.17)	(-2.39)	(-2.72)	(-1.18)	(-0.69)
Fama MacBeth	0.043	-0.096	0.162	0.269	0.197	0.11	0.054
	(-0.69)	(-0.52)	(-1.26)	(-1.74)	(-1.95)	(-1.44)	(-0.60)
Probit	-0.038	0.013	0.078	0.184	0.08	0.081	0.114
	(-1.40)	(-0.47)	(-2.85)	(-6.47)	(-2.70)	(-2.50)	(-3.44)
Number of Observations	14252	14253	13678	12995	12359	11426	10991
Panel C: Size Quartile 3							
OLS	0.090	0.069	0.025	0.042	0.223	-0.050	-0.011
	(-1.14)	(-0.84)	(-0.22)	(-0.47)	(-2.42)	(-0.58)	(-0.11)
Fama MacBeth	0.064	0.062	-0.048	0.009	0.185	-0.048	0.023
	(-0.93)	(-0.94)	(-0.30)	(-0.11)	(-1.49)	(-0.60)	(-0.29)
Probit	-0.006	0.046	0.078	0.182	0.101	-0.034	-0.018
	(-0.26)	(-2.09)	(-3.51)	(-7.99)	(-4.25)	(-1.32)	(-0.67)
Number of Observations	19914	19915	19278	18565	17686	16358	15697
Panel D: Size Quartile 4 (Largest)							
OLS	0.030	0.087	0.048	0.113	0.124	0.008	0.048
	(-0.52)	(-1.76)	(-1.06)	(-2.35)	(-2.70)	(-0.17)	(-0.95)
Fama MacBeth	0.045	0.052	0.075	0.104	0.126	0.019	0.064
	(-0.88)	(-1.20)	(-1.58)	(-1.75)	(-2.84)	(-0.38)	(-1.12)
Probit	-0.001	0.028	0.062	0.209	0.125	0.068	0.013
	(-0.05)	(-1.68)	(-3.56)	(-11.85)	(-6.89)	(-3.58)	(-0.69)
Number of Observations	33428	33431	32528	31575	30159	28103	26925

Table 2.9: Consensus Control Variables

This table reports estimated regression coefficients from the main test (identical to Table 2.5) with the addition of consensus recommendation change control variables. OLS, Fama and MacBeth [1973] style, and ordered probit results are shown in Panels A, B, and C, respectively. Recommendations occur in period t, and trades occur in period i (from $t-3$ to $t+3$). Dummy variables for previous recommendation level (D_1 to D_5) are included, but dummy coefficients are not reported (available on request).

i	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: OLS Regression							
Upgrade Dummy	0.053	0.091	0.086	0.107	0.121	0.050	0.023
	(-1.38)	(-2.21)	(-1.96)	(-2.77)	(-3.32)	(-1.39)	(-0.62)
Consensus Rec Change	-0.006	-0.010	-0.003	0.013	0.006	-0.004	-0.008
	(-1.10)	(-1.68)	(-0.46)	(-2.28)	(-1.12)	(-0.81)	(-1.39)
Panel B: Fama MacBeth Regression							
Upgrade Dummy	0.027	0.073	0.074	0.106	0.115	0.061	0.023
	(-0.81)	(-1.47)	(-1.29)	(-2.06)	(-2.70)	(-1.91)	(-0.63)
Consensus Rec Change	0.000	-0.016	-0.006	0.005	0.007	-0.006	-0.008
	(-0.04)	(-2.63)	(-0.94)	(-0.79)	(-1.25)	(-0.83)	(-1.46)
Panel C: Probit Regression							
Upgrade Dummy	0.002	0.043	0.078	0.177	0.084	0.046	0.013
	(-0.20)	(-3.86)	(-6.97)	(-15.41)	(-7.03)	(-3.63)	(-1.01)
Consensus Rec Change	-0.005	-0.006	-0.004	0.008	0.009	0.002	0.002
	(-2.80)	(-3.40)	(-2.27)	(-4.80)	(-5.27)	(-1.27)	(-1.14)

Table 2.10: Return Control Variables

This table reports estimated regression coefficients from the main test (identical to Table 2.5) with the addition of return control variables. OLS, Fama and MacBeth [1973] style, and ordered probit results are shown in Panels A, B, and C, respectively. Return(i) to Return($i-3$) are quarterly returns from period i to $i-3$. Recommendations occur in period t, and trades occur in period i (from $t-3$ to $t+3$). Dummy variables for previous recommendation level (D_1 to D_5) are included, but dummy coefficients are not reported (available on request).

i	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: OLS Regression							
Upgrade Dummy	0.036	0.038	0.030	0.106	0.104	0.007	0.020
	(0.79)	(0.95)	(0.62)	(2.42)	(2.48)	(0.16)	(0.46)
Return(i)	0.160	0.179	0.057	0.132	0.098	0.225	0.163
	(3.07)	(3.75)	(1.06)	(2.90)	(2.18)	(5.28)	(3.55)
Return($i-1$)	0.124	0.143	0.149	0.085	0.210	0.175	0.132
	(2.38)	(3.13)	(2.66)	(1.75)	(4.73)	(3.94)	(2.85)
Return($i-2$)	0.004	0.054	-0.024	-0.042	0.123	0.049	0.036
	(0.08)	(1.20)	(-0.45)	(-0.84)	(2.64)	(1.12)	(0.76)
Return($i-3$)	0.032	-0.030	-0.017	-0.032	-0.035	-0.097	-0.030
	(0.62)	(-0.68)	(-0.32)	(-0.69)	(-0.74)	(-2.16)	(-0.65)
Panel B: Fama MacBeth Regression							
Upgrade Dummy	0.028	0.025	0.008	0.094	0.111	0.020	0.016
	(0.57)	(0.56)	(0.13)	(1.55)	(2.18)	(0.65)	(0.42)
Return(i)	0.076	0.104	0.000	0.126	0.066	0.120	0.123
	(0.89)	(1.49)	(0.00)	(1.65)	(0.89)	(1.37)	(1.72)
Return($i-1$)	0.097	0.111	0.222	0.030	0.103	0.144	0.069
	(1.19)	(1.89)	(2.28)	(0.43)	(1.45)	(2.27)	(1.13)
Return($i-2$)	0.027	0.048	-0.030	-0.046	0.149	-0.018	-0.091
	(0.30)	(0.73)	(-0.53)	(-0.55)	(1.99)	(-0.30)	(-1.29)
Return($i-3$)	0.061	-0.008	0.007	-0.033	-0.023	-0.107	0.024
	(0.93)	(-0.11)	(0.09)	(-0.45)	(-0.27)	(-1.45)	(0.38)
Panel C: Probit Regression							
Upgrade Dummy	-0.020	0.024	0.050	0.178	0.084	0.027	0.013
	(-1.61)	(1.96)	(4.15)	(14.31)	(6.57)	(1.97)	(0.97)
Return(i)	0.042	0.047	0.020	0.048	0.055	0.068	0.049
	(3.03)	(3.30)	(1.47)	(3.68)	(4.01)	(4.91)	(3.39)
Return($i-1$)	0.075	0.084	0.068	0.073	0.082	0.078	0.093
	(5.36)	(6.16)	(4.73)	(5.30)	(6.06)	(5.34)	(6.34)
Return($i-2$)	0.092	0.039	0.064	0.025	0.062	0.072	0.049
	(6.66)	(2.93)	(4.78)	(1.74)	(4.36)	(5.04)	(3.18)
Return($i-3$)	0.068	0.045	0.049	0.034	0.014	0.003	0.050
	(5.01)	(3.38)	(3.70)	(2.50)	(0.95)	(0.19)	(3.42)

Table 2.11: Recommendation Changes

This table reports estimated regression coefficients from regressing firm trades on recommendations and control variables.

$$\text{Trade}(i) = \beta_{\text{RecChange}(t)} \cdot \text{RecChange}(t) + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \epsilon$$

The OLS and Fama and MacBeth [1973] style regression specifications are both given by the above equation, with results reported in Panels A and B. Trade(i) is defined as the firms net trade in a given stock divided by the shares outstanding. RecChange represents the actual difference in I/B/E/S recommendation level, from the previous to current recommendation. $\beta_{\text{RecChange}(t)}$ represents the difference in mean trade for each level of recommendation change. Recommendations occur in period t, and trades occur in period i (from $t-3$ to $t+3$). Dummy variables for previous recommendation level (D_1 to D_5) are included, but dummy coefficients are not reported (available on request). Panel C reports results from the ordered probit specification as shown below:

$$\begin{aligned}
p_1 &= \Phi(\alpha_1 + \beta' x) \\
p_2 &= \Phi(\alpha_2 + \beta' x) - \Phi(\alpha_1 + \beta' x) \\
p_3 &= 1 - \Phi(\alpha_2 + \beta' x) \\
\beta' x &= \beta_{\text{RecChange}(t)} \text{RecChange}(t) + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \epsilon
\end{aligned}$$

We use an ordered trade variable to denote firm actions of buying (1), no trade (2), and selling (3), where all other variables remain the same as in the OLS and FM specification. Φ is the cumulative standard normal distribution function. A significantly positive (negative) value of $\beta_{\text{RecChange}(t)}$ would indicate the amount by which each level of upgrade would increase (decrease) the probability, or z-score, of a firm buying and decrease (increase) the probability of a firm selling. The effect on the probability of a firm not trading is dependent on the net effects on buying and selling combined. The magnitude of these effects would vary depending on the natural response levels, which essentially correspond to a location on the cumulative normal distribution function.

i	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: OLS Regression							
RecChange(t)	0.023	0.033	0.027	0.055	0.067	0.015	0.004
	(1.61)	(2.17)	(1.66)	(3.92)	(4.94)	(1.13)	(0.28)
Panel B: Fama MacBeth Regression							
RecChange(t)	0.018	0.023	0.021	0.050	0.064	0.018	0.007
	(1.37)	(1.66)	(1.14)	(2.86)	(4.28)	(1.64)	(0.61)
Panel C: Probit Regression							
RecChange(t)	0.002	0.016	0.027	0.081	0.049	0.021	0.014
	(0.48)	(3.86)	(6.47)	(19.15)	(11.15)	(4.49)	(2.86)

Table 2.12: Sub-Period Results

This table reports estimated regression coefficient of the upgrade dummy variable from the main test (identical to Table 2.5) for sub-periods. We split the sample chronologically, by half and by "internet boom" period. OLS, Fama and MacBeth [1973] style, and ordered probit results are shown in Panels A, B, and C, respectively. Recommendations occur in period t, and trades occur in period i (from $t-3$ to $t+3$). Dummy variables for previous recommendation level (D_1 to D_5) are included, but dummy coefficients are not reported (available on request).

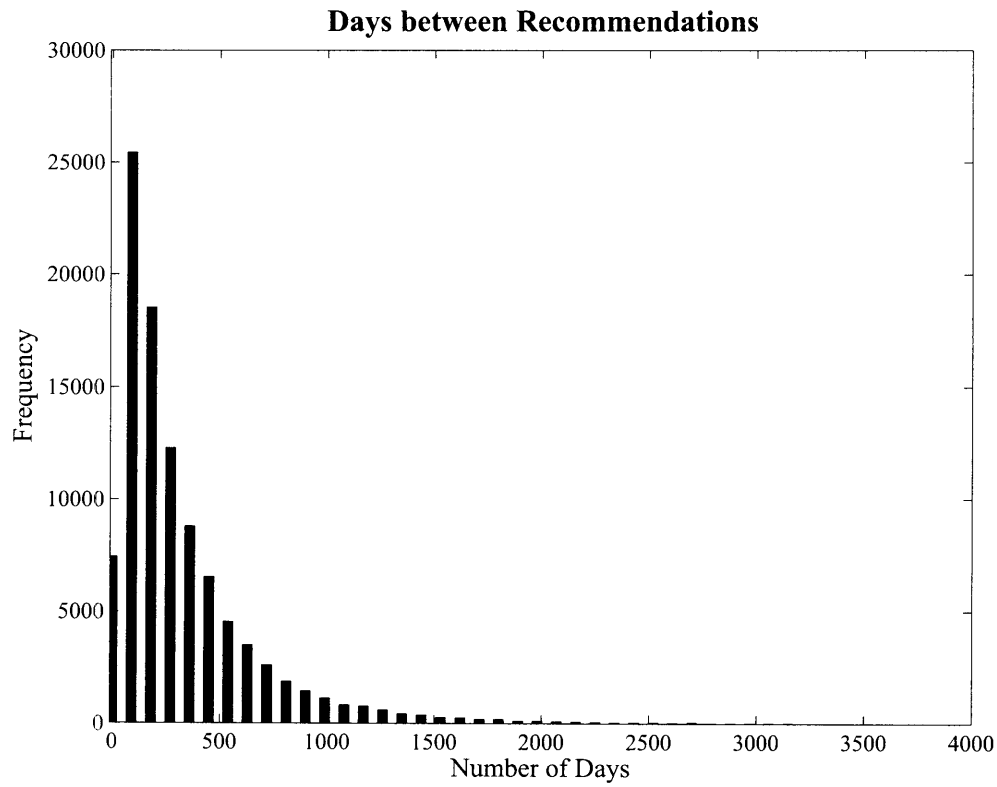
i	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: First Half Period (1993–1997)							
OLS	-0.041	0.053	0.073	0.231	0.127	0.057	-0.009
	(-1.02)	(1.26)	(1.86)	(5.00)	(3.17)	(1.27)	(-0.24)
Fama MacBeth	-0.051	0.055	0.081	0.238	0.133	0.076	-0.008
	(-1.64)	(1.08)	(2.00)	(3.31)	(2.37)	(1.60)	(-0.23)
Probit	0.022	0.005	0.089	0.234	0.096	0.065	0.032
	(1.17)	(0.29)	(4.76)	(12.49)	(5.11)	(3.47)	(1.69)
Panel B: Second Half Period (1998–2002)							
OLS	0.076	0.071	0.078	0.085	0.141	0.036	0.022
	(1.52)	(1.32)	(1.31)	(1.71)	(2.85)	(0.74)	(0.41)
Fama MacBeth	0.067	0.031	0.048	0.048	0.126	0.025	0.016
	(1.19)	(0.41)	(0.57)	(0.76)	(2.40)	(0.59)	(0.30)
Probit	-0.020	0.036	0.060	0.182	0.111	0.046	0.012
	(-1.61)	(2.90)	(4.69)	(13.69)	(7.97)	(3.01)	(0.78)
Panel C: Internet Boom (1998–2000)							
OLS	0.043	0.056	0.071	0.096	0.117	0.085	-0.021
	(0.63)	(0.65)	(0.73)	(1.46)	(1.84)	(1.61)	(-0.35)
Fama MacBeth	0.050	0.010	0.065	0.107	0.135	0.090	-0.014
	(0.78)	(0.08)	(0.55)	(1.47)	(1.96)	(2.09)	(-0.23)
Probit	0.029	0.036	0.053	0.209	0.139	0.065	0.026
	(1.47)	(1.84)	(2.78)	(10.85)	(7.22)	(3.35)	(1.33)
Panel D: Excluding Internet Boom (1993–1997, 2001–2002)							
OLS	0.027	0.069	0.084	0.147	0.146	0.017	0.029
	(0.65)	(1.67)	(2.08)	(3.40)	(3.61)	(0.39)	(0.68)
Fama MacBeth	0.013	0.053	0.058	0.128	0.124	0.020	0.018
	(0.29)	(1.16)	(1.08)	(1.97)	(2.72)	(0.47)	(0.50)
Probit	-0.025	0.030	0.080	0.190	0.090	0.043	0.017
	(-1.99)	(2.40)	(6.29)	(14.55)	(6.57)	(2.90)	(1.08)

Table 2.13: Individual Firm Results

The table reports t-statistics for individual firm tests of the main result (identical to Table 2.5). We run the test for each firm and record t-statistics for each coefficient of the upgrade dummy variable. We report the mean and median t-statistics, as well as the percentage that are positive (across firms). OLS and ordered probit results are shown in Panels A and B, respectively. Recommendations occur in period t, and trades occur in period i (from $t-3$ to $t+3$). Dummy variables for previous recommendation level (D_1 to D_5) are included, but dummy coefficients are not reported (available on request).

i	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: Ordinary Least Square							
Average t-statistics	-0.19	0.13	0.32	0.71	0.54	0.34	0.04
Median	-0.16	0.27	0.16	0.58	0.54	0.29	0.19
% Positive	42.6%	53.7%	59.3%	66.7%	75.9%	59.3%	55.8%
Panel B: Probit							
Average t-statistics	-0.22	0.40	0.71	1.96	1.10	0.45	0.30
Median	-0.32	0.55	0.73	1.76	1.06	0.26	0.58
% Positive	40.7%	66.7%	64.8%	75.9%	74.1%	57.4%	63.5%

Figure 2-1: Histogram of Days between Matched Stock Recommendations This figure displays a histogram of the number of days between analyst recommendations as recorded in the I/B/E/S database, after merging with the CDA Spectrum database but before applying any data filters. As displayed, the distribution is highly non-normal and peaks around 100–150 days.



Chapter 3

Dealer versus Auction Markets: Comparison of Execution Costs and Intraday Volatilities

3.1 Introduction

In light of the recently intensified competition between the National Association of Securities Dealers Automatic Quotations (NASDAQ) system and the New York Stock Exchange (NYSE) to attract new listings, there have been a lot of media and academic attentions focusing on the relative merits of the auction and dealer markets. Although their primary function is to provide price discovery and liquidity services for equity shares, both markets differ substantially in terms of their operation and structural design. In the auction market, trading takes place on a centralized trading floor through specialists, whose responsibilities are to manage trades between different limit and market orders and to maintain liquidity and continuous trading. Market orders are executed against limit orders placed on the limit order book or against the quotes disseminated by the specialists. Comparatively, trades in the dealer market are negotiated directly through dealers, and both market and limit orders are executed against the dealers' quotes.

Proponents of the auction market assert that the presence of specialists, who are trained to maintain order in trading and smooth out large swings in stock prices, produces the tightest spreads to the investors. The narrow spreads lower the market makers' profit margins, thereby guaranteeing the best price available for both sides in a stock trade. In criticism of the dealer market, these critics argue that its lack of regulations and monitor activities allow room for collusive collaboration among dealers as well as excessive stock price movements. Preferencing arrangements that rout order flow from brokers to specific dealers [see Dutta and Madhavan, 1997] and the avoidance of odd-eighth quotes on the NASDAQ documented by Christie and Schultz [1994] are some examples that suggest that the organization of the dealer market may not provide enough incentives for the dealers to improve quotes and therefore may result in higher trading costs.

Proponents of the dealer market point to the flexibility of such market in handling different types of securities and different types of customers and to the advantages of competing dealers. Dealer markets have no seats, entry is easy, and the intense competition for trades among the dealers may benefit investors in terms of better execution services and lower transaction costs. In addition, the electronic system of the NASDAQ can provide much faster trade executions and its open market structure offers a high level of transparency not found on the other major U.S. markets. Indeed, it is the lack of transparency that makes the NYSE a recent target for regulatory scrutiny. A high-profiled law suit filed last year can illustrate this point. At the end of 2003, the California State Public Employees Retirement System, the nation's largest public pension fund, sued the NYSE over failing to curb allege abuses, which include front-running, or using knowledge of existing orders and how they will affect prices to make surefire bets before executing customer orders. The possibility that the specialists can abuse their informational advantage over regular investors poses a serious challenge to the integrity of the auction market. As each market system has its own pros and cons, it is not clear if one is better than the other.

One way to compare the two market systems is to examine the execution costs and volatilities of the stocks traded in the two markets. An extensive number of literatures have been written along this direction.[1] Huang and Stoll [1996] compare the execution costs and volatilities between a sample of NASDAQ stocks and a matched sample of NYSE stocks. Their study is extended by Bessembinder and Kaufman [1997] to include smaller firms. Bessembinder [1999] examines transaction costs and volatilities after the NASDAQ market reform in 1997. All these articles conclude that the execution costs and volatilities on the NASDAQ are higher than those on the NYSE. In contrast, Affleck-Graves, Hegde, and Miller [1994] use a subset of the 1985 transaction and quotation data to compare bid-ask spreads on the NASDAQ and on the NYSE and the American Stock Exchange (AMEX) and find that spreads in the dealer and auction markets are not statistically different. However, these prior empirical studies all employ the matched-stock approach and therefore may not have adequately controlled for the differences in individual stock characteristics such as size and volatility which may be crucial in determining the transaction costs.

To address the concern that the stock samples in these previous studies are not perfectly-matched, I use a sample of stocks that is specifically chosen to eliminate the issue of inadequate control for individual stock characteristics that arises from the matched-stock procedure. My data sample is made up of the 126 stocks that are listed on both the NASDAQ and AMEX in 2003. In August 2002, AMEX started trading NASDAQ securities and since then has expanded its trading program from only eight securities originally to more than 120 securities now. The dual-listing property of these securities should provide a close-to-perfect control environment for comparison of transaction costs and volatilities between the two market structures. Another contribution of this paper to the existing literature is that I use standard deviation of intraday returns instead of daily returns as measure of volatility. Daily volatility is often driven by information-related price changes whereas intraday volatility may capture variations due to transitory liquidity-driven price changes. These temporary price fluctuations usually happen in the middle of regular trading hours and their frequencies of occurrence and magnitudes may vary across different market mecha-

[1]See Macey and O'Hara [1997] for a comprehensive survey of literature on comparing execution costs between different markets.

nisms. By studying intraday volatilities, I can draw inference on whether one market structure is more prone to excessive temporary price movement than the other.

Aside from the empirical literature, there are several papers that provide theoretical comparisons of dealer and auction markets. Ho and Stoll [1983] model quote setting in a competing dealer from an inventory perspective and compare the result to a model with a single specialist. Pagano and Roell [1996] compare dealer and auction markets in the presence of informed trading. Madhavan [1992] analyzes price formation under a continuous quote-driven system as well as under an order-driven system. Dutta and Madhavan [1997] provide a game-theoretic model of implicit collusion in dealer markets. Stoll [1992] analyzes general principles of market structure and related policy issues.

The rest of this paper is organized as follows. Section 3.2 provides a brief description of the data sample. Section 3.3 defines the measures of trading costs and volatilities that are employed in my study and describes the methodology of comparing trading costs and volatilities. Section 3.4 presents the results and Section 3.5 concludes.

3.2 Description of Data

This section describes the database from which I obtain the transaction and quote data as well as the stock sample that I use to compare execution costs and volatilities between the dealer and auction markets.

3.2.1 Transactions and Quotation Data

I measure executions costs and volatilities using the transaction and quote data supplied by the Trade and Quote (TAQ) database made available by the NYSE. I only include trades and quotes that were recorded during regular trading hours, i.e. from 9:30 in the morning to 4:00 in the afternoon. All trades of which the sale condition indicates regular trade and of which the correction indicator shows that the record is not corrected, changed, or signified as cancel or error, and all quotes of which the quote condition specifies regular trading environment are retained.[2] To further minimize data errors, I eliminate all quotes of which the ratio of spread (defined as ask minus bid) to the mid-point of the bid and ask quote is less than 20%. The purpose of this filter is to remove any potential erroneous quotes that can be characterized by unreasonably high bid-ask spreads. I also remove quote records of which the ask price is less than the bid price and any price or quote that has more than ten percent change from its previous record. Finally, I ensure that the ask price, bid price, bid size and ask size of all quotes, and the price and size of all trades are all greater than zero.

3.2.2 NASDAQ UTP Stocks

AMEX first began trading NASDAQ securities in August 2002 under the unlisted trading privileges (UTP), following approval from the Securities and Exchange Commission (SEC).[3] Since then, AMEX has continued to expand its trading program from originally eight securities to more than a hundred in 2004. The idea of the program is to provide investors with the benefits of an auction-market environment and the ability to trade large blocks of stocks. For institutional investors, it is often difficult to execute large block orders on the NASDAQ at a single price. AMEX claims that their specialists are able to provide deep liquidity for large institutional size orders. Table 3.6 lists the 126 NASDAQ UTP stocks used in this paper. For concision and clarity purpose, I will refer to this sample of stocks as the UTP sample for the remaining discussion.

Table 3.1 shows the summary statistics of the stocks in the UTP sample. The price, volume and share outstanding data are obtained from the CRSP database. The stocks in this sample are among some of the most heavily-traded and largest stocks in the stock market. The median market capitalization is more than $4 billion and the

[2]Specifically, I only include trade records from the consolidated trade file of which both the field name CORR shows a value of 0 and the field name COND has either blank entry or a value of *. For quotes, I only include those from the consolidated quote file of which the field name MODE has a value of 12.

[3]For more information about the NASDAQ UTP stocks traded on the AMEX, interested readers are referred to the AMEX webpage http://www.amex.com.

average daily volume across those stocks is more than 7 million shares. From Table 3.1, it can be observed that quotes are updated more frequently on the NASDAQ than on the AMEX, by at least two times. This can be explained by the existence of multiple dealers in the dealer market, which results in a higher probability of quote updates relative to the auction market in which there is only one single dealer (specialist). The trading activities on the AMEX are quite low. Average daily number of trades recorded on the AMEX is only around 4, compared to 5776 on the NASDAQ. Volumes in the two markets are different by a large extent too. Daily average total trades are 6746 on the AMEX, compared to more than 4 million on the NASDAQ. It should be noted, however, that trades from the auction market and dealer market are not directly comparable because of the different handling of trades in the two markets. In an auction market, a cross-trade between a buy and a sell limit order is counted as one trade, whereas in a dealer market, most trades[4] are executed by the market makers and as a result, two opposing orders will usually be recorded as two trades. But even after accounting for this factor, trading activities are still extremely limited on the AMEX relative to those on the NASDAQ.

Different measures of transaction costs and volatilities of each stock in the UTP sample are calculated for each month of the sample period for both stock exchanges. In other words, my basic data set is made up of observations of 126 companies for 12 months or 1512 stock-months for each exchange. I impose a minimum number of 600 quotes on each of the stock-month observations.[5] Several observations associated with the AMEX fail to meet this minimum criterion and therefore are removed which results in a final sample size of 1342 observations for each exchange.

Besides enabling a perfect control environment for comparison of volatilities and

[4]An increasing number of NASDAQ trades are now executed through electronic communication network (ECN), which is an electronic system that is designed to facilitate (for market makers) or eliminate (for individual investors) third party orders entered by a client's brokerage to be executed in whole or in part. It is estimated that ECN has already captured around 30% of the trading volume in NASDAQ-listed stocks, which suggests that a non-trivial proportion of trades on the NASDAQ is now recorded as single cross-trades instead of dual-counted trades with market makers.

[5]In later subsection, I will explain how I calculate the intraday volatilities using 15-minute return. The minimum number of 600 is motivated by the minimum number of observations required to calculate the intraday volatilities. It is the rounded figure of 26 (number of 15-minute intervals during the regular trading hours) multiplied by 22 (number of weekdays in a month).

transaction costs between markets, my data sample has another advantage, which is the integration of the effects of the structural change in the NASDAQ market after the enactment of the new order-handling rules[6] and the adoption of decimal pricing in 2001. Previous literatures that study trading costs have hypothesized that the higher execution costs on the NASDAQ can possibly be explained by the tendency of the market makers to collude to maintain excessively high bid-ask spreads [for example, see Christie and Schultz, 1994]. Part of the motivations behind the NASDAQ market reform is to address those issues. Indeed, McInish, Van Ness, and Van Ness [1998] document that the transaction costs on the NASDAQ are lower after the new rules are implemented. Bessembinder [2003] also shows that the bid-ask spreads decline substantially after the decimalization. Since I am interested in studying whether one market structure is inherently less efficient than the other, I want to control for as many external factors as possible and the sample period of 2003 allows me to neutrally compare market structures after the decimalization and the NASDAQ market reform went into effects.

3.3 Measures of Execution Costs and Volatilities and Empirical Methods

In this section, I will describe my measures of executions costs and volatilities, and the empirical methods that I use to compare the differences in execution costs and volatilities between the auction and dealer markets.

3.3.1 Execution Costs

I use three empirical measures of trading costs in this paper. These measures are commonly used by similar literatures that study transaction costs [for example, see Bessembinder and Kaufman, 1997, Huang and Stoll, 1996]. The simplest one is the bid-ask spread, which is the difference between the quoted ask price and the quoted

[6]See Barclay, Christie, Harris, Kandel, and Schultz [1999] for a detailed description of the new order-handling rules.

bid price. My quoted bid-ask spread is defined as the ratio of the spread to the mid-point of the bid and ask quotes. Specifically, it is computed as follows:

$$\text{Quoted Half-Spread}_{it} = \frac{A_{it} - B_{it}}{2 \cdot M_{it}}$$

where A_{it} is the quoted ask price for security i at time t, B_{it} is the quoted bid price for security i at time t and M_{it} is the mean of A_{it} and B_{it}. Trade-weighted average of the quoted half-spreads is calculated for each stock-month group in the UTP sample.[7] For the rest of the paper, whenever trade prices are compared to quotes, I apply a methodology similar to the one employed by Lee and Ready [1991] and use the most recent prior quote that is time-stamped at least one second earlier than the trade. The one-second rule is just an arbitrary approximation to compensate for the speedier reporting of quotes than that of trades. I choose to use the one-second rule because of the vast quantities of trades that are less than 1000, which can be executed within a short time by the Small Order Execution System. I have repeated my tests using the five-second rule suggested by Lee and Ready or the twenty-second rule used by Bessembinder and Kaufman [1997] and the results remain qualitatively identical.

Bid and ask quotes are not necessarily the prices at which trades take place since it is possible to trade inside the quotes, implying that the quote spreads may not be an adequate measure of the actual execution costs. In order to mitigate this issue, another measure of trading cost is suggested. The effective spread estimates the execution cost actually paid by the trader and is defined as follows:

$$\text{Effective Half-Spread}_{it} = \frac{|P_{it} - M_{it}|}{M_{it}}$$

where P_{it} is the execution price of security i at time t and M_{it} is the mid-point of the bid and ask quotes of security i time-stamped at least one second earlier than the time-t trade.

My final measure of transaction cost is the realized spread, which is the average

[7] I also use other averaging methods such as simple average and time-weighted average and the results do not change qualitatively. I do not report those results but they are available upon request.

price reversal after trades and market-making revenue. Glosten and Milgrom [1985] show that market-makers must widen spreads to compensate for losses to better-informed traders and this measure of transaction costs can help explain whether the higher spreads in one market can be attributed to adverse information. Realized spread is defined as follows:

$$\text{Realized Half-Spread}_{it} = D_{it}\frac{P_{it} - P_{it+n}}{M_{it}}$$

where P_{it} is the transaction price of security i at time t, M_{it} is the mid-point of the bid and ask quotes of security i time-stamped at least one second earlier than the time-t trade, P_{it+n} denotes the trade price observed at time $t+n$ and D_{it} is a binary variable that equals one for buy orders and negative one for sell orders. P_{it+n} is a proxy for security i's post-trade economic value. I use two proxies for a security's post-trade economic value – the first trade price observed at least thirty minutes after the trade and the first trade price observed one day after the trade. In other words, n is defined to be either thirty minutes or twenty four hours. To determine whether the order is buy-initiated or sell-initiated, or the value of D_{it}, I use the algorithm recommended by Lee and Ready [1991]. If the price at which the trade is executed is higher than the mid-point of the bid and offer quotes time-stamped at least one second ago, the trade is interpreted as buy, and vice versa. The calculation of realized spread contains measurement errors arising from potential errors in determining the directions of trades, as well as errors from estimating the post-trade economic value. However, it should still provide a reliable estimate of the net market-making revenues when computed over a large number of trades.

Finally, one should be reminded that these measures of trading costs do not factor in the commission charges or take account of the quality of execution services into consideration. These effects may vary across exchanges and trades and have the potential of narrowing or widening the differences in transaction costs between the two market structures.

3.3.2 Volatilities

Previous studies that compare volatilities between the auction and dealer markets mainly focus on volatilities estimated from daily returns [for example, see Bessembinder and Kaufman, 1997, Bessembinder and Rath, 2002]. The drawback is that such measure of volatilities is more likely to capture information-related stock price fluctuations rather than the transitory stock price movements that are caused by liquidity issues. The following example may illustrate this point. Suppose that a very large information-unrelated sell order comes in and outstrips short-term liquidity. The stock price will plummet temporarily until additional liquidity arrives. These kinds of temporary movement can hardly be revealed from the volatility measures that are calculated from daily returns as such events are more likely to happen during the middle of regular trading hours and therefore may not affect the closing prices. By the time when the market is closed, the temporary price drop is already neutralized by new arrivals of liquidity. So, if there is any fluctuation in stock prices due to transitory liquidity shocks, measures of intraday volatility will do a better job capturing such variations than daily volatility estimates.

Specialists in the auction markets are obligated to maintain a continuous market and supply liquidity when needed, whereas dealers in the dealer markets do not have such obligations. Theoretically, such institutional features of the auction market should make the aforementioned type of temporary price fluctuations small and less frequent, therefore resulting in lower volatilities for stocks traded in the auction market in comparison to the dealer market. In order to capture the differences in volatilities due to different market mechanisms instead of information-related or economic factors, I compare intraday volatilities as opposed to the commonly-used daily volatilities between the two market structures.

Consistent with Schwert [1990], I measure the intraday volatility using fifteen-minute returns during the regular trading hours. Fifteen-minute returns are calculated based on the mid-points of the latest bid and ask quotes at the end of every fifteen-minute interval between 9:30 am and 4:00 pm. I use the mid-points of the bid and ask quotes instead of the trade prices for two reasons. Firstly, using mid-points can reduce the effect of the bid-ask bounce on the volatility estimate. If trade prices are used, the estimation of the volatility may be contaminated by the stock price movements associated with the randomly alternating trade executions at the respective bid and ask quotes. Secondly, it may be difficult to measure intraday volatilities using trade prices because of the insufficient transaction data. The timely updated quotation data provide a better reflection of the current market condition compared to the less frequently observed trades. Such improvement is especially noticeable for the AMEX in which the number of trades on a day is sometimes as low as one. I calculate the intraday volatility as the standard deviation of the continuously compounded fifteen-minute returns.

3.3.3 Empirical Methods

To compare transaction costs and volatilities, I run the following regression.

$$z_{it} = \beta_A D_i^A + \beta_N D_i^N + \epsilon_{it}$$

where z_{it} is the variable of interest of security i at time t, which can be the different measures of transactions costs or intraday volatility, D_i^A is a dummy variable which takes a value of one if the observation is made from the AMEX and zero otherwise, and D_i^N is defined similarly as D_i^A except that it is used to indicate observations made from the NASDAQ. Since individual stock characteristics such as market capitalizations and returns can potentially explain the variations in execution costs and volatilities, I also run the following regression to control for the cross-sectional differences in stock characteristics:

$$z_{it} = \beta_A D_i^A + \beta_N D_i^N + \sum_j \gamma_j^A X_{ijt}^A D_i^A + \sum_j \gamma_j^N X_{ijt}^N D_i^N + \epsilon_{it}$$

where z_{it}, D_i^A and D_i^N are defined the same as previously mentioned, X_{ijt}^A is the jth control variable at time t for security i traded on the AMEX and X_{ijt}^N is defined similarly as X^A_{ijt}, but for stocks traded on the NASDAQ. The control variables used in my regression are daily volatility, monthly return, logarithm of market capitalization, logarithm of price, logarithm of average daily number of quote updates and logarithm of average daily trades. A potential problem may arise from using daily trades as control variable because of the structural difference in handling trades in the auction and dealer markets as pointed out before. Fortunately, the advent of alternative trading systems on the NASDAQ that increases the number of trades where public orders meet each other and the increasing proportion of trades that are executed with the specialist in the auction market should make this issue less severe than it may seem.[8] Moreover, my specification of the regression is intended to provide the flexibility to process the different types of trade handlings in the two markets through the interaction of the control variables with the exchange dummy variables. Nevertheless, comparison between the corresponding coefficients of the trade control variables for the two exchanges should still be interpreted with caution.

Another reason to use control variables conditional on the market source of observations is that the sensitivities of transaction costs (or volatilities) to various stock characteristics may vary across different exchanges. For example, since the specialists in the auction market are expected to attenuate excess volatilities in stock prices while the dealers in the dealer market do not have such obligations, daily volatilities are likely to affect the intraday volatilities more in the dealer market than in the auction market. The regressions interacting the exchange dummies with the control variables make examination of these scenarios feasible.

The coefficient of the dummy variable for each stock exchange can be interpreted as the average transaction cost (or volatility) associated with that exchange. Therefore, the difference in transaction costs (or volatilities) between the two exchanges is simply the difference between the coefficients of the dummy variables. Whether it is more expensive to trade in one market or not can be tested using the t-statistics of the

[8]To be on the safe side, I also run regressions omitting trades and quotes as control variables as well as regressions assuming an arbitrary constant multiplier between the transaction and quote data observed in the auction market and those observed in the dealer market. The conclusion in this paper remains intact.

difference between the two coefficients.

I use the Fama and MacBeth [1973] regression to adjust for the potential serial correlation among the 2684 stock-month observations. Cross-sectional regression is run across the 126 stocks in the sample for each month during the sample period. Point estimate and standard error of the coefficients are respectively the time-series average and standard deviation of the cross-sectional regression coefficients.

3.4 Results of UTP Sample

Figure 3-1 shows the distribution of the differences in the quoted half-spreads between the AMEX and NASDAQ. Most of the observations cluster around 0 but numerous observations are also found around the highly negative region. It can be easily inferred from the diagram that the trading costs are generally higher on the AMEX than on the NASDAQ due to the substantial number of negative observations.

Table 3.2 shows the regression results for the quoted half-spreads. Panel A shows the results of the regression run only on the exchange dummies. On average, quoted half-spreads on the AMEX (0.73) are much higher than the quoted half-spreads (0.07) on the NASDAQ. Without controlling for any stock characteristics, the difference in average execution costs between the two exchanges is 0.66 cents and is highly significant (t-statistic is 6.72).

Panel B shows the results from the regression of quoted half-spreads on both exchange dummies and control variables. After controlling for individual stock characteristics, the average quoted half-spread of stocks traded on the NASDAQ becomes higher than that of stocks traded on the AMEX by more than 3 cents. The coefficients for the daily volume are negative and are highly significant for both exchanges. The evidence is consistent with the empirical prediction of Rosu [2004] who theorizes that trading activities are negatively related to the bid-ask spreads. The coefficients for the logarithm of price are also negative and significant for both exchanges, which imply that higher prices will result in tighter spreads. The significantly positive coefficients for the logarithm of market capitalization are counterintuitive as the conventional wisdom is that size is usually negatively related to trading costs. However, such conventional wisdom may not be applicable in this case as the stocks included in my study are among some of the largest stocks traded in the market. Even the smallest stock in my sample has a total market capitalization of at least 300 million dollars which can be hardly considered as a small stock at all.

The results for the daily volatility coefficients are not consistent across the two exchanges. The coefficient is significantly positive for the NASDAQ's observations but negative although statistically insignificant for the AMEX's. Similar inconsistency can also be observed for the return and daily quote control variables. The empirical evidence suggests that the quote spreads may have different sensitivities to various stock characteristics in different market structures. In other words, individual stock characteristics such as volatility and size may affect the transaction costs differently if the stocks are traded in different markets. In unreported results, I find that the coefficients of each of the control variables for the AMEX and NASDAQ are significantly different. Those results are available upon request.

My results of narrower spreads in the dealer market are at odds with the existing literature [for example, Bessembinder and Kaufman, 1997, Huang and Stoll, 1996] that documents higher trading costs on the NASDAQ market. There are several possible explanations that can reconcile such discrepancy. First of all, these previous studies usually do not control for the differences in stock characteristics in their matched-stock samples. For example, in Huang and Stoll [1996], one of their matched pairs is Apple Computer, Inc and Compaq Computer Corporation. It is implausible to expect this pair of stocks to behave similarly even given the best efforts to control for the differences in individual stock characteristics.

Another reason for the larger spreads on the AMEX is its lack of trading activities. As shown in Table 3.1, the daily average total trades on the NASDAQ is more than 500 times than that on the AMEX. Accounting for the difference in trading volume between the two markets can make up for more than half of the differences in the quoted half-spreads.

Table 3.3 shows the results for another measure of execution costs, effective half-spread, which takes into account the possibility that trades can take place inside the quotes. Panel A and B shows the regression results with and without the control variables respectively. In general, the results on this table are qualitatively similar to those on Table 3.2. Transaction costs are significantly higher on the AMEX without controlling for stock characteristics. The difference is around 0.15 cents with a t-statistic of 7.79. Coefficients on size and daily volatility are positive and somewhat significant for both exchanges. The coefficients are all negative for daily quote, daily volume and price but their significances vary across different markets. After controlling for stock characteristics, much of the significance of the difference in the average effective half-spreads between the AMEX and NASDAQ originally observed disappears. Figure 3-2 shows the distribution of the differences in the effective half-spreads.

Table 3.4 shows the results for the realized half-spreads. Realized half-spread measures the market making revenue or the loss to informed traders due to adverse information. Panel A and B show the results when the proxy for a stock's post-trade economic value is its price 30 minutes after the trade. Figure 3-3 shows the distribution of the differences in the realized half-spreads. Panel C and D show the regression results and Figure 3-4 shows the distribution of the differences when the proxy for a stock's post-trade economic value is its price 24 hours after the trade. Both sets of panels and figures show similar results and conclusions. If the market makers widen the spreads to compensate for their losses to better informed traders, we should observe a reverse in sign of the difference in average realized half-spreads between the NASDAQ or AMEX compared to earlier results, i.e., we should observe that the realized half-spreads should be lower on the AMEX than on the NASDAQ. We find the contrary, which suggests that adverse information costs cannot explain the differences in the quoted and effective half-spreads.

Figure 3-5 shows the distribution of the differences in intraday volatilities between the AMEX and NASDAQ and Table 3.5 reports the regression results. Results shown in Panel A can be interpreted as the average intraday volatilities for each exchange. Stocks traded on the AMEX have an average intraday volatility of 0.46

percent whereas stocks traded on the NASDAQ have an average of 0.48 percent. Although the difference is economically trivial, it is statistically significant with a t-statistic of 5.53. After controlling for stock characteristics and trading activities, the differences in intraday volatilities remain significant. The average intraday volatility for stocks traded on the NASDAQ is higher by 0.38 basis points than that on the AMEX. The results in this table therefore provides strong evidence in support of the claims made by the auction market advocates that specialists in the auction market may help managing continuous market and smoothing out large swing in stock prices. Skeptics may question that my measure of intraday volatility may be biased downwards because of the potential issue of stale quotes in the less heavily traded market like AMEX. One should be noted, however, that although the quotes on the AMEX are not updated as frequent as those on the NASDAQ, they are updated at a frequency much higher than the 15-minute frequency that I use to calculate the intraday volatility. So the intraday volatility estimated from the 15-minute return should well reflect the most updated market information, at least at the 15-minute frequency.

3.5 Conclusion

In this paper, I compare transaction costs and volatilities between the dealer and auction markets using the sample of NASDAQ UTP stocks that are traded on both the AMEX and NASDAQ. I find that the transaction costs, measured in terms of quoted half-spreads, effective spreads and realized spreads, are higher on the AMEX than on the NASDAQ. These findings are at odds with the existing literatures which document that execution costs are higher in the dealer market (NASDAQ) than in the auction market (NYSE, AMEX). One of the possible explanations for the higher spreads on the AMEX is its much less frequent trading activities than those of the NASDAQ.

Consistent with the existing literatures, I find that intraday volatilities are lower on the AMEX than on the NASDAQ, with or without the controlling variables. This finding corroborates with the claims of the auction market proponents that the presence of trained specialist may help reduce excessive stock price movements. Since I am comparing the same stocks that are traded on different exchanges at the same time, my results should provide the most reliable evidence on the role of the auction market structure on attenuating price movement. One should be warned that the results of this paper are mainly drawn from the analysis of some of the largest stocks traded in the stock market. If the impacts of the market mechanism on trading costs and volatilities are most influential on small stocks, my study may fail to illustrate this.

On 12th January, 2004, NASDAQ announced that six companies had decided to list on the NASDAQ as well as the NYSE, the first in the NASDAQ's new dual listing program. The six companies are computer maker Hewlett-Packard, financial giant Schwab, petroleum firm Apache Corporation, electronic design company Cadence Design Systems, financial services company Countrywide Financial and drugstore retailer Walgreen Company. If this trend continues, we should see more companies opt for dual-listing in the future. If trading activities pick up on the NASDAQ for these stocks, this will provide another excellent opportunity for future research to compare trading costs and microscopic stock price behaviors between different market designs.

Table 3.1: Summary Statistics

This table displays the characteristics for the stocks in the UTP sample. Stock price and market capitalization (in millions of dollars) are obtained from June 2003, while volume (in thousands of shares) and turnover (in percentage of shares outstanding) are calculated as daily averages for year 2003. All these data are supplied by the CRSP database. Number of quotes, number of trades and total trades are calculated as daily averages for year 2003. These transaction data are provided by the TAQ database. The statistics shown are the cross-sectional statistics among the 126 stocks in the UTP sample.

	Average	Maximum	Minimum	Median
Price	27.74	104.00	1.69	27.01
Market Capitalizations (1,000,000's)	11467	274810	333	4501
Daily Volume (1,000's)	7029	61478	377	3473
Daily Turnover	0.019	0.105	0.002	0.016
Daily Average Number of Quotes				
AMEX	4410	19167	368	3655
NASDAQ	22088	109792	1522	16918
Daily Average Number of Trades				
AMEX	4	31	1	2
NASDAQ	5776	37391	713	4054
Daily Average Total Trades				
AMEX	6746	86514	489	2986
NASDAQ	4022067	33589036	195352	2038723

Table 3.2: Quoted Half-Spreads

This table compares the quoted half-spreads between the dealer and auction markets using the stocks in the UTP sample. Quoted half-spread is defined as:

$$\text{Quoted Half-Spread}_{it} = \frac{A_{it} - B_{it}}{2 \cdot M_{it}}$$

where A_{it} is the quoted ask price for security i at time t, B_{it} is the quoted bid price for security i at time t and M_{it} is the mean of A_{it} and B_{it}. Trade-weighted average of the quoted half-spreads is calculated for all observations within each stock-month group. Panel A shows the results from the following regression:

$$z_{it} = \beta_A D_i^A + \beta_N D_i^N + \epsilon_{it}$$

where z_{it} is the quoted half-spread of security i at time t, and D_i^A and D_i^N are the dummy variables for stocks traded on the AMEX and NASDAQ respectively. The difference between the exchange dummy coefficients can be interpreted as the differences in the average quote half-spreads between the two exchanges. Panel B shows the results from the following regression:

$$z_{it} = \beta_A D_i^A + \beta_N D_i^N + \sum_j \gamma_j^A X_{ijt}^A D_i^A + \sum_j \gamma_j^N X_{ijt}^N D_i^N + \epsilon_{it}$$

where z_{it}, D_i^A and D_i^N are defined the same as previously mentioned, and X_{ijt}^A and X_{ijt}^N are the jth control variables at time t for security i traded on the AMEX and NASDAQ respectively. The control variables are monthly return, logarithm of market capitalization, daily volatility, logarithm of price, logarithm of average daily number of quote updates and logarithm of average daily trades. The t-statistics to test the hypothesis whether the estimate is greater than zero are shown in parenthesis. All regressions are estimated using the Fama-MacBeth (1973) specification and all point estimates are expressed in percentage.

Panel A: Regression of Quoted Half-Spreads on Exchange Dummies

AMEX	0.73
NASDAQ	0.07
Difference ($\beta_N - \beta_A$)	-0.66
	(-6.72)

Panel B: Regression of Quoted Half-Spreads on Exchange Dummies and Control Variables

	Return	Size	Daily Volatility	Price	Daily Quote	Daily Volume	Exchange Dummy
AMEX	0.66	0.22	-0.45	-0.47	0.08	-0.07	-2.80
	(2.98)	(3.07)	(-0.08)	(-4.76)	(1.00)	(-2.07)	(-2.84)
NASDAQ	0.00	0.01	1.22	-0.05	-0.02	-0.01	0.39
	(0.01)	(4.36)	(7.49)	(-14.97)	(-4.29)	(-2.08)	(16.84)
Difference ($\beta_N - \beta_A$)							3.20
							(3.23)

Table 3.3: Effective Half-Spreads

This table compares the effective half-spreads between the dealer and auction markets using the stocks in the UTP sample. Effective half-spread is defined as:

$$\text{Effective Half-Spread}_{it} = \frac{|P_{it} - M_{it}|}{M_{it}}$$

where P_{it} is the execution price of security i at time t and M_{it} is the mid-point of the bid and ask quotes of security i time-stamped at least one second earlier than the time-t trade. Trade-weighted average of the effective half-spreads is calculated for all observations within each stock-month group. Panel A shows the results from the regression of effective half-spreads on exchange dummies. Panel B shows the results from the regression of effective half-spreads on exchange dummies and control variables. See Table 3.2 for the regression specifications. The difference between the exchange dummy coefficients can be interpreted as the difference in the average effective half-spreads between the two exchanges. The t-statistics to test the hypothesis whether the estimate is greater than zero are shown in parenthesis and all point estimates are expressed in percentage.

Panel A: Regression of Effective Half-Spreads on Exchange Dummies

AMEX	0.25
NASDAQ	0.09
Difference ($\beta_N - \beta_A$)	-0.15
	(-7.79)

Panel B: Regression of Effective Half-Spreads on Exchange Dummies and Control Variables

	Return	Size	Daily Volatility	Price	Daily Quote	Daily Volume	Exchange Dummy
AMEX	0.41	0.05	5.85	-0.09	-0.09	-0.01	0.01
	(2.01)	(1.63)	(1.34)	(-1.02)	(-1.07)	(-0.34)	(0.02)
NASDAQ	0.00	0.00	1.74	-0.05	-0.02	-0.01	0.40
	(-0.30)	(2.36)	(9.45)	(-11.77)	(-3.99)	(-3.58)	(16.10)
Difference ($\beta_N - \beta_A$)							0.39
							(0.95)

Table 3.4: Realized Half-Spreads

This table compares the realized half-spreads between the dealer and auction markets using the stocks in the UTP sample. Realized half-spread is defined as:

$$\text{Realized Half-Spread}_{it} = D_{it}\frac{P_{it} - P_{it+n}}{M_{it}}$$

where P_{it} is the transaction price of security i at time t, M_{it} is the mid-point of the bid and ask quotes of security i time-stamped at least one second earlier than the time-t trade, P_{it+n} denotes the trade price observed at time $t+n$ and D_{it} is a binary variable that equals one for buy orders and negative one for sell orders. Trade-weighted average of the realized half-spreads is calculated for all observations within each stock-month group. In Panel A and B, the proxy for a stock's post-trade economic value is its stock price 30 minutes after the trade. In other words, n is defined as 30 minutes. Panel A shows the results from the regression of realized half-spreads on exchange dummies. Panel B shows the results from the regression of realized half-spreads on exchange dummies and control variables. See Table 3.2 for the regression specifications. The difference between the exchange dummy coefficients can be interpreted as the difference in the average realized half-spreads between the two exchanges. The t-statistics to test the hypothesis whether the estimate is greater than zero are shown in parenthesis and all point estimates are expressed in percentage.

Panel A: Regression of Realized Half-Spreads (30 minutes) on Exchange Dummies

AMEX	0.12
NASDAQ	0.05
Difference ($\beta_N - \beta_A$)	-0.07
	(-1.63)

Panel B: Regression of Realized Half-Spreads (30 minutes) on Exchange Dummies and Control Variables

	Return	Size	Daily Volatility	Price	Daily Quote	Daily Volume	Exchange Dummy
AMEX	-0.50	0.03	5.10	-0.02	0.00	-0.04	-0.36
	(-1.56)	(0.93)	(0.81)	(-0.21)	(-0.04)	(-0.87)	(-0.64)
NASDAQ	-0.03	0.00	0.19	-0.03	-0.02	0.00	0.25
	(-2.14)	(-0.04)	(0.86)	(-4.60)	(-5.88)	(0.54)	(8.08)
Difference ($\beta_N - \beta_A$)							0.61
							(1.09)

Table 3.4: continued

In Panel C and D, the proxy for a stock's post-trade economic value is its stock price 24 hours after the trade. In other words, n is defined as 24 hours. Panel C shows the results from the regression of realized half-spreads on exchange dummies. Panel D shows the results from the regression of realized half-spreads on exchange dummies and control variables.

Panel C: Regression of Realized Half-Spreads (24 hours) on Exchange Dummies	
AMEX	0.17
NASDAQ	0.03
Difference ($\beta_N - \beta_A$)	-0.14
	(-1.92)

Panel D: Regression of Realized Half-Spreads (24 Hours) on Exchange Dummies and Control Variables

	Return	Size	Daily Volatility	Price	Daily Quote	Daily Volume	Exchange Dummy
AMEX	-0.89	0.20	43.40	-0.03	-0.22	-0.05	-3.22
	(-0.60)	(2.84)	(2.85)	(-0.10)	(-0.86)	(-0.67)	(-1.93)
NASDAQ	-0.33	0.00	-2.95	-0.05	0.00	-0.01	0.38
	(-4.58)	(-0.02)	(-2.01)	(-2.43)	(0.17)	(-0.54)	(3.39)
Difference ($\beta_N - \beta_A$)							3.60
							(2.08)

Table 3.5: Intraday Volatilities

This table compares the intraday volatilities between the auction and dealer markets using the stocks in the UTP sample. Intraday volatility is calculated for each month in 2003 as the standard deviation of the continuously compounded 15-minute return. 15-minute returns are the returns over the subsequent mid-points of the bid and ask quotes posted at the end of every 15-minute interval between 9:30 am and 4:00 pm. Panel A shows the results from the regression of intraday volatilities on exchange dummies. Panel B shows the results from the regression of intraday volatilities on exchange dummies and control variables. See Table 3.2 for the regression specifications. The difference between the exchange dummy coefficients can be interpreted as the difference in the average intraday volatilities between the two exchanges. The t-statistics to test the hypothesis whether the estimate is greater than zero are shown in parenthesis and all point estimates are expressed in percentage.

Panel A: Regression of Intraday Volatilities on Exchange Dummies

AMEX	0.46
NASDAQ	0.48
Difference ($\beta_N - \beta_A$)	0.02
	(5.53)

Panel B: Regression of Intraday Volatilities on Exchange Dummies and Control Variables

	Return	Size	Daily Volatility	Price	Daily Quote	Daily Volume	Exchange Dummy
AMEX	0.03	-0.02	6.19	-0.12	0.07	0.00	0.62
	(0.70)	(-5.07)	(7.04)	(-10.77)	(8.31)	(0.43)	(6.23)
NASDAQ	0.01	-0.03	8.18	-0.08	0.03	-0.02	1.00
	(0.25)	(-6.53)	(11.84)	(-10.63)	(4.84)	(-3.32)	(16.57)
Difference ($\beta_N - \beta_A$)							0.38
							(4.52)

Table 3.6: Stocks in UTP Sample

CUSIP	Company	CUSIP	Company
03783310	Apple Computer, Inc	48248010	KLA-Tencor Corp
00339B10	Abgenix, Inc	51281510	Lamar Advertising Company
00724F10	Adobe Systems Inc	53567810	Linear Technology Corp
00088610	ADC Telecommunications, Inc	53279110	Lincare Holdings Inc
03455310	Andrx Group	59501710	Microchip Technology Inc
05276910	Autodesk, Inc	58469910	MedImmune, Inc
02144110	Altera Corp	58940510	Mercury Interactive Corp
03822210	Applied Materials, Inc	59990210	Millennium Pharmaceuticals, Inc
03822W10	Applied Micro Circuits Corp	60855410	Molex Inc
03116210	Amgen Inc	G5876H10	Marvell Technology Group
02313510	Amazon.com, Inc	59491810	Microsoft Corp
03442510	Andrew Corp	57772K10	Maxim Integrated Products, Inc
02906610	American Power Conversion Corp	67000610	Novell, Inc
03760410	Apollo Group, Inc	64120L10	Network Appliance, Inc
N0705911	ASML Holding N.V.	66585910	Northern Trust Corp
04951310	Atmel Corp	67066G10	NVIDIA Corp
07589610	Bed Bath and Beyond Inc	67000810	Novellus Systems, Inc
07332510	BEA Systems, Inc	65332V10	Nextel Communications, Inc
09061310	Biomet, Inc	68389X10	Oracle Corp
11162110	Brocade Communications Systems, Inc	70432610	Paychex, Inc
11132010	Broadcom Corp	69371810	PACCAR Inc
15670810	Cephalon, Inc	70341210	Patterson Dental
17004010	Chiron Corp	74369L10	Protein Design Labs, Inc
M2246510	Check Point Software Tech Ltd	71676810	PETsMART, Inc
12541W10	C.H. Robinson Worldwide, Inc	72581110	Pixar
16117M10	Charter Communications, Inc	69344F10	PMC - Sierra, Inc
17177910	CIENA Corp	69917310	Parametric Technology Corp
17206210	Cincinnati Financial Corp	71271310	PeopleSoft, Inc
20030N10	Comcast Corp (Class A)	70348110	Patterson-UTI Energy, Inc
20030N20	Comcast Corp (Class A Special)	73930810	Power-One, Inc
20586240	Comverse Technology, Inc	74752510	QUALCOMM Inc
20714210	Conexant Systems, Inc	74727710	QLogic Corp
22160K10	Costco Wholesale Corp	74994110	RF Micro Devices, Inc
20563810	Compuware Corp	77829610	Ross Stores, Inc
17275R10	Cisco Systems, Inc	78351310	Ryanair Holdings plc
17290810	Cintas Corp	78642910	SAFECO Corp
17737610	Citrix Systems, Inc	80090710	Sanmina-SCI Corp
23294610	Cytyc Corp	80306210	Sapient Corp
27876210	EchoStar Communications Corp	85524410	Starbucks Corp
25674710	Dollar Tree Stores, Inc	82617010	Siebel Systems, Inc
27864210	eBay Inc	81731510	Sepracor Inc
29482160	LM Ericsson Telephone Company	82655210	Sigma-Aldrich Corp
28551210	Electronic Arts Inc	82966U10	Sirius Satellite Radio Inc
30218210	Express Scripts, Inc	80004C10	SanDisk Corp
30213010	Expeditors Int of Washington	87160710	Synopsys, Inc
31190010	Fastenal Company	84473010	SouthTrust Corp
32096010	First Health Group Corp	85503010	Staples, Inc
33773810	Fiserv, Inc	69793310	PanAmSat Corp
31677310	Fifth Third Bancorp	83272710	Smurfit-Stone Container Corp
Y2573F10	Flextronics International Ltd	86681010	Sun Microsystems, Inc
37291710	Genzyme Corp	87150310	Symantec Corp
37555810	Gilead Sciences, Inc	88162420	Teva Pharmaceutical Industries Limited
37190110	Gentex Corporation	87966410	Tellabs, Inc
44615010	Huntington Bancshares Inc	74144T10	T. Rowe Price Group, Inc
44490310	Human Genome Sciences, Inc	92343E10	VeriSign, Inc
80640710	Henry Schein, Inc	92343610	VERITAS Software Corp
44929510	ICOS Corp	92849710	Vitesse Semiconductor Corp
45811810	Integrated Device Technology, Inc	96683710	Whole Foods Market, Inc
45814010	Intel Corp	98391910	Xilinx, Inc
46120210	Intuit Inc	98375910	XM Satellite Radio Holdings Inc
46185R10	Invitrogen Corp	24903010	DENTSPLY International Inc
46612J10	JDS Uniphase Corp	98433210	Yahoo! Inc
48203R10	Juniper Networks, Inc	98970110	Zions Bancorporation

Figure 3-1: Histogram of Differences in Quoted Half-Spreads

This figure displays a histogram of the differences in quoted half-spreads between stocks traded on the NASDAQ and those traded on the AMEX. See Table 3.2 for the definition of the quoted half-spread.

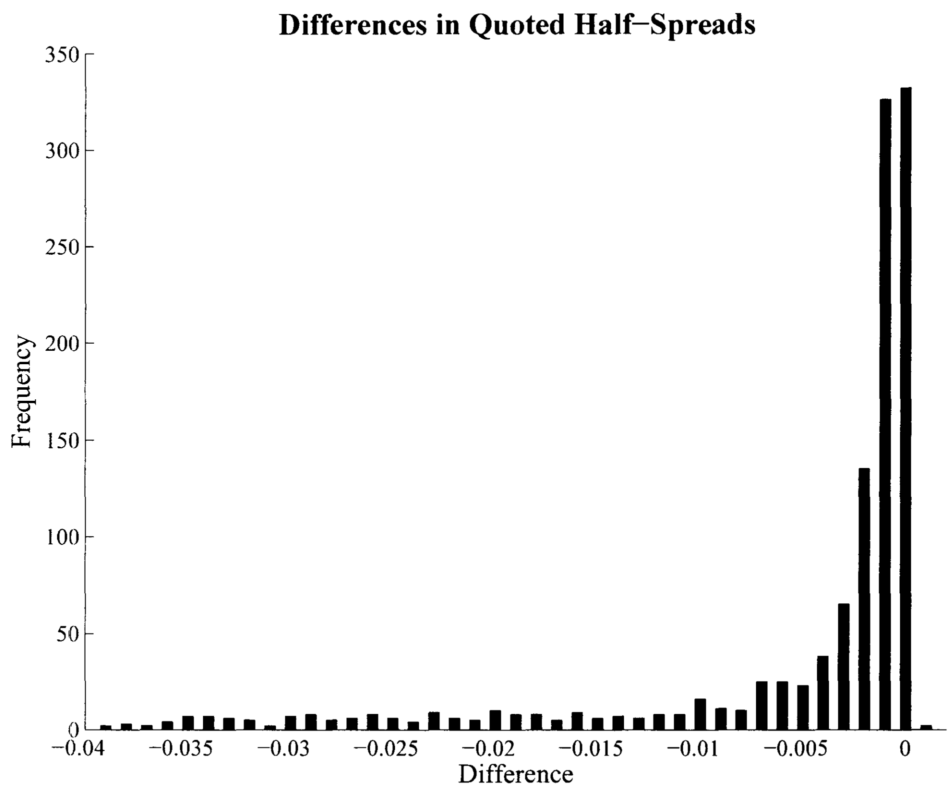


Figure 3-2: Histogram of Differences in Effective Half-Spreads
This figure displays a histogram of the differences in effective half-spreads between stocks traded on the NASDAQ and those traded on the AMEX. See Table 3.3 for the definition of the effective half-spread.

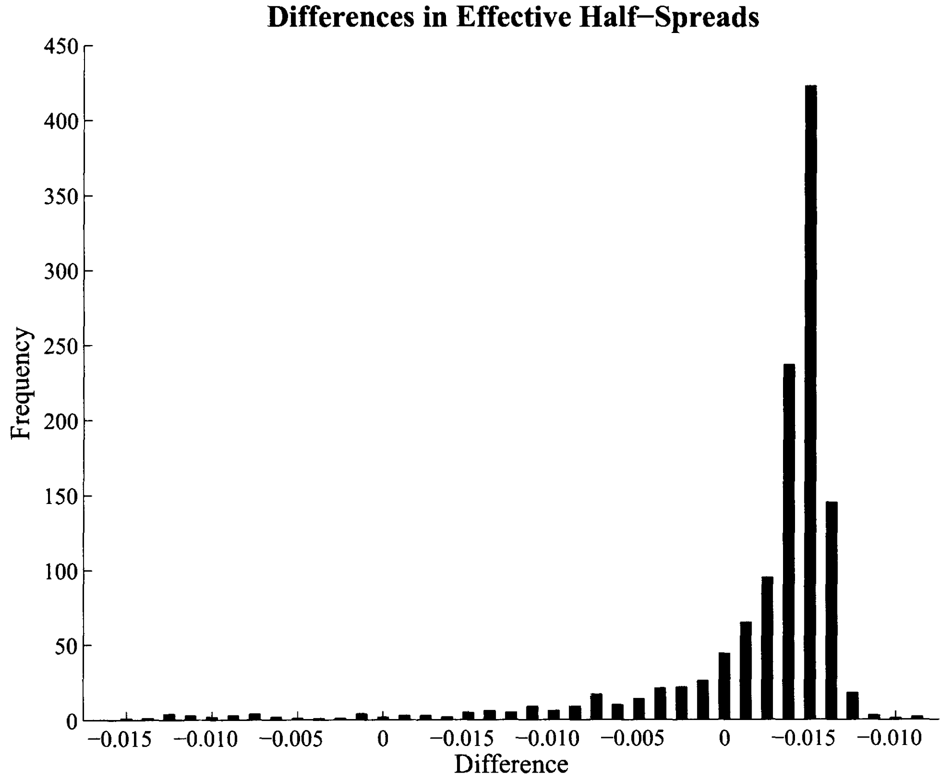


Figure 3-3: Histogram of Differences in Realized Half-Spreads (30 minutes)
This figure displays a histogram of the differences in realized half-spreads between stocks traded on the NASDAQ and those traded on the AMEX when the proxy for a stocks post-trade economic value is its stock price 30 minutes after the trade. See Table 3.4 for the definition of the realized half-spread.

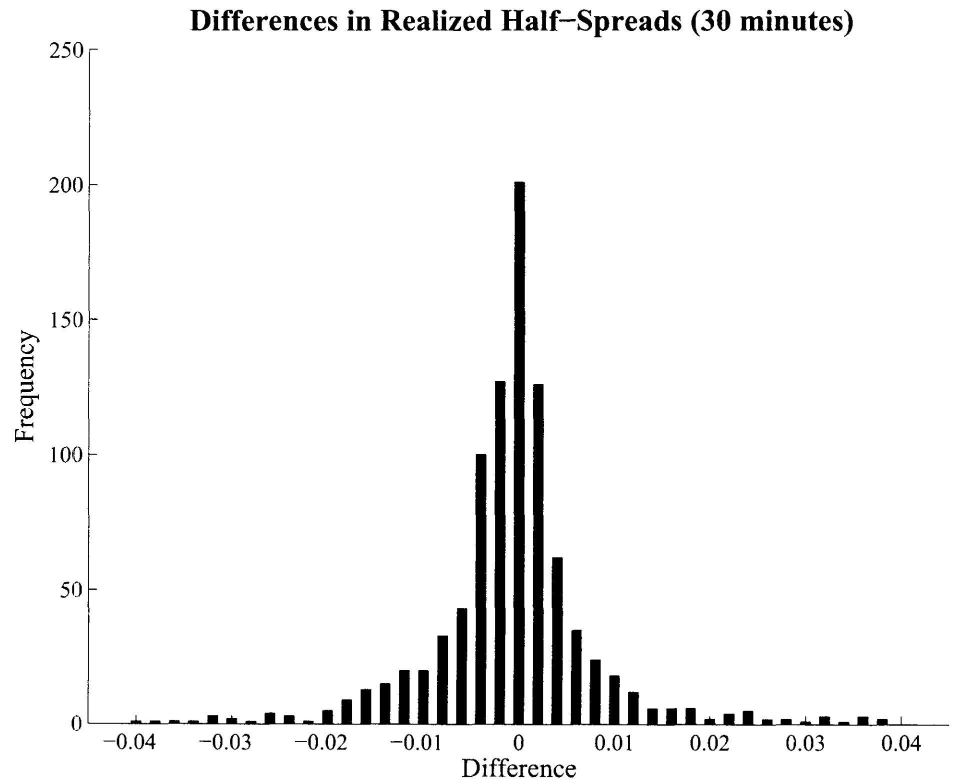


Figure 3-4: Histogram of Differences in Realized Half-Spreads (24 hours) This figure displays a histogram of the differences in realized half-spreads between stocks traded on the NASDAQ and those traded on the AMEX when the proxy for a stocks post-trade economic value is its stock price 24 hours after the trade. See Table 3.4 for the definition of the realized half-spread.

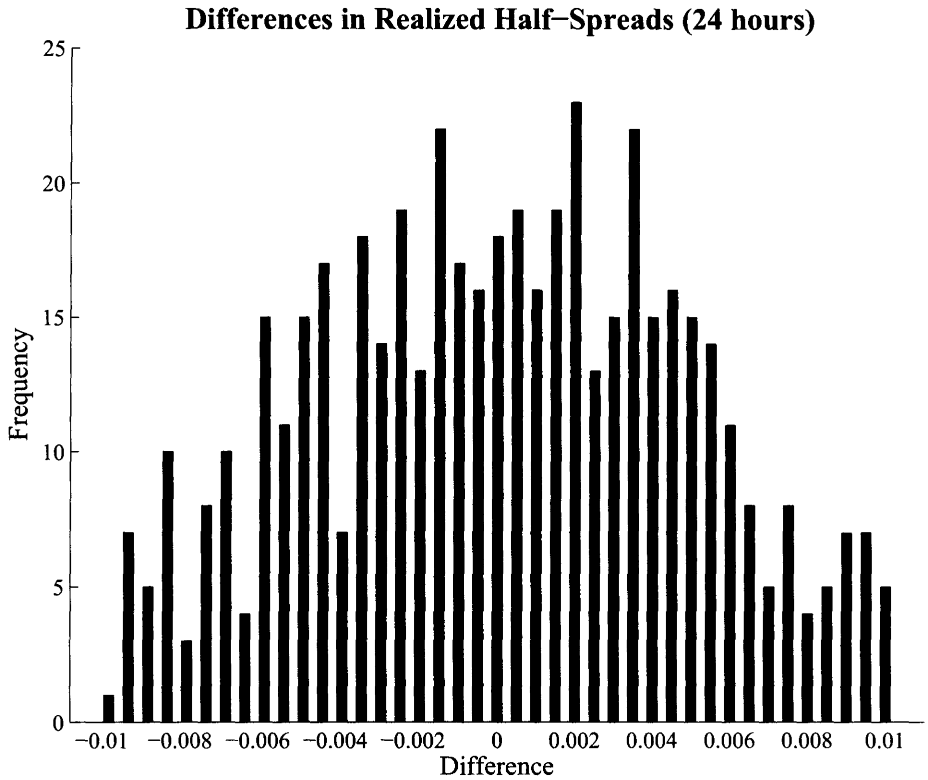
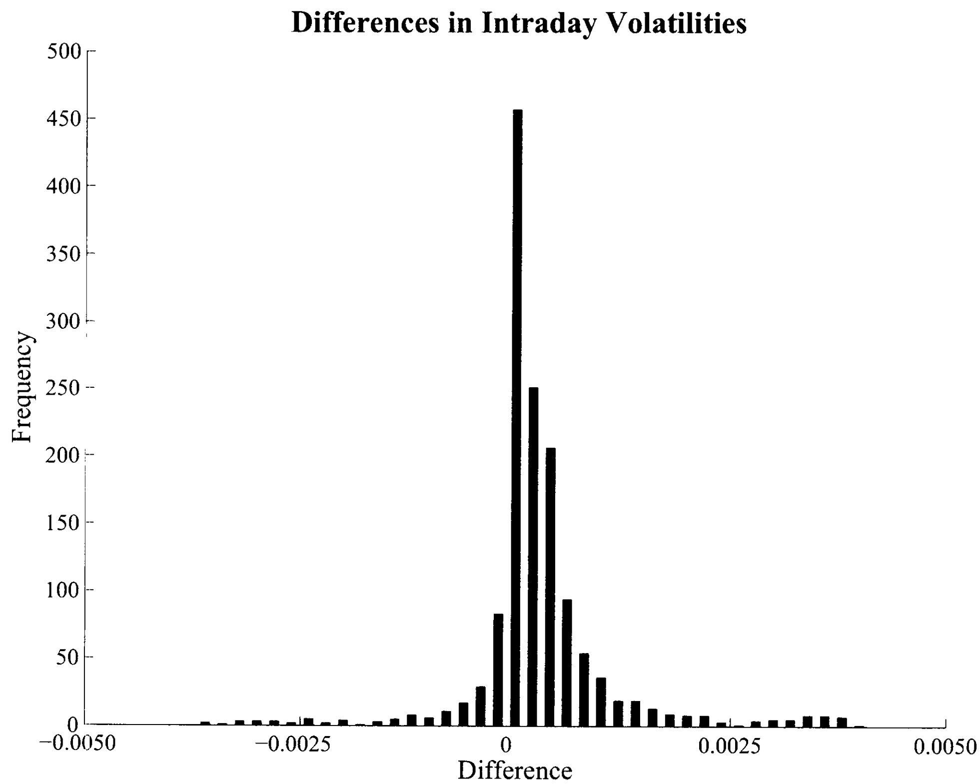


Figure 3-5: Histogram of Differences in Intraday Volatilities
This figure displays a histogram of the differences in intraday volatilities between stocks traded on the NASDAQ and those traded on the AMEX. See Table 3.5 for the definition of the intraday volatilities.



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