Short Term Momentum: Role of Investor Sentiment in Return Formation

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ABSTRACT

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Using transaction level data spanning across eighteen years over 1993 to 2010, we show that heavily bought stocks or heavily sold stocks display persistence in buy and sell order respectively. We show that over one trading day horizon, the persistence is strong enough to generate economically significant return. CAPM market factor, Fama-French Size and Book to Market factors, as well as Carhart's momentum factor do not explain these results. However, the returns can be at least partially explained by investor sentiment variables and macroeconomic condition variables such as term and default spread and business cycle.

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Introduction

This paper attempts to explore the existence of short-term momentum in daily buying and selling pressure and its implications for daily stock returns. Our analysis is based on approx. 38 billion pairs of matched trades and quotes, spreading across all stocks in the CRSP database and spanning across eighteen years (January 1993 to December 2010). In the first part of this study, we identify the portfolio of most heavily bought stocks in the market on a given day and the portfolio of most heavily sold stocks in the market. We look for persistence in buying and selling pressures for these portfolios and explore the resulting short-term momentum in prices. In the second part of the study we examine the role of sentiment in the formation of the portfolio's return.

Our investigation is motivated by the behavioral theory of price dynamics, proposed by Shiller (1984) and Shleifer and Summers (1990). According to this theory, the dynamic interplay between noise traders and rational arbitrageurs establishes prices. According to this view, returns are not only dependent on changes in fundamentals, but could also be affected by other factors such as persistence in buying and selling by uninformed traders.

Design of our investigation is motivated by the findings of two papers: First, Barber and Odean (2008), where they find that individual investors are net buyers of attention-grabbing stocks, e.g., stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns. We conjecture that most small investors will see these attention-grabbing stocks at the end of the day and act on it in the following day. The second paper, which plays a key role in motivating our design, is Chorida and Subrahmanyam (2004). This paper presents evidence of positive autocorrelation in daily order imbalances. This suggests that an excess of buyer or seller initiated trade for a particular security on any given day is likely to be followed by excess of buyer or seller initiated trade (respectively) in that security the next day.

Our study builds on the findings of Kumar and Lee (2006). They find that retail investor's trades are systematically correlated. They further argue that the correlation is a result to trading habits of retail investors, whereby these traders buy or sell stocks in concert with each other. By highlighting sentiment based trading among retail investors, the authors find evidence in support of the role of investor sentiment in the formation of returns. We add to their findings in at least two ways. First: We show that the correlated trading effect is strong enough to affect the entire market and it might not be necessarily limited to retail trading. Secondly, our study spans across eighteen years time horizon covering expansion, recession and normal phases of the market. Our results throw new light on the role of investor sentiment in return formation in various phases of the business cycle.

This paper reports the results from two stages of analysis. First, at the close of market, we identify 10% of the stocks with highest buy pressure (BUY portfolio) and 10% of the stocks with highest sell pressure (SELL portfolio) during that trading day. Simple autocorrelation analysis finds that both portfolios demonstrate strong momentum. This result is in concurrence with the findings of Chordia and Subrahmanyam (2004), whereby stocks in the BUY portfolio continue to attract buyer-initiated trade and the stocks in the SELL portfolio continue to attract seller-initiated trade in the following day. We develop a short-term naïve trading strategy whereby, at the opening of the following day market, the investor takes long position in the BUY portfolio and a simultaneous short position in the SELL portfolio. He holds this position for the full trading day and exits the market with zero position at market close. In each of the eighteen years in the sample, the strategy earns positive returns ranging from 18.22% in 2007 to 119.11% in 1996. Moreover, controlling for market, size, book to market ratio, and momentum factors does not subsume these returns.

These results are informative. They show that strong momentum exists at very short investment horizons. More importantly, the evidence shows that this short horizon momentum cannot be attributed solely to the established Jegadeesh and Titman (1993) momentum.[1] These results imply one of the two things: either the short horizon momentum documented here, cannot be explained by factors such as short-term under-reaction, which are responsible for the JTM, or there must be multiple sources of momentum in returns which work differentially at differing time horizons.

The second set of tests focuses on exploring the systematic vs. idiosyncratic nature of the factor responsible for the short horizon momentum documented in this

[1] Hereafter we will refer to the Jegadeesh and Titman (1993) momentum as JTM.

study. We construct a daily BUY minus SELL (BMS) portfolio by taking a long position in the BUY portfolio and a simultaneous short position in the SELL portfolio. The return from this long and short position constitutes the BMS factor. Following Fama and French (1993), we construct a five-factor model (Market, Size, book to market ratio, momentum, and BMS). We estimate this model by year, across various size and industry portfolios. We find that the BMS factor marginally improves the explanatory power of the pricing model. The factor loading is found to be generally positive for large stocks and negative for small stocks. This result suggests that on average investors tend to be more on the buy side for large stocks and on the sell side for small stocks.

A close examination of the results reveal that the loadings are significantly positive for large-size portfolios in the bull market (1994 to 1999) and during a bear market (2005 to 2008), the factor loading is significantly negative for small-size portfolios. One interpretation of this could be that in an expansionary period people tend to buy large-cap stocks while in recession, investors tend to sell more of small-cap stocks. Overall, the results seem to suggest that there might be a systematic factor explaining (at least partially) the observed short-term momentum. We also find that the BMS factor is negatively related to business cycle and positively related to investor sentiment (as measured by Baker and Wurgler, 2007). Overall, the evidence suggests that to a large extent, investor sentiment in the market is responsible for the observed short-term momentum. The magnitude of the daily returns (average 26 basis points) from the BUY-SELL positions suggests that at least large investors should be able to capitalize from this strategy. Its persistence throughout the studied eighteen years time period poses a challenge to the weak form of market efficiency.

The remainder of this paper is organized as follows: Section 1 briefly reviews the related literature. Section 2 describes the data and summary statistics and presents our test methodology. Sections 3 discuss our empirical results, and Section 4 concludes our paper.

1. Background

Jagadeesh and Titman (1993) show that past winners continue to outperform past losers over horizons of three to twelve months. The momentum trading strategy is a simple buy and hold strategy which requires the investor to buy stocks with high returns over the preceding three to twelve months and simultaneously sell stocks with poor returns over the same past horizons. For Example, a zero-cost portfolio that is long the past six-month winners (stocks whose past six-month returns rank among the best performing 10% stocks) and short the past six-month losers (stocks whose past six-month returns rank among the worst performing 10% stocks) generates an excess return of about 12% per annum from 1965 to 1989. Their findings lend support to the relative strength strategies such as the one discussed in Levy (1967): a trading rule that buys stocks with current prices that are substantially higher than their average prices over the past 27 weeks, realize significant abnormal returns.

The momentum profitability does not seem to be market specific. For example Rouwenhorst (1998) find that momentum profits are also significant across various European markets. Chui, Titman and Wei (2000) document that with the exception of

Japan and Korea, momentum strategies work in Asian markets. Similarly Griffin, Ji, and Martin (2005) find support for the economically and statistically significant momentum profit around the world. In a follow-up work to their 1993 paper, Jegadeesh and Titman (2001) document that unlike various other anomalies (such as size effect and book-to-market effect), which disappeared after being reported, momentum profit has persisted throughout the 1990s. A word of caution is warranted at this stage, whereby; the documented profitability of the momentum strategy should not be mistakenly interpreted as evidence of arbitrage. Grundy and Martin (2001) show that over the 828 months between 1926 and 1995, the return momentum strategy earns a negative return in 322 of 828 months. Jegadeesh and Titman (1993) also report that from 1965 to 1989 momentum strategy loses about 7% on average in the month of January.

As discussed above, the extant literature provides substantial domestic and international evidence in support of the long-horizon momentum (six month to one year). However, in contrast to this, the evidence of short-horizon momentum is relatively scant. Pan, Liano, and Huang (2004) first document momentum in weekly industry portfolio returns，while Lehmann (1990) and Jegadeesh (1990) find reversals in individual stock returns of one week to one month. More recently, Gutierrez and Kelley (2008) find that “an opposing and long-lasting continuation in returns follows the well-documented brief reversal” (p415), and that the momentum in individual stock returns is not simply a manifestation of the long-horizon momentum.

This study examines a very short horizon relative strength type strategy (one day holding period), which may be classified (in terms of the style) as a variant of the momentum trading strategy. We examine a buy and hold strategy, which requires the investor to buy stocks with high buy pressure (stocks with highest 10% buyer initiated fractional trading volume) on the previous trading day, and simultaneously sell stocks with high sell pressure (stocks with highest 10% seller initiated fractional trading volume) on the previous trading day. The investor takes position at market open and exits the market with zero position at market close. The trading strategy is based on the conjectures that the dominant buy/sell pressures experienced by a given stocks on the previous day are likely to be persistent through the next day. To the extent that dominant buy pressure would lead to price increase and similarly, dominant sell pressure would lead to price decrease, the trading strategy should earn (on average) a positive return.

Persistence in buy or sell pressure can arise due to either rational or irrational factors. From a rational perspective, strategic trading by informed traders can potentially give rise to persistence in order-imbalance. According to Chordia & Subrahmanyam (2004), traders are inclined to split their orders over time to minimize the price impact of trades, thus causing positive autocorrelation in order imbalances. In turn, this autocorrelation causes correlation in price pressures, which potentially gives, rise to a positive autocorrelation in returns. Kumar and Lee (2006) in their study on retail investor sentiment and return comovement find that when one group of retail investor buys (sells) stocks, another group of retail investors also buys (sells) stocks. This correlated trading causes persistence in volume of buyer-initiated trades or volume of seller-initiated trades. In a Barclay and Warner (1993) type investigation of order size and price impact, Yang (2009) show that in the period before quarterly announcements, informed traders change their trading preference over time. His results show that in the pre-announcement period (from day -10 to day -6), informed traders use small orders to trade stealthily. Within five days before the announcements, they trade more aggressively to use increasingly large orders because they expect their information advantage to disappear after the announcements.

From the irrational perspective, uninformed traders are likely to be swayed by prevailing sentiments in the market. When they believe the market is bullish on a given stock, they are likely to continue buying that stock, thus driving its prices up. In contrast, when the popular outlook is perceived to be pessimistic about a given stock, these investors will sell that stock thus driving its prices down. De Long, Shleifer, Summers, and Waldmann (1990) study the effect of noise traders' activities on stock prices and returns. They argue that when noise traders are pessimistic about an asset, they would drive down the asset's prices and in the near future, they might become even more pessimistic and drive down the prices further. Conversely, when investors are optimistic, they might buy stocks and drive asset prices up. Lee, Jiang and Indro (2002) argue that bullish (bearish) shifts in sentiment lead to higher (lower) future excess returns. They find that noise traders increase their holdings of an asset when their sentiment becomes more bullish and conversely sell more stocks when they believe the market is bearish. This "hold-more" effect is likely to cause a short-term positive autocorrelation in stock returns.

2. Data and Methodology

2.1. Data

This study involves several different types of data sets. The primary data for our study consist of the intraday trades from TAQ and daily stock files from Center for Research on Security Prices (CRSP). Our sample period spans from January 1st 1993 to December 31st 2010 (for a total of 18 years). This span includes all phases of the market cycle ranging from the booming technology bubble in the mid to late 90s, its crash in 2000 and then the recessionary years post 2006. Our sample consists of the entire universe of stocks for which CRSP and TAQ contains the market data. We start our analysis with a sample size of 34,793,186 stock days (spread across 18 years). Since our trading strategy involves fractional buyer and seller-initiated trade, illiquid stocks could bias the results. To get around this problem, we delete all stocks below the lowest 20 percentile (by trading volume) in each trading year. The final sample consists of 22,475,317 stock days worth of data. The sample distribution by year is presented in Table I.

The opening prices, closing prices, numbers of shares outstanding, and returns for our sample are obtained from the CRSP database. We obtain transaction level trade and quote data from the TAQ database. Following Chordia, Roll, and Subrahmanyam (2001), several filters were employed to ensure the validity of the TAQ data.[2] The TAQ database does not eliminate auto-quotes (passive quotes by

[2] We drop all trades with a correction indicator other than 0 or 1, and retain only those trades for which the condition is B, J, K, or S. We also drop all trades with non-positive trade size or price. Finally, we omit all trades recorded before opening time or after the closing time of the market.

secondary market dealers), which may cause the quoted spread to be artificially inflated. Since no reliable method can exclude auto-quotes in TAQ, only BBO (best bid or offer) eligible primary market (NYSE) quotes were used (Chordia, Roll, and Subrahmanyam 2001, 2002).

The daily Fama-French three factors, the momentum factor and the twelve industry portfolios definitions are obtained from Professor Kenneth R. French's data library.[3] The monthly investor sentiment index used in our study comes from Baker and Wurgler (2007)'s paper, and the data is available from Jeffrey Wurgler's website at Stern, NYU.[4] The business cycle indicator is obtained from Federal Reserve Bank of St. Louis' FRED database. The treasury 10-year interest rates, treasury 3-month interest rates and the Moody's AAA corporate bond yields (which are used to calculate default spread and term spread) are obtained from Wharton Research Data Services (WRDS) 'Federal Reserve Bank Reports' dataset.

2.2. Methodology

We follow the Lee and Ready (1991) procedure for merging trade and quote data and classifying trades. According to this algorithm, a trade is classified as buyer- (seller-) initiated if the transaction price is closer to the ask (bid) price of the

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Negative bid-ask spreads and transaction prices are also eliminated. In addition, only quotes that satisfy the following filter conditions are retained: we eliminate all quotes for which the quoted spread is greater than 20% of the quote midpoint, when the quote midpoint is greater than $10 or when the quoted spread is greater than $2, when the quote midpoint is less than $10. We also eliminate all quotes for which either the ask or the bid moves by more than 50%. All quotes with condition 5, 7, 8, 9, 11, 13, 14, 15, 16, 17, 19, 20, 27, 28, 29 were excluded.

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[4] http://people.stern.nyu.edu/jwurgler/

prevailing quote. The quote must be at least one second old. If the trade is at the exact midpoint of the quote, a "tick test" classifies the trade as buyer- (seller-) initiated if the last price change prior to the trade is positive (negative). Since the trade direction is inferred from the available information and not observed, some assignment error is inevitable. Hence, the resulting order-flow data is an estimate. Nevertheless, as shown by Lee and Radhakrishna (2000) and Odders-White (2000), the Lee and Ready (1991)'s algorithm is largely accurate; thus, inferences based on the estimated order-flow should be reliable.[5] After merging and signing, the rest of our analysis is based on 37,227,391,369 pairs of trades and quotes. The annual distribution is presented in Table I.

We count the total number of buyer-initiated trades and seller-initiated trades for each stock each day and then calculate the percentage of buyer-initiated trades as the total number of buyer-initiated trades divided by the total number of trades. Decile portfolios are constructed on the basis of the fractional buy volume.[6]

At the end of each trading day, we rank the sample stocks by the fraction of buyer-initiated trade in each stock on that day. Using this ranking, we split the sample into decile portfolios. Thus, a stock gets assigned to portfolio 1 on any given day if it ranks among the top 10% stocks in terms of fraction of buyer initiated trade in that stock on that day. Stocks ranking among the 81st to 90th percentile form portfolio 2

[5] As robustness, we classify all the trades into buyer or seller initiated using only the tick-test. It does not qualitatively affect the results.

[6] As test of robustness, we construct portfolios using fractional buyer initiated trading volume instead of the fractional number of buyer-initiated trade. The results remain qualitatively similar. For sake of brevity, we present only results obtained using the fractional number of buy trade decile portfolios.

and those falling among the 71st to 80th percentile form portfolio 3. We classify the portfolio of stocks falling among 21st to 30th percentile buy stocks as portfolio 4 and those in 11th to 20th percentile as portfolio 5. The lowest 10% of buy stocks are classified as portfolio 6. In other words, a stock gets assigned to portfolio 6 if it ranks among the top 10% stocks in terms of fraction of seller initiated trade in that stock on that day. The construction of our portfolios is based on the hypothesis of persistence in buys and sells. Therefore we only focus on the stocks ranking among the top three and bottom three deciles.

2.2.1. Autocorrelation in Stock Returns

The first set of tests focus on the autocorrelation patterns in returns of the stocks constituting the six portfolios formed above. Intuitively, a positive autocorrelation in stock returns would suggest that its own past high return predicts its future high return and similarly negative past return predicts negative future returns. Extant literature attributes daily return autocorrelation to three main sources. First: spurious autocorrelation caused by the use of stale prices (SA), second: autocorrelation caused by bid-ask bounce (BA), and third: autocorrelation arising due to partial price adjustment (PA). Often a fourth source in the form of time varying risk premia is also cited as a possible source of positive autocorrelation (RA). However, Anderson (2011) shows that the RA effect is sufficiently small and in the daily setting it can be safely ignored.

Atchison, Butler and Simonds (1987), Lo and MacKinlay (1990) find that SA explains a very small part of total autocorrelation in portfolio returns. In a more recent study Bernhardt and Davis (2008) find that the impact of SA on portfolio return autocorrelation is negligible. We use a very large sample in this study, ranging across eighteen years. Spurious correlation is unlikely to be the variable consistently driving our results across all days/years. We ignore this effect in this study. We address the bid-ask bounce related autocorrelation (BA) concern by running our analysis separately using two types of returns: first, daily return calculated by using daily opening to closing prices, and second: daily return calculated by using daily opening to closing bid-ask midpoint.

The intuition of our study is based on expectation of persistence in buying and selling pressure across stocks. Thus:

Hypothesis 1: On average the stocks across each of the six portfolios should display significant positive autocorrelation.

Hypothesis 2: The autocorrelation in daily returns should be strongest for portfolios 1 and 6, and display monotonic decline from 1 to 3 and from 6 to 4.

We estimate the autocorrelation of returns for each stock each day by using a simple first-order autoregressive model[7]:

$$R_{t,i} = \alpha + \beta R_{t-1,i} + \varepsilon_t \tag{1}$$

Where $R_{t,i}$ is stock i's return on day t and $R_{t-1,i}$ is stock i's return on its previous day. Autocorrelation is measured by the coefficient β. We expect β to be positive on average. The magnitude of β is expected to be highest for stocks comprising portfolio 1 and 6. The magnitude is expected to decline from portfolio 1 to 3 and also

[7] The choice of AR(1) model is driving by the data whereby we checked for existence of up to 10 lag correlation, and found AR(1)should be the best fit.

from portfolio 6 to 4.

2.2.2. BUY and SELL Portfolio Returns

The second set of tests focus on constructing the 6 portfolios based on differing buy and sell pressures and estimating their returns over 1 day holding period. The strategy calls for, first: we identify the six portfolios after market close on day (t-1). Second: in the morning of day (t), we take a long position in the buy dominant portfolio and simultaneous short position in the corresponding sell dominant portfolio. For example, long portfolio 1, short portfolio 6. Third: we close our position at market close on day (t). Thus, in terms of the 1-6 example, we sell our long position in portfolio 1 and close the short position in portfolio 6. The portfolio return is calculated as the open to close return on day (t). We have used equally weighted portfolio returns for this part of the analysis. We repeat the buy-hold-sell strategy every day for 4,535 trading days spanning across 18 years from January 1993 to December 2010.

Hypothesis 3: Portfolios 1, 2 and 3 are expected to yield positive returns, while portfolios 4, 5 and 6 are expected to earn negative returns.

Hypothesis 4: Since the buying pressure declines from portfolio 1 to portfolio 3 and the selling pressure declines from portfolio 6 to portfolio 4, we expect the portfolio returns to decrease from portfolio 1 to portfolio 3, and we expect the absolute value of portfolio returns to decrease from portfolio 6 to portfolio 4.

The robustness of the portfolio returns is tested by risk adjusting the returns using several factor model specifications. First, Capital Asset Pricing Model (CAPM) described in Sharpe (1964) and Litner (1965) is used with MKT (market) as a single source of adjustment. A second model includes the two Fama-French (1993) factors SMB (Size) and HML (Book-to-market). In order to differentiate the BUY and SELL returns from the more popular momentum returns, we add the MOM (momentum) factor (Carhart (1997) 4-factor model) and re-examine the returns of portfolio 1 through 6.

2.2.3. Determinants of BUY minus SELL Portfolio Returns

We construct the Buy minus Sell Portfolio by taking a long position in Portfolio 1 and a simultaneous short position in Portfolio 6. The difference between the returns of Portfolio 1 and Portfolio 6 gives us the Buy minus Sell (BMS) return. We identify eight variables that could potentially explain the BMS factor. The variables are: The first variable is Business Cycle (BC). Extant literature suggests that momentum returns vary with business cycle (Avramov and Chordia (2006), Chordia and Shivakumar (2002)). To the extent persistence in buying and selling could be caused by herding of uninformed traders, we believe it is likely to vary across expansionary vs. contractionary phases in the market. The business cycle indicator is obtained from the Federal Reserve Bank of St. Louis's FRED database.

Default spread and term spread are two standard macroeconomic variables used to predict market returns. The default spread (DS) is defined as the difference between the average yield of bonds rated BAA by Moody's and the average yield of bonds with a Moody's rating of AAA, and is included to capture the effect of default premiums. Fama and French (1988) show that default premiums track long-term business cycle conditions, and document the fact that this variable is higher during recessions and lower during expansions. The term spread (TS) is measured as the difference between the average yield of Treasury bonds with more than 10 years to maturity and the average yield of T-bills that mature in three months. Fama and French (1988) show that this variable is closely related to short-term business cycles.

We also use three different measures of market sentiment. The variables are: (1) the percentage of stocks whose price decreased via-a-vis the previous trading day (PCT_down), (2) The natural logarithm of the volatility index VIX, which is used to measure market's expectation of stock market volatility in short term, (3) Baker and Wurgler's Investor sentiment index. Apart from these, we include market capitalization of the portfolio and the return on S&P 500 index (Market proxy) in the regression specification. The specification used is:

$$\mathrm{BMS_t} = \alpha + \beta_1 \mathrm{BC_t} + \beta_2 \mathrm{CAP_t} + \beta_3 \mathrm{PCT\_down_t} + \beta_4 \mathrm{ln\_SP500_t} + \beta_5 \mathrm{ln\_VIX_t} + \beta_6 \mathrm{DS_t} + \beta_7 \mathrm{TS_t} + \beta_8 \mathrm{SI_t} + \varepsilon_t \quad (2)$$

3. Empirical Results

Table I presents some annual descriptive statistics of the sample used in this study. The number of stocks in each year is fairly uniform. There is a slight decline in 2009 and 2010. Similarly the number of daily stock data in each year (sum of all the trading days across all the stocks in the sample) is also fairly uniform. This number is less than (Number of trading days in the year) * (Number of stocks), because not all stocks survive in the sample for the entire year. Some stocks drop out because of delisting; however the majority of the lost data point losses may be attributed to illiquidity. On each trading day we drop 20% of the most illiquid stocks from the sample. Total market capitalization and the trading volume have increased through time.

Table II presents the descriptive statistics (by year) for the six portfolios described in section 2.2. Portfolio 1 (P1) consists of the 10% most heavily bought stocks (in terms of fraction of buyer vs. seller initiated trades in the stock). P6 represents the 10% most heavily sold stocks in the sample. Panel A presents the average daily market capitalization of the portfolios in each year. Comparing these numbers with the sample market cap in Table I, Panel A of Table II suggests that our portfolios (heavily bought and heavily sold stocks) mostly consist of relatively larger stocks in the sample. The smaller stocks seem to fall in the 30th to the 70th percentile in terms of fraction of buyer vs. seller initiated stocks. Once again, we do see the increase in market capitalization through time. It declines post 2007.

Table II, Panel B presents the portfolio breakpoints in terms of the fraction of buyer vs. seller initiated trades. For example, we see that in 1993, portfolio 1 consisted of stocks which had 89.69% of all trades initiated from the buy side, as opposed to portfolio 6 which had only 9.89% trades initiated by buyers (91.11% trades initiated by the seller). Similarly Portfolio 2 consisted of stocks with 75.62 to 89.69% of the trades coming from the buy side. An interesting observation, which may be made from this table, is that through time, all the breakpoints seem to be gravitating towards 50%. That is the P1, P2, and P3 breakpoints are declining while the P4, P5, and P6 breakpoints are increasing. While we do not explore what could be causing this trend, the numbers could have implication for the profitability of the strategy we are exploring in this paper. Hypothesis 4 would suggest that the declining buying pressure (through time) in portfolio 1 and the decreasing selling pressure in portfolio 6 should lead to declining strategy returns through time. We do observe a declining trend especially in portfolios 1, 2, and 3 (Table IV) as well as in the overall strategy (Figure 1).

3.1. Autocorrelation in Stock Returns

The average annual first order autocorrelation in stock returns is summarized in Table III. Panel A reports the autocorrelations based on open to close trade price. Since returns based on trade prices are likely to be affected by concerns of bid-ask bounce, we present autocorrelations based on quote mid-point returns. The numbers in the two panels are qualitatively similar and therefore we believe that our results are not driven by bid-ask bounces. The reported numbers are calculated as the average equation (1) β coefficient. The coefficients are averaged across all stocks for each of the six portfolios, by year. Two main results are of interest here. First, almost all autocorrelations are almost always positive. This supports our Hypothesis 1. To the extent that the reported autocorrelation is at a stock level (averaged within each portfolio classification), it is not entirely surprising to see several non-significant numbers.[8]

A second result lies in the relative strength of the autocorrelation. In general

[8] Most studies of autocorrelation in individual stock returns have focused on the average autocorrelation of groups of firms, finding it to be usually statistically insignificant. For example see Safvenblad (2000).

the magnitude of autocorrelation is higher for Portfolios 6 and portfolio 1 respectively. The average autocorrelation (across the 18 years) in stock returns is found to be 3%, 1.4%, 0.9% among portfolios 1, 2 and 3 stocks respectively. Among the sell pressure portfolio stocks, the average autocorrelations are 2.9%, 1.8%, and 1.2% for portfolios 6, 5 and 4 respectively. These results lend support to hypothesis 2.

The results in Table III generally support the underlying assumption of persistence in buyer and seller initiated trades. The positive autocorrelations suggest that stocks that earned positive returns on day (t-1) are also likely to earn positive return on day (t), and similarly vice versa for stocks that earned negative returns on day (t-1). Since the grouping of the stocks are based on the relative buy or sell pressures, the persistence in the performance from day (t-1) to day (t) might be indicative of persistence in buying and selling. In other words, on average, stocks those were among the most bought stocks on day (t-1) are more likely to have greater volume of buyer initiated trade on day (t) then seller initiated trades. Similarly, the set of stocks that were heavily sold on day (t-1) are more likely to be sold than bought on day (t).

3.2. BUY and SELL Portfolio Returns

Table IV, Panel A presents the returns from buying the portfolios on day (t) morning and selling them at market close on the same day. The portfolios are constructed using the fractional buy and sell volumes on day (t-1). All returns in Portfolio 1 (Barring 2007 and 2008) are positive. Portfolios with relatively lower buy pressure (Portfolio 2 and portfolio 3) have mixed positive and negative returns. In all but three years (2003, 2004, and 2006) the SELL portfolio (P6) earns a negative return. Interestingly on the sell side portfolios, P4 and P5 continue to demonstrate negative returns. These results suggest that the top 10% most bought stocks on day (t-1) are more likely to be purchased on day (t). However, this trend dissipates fairly quickly as the buy pressure reduces. The day (t) returns are found to be about 33.9% average per annum for portfolio 1; this reduces to 12.4% for portfolio 2 and 0% for portfolio 3. The day (t) returns are most negative for the 10% of the stocks, which were most heavily sold on day (t-1). Portfolio 6 earns an average return of about -36% per annum. It reduces to -35% per annum for portfolio 5 and -31.7% for portfolio 4. Thus, the selling effect seems to be more persistent in that, stocks that were heavily sold on day (t-1) are more likely to be sold on day (t). A possible explanation for this could be stronger sentiments in the market following selling than buying.

In the next set of analysis, we try to adjust the portfolio returns for various known risk factors. Table IV, Panel B1 presents the CAPM market adjusted daily alphas for the various portfolios. Portfolio 1 earns an average of 12 basis points daily abnormal return, while portfolio 6 loses about 16 basis points per day. T-stats are presented in the parenthesis below the coefficients. The numbers are almost all highly significant. Table IV, Panel B2 adjusts the daily portfolio returns for the Fama and French SMB (Size) and HML (Book to market) factors. Portfolios 1 and 6 continue to demonstrate abnormal returns similar to that seen in Panel B1. Since our BUY and SELL portfolio returns could potentially be simply a short-term manifestation of the well-established momentum effect, we use the Carhart (1995) four factor model to risk adjust the returns. Table IV, Panel B3 presents the alphas adjusted for the two Fama-French factors, the CAPM market factor, and the momentum factor (MOM). Portfolio 1 and portfolio 6 returns remain qualitatively unchanged.

Our naïve strategy involves taking a long position in portfolio 1 and a simultaneous short position in portfolio 6 at market open. We hold these positions till the end of the trading day and before the market closes, we reverse our positions and exit the market. Table V presents the results of this trading strategy, by year. The numbers represent the average daily return from holding the above long-short positions. The first column presents the raw unadjusted returns. Second column adjusts the returns for the CAPM market factor. Third column adds the two Fama-French factors (HML, SMB), and finally the fourth column brings in the MOM (momentum) factor. The daily returns range from 48 bp to 42 bp from 1993 to 1998. Post 1998 the returns decline steadily and the lowest returns are in 2006 and 2007 (about 7.3 bp per day).

The positive return in 2007 might seem puzzling at first glance because all stock returns declined in that year; however, by taking a closer look at Table IV, Panel A reveals that in 2007, sell portfolio observed a greater decline (short position) than the buy portfolio (long position) thus leading to an overall positive return. Figure 1 presents the annualized, unadjusted returns of the above trading strategy. The annualized numbers are calculated as the sum of the daily returns in each year. The average annual daily return from the long-short trading strategy is found to be about 27.89 bp. Adjusting for CAPM reduces it marginally to 26.57 bp. Additional risk adjustment using the Fama-French factors and the momentum factors do not make any significant difference.

Momentum factors have been noted to earn negative returns in January. Figure 2 presents the daily returns from the BUY-SELL portfolio, by year and month. There are no consistent patterns in any monthly return. Figure 3 presents the BUY-SELL returns by day of the week. For sake of clarity, we present only Monday and Friday returns in the figure. Monday returns are found to be consistently greater than Friday returns. A possible explanation for this may be found in Abraham and Ikenberry, (1994), and, Lakonishok, and Maberly (1990). According to them, Individual investors are likely to devote weekends for fundamental research and therefore, they are more likely to be active on Monday than on other weekdays. At the same time, institutional investors devote Monday morning to strategically planning the remaining week, thereby being less active traders than usual.

Ariel (1987) reported a noticeable difference in mean returns for the nine-day period stretching from the last business day of a month to the eighth business day of the subsequent month as compared to returns measured over a nine-day period preceding the month-end. This effect was named “turn of the month effect” and has since become another of the widely researched and debated calendar anomalies in the financial market. Figure 4 compares the daily BUY-SELL portfolio returns by year, for the first 10 days of the month, vs. the last 10 days of the month. We find that in all the sample years, the strategy earned higher return during the first ten days of the month, compared to the last 10 days of the month.

3.3. Taking a Closer Look at the Returns

The results thus far seem to suggest that the BUY-SELL portfolio tends to earn a significant positive abnormal return even after adjusting for the CAPM, Fama-French and Momentum risk factors. In this section we use the specification laid out in equation (2) to get some understanding of the potential driver of the above-observed BUY SELL portfolio returns. Table VI presents the Spearman and Pearson correlation coefficients between BMS and the explanatory variables in equation (2).

Table VII presents the results of running reduced and full from of equations (2) while controlling for the market cap of the BUY minus SELL portfolio, we find the following results: BMS is positively related with the Baker and Wurgler's Investor sentiment index (SI) suggesting that the returns from the BUY-SELL portfolio is likely to be higher in periods of high sentiment. This can be a result of either strong persistence in BUY portfolio and/or strong persistence in SELL portfolio. PCT_down is estimated as the fraction of stocks whose price went down on the given day, vis-à-vis their closing prices on the previous day. A high value of this variable would denote a slump in the market. VIX measures investor expectations for market volatility in the next 30 days as implied by the skew of S&P 500 index options, and has been dubbed the "Investor Fear Gauge" When the VIX is high (i.e. when implied volatility is high), investor sentiment is presumed to be low since investors are assumed to be risk averse. Therefore the negative correlation between these variables and BMS is consistent with the positive relation between BMS and SI.

The Business Cycle dummy takes the value 1 for recession and 0 for expansion. The negative coefficient suggests that the BUY-SELL returns are likely to be low during periods of recession. A possible explanation for this could be small investors and sentiment traders are likely to keep out of the market during periods of recession. The coefficients on default spreads are significantly positive, while the coefficients on term spreads are significantly negative. To the extent that Default spreads are high during recession and low during expansion (Fama-French 1988), this result is somewhat puzzling. The S&P 500 coefficient is significantly positive suggesting that the BUY-SELL strategies earn higher return when the market moves up.

4. The BMS Factor

The analysis thus far seems to suggest that the BUY-SELL return is not entirely related to the characteristics of the constituent stocks. The results in Table VII bring up the role of investor sentiments, business cycle and economic stability (default and term spreads). The results from Table IV, similarly brings out the inability of the various factor models to explain the BUY and SELL portfolio returns. We conjecture that the BMS returns might be possibly picking a short-term asset-pricing factor, which is not accounted for by either the CAPM market factor, or, the Fama-French SMB and HML factors, or the Carhart Momentum factor. We explore this aspect of the BUY – SELL return in two set of tests.

First, we examine how the BMS return factor performs vis-à-vis the Capital Asset Pricing Model (CAPM), Fama-French (1993) model, and, Carhart (1997) model.

This is achieved by comparing the following three pairs of model R^2:

$$R_{it} - R_{rt} = \alpha_{iT} + b_{iT}RMRF_t + \varepsilon_{it} \quad (3)$$

$$R_{it} - R_{rt} = \alpha_{iT} + m_{iT}BMS_t + b_{iT}RMRF_t + \varepsilon_{it} \quad (4)$$

$$R_{it} - R_{rt} = \alpha_{iT} + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + \varepsilon_{it} \quad (5)$$

$$R_{it} - R_{rt} = \alpha_{iT} + m_{iT}BMS_t + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + \varepsilon_{it} \quad (6)$$

$$R_{it} - R_{rt} = \alpha_{iT} + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + u_{iT}UMD_t + \varepsilon_{it} \quad (7)$$

$$R_{it} - R_{rt} = \alpha_{iT} + m_{iT}BMS_t + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + u_{iT}UMD_t + \varepsilon_{it} \quad (8)$$

We estimate each model specification for each stock in each year. The model R^2 in a given year is estimated as the cross-sectional average of adjusted R-squares from the stock level regression in that year. This provides an intuitive measure that expresses the fraction of the average excess returns captured by the model. We compare adjusted R^2 of equations (3) with (4); (5) with (6); and finally (7) with (8). The results are presented in Table VIII. Although the adjusted R^2 show a very small increase across each comparison, the magnitude of the increase is very small.

Second, the results in Table VII seem to suggest that there might be some relation between firm size and the BUY-SELL returns. In order to explore this, we sort all the stocks in the sample into size quintile portfolios. Thus portfolio Q1 consists of the 20% of the largest stocks by market capitalization and Q5 represents the 20% of the smallest stocks in the sample. Portfolio return is estimated as the equally weighted average return of all constituents. We run the following regression to identify the relationship between size and the BMS return:

$$R_{it} - R_{rt} = \alpha_{iT} + \beta_{1iT}BMS_t + \beta_{2iT}MRF_t + \beta_{3iT}SMB_t + \beta_{4iT}HML_t + \beta_{5iT}UMD_t + \varepsilon_{it}$$

(9)

We estimate the above equation for each size quintile portfolio in each year. The results are presented in Table IX.

The BMS coefficients for all the Q1 portfolios in all the years (except 2001, 2004, 2005, 2006 and 2007) are positive. The negative coefficients in the above five years are statistically non-significant. All the Q5 portfolios have negative coefficient except in years 2001, 2003, and 2009. This suggests that in general the trades in big stocks are more likely to be buyer initiated while the small stock transactions are more likely to be seller initiated. A closer examination of the numbers in Table IX reveals that from 1994 to 1999, which was a rising market, BMS coefficients are positive and significant in all Q1 portfolios (In 1996, the t-statistic is equal to 1.64, which is marginally significant). The coefficients are relatively insignificant for Q5 portfolios, suggesting that there was no significant buying or selling behaviours for small-cap stock portfolios. Thus, high volume of buyer initiated trading in large cap stocks marked the bullish period. The Q5 portfolio BMS coefficients are significantly negative from 2005 to 2008 (t-values are equal to -6.22, -4, -8.795 and -5.25 respectively). The Q1 coefficients are non-significant during these years. This suggests that high volume of seller initiated trading in small stocks marked the market downturn.

5. Conclusion

We start this study with a conjecture that in the short run, buying and selling pressures are likely to be persistent. We attempt to find evidence in support of this conjecture by devising a three-step naïve trading strategy. Step 1: We observe all buying and selling across all stocks in the market on day (t). At market close, we eliminate 20% of the least liquid stocks from the population and rank the remaining 80% into deciles based on the fraction of buyer initiated trade to total traded volume. We designate the decile with the 10% most heavily bought stocks as BUY portfolio and the decile with 10% most heavily sold stock as SELL portfolio. Step 2: On day (t+1), at market open, take a long position in BUY portfolio and a simultaneous short position in SELL portfolio. Step 3: reverse the positions at market close on day (t+1), and exit the market. We find that this strategy earned an average return of about 47 basis points per day in 1993, decreased to 7.3 basis points per day in 2006 and 2007. Since then the returns have increased 20.5 bp in 2008 and 2009 and 10 bp in 2010.

The strategy returns are robust to CAPM, Fama-French and Momentum factor risk adjustment. The returns are positively related to investor sentiment in the market as well as to economic stability measures such as term spread and de-stability factors such as default spread. At least some of the returns seem to be related to market cap, with large cap stocks contributing to the BUY portfolio and the small cap stocks contributing to SELL portfolio. The results suggest that during expansionary phase in the market, the trading in large cap stocks are more likely to be buyer initiated, while in recessionary periods, the trading in small stocks are more likely to be seller initiated.

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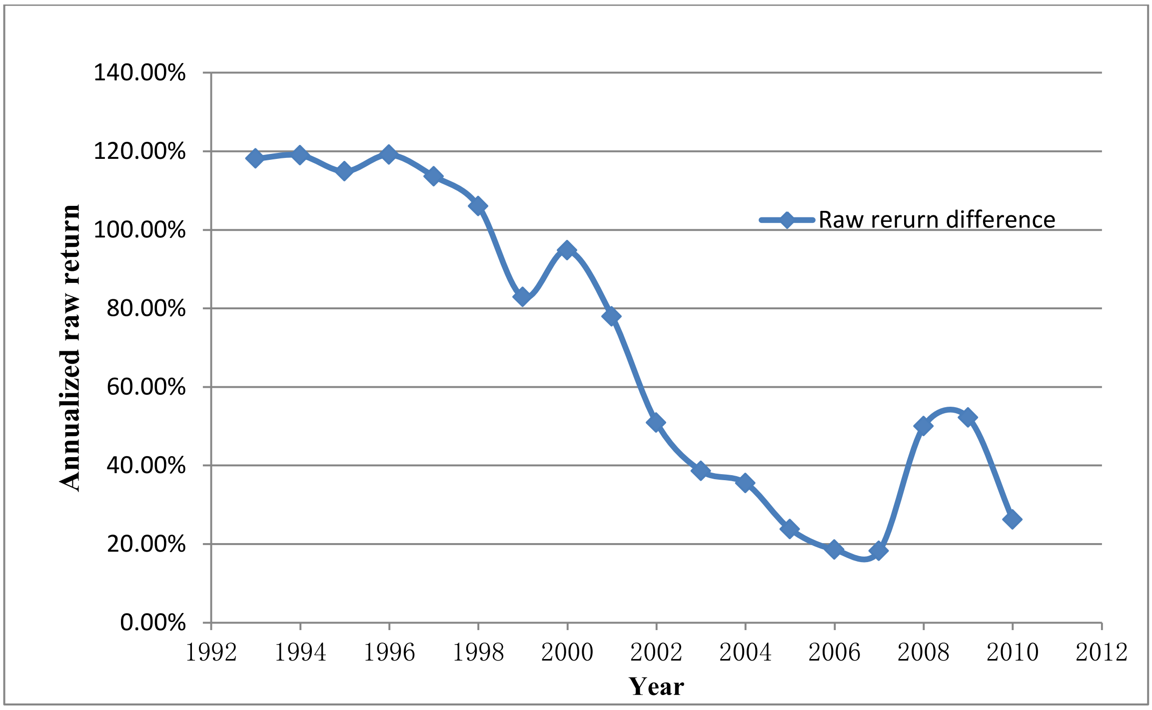

Figure 1: This figure presents the annualized portfolio return differences between the "buy" portfolio (Portfolio 1) and the "sell" portfolio (Portfolio 6) before adjusting common risk factors from 1993 to 2010. The return differences are presented in percentage.

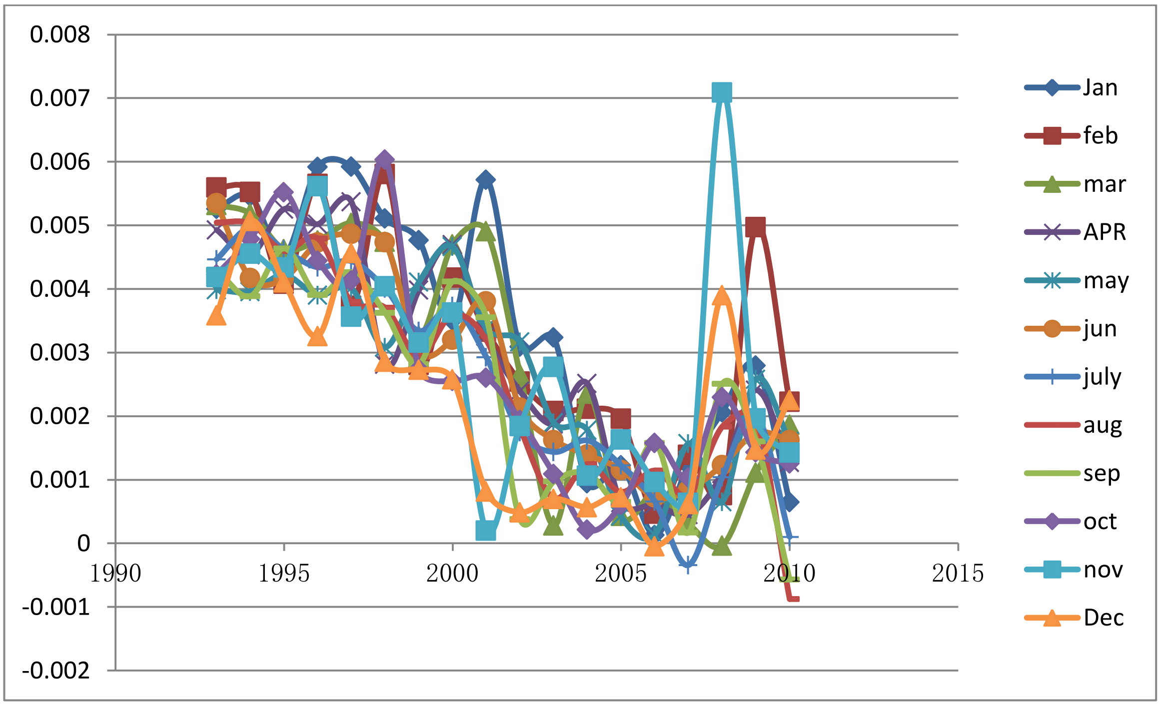

Figure 2: This figure presents the equal-weighted average portfolio return differences between the "buy" portfolio (Portfolio 1) and the "sell" portfolio (Portfolio 6) in each month and each year before adjusting common risk factors from 1993 to 2010.

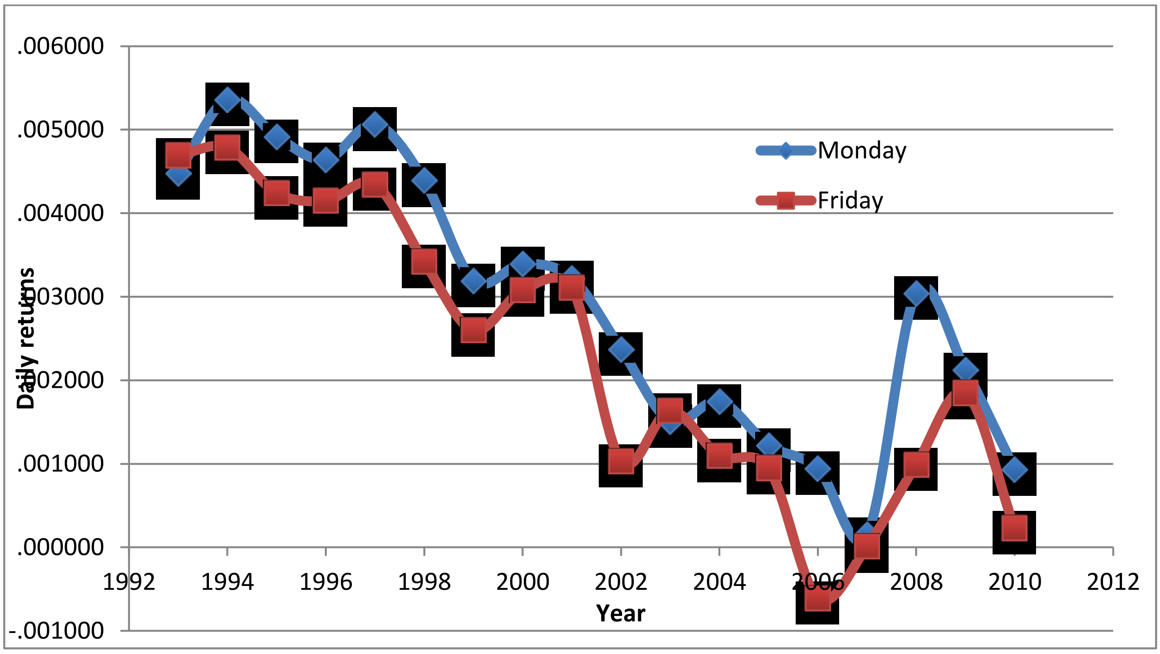

Figure 3: This figure presents the equal-weighted average portfolio return differences between the "buy" portfolio (Portfolio 1) and the "sell" portfolio (Portfolio 6) in each day of a week each year before adjusting common risk factors from 1993 to 2010.

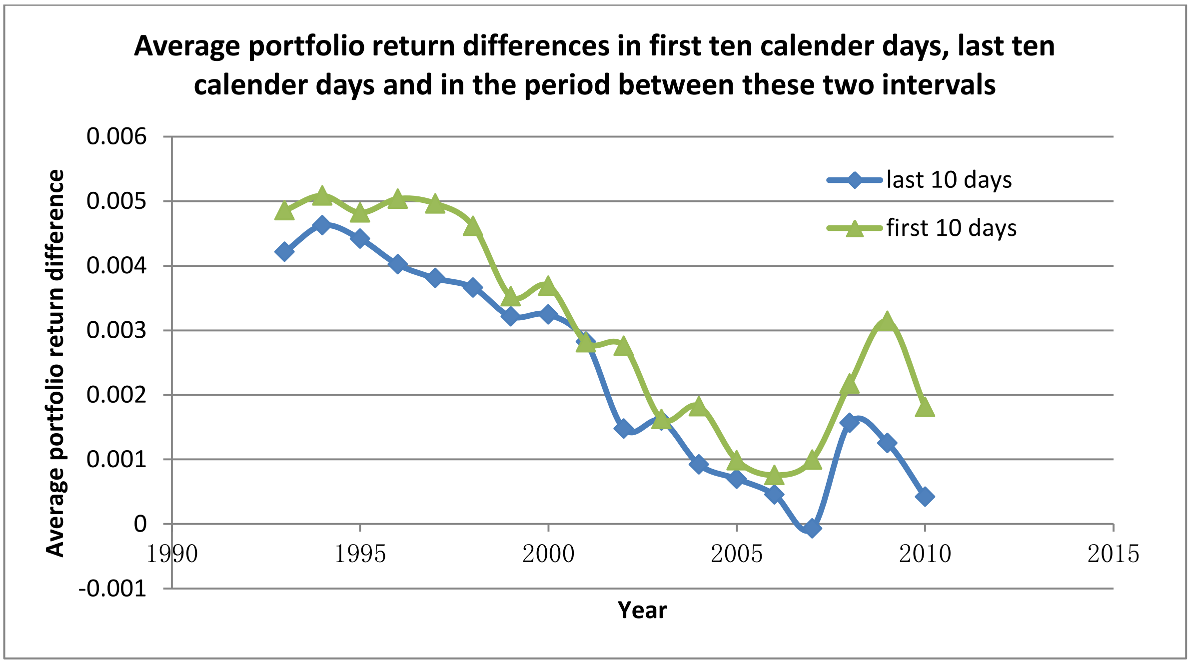

Figure 4: This figure presents the equal-weighted average portfolio return differences between the "buy" portfolio (Portfolio 1) and the "sell" portfolio (Portfolio 6) in the first ten calendar days, in the last ten calendar days, and in the period between these two intervals before adjusting common risk factors from 1993 to 2010.

Table I
Sample Description

This table provides various aggregate trading statistics for our sample for the period 1993-2010. We report the total number of stocks, the total number of firm days, the total number of trades, the average market capitalization per stock per day and the average trading volume per stock per day in each year. For the whole 18 year, there are total numbers of 145,060 stocks and total 37,227,391,369 trades in our sample.

year	# of stocks	# of firm days	# of trades	mean market cap	mean trading vol
1993	7892	1,181,370	78,589,384	583,321	246,797.16
1994	8471	1,281,050	83,697,192	615,488	189,459.94
1995	8886	1,364,282	111,929,561	589,924	219,201.82
1996	9495	1,481,532	146,581,934	756,729	306,879.65
1997	9759	1,561,355	192,878,907	875,534	260,734.83
1998	9634	1,510,495	269,244,475	1,170,438	249,968.42
1999	9289	1,390,991	464,255,230	1,507,089	640,073.45
2000	8954	1,317,221	787,857,366	2,002,587	668,383.48
2001	8252	1,259,259	800,526,157	1,870,884	525,418.99
2002	7627	1,244,234	908,860,888	1,861,941	515,112.89
2003	7158	1,148,429	1,123,368,844	1,588,919	491,742.53
2004	7035	1,146,849	1,480,623,113	2,131,592	629,972.02
2005	7112	1,144,324	1,824,460,442	2,339,777	790,712.20
2006	7176	1,111,171	2,502,699,322	2,555,054	880,571.47
2007	7437	1,122,263	4,425,067,834	2,727,543	1,048,712.59
2008	7176	1,127,460	7,861,167,695	2,886,805	884,123.80
2009	6876	1,035,774	7,253,222,578	1,884,208	997,419.25
2010	6831	1,047,258	6,912,360,447	2,468,316	1,151,182.42
Total	145,060	22,475,317	37,227,391,369		

Table II
Summary Statistics

These two tables provide descriptive statistics for our sample for the period 1993-2010. Panel A reports the average portfolio market capitalizations in each year. Panel B reports the average breakpoints of deciles of percentage of buyer-initiated trades in each portfolio each year. Portfolio 1 contains 10% of stocks with the highest fraction of buyer-initiated trades and Portfolio 6 contains 10% of stocks with the highest fraction of seller-initiated trades. Portfolio 2 (5) contains stocks which 80% to 90% of trades are buyer (seller)-initiated trades; Portfolio 3(4) contains stocks which over 70% but less than 80% of trades are buyer (seller)-initiated trades.

Panel A Mean Market Cap

year	P1	P2	P3	P4	P5	P6
1993	1,524,393.00	2,820,703.92	3,908,142.41	2,536,372.33	1,635,667.08	1,023,626.16
1994	1,495,695.82	2,901,284.48	4,092,544.80	2,338,646.57	1,521,696.73	1,025,810.32
1995	1,718,911.65	3,454,296.84	5,018,781.11	2,879,761.02	1,809,281.68	1,124,418.78
1996	1,965,271.04	4,126,630.92	6,054,684.26	3,350,161.26	2,095,048.94	1,254,366.83
1997	1,915,103.43	4,669,096.03	7,729,877.28	4,118,604.82	2,284,345.59	1,325,057.41
1998	2,030,959.78	5,928,527.03	10,575,362.55	4,208,049.76	2,200,827.31	1,143,328.99
1999	2,062,072.63	7,949,646.17	14,331,244.80	5,786,366.44	2,522,139.77	1,063,294.62
2000	2,959,733.71	12,093,751.19	20,479,866.52	8,033,718.34	2,958,517.96	1,097,862.94
2001	2,873,358.97	10,960,566.84	17,630,518.05	7,302,318.75	2,547,067.37	899,213.85
2002	2,777,025.57	10,842,320.51	17,401,798.23	6,375,601.15	2,162,369.67	856,524.47
2003	3,470,975.49	10,997,262.87	16,631,860.82	9,228,414.49	3,185,355.93	1,173,811.71
2004	6,251,138.62	15,637,598.04	20,904,716.75	12,865,198.83	4,739,334.86	1,849,104.61
2005	7,197,260.80	18,268,667.08	24,600,307.77	16,960,997.44	6,624,377.56	2,196,867.45
2006	8,907,147.75	21,966,109.04	30,483,615.00	24,449,741.13	9,574,647.43	3,503,209.13
2007	10,195,004.38	25,826,981.01	43,407,168.78	26,832,309.58	12,320,317.73	4,632,299.98
2008	5,199,274.10	18,827,157.49	46,022,435.10	26,801,094.29	10,773,778.76	2,907,741.71
2009	3,713,178.99	14,225,741.11	32,454,141.95	26,279,197.09	10,519,117.89	3,158,865.27
2010	5,786,539.23	17,855,788.04	37,346,052.53	32,781,873.70	14,881,761.05	4,928,453.67

Panel B	**Percentage of buyer-initiated trades**					
year	P1	P2	P3	P4	P5	P6
1993	89.69%	75.62%	66.07%	33.58%	23.90%	9.89%
1994	89.28%	74.78%	65.14%	32.50%	22.81%	9.27%
1995	89.30%	74.85%	65.32%	34.17%	24.48%	10.15%
1996	88.65%	73.77%	64.40%	34.73%	25.21%	10.54%
1997	87.80%	72.94%	64.04%	35.67%	26.47%	11.56%
1998	86.65%	71.53%	62.97%	35.44%	26.18%	11.32%
1999	86.07%	70.44%	62.01%	36.03%	26.76%	11.51%
2000	84.63%	68.88%	60.99%	37.67%	28.76%	12.72%
2001	83.99%	69.03%	61.87%	39.87%	31.42%	14.93%
2002	82.38%	67.82%	61.42%	40.75%	32.53%	16.02%
2003	80.82%	67.24%	61.43%	43.26%	36.23%	20.13%
2004	78.07%	65.25%	60.25%	44.25%	38.25%	22.40%
2005	76.21%	63.89%	59.20%	44.23%	38.57%	23.54%
2006	74.60%	62.84%	58.48%	44.79%	39.67%	25.36%
2007	71.10%	59.80%	56.05%	44.50%	39.90%	26.45%
2008	69.60%	57.29%	53.79%	44.40%	39.94%	25.68%
2009	70.36%	58.20%	54.47%	44.89%	40.74%	27.61%
2010	69.49%	58.61%	54.91%	44.94%	41.00%	29.50%

Table III
The average coefficients of AR (1) model for six portfolios and the p-values of mean coefficients test

These two tables report the average coefficients of the first order autocorrelation of stock returns for six portfolios formed according to the percentage of buyer-initiated trades in each year. These tables also presents the p-values of the one-tailed means test to verify whether the average coefficients in each portfolio are significantly greater than zero or not. Ave_coef is the average coefficient in each portfolio each year from 1993 to 2010 and mean_test_p is the p-value of the hypothesis test. The AR (1) model is shown as $R_{t,i} = \alpha + \beta R_{t-1,i} + \varepsilon_t$, where $R_{t,I}$ is stock i's return on day t and R_{t-1} is stock i's return on its previous day. In Panel A, the stock return is calculated by using the natural logarithm of stock's closing price divided by opening price. In order to remove the bid ask bounce effect, we also use the natural logarithm of the midpoint of closing bid and closing ask price divided by stock's opening price to calculate stock return. Panel B reports these robustness results for adjusting bid ask bounce. Portfolio 1 contains 10% of stocks with the highest fraction of buyer-initiated trades in a particular day and Portfolio 6 contains 10% of stocks with the highest fraction of seller-initiated trades. Portfolio 2 (5) contains stocks which 80% to 90% of trades are buyer (seller)-initiated trades; Portfolio 3(4) contains stocks which over 70% but less than 80% of trades are buyer (seller)-initiated trades. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A

	Port 1		Port 2		Port3		Port 4		Port 5		Port 6	
year	Ave_coef	mean_test_p	Ave_coef	mean_test_p	Ave_coef	mean_test_p	Ave_coef	mean_test_p	Ave_coef	mean_test_p	Ave_coef	mean_test_p
1993	0.016	0.041**	0.027	0.000***	0.037	0.000***	0.020	0.010***	0.016	0.009***	0.035	0.009***
1994	0.021	0.004***	0.026	0.000***	0.047	0.002***	0.012	0.081*	0.009	0.133	0.020	0.015**
1995	0.033	0.000***	0.016	0.004***	-0.004	0.423	0.011	0.029**	-0.003	0.299	0.004	0.329
1996	0.039	0.000***	0.028	0.000***	0.013	0.038**	0.017	0.001***	0.022	0.080*	0.032	0.083*
1997	0.062	0.042**	0.011	0.031**	0.001	0.419	-0.003	0.394	0.013	0.013**	0.013	0.028**
1998	0.051	0.000***	0.032	0.000***	0.036	0.000***	0.035	0.004***	0.044	0.000***	0.025	0.001***
1999	0.038	0.000***	0.020	0.002***	0.017	0.008***	0.022	0.001***	0.025	0.000***	0.004	0.366
2000	0.034	0.016**	0.015	0.122	0.010	0.133	0.027	0.011**	0.016	0.079*	0.141	0.108
2001	0.031	0.000***	0.050	0.005***	0.046	0.000***	0.039	0.000***	0.048	0.000***	0.026	0.001***
2002	0.012	0.111	-0.001	0.431	-0.009	0.296	0.007	0.221	0.031	0.001***	0.028	0.017**
2003	0.009	0.171	0.029	0.086*	-0.002	0.411	0.017	0.041**	0.003	0.374	0.019	0.042**
2004	0.160	0.112	0.011	0.156	0.011	0.074*	0.026	0.000***	0.047	0.000***	0.030	0.023**
2005	0.012	0.111	0.011	0.074*	0.003	0.311	0.008	0.291	0.012	0.056*	0.033	0.010***
2006	0.003	0.389	0.000	0.495	0.005	0.264	-0.018	0.179	-0.001	0.437	0.032	0.009***
2007	-0.007	0.221	-0.005	0.288	-0.009	0.087*	-0.018	0.029**	-0.012	0.052*	0.001	0.471
2008	0.010	0.146	-0.007	0.194	-0.036	0.015**	0.005	0.287	0.011	0.154	0.046	0.000***
2009	0.015	0.063*	-0.003	0.348	-0.005	0.262	-0.005	0.240	0.016	0.020**	0.016	0.058*
2010	0.007	0.287	0.001	0.470	-0.001	0.435	0.014	0.027**	0.022	0.097*	0.013	0.182

Panel B												
	Port 1		Port 2		Port3		Port 4		Port 5		Port 6	
year	Ave_coef	mean_test_p	Ave_coef	mean_test_p	Ave_coef	mean_test_p	Ave_coef	mean_test_p	Ave_coef	mean_test_p	Ave_coef	mean_test_p
1993	0.040	0.072*	0.064	0.000***	0.072	0.004***	0.033	0.002***	0.037	0.003***	0.044	0.000***
1994	0.022	0.211	0.050	0.000***	0.048	0.000***	0.060	0.003***	0.067	0.000***	0.006	0.392
1995	0.069	0.000***	0.072	0.000***	0.052	0.039**	0.015	0.215	0.033	0.088*	-0.057	0.263
1996	0.041	0.195	0.059	0.000***	0.022	0.012**	0.068	0.003***	0.047	0.001***	0.006	0.419
1997	0.055	0.000***	0.023	0.009***	0.022	0.011**	0.029	0.014**	0.041	0.000***	0.015	0.154
1998	0.077	0.000***	0.033	0.028**	0.045	0.000***	0.052	0.000***	0.061	0.000***	0.037	0.000***
1999	0.069	0.000***	0.023	0.127	0.044	0.000***	0.033	0.000***	0.044	0.001***	0.047	0.111
2000	0.075	0.017**	0.038	0.000***	0.050	0.002***	0.049	0.000***	0.036	0.262	0.070	0.003***
2001	0.052	0.000***	0.047	0.000***	0.061	0.000***	0.057	0.000***	0.064	0.000***	0.051	0.000***
2002	0.021	0.025**	0.010	0.181	0.013	0.110	0.021	0.004***	0.031	0.005***	-0.055	0.269
2003	0.023	0.050**	0.011	0.086*	0.015	0.043**	0.023	0.005***	0.010	0.326	0.039	0.000***
2004	0.048	0.000***	0.025	0.025**	0.021	0.044**	0.027	0.002***	0.057	0.000***	0.047	0.001***
2005	0.018	0.039**	0.015	0.030**	0.019	0.005***	0.015	0.066*	0.022	0.020**	0.050	0.053*
2006	0.035	0.003***	0.014	0.050**	0.020	0.011**	0.036	0.004***	0.004	0.343	0.038	0.004***
2007	0.000	0.494	0.009	0.174	-0.008	0.188	-0.010	0.221	-0.012	0.109	0.009	0.219
2008	0.151	0.155	-0.027	0.121	-0.009	0.147	0.022	0.019**	0.027	0.001***	0.045	0.056*
2009	0.035	0.001***	-0.002	0.406	0.005	0.267	0.490	0.158	0.017	0.049**	0.028	0.007***
2010	0.037	0.006***	0.005	0.278	0.006	0.255	0.014	0.056*	0.007	0.207	0.009	0.279

Table IV
The six portfolio returns before and after adjusting the common risk factors

These tables report the returns of six different portfolios formed according to stocks' percentage of buyer-initiated trades. Portfolio 1 contains 10% of stocks with the highest fraction of buyer-initiated trades in a particular day and Portfolio 6 contains 10% of stocks with the highest fraction of seller-initiated trades. Portfolio 2 (5) contains stocks which 80% to 90% of trades are buyer (seller)-initiated trades; Portfolio 3(4) contains stocks which over 70% but less than 80% of trades are buyer (seller)-initiated trades. Panel A reports the portfolio returns before adjusting common risk factors. All of the portfolios have equal weights, and in each year, the portfolio returns are calculated by taking the simple average of daily portfolio returns. Panel B1 reports the portfolio alphas after adjusting the market risk factor. Panel B2 reports the portfolio alphas after adjusting the market factor, size factor, and book-to-market factor. Panel B3 reports the portfolio alphas after adjusting the market, size, book-to-market and then momentum factor. The t-statistics are given in the parentheses.

Panel A

Year	P1	P2	P3	P4	P5	P6
1993	0.00308	0.00224	0.00191	-0.00138	-0.00147	-0.00160
1994	0.00246	0.00172	0.00121	-0.00183	-0.00198	-0.00230
1995	0.00336	0.00288	0.00238	-0.00048	-0.00098	-0.00120
1996	0.00301	0.00221	0.00153	-0.00156	-0.00169	-0.00168
1997	0.00247	0.00174	0.00090	-0.00134	-0.00141	-0.00202
1998	0.00096	-0.00007	-0.00077	-0.00263	-0.00296	-0.00325
1999	0.00115	0.00015	-0.00067	-0.00219	-0.00239	-0.00214
2000	0.00033	-0.00068	-0.00222	-0.00458	-0.00457	-0.00343
2001	0.00204	0.00119	0.00028	-0.00114	-0.00132	-0.00111
2002	0.00167	-0.00010	-0.00077	-0.00082	-0.00054	-0.00035
2003	0.00305	0.00149	0.00122	0.00109	0.00118	0.00152
2004	0.00170	0.00029	-0.00026	-0.00006	-0.00004	0.00029
2005	0.00067	-0.00033	-0.00075	-0.00068	-0.00066	-0.00027
2006	0.00083	0.00000	-0.00017	0.00014	0.00004	0.00009
2007	-0.00011	-0.00103	-0.00113	-0.00071	-0.00091	-0.00083
2008	-0.00301	-0.00303	-0.00250	-0.00315	-0.00384	-0.00506
2009	0.00045	-0.00010	-0.00008	-0.00075	-0.00107	-0.00169
2010	0.00008	0.00002	-0.00015	-0.00064	-0.00066	-0.00097
Average	0.00134	0.00048	0.00000	-0.00126	-0.00140	-0.00144

Panel B1 CAPM-model						
	P1	P2	P3	P4	P5	P6
year	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha
1993	0.00293	0.00206	0.00175	-0.00155	-0.00162	-0.00176
	(13.317)	(8.669)	(6.113)	(-5.028)	(-6.050)	(-6.872)
1994	0.00232	0.00158	0.00107	-0.00197	-0.00211	-0.00244
	(9.227)	(5.571)	(3.304)	(-6.122)	(-6.957)	(-8.756)
1995	0.00309	0.00254	0.00204	-0.00081	-0.00126	-0.00151
	(15.442)	(10.755)	(7.565)	(-2.824)	(-5.191)	(-6.900)
1996	0.00274	0.00195	0.00128	-0.00181	-0.00192	-0.00192
	(11.293)	(6.717)	(3.658)	(-4.758)	(-6.008)	(-6.936)
1997	0.00226	0.00158	0.00076	-0.00149	-0.00158	-0.00219
	(7.174)	(3.628)	(1.573)	(-3.161)	(-3.774)	(-6.345)
1998	0.00068	-0.00034	-0.00104	-0.00289	-0.00322	-0.00352
	(1.494)	(-0.644)	(-1.740)	(-4.577)	(-5.655)	(-7.455)
1999	0.00094	-0.00008	-0.00092	-0.00243	-0.00262	-0.00235
	(3.121)	(-0.222)	(-2.290)	(-6.055)	(-8.107)	(-8.205)
2000	0.00016	-0.00084	-0.00237	-0.00469	-0.00470	-0.00358
	(0.392)	(-1.506)	(-3.247)	(-5.280)	(-6.569)	(-6.939)
2001	0.00194	0.00108	0.00018	-0.00124	-0.00142	-0.00121
	(4.309)	(1.903)	(0.284)	(-1.655)	(-2.249)	(-2.502)
2002	0.00166	-0.00014	-0.00081	-0.00085	-0.00058	-0.00038
	(3.476)	(-0.217)	(-1.118)	(-1.172)	(-0.942)	(-0.817)
2003	0.00297	0.00143	0.00114	0.00099	0.00108	0.00139
	(8.906)	(3.114)	(2.281)	(1.838)	(2.506)	(4.262)
2004	0.00159	0.00016	-0.00039	-0.00019	-0.00020	0.00017
	(4.843)	(0.382)	(-0.856)	(-0.360)	(-0.444)	(0.533)
2005	0.00053	-0.00046	-0.00088	-0.00081	-0.00080	-0.00041
	(1.813)	(-1.206)	(-2.057)	(-1.854)	(-2.098)	(-1.512)
2006	0.00058	-0.00024	-0.00043	-0.00011	-0.00022	-0.00017
	(1.785)	(-0.576)	(-0.927)	(-0.228)	(-0.535)	(-0.593)
2007	-0.00029	-0.00121	-0.00131	-0.00089	-0.00110	-0.00102
	(-0.784)	(-2.388)	(-2.369)	(-1.675)	(-2.323)	(-3.027)
2008	-0.00305	-0.00315	-0.00268	-0.00326	-0.00389	-0.00505
	(-2.796)	(-2.210)	(-1.747)	(-2.147)	(-2.852)	(-4.795)
2009	0.00043	-0.00007	-0.00006	-0.00072	-0.00103	-0.00168
	(0.543)	(-0.064)	(-0.052)	(-0.629)	(-0.952)	(-1.994)
2010	0.00003	-0.00003	-0.00021	-0.00069	-0.00072	-0.00102
	(0.049)	(-0.056)	(-0.318)	(-1.062)	(-1.163)	(-1.996)
Average alphas	0.00119	0.00032	-0.00016	-0.00141	-0.00155	-0.00159

Panel B2 F&F-3-factor model						
	P1	P2	P3	P4	P5	P6
year	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha
1993	0.00298	0.00213	0.00192	-0.00135	-0.00143	-0.00162
	(13.235)	(8.791)	(6.676)	(-4.321)	(-5.320)	(-6.252)
1994	0.00232	0.00158	0.00107	-0.00197	-0.00212	-0.00243
	(9.258)	(5.578)	(3.306)	(-6.109)	(-7.031)	(-8.784)
1995	0.00305	0.00250	0.00200	-0.00080	-0.00127	-0.00151
	(15.102)	(10.507)	(7.352)	(-2.771)	(-5.173)	(-6.844)
1996	0.00282	0.00205	0.00140	-0.00168	-0.00178	-0.00182
	(11.817)	(7.232)	(4.085)	(-4.502)	(-5.764)	(-6.745)
1997	0.00250	0.00192	0.00110	-0.00117	-0.00130	-0.00195
	(7.843)	(4.352)	(2.212)	(-2.441)	(-3.037)	(-5.582)
1998	0.00097	-0.00006	-0.00074	-0.00251	-0.00285	-0.00315
	(2.177)	(-0.110)	(-1.258)	(-4.078)	(-5.148)	(-7.020)
1999	0.00087	-0.00015	-0.00103	-0.00258	-0.00271	-0.00243
	(2.892)	(-0.400)	(-2.541)	(-6.395)	(-8.371)	(-8.457)
2000	0.00006	-0.00096	-0.00243	-0.00473	-0.00473	-0.00372
	(0.137)	(-1.676)	(-3.243)	(-5.217)	(-6.512)	(-7.133)
2001	0.00187	0.00108	0.00018	-0.00130	-0.00151	-0.00127
	(4.117)	(1.882)	(0.267)	(-1.721)	(-2.381)	(-2.604)
2002	0.00171	-0.00004	-0.00070	-0.00076	-0.00053	-0.00033
	(3.604)	(-0.062)	(-0.976)	(-1.054)	(-0.865)	(-0.716)
2003	0.00288	0.00127	0.00105	0.00090	0.00097	0.00129
	(8.530)	(2.736)	(2.068)	(1.637)	(2.226)	(3.899)
2004	0.00151	0.00007	-0.00048	-0.00030	-0.00026	0.00012
	(4.631)	(0.163)	(-1.075)	(-0.564)	(-0.587)	(0.380)
2005	0.00052	-0.00047	-0.00089	-0.00083	-0.00082	-0.00043
	(1.741)	(-1.215)	(-2.081)	(-1.886)	(-2.126)	(-1.575)
2006	0.00062	-0.00020	-0.00038	-0.00004	-0.00013	-0.00011
	(1.866)	(-0.456)	(-0.795)	(-0.090)	(-0.308)	(-0.369)
2007	-0.00032	-0.00123	-0.00132	-0.00087	-0.00105	-0.00097
	(-0.845)	(-2.397)	(-2.346)	(-1.600)	(-2.166)	(-2.816)
2008	-0.00302	-0.00308	-0.00263	-0.00320	-0.00386	-0.00503
	(-2.797)	(-2.178)	(-1.725)	(-2.121)	(-2.862)	(-4.915)
2009	0.00052	0.00004	0.00003	-0.00061	-0.00096	-0.00157
	(0.654)	(0.036)	(0.029)	(-0.535)	(-0.880)	(-1.869)
2010	0.00002	-0.00003	-0.00020	-0.00070	-0.00073	-0.00106
	(0.037)	(-0.042)	(-0.303)	(-1.059)	(-1.162)	(-2.053)
Average alphas	0.00121	0.00036	-0.00012	-0.00136	-0.00150	-0.00155

Panel B3 Carhart 4-factor model						
	P1	P2	P3	P4	P5	P6
year	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha
1993	0.00297	0.00212	0.00191	-0.00136	-0.00144	-0.00163
	(13.253)	(8.805)	(6.666)	(-4.388)	(-5.397)	(-6.339)
1994	0.00230	0.00157	0.00104	-0.00197	-0.00213	-0.00243
	(9.205)	(5.526)	(3.236)	(-6.108)	(-7.072)	(-8.791)
1995	0.00305	0.00250	0.00204	-0.00079	-0.00125	-0.00151
	(14.930)	(10.359)	(7.391)	(-2.706)	(-5.025)	(-6.742)
1996	0.00283	0.00206	0.00141	-0.00168	-0.00178	-0.00182
	(11.842)	(7.249)	(4.109)	(-4.486)	(-5.746)	(-6.727)
1997	0.00252	0.00193	0.00110	-0.00114	-0.00128	-0.00195
	(7.882)	(4.343)	(2.201)	(-2.372)	(-2.986)	(-5.531)
1998	0.00107	0.00005	-0.00062	-0.00237	-0.00270	-0.00306
	(2.408)	(0.096)	(-1.046)	(-3.844)	(-4.899)	(-6.808)
1999	0.00088	-0.00014	-0.00102	-0.00257	-0.00270	-0.00242
	(2.997)	(-0.374)	(-2.542)	(-6.403)	(-8.476)	(-8.587)
2000	0.00015	-0.00089	-0.00242	-0.00469	-0.00468	-0.00370
	(0.364)	(-1.534)	(-3.197)	(-5.131)	(-6.382)	(-7.031)
2001	0.00180	0.00105	0.00013	-0.00139	-0.00160	-0.00134
	(3.953)	(1.821)	(0.193)	(-1.840)	(-2.512)	(-2.743)
2002	0.00174	0.00000	-0.00068	-0.00070	-0.00047	-0.00029
	(3.660)	(-0.005)	(-0.944)	(-0.969)	(-0.769)	(-0.636)
2003	0.00289	0.00133	0.00109	0.00098	0.00106	0.00131
	(8.434)	(2.822)	(2.118)	(1.771)	(2.396)	(3.925)
2004	0.00157	0.00012	-0.00042	-0.00022	-0.00018	0.00017
	(4.806)	(0.286)	(-0.923)	(-0.414)	(-0.400)	(0.519)
2005	0.00051	-0.00047	-0.00091	-0.00084	-0.00083	-0.00042
	(1.706)	(-1.216)	(-2.106)	(-1.899)	(-2.135)	(-1.535)
2006	0.00060	-0.00020	-0.00040	-0.00009	-0.00019	-0.00014
	(1.765)	(-0.457)	(-0.821)	(-0.194)	(-0.437)	(-0.457)
2007	-0.00023	-0.00108	-0.00115	-0.00070	-0.00092	-0.00089
	(-0.595)	(-2.105)	(-2.056)	(-1.301)	(-1.902)	(-2.579)
2008	-0.00299	-0.00304	-0.00260	-0.00315	-0.00381	-0.00496
	(-2.763)	(-2.144)	(-1.699)	(-2.087)	(-2.821)	(-4.857)
2009	0.00050	0.00014	0.00014	-0.00043	-0.00083	-0.00150
	(0.617)	(0.134)	(0.127)	(-0.370)	(-0.748)	(-1.754)
2010	0.00002	-0.00003	-0.00020	-0.00070	-0.00073	-0.00106
	(0.039)	(-0.041)	(-0.305)	(-1.068)	(-1.173)	(-2.072)
Average alphas	0.00123	0.00039	-0.00009	-0.00132	-0.00147	-0.00153

Table V
Alphas for the long short portfolio

This table studies the profitability of a trading strategy that long stocks with highest percentage of buyer-initiated trades and short stocks with the highest percentage of seller-initiated trades. Stocks which over 90% of trades are buyer-initiated trades are classified as the long portfolio and over 90% of trades are seller-initiated trades are classified as the short portfolio. Both of the portfolios are calculated by using equally-weighted stock returns, and both remain in portfolio for one day after the portfolio formation. The intercepts presented in this table are the return difference of the long short portfolio under the Carhart 4-factor model, Fama-French 3-factor model, and the CAPM model respectively. The t-statistics are given in the parentheses.

Year	Unadjusted	CAPM Intercept	3-factor Intercept	4-factor Intercept
1993	0.004688	0.004583	0.004490	0.004493
		(25.6591)	(24.5175)	(24.5298)
1994	0.004759	0.004606	0.004589	0.004583
		(25.6301)	(25.6384)	(25.5636)
1995	0.00456	0.004383	0.004341	0.004344
		(25.3257)	(24.9355)	(24.6247)
1996	0.004689	0.004463	0.004443	0.004444
		(26.8678)	(26.6082)	(26.5650)
1997	0.004492	0.004248	0.004256	0.004267
		(24.5485)	(23.8070)	(23.7923)
1998	0.004208	0.004014	0.003936	0.003949
		(20.9921)	(20.6150)	(20.5282)
1999	0.00329	0.003105	0.003113	0.003115
		(14.3531)	(14.1700)	(14.1558)
2000	0.003761	0.003520	0.003550	0.003626
		(12.2905)	(12.4278)	(12.6996)
2001	0.003143	0.003003	0.002990	0.002987
		(11.4315)	(11.2887)	(11.2022)
2002	0.002021	0.001969	0.001977	0.001971
		(8.9285)	(8.9225)	(8.8608)
2003	0.001539	0.001540	0.001553	0.001535
		(8.5454)	(8.4520)	(8.2428)
2004	0.001409	0.001364	0.001335	0.001348
		(8.2826)	(8.0887)	(8.1159)
2005	0.000945	0.000832	0.000834	0.000817
		(6.0064)	(5.9589)	(5.8365)
2006	0.000739	0.000557	0.000537	0.000548
		(3.7505)	(3.5421)	(3.5212)
2007	0.000726	0.000547	0.000464	0.000477
		(2.8585)	(2.3978)	(2.4436)
2008	0.002048	0.001935	0.001946	0.001903
		(4.4611)	(4.5369)	(4.4740)
2009	0.002138	0.002109	0.002089	0.001996
		(6.8917)	(6.8029)	(6.4332)
2010	0.001053	0.001047	0.001077	0.001077
		(6.8917)	(5.2419)	(5.2313)
Average alphas	0.002789	0.002657	0.002640	0.002638

Table VI
Correlation statistics

These two tables provide the Spearman correlation and Pearson Correlation estimates for the possible variables that may explain the BMS factor. BMS is our created factor which formed by taking the daily return difference between the "buy" portfolio, which includes stocks with the top 20% of buyer-initiated trades and the "sell" portfolio, which includes stocks with the top 20% of seller-initiated trades. Both the "buy" portfolio and "sell" portfolio have equal weights. ln_CAP, which is the natural logarithm of the absolute value of stock's market capitalization which is calculated by using the average stocks' market capitalizations in the buy portfolio (all stocks assigned to portfolio 1 and 2 are called buy portfolio) minus the average stocks sizes in the sell portfolio (all stocks assigned to portfolio 5 and 6 are called sell portfolio) in order to match the BMS factor that calculated by using return of buy portfolio minus return of sell portfolio, PCT_down, which is the daily percentage of stocks which their prices are decreasing from day t to its previous day, RET_SP500 is the daily return on S&P 500 index, ln_VIX is the daily return of volatility index, DS is the daily default spread and TS is the daily term spread, and SI is the month investor sentiment index. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A Spearman correlation

	BMS	ln_CAP	PCT_down	RET_SP500	DS	TS	ln_VIX	SI
BMS	1							
ln_CAP	-0.30***	1						
PCT_down	-0.29***	0.42***	1					
RET_SP500	0.24***	-0.12***	-0.82***	1				
DS	0.24***	0.06***	0.10***	-0.02	1			
TS	-0.14***	-0.28***	-0.03**	-0.01	0.39***	1		
ln_VIX	-0.16***	0.11***	0.64***	-0.73***	-0.02	-0.02	1	
SI	0.27***	0.22***	0.07***	-0.02	-0.05***	-0.41***	0.02	1

Panel B Pearson Correlation

	BMS	ln_CAP	PCT_down	RET_SP500	DS	TS	ln_VIX	SI
BMS	1							
ln_CAP	-0.21***	1						
PCT_down	-0.31***	0.42***	1					
RET_SP500	0.30***	-0.17***	-0.79***	1				
DS	0.29***	0.03**	0.11***	-0.03*	1			
TS	-0.15***	-0.28***	-0.01	-0.01	0.39***	1		
ln_VIX	-0.20***	0.13***	0.67***	-0.72***	-0.01	-0.01		
SI	0.34***	0.23***	0.05***	-0.03**	0.17***	-0.35***	0.01	1

Table VII
Simple pooled OLS for explaining BMS factor

This table reports different factor model estimates through the whole 18 years from 1993 to 2010 in order to examine the relation between BMS loading and those possible variables which may explain BMS. BMS is our created dependent variable. The other possible independent variables that may explain BMS are: BC, which is the daily business cycle index, ln_CAP, which is the natural logarithm of the absolute value of stock's market capitalization which is calculated by using the average stocks' market capitalizations in the buy portfolio (all stocks assigned to portfolio 1 and 2 are called buy portfolio) minus the average stocks sizes in the sell portfolio (all stocks assigned to portfolio 5 and 6 are called sell portfolio) in order to match the BMS factor that calculated by using return of buy portfolio minus return of sell portfolio, PCT_down, which is the daily percentage of stocks which their prices are decreasing from day t to its previous day, RET_SP500 is the daily return on S&P 500 index, ln_VIX is the daily return of volatility index, DS is the daily default spread and TS is the daily term spread, and SI is the month investor sentiment index. The t-statistics are given in the parentheses.

Intercept	BC	ln_CAP	PCT_down	RET_SP500	DS	TS	ln_VIX	SI	Adj. R-Square
0.026								0.006	0.117
(191.367)								(24.377)	
0.027							-0.031		0.038
(193.820)							(-13.327)		
0.029						-0.115			0.022
(122.489)						(-10.045)			
0.019					0.576				0.084
(46.905)					(20.276)				
0.027				0.231					0.085
(198.160)				(20.361)					
0.036			-0.020						0.095
(83.202)			(-21.741)						
0.100	-0.004	-0.004	-0.007	0.164	0.920	-0.229	0.011	0.005	0.401
(28.360)	(-9.954)	(-20.643)	(-5.014)	(9.742)	(30.003)	(-20.088)	(3.777)	(20.417)	
0.101	-0.004	-0.004	-0.006	0.142	0.916	-0.231		0.005	0.399
(28.950)	(-10.151)	(-21.457)	(-4.048)	(8.977)	(29.842)	(-20.196)		(20.485)	

Table VIII
Examination of BMS loadings

This table presents the average R-squares from year 1993 to 2010 by regressing the stock returns on different risk factors. The daily BMS factor is formed by taking the daily return difference between the "buy" portfolio, which includes stocks with the top 10% of buyer-initiated trades and the "sell" portfolio, which includes stocks with the top 10% of seller-initiated trades. Both the "buy" portfolio and "sell" portfolio have equal weights. The R-squares of six different regression models with and without BMS loading are used to examine whether our new BMS factor can improve the explanation of stock returns. The first set of comparison models are Model 1 which is the CAPM model and Model 2 which is the CAPM model by adding the BMS factor:

$$R_{it} - R_{rt} = \alpha_{iT} + b_{iT}RMRF_t + \varepsilon_{it}$$
$$R_{it} - R_{rt} = \alpha_{iT} + m_{iT}BMS_t + b_{iT}RMRF_t + \varepsilon_{it}$$

Where R_{it} is the return of stock i; α_{iT} is the estimated abnormal return of stock i each time period from 1 to T after adjusting these factors; BMS is factor we create; RMRF is the market return minus the risk free rate; SMB, HML, and UMD are the size factor, book-to-market factor and the momentum factor. Similarly, Model 3 is the Fama-French 3-factor model and Model 4 is based on Model 3 by adding the BMS factor:

$$R_{it} - R_{rt} = \alpha_{iT} + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + \varepsilon_{it}$$
$$R_{it} - R_{rt} = \alpha_{iT} + m_{iT}BMS_t + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + \varepsilon_{it}$$

Model 5 is the Carhart 4-factor model and Model 6 is the model based on Model 5 but adding the BMS loading:

$$R_{it} - R_{rt} = \alpha_{iT} + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + u_{iT}UMD_t + \varepsilon_{it}$$
$$R_{it} - R_{rt} = \alpha_{iT} + m_{iT}BMS_t + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + u_{iT}UMD_t + \varepsilon_{it}$$

Year	Model1 (MKTRF)	Model2 (MKTRF,BMS)	Model3 (SMB,HML ,MKTRF)	Model4 (SMB,HML, MKTRF,BMS)	Model5 (SMB,HML, MKTRF,UMD)	Model6 （SMB,HML, MKTRF,UMD, BMS)
1993	0.0284	0.0359	0.0534	0.0594	0.0610	0.0663
1994	0.0414	0.0472	0.0628	0.0681	0.0689	0.0738
1995	0.0292	0.0364	0.0527	0.0580	0.0589	0.0631
1996	0.0419	0.0486	0.0696	0.0752	0.0767	0.0818
1997	0.0590	0.0657	0.0869	0.0924	0.0930	0.0984
1998	0.0810	0.0865	0.1137	0.1186	0.1215	0.1256
1999	0.0335	0.0413	0.0617	0.0678	0.0688	0.0747
2000	0.0668	0.0741	0.1015	0.1072	0.1104	0.1161
2001	0.0899	0.0973	0.1243	0.1308	0.1380	0.1442
2002	0.1215	0.1276	0.1498	0.1556	0.1638	0.1689
2003	0.1143	0.1197	0.1418	0.1464	0.1489	0.1524
2004	0.1220	0.1283	0.1534	0.1588	0.1600	0.1658
2005	0.1225	0.1282	0.1519	0.1572	0.1606	0.1659
2006	0.1462	0.1540	0.1739	0.1805	0.1851	0.1902
2007	0.1993	0.2112	0.2281	0.2378	0.2426	0.2515
2008	0.2987	0.3082	0.3387	0.3460	0.3482	0.3554
2009	0.2946	0.2991	0.3195	0.3230	0.3291	0.3328
2010	0.3029	0.3088	0.3288	0.3337	0.3372	0.3418

Table IX
Five-factor model estimates for size portfolio

This table presents the estimated results for the five size-quintile portfolios. All the stocks are sorted into 5 groups according to their market capitalizations at the end of December in each year from 1993 to 2010. Q1 consists of stocks with the highest market size and Q5 contains stocks with the lowest market capitalization. For each size-quintile portfolio, the daily portfolio return is calculated by taking an equal-weighted average of all stocks in that portfolio. BMS is our created factor which formed by taking the daily return difference between the "buy" portfolio, which includes stocks with the top 10% of buyer-initiated trades and the "sell" portfolio, which includes stocks with the top 10% of seller-initiated trades. Both the "buy" portfolio and "sell" portfolio have equal weights. MKTRF is the market return minus the risk-free rate. SMB is the difference between the return of portfolio of small stocks and the return of portfolio of large stocks. HML is the difference between the return of a portfolio with high B/M stocks and the return of a portfolio with low B/M stocks. UMD is the difference between the return of a portfolio of stocks with high 30% of returns from t-12 to t-2 months before formation and the return of a portfolio of stocks with low 30% of returns during the same time period. The t-statistics are given in the parentheses.

		BMS	MKTRF	SMB	HML	UMD	_RSQ_
1993	Q1	0.023	1.037	0.392	0.036	0.083	0.974
		(1.091)	(67.206)	(23.647)	(1.986)	(5.338)	
	Q2	-0.016	0.943	0.809	0.070	-0.020	0.957
		(-0.659)	(51.266)	(40.877)	(3.198)	(-1.084)	
	Q3	-0.031	0.863	0.852	0.182	-0.079	0.900
		(-0.874)	(33.364)	(30.637)	(5.945)	(-3.040)	
	Q4	0.033	0.699	0.819	0.260	-0.119	0.657
		(0.528)	(15.132)	(16.484)	(4.760)	(-2.570)	
	Q5	-0.074	0.519	0.698	0.228	-0.044	0.324
		(-0.751)	(7.137)	(8.933)	(2.659)	(-0.602)	
1994	Q1	0.042	1.043	0.373	0.082	0.080	0.986
		(2.443)	(90.414)	(25.625)	(4.144)	(4.682)	
	Q2	0.003	1.004	0.833	0.197	-0.043	0.973
		(0.156)	(68.685)	(45.164)	(7.814)	(-1.968)	
	Q3	-0.057	0.953	0.893	0.212	-0.158	0.872
		(-1.255)	(30.816)	(22.875)	(3.989)	(-3.453)	
	Q4	-0.125	0.825	0.826	0.286	-0.211	0.768
		(-2.333)	(22.759)	(18.049)	(4.579)	(-3.926)	
	Q5	-0.196	0.738	0.831	0.225	-0.356	0.537
		(-2.497)	(13.893)	(12.396)	(2.460)	(-4.527)	
1995	Q1	0.061	1.115	0.446	0.146	0.023	0.965
		(2.466)	(59.133)	(22.319)	(5.348)	(1.077)	
	Q2	0.050	1.045	0.870	0.212	-0.038	0.959
		(1.985)	(54.067)	(42.537)	(7.562)	(-1.697)	
	Q3	0.062	0.911	0.760	0.103	-0.133	0.870
		(1.487)	(28.549)	(22.514)	(2.219)	(-3.634)	
	Q4	0.022	0.736	0.637	0.082	-0.171	0.713
		(0.409)	(17.805)	(14.546)	(1.366)	(-3.620)	
	Q5	-0.015	0.541	0.553	-0.032	-0.337	0.328
		(-0.160)	(7.365)	(7.107)	(-0.304)	(-4.003)	

Table IX (Continued)

		BMS	MKTRF	SMB	HML	UMD	_RSQ_
1996	Q1	0.037	1.029	0.430	0.069	-0.052	0.977
		(1.635)	(57.725)	(24.757)	(2.925)	(-2.656)	
	Q2	0.044	1.009	0.867	0.170	-0.020	0.973
		(1.803)	(52.651)	(46.428)	(6.706)	(-0.964)	
	Q3	0.004	0.962	0.915	0.214	-0.063	0.933
		(0.119)	(34.054)	(33.215)	(5.732)	(-2.042)	
	Q4	-0.076	0.880	0.887	0.167	-0.144	0.849
		(-1.483)	(21.835)	(22.577)	(3.125)	(-3.262)	
	Q5	-0.207	0.736	0.784	0.111	-0.177	0.557
		(-2.333)	(10.520)	(11.493)	(1.199)	(-2.309)	
1997	Q1	0.059	1.043	0.529	0.169	-0.027	0.981
		(2.448)	(57.071)	(27.561)	(6.542)	(-1.059)	
	Q2	0.078	0.997	0.878	0.206	-0.037	0.981
		(3.741)	(63.397)	(53.187)	(9.263)	(-1.696)	
	Q3	0.009	0.925	0.856	0.267	-0.091	0.918
		(0.241)	(31.835)	(28.047)	(6.495)	(-2.280)	
	Q4	-0.066	0.877	0.816	0.312	-0.142	0.806
		(-1.198)	(21.035)	(18.652)	(5.299)	(-2.475)	
	Q5	-0.359	0.758	0.682	0.212	-0.254	0.516
		(-4.316)	(12.050)	(10.333)	(2.380)	(-2.933)	
1998	Q1	0.049	1.112	0.511	0.231	-0.104	0.981
		(2.882)	(66.569)	(24.615)	(7.014)	(-4.652)	
	Q2	0.048	1.040	0.896	0.291	-0.079	0.986
		(3.567)	(78.312)	(54.282)	(11.116)	(-4.475)	
	Q3	0.020	0.906	0.825	0.356	-0.131	0.938
		(0.831)	(37.231)	(27.285)	(7.433)	(-4.041)	
	Q4	-0.040	0.855	0.797	0.397	-0.144	0.871
		(-1.203)	(25.941)	(19.434)	(6.120)	(-3.260)	
	Q5	-0.066	0.773	0.743	0.459	-0.290	0.735
		(-1.415)	(16.886)	(13.050)	(5.093)	(-4.729)	
1999	Q1	0.118	1.183	0.584	0.391	-0.010	0.947
		(4.361)	(39.498)	(17.707)	(9.086)	(-0.367)	
	Q2	0.119	0.997	0.873	0.472	-0.083	0.927
		(5.039)	(38.147)	(30.321)	(12.584)	(-3.379)	
	Q3	0.065	0.763	0.691	0.353	-0.135	0.851
		(2.489)	(26.337)	(21.620)	(8.481)	(-4.951)	
	Q4	-0.018	0.608	0.558	0.276	-0.148	0.603
		(-0.475)	(14.408)	(11.984)	(4.549)	(-3.741)	
	Q5	-0.037	0.525	0.495	0.204	-0.210	0.446
		(-0.803)	(10.353)	(8.858)	(2.808)	(-4.409)	
2000	Q1	0.132	1.112	0.445	0.321	-0.220	0.943
		(3.859)	(31.428)	(12.298)	(6.904)	(-9.159)	
	Q2	0.100	0.957	0.826	0.233	-0.254	0.939
		(2.850)	(26.306)	(22.175)	(4.873)	(-10.276)	
	Q3	0.042	0.770	0.780	0.251	-0.206	0.863
		(0.959)	(17.095)	(16.913)	(4.236)	(-6.732)	
	Q4	-0.082	0.746	0.782	0.344	-0.174	0.748
		(-1.481)	(12.996)	(13.305)	(4.559)	(-4.460)	
	Q5	-0.146	0.781	0.965	0.408	-0.177	0.583
		(-1.645)	(8.520)	(10.281)	(3.386)	(-2.837)	

Table IX (Continued)

		BMS	MKTRF	SMB	HML	UMD	_RSQ_
2001	Q1	-0.009	1.099	0.445	0.228	-0.042	0.968
		(-0.404)	(55.311)	(14.397)	(6.414)	(-2.000)	
	Q2	0.051	0.986	0.949	0.363	-0.110	0.970
		(2.594)	(53.670)	(33.211)	(11.050)	(-5.709)	
	Q3	0.059	0.676	0.691	0.381	-0.204	0.888
		(1.980)	(24.492)	(16.095)	(7.715)	(-7.046)	
	Q4	0.056	0.456	0.491	0.416	-0.312	0.745
		(1.436)	(12.573)	(8.712)	(6.410)	(-8.202)	
	Q5	0.141	0.327	0.429	0.446	-0.427	0.620
		(2.707)	(6.720)	(5.674)	(5.134)	(-8.383)	
2002	Q1	0.087	0.995	0.302	0.260	-0.033	0.982
		(2.901)	(60.820)	(13.578)	(10.167)	(-1.984)	
	Q2	0.057	0.936	0.819	0.336	-0.106	0.989
		(2.707)	(81.053)	(52.240)	(18.659)	(-9.124)	
	Q3	-0.023	0.706	0.649	0.417	-0.169	0.960
		(-0.731)	(41.096)	(27.828)	(15.562)	(-9.738)	
	Q4	-0.083	0.424	0.351	0.397	-0.234	0.780
		(-1.539)	(14.329)	(8.720)	(8.590)	(-7.812)	
	Q5	-0.088	0.352	0.238	0.464	-0.303	0.573
		(-1.051)	(7.735)	(3.845)	(6.532)	(-6.583)	
2003	Q1	0.016	0.986	0.286	0.188	-0.096	0.978
		(0.513)	(73.782)	(13.956)	(5.774)	(-5.293)	
	Q2	0.050	0.972	0.819	0.307	-0.089	0.990
		(2.259)	(104.461)	(57.460)	(13.569)	(-7.026)	
	Q3	-0.003	0.814	0.795	0.349	-0.087	0.966
		(-0.088)	(56.246)	(35.859)	(9.907)	(-4.433)	
	Q4	0.042	0.422	0.456	0.290	-0.132	0.782
		(0.802)	(19.129)	(13.498)	(5.406)	(-4.408)	
	Q5	0.091	0.284	0.335	0.265	-0.131	0.495
		(1.241)	(9.340)	(7.185)	(3.582)	(-3.160)	
2004	Q1	-0.008	0.991	0.246	0.143	0.028	0.977
		(-0.274)	(62.138)	(12.120)	(5.330)	(1.391)	
	Q2	-0.030	1.007	0.806	0.231	-0.094	0.988
		(-1.113)	(70.606)	(44.339)	(9.629)	(-5.167)	
	Q3	-0.151	0.903	0.807	0.145	-0.021	0.969
		(-3.811)	(42.381)	(29.720)	(4.045)	(-0.791)	
	Q4	-0.234	0.591	0.417	0.199	0.064	0.781
		(-3.322)	(15.623)	(8.641)	(3.129)	(1.323)	
	Q5	-0.133	0.434	0.341	0.213	0.100	0.561
		(-1.412)	(8.550)	(5.264)	(2.487)	(1.539)	
2005	Q1	0.000	0.980	0.249	0.121	0.069	0.982
		(-0.017)	(66.743)	(13.723)	(4.009)	(3.671)	
	Q2	-0.025	1.019	0.757	0.166	-0.022	0.992
		(-1.126)	(87.660)	(52.661)	(6.951)	(-1.466)	
	Q3	-0.108	0.868	0.754	0.136	-0.053	0.967
		(-2.646)	(41.285)	(28.979)	(3.147)	(-1.970)	
	Q4	-0.331	0.513	0.345	0.089	0.017	0.759
		(-5.348)	(16.100)	(8.760)	(1.363)	(0.412)	
	Q5	-0.528	0.460	0.251	0.110	0.017	0.494
		(-6.222)	(10.517)	(4.635)	(1.229)	(0.304)	

Table IX (Continued)								
		BMS	MKTRF	SMB	HML	UMD	_RSQ_
2006	Q1	-0.004	0.979	0.238	0.038	0.086	0.985
		(-0.153)	(60.470)	(13.035)	(1.279)	(4.924)	
	Q2	-0.036	1.030	0.724	0.119	-0.044	0.993
		(-1.694)	(80.188)	(49.890)	(5.022)	(-3.153)	
	Q3	-0.141	0.913	0.785	0.127	-0.059	0.980
		(-4.128)	(44.045)	(33.547)	(3.316)	(-2.638)	
	Q4	-0.227	0.442	0.409	0.056	0.183	0.808
		(-3.585)	(11.496)	(9.419)	(0.796)	(4.432)	
	Q5	-0.305	0.304	0.250	-0.012	0.237	0.597
		(-3.996)	(6.585)	(4.801)	(-0.141)	(4.765)	
2007	Q1	-0.037	1.032	0.201	0.108	0.085	0.987
		(-1.988)	(115.552)	(9.663)	(3.618)	(5.656)	
	Q2	-0.014	1.054	0.761	0.165	0.004	0.993
		(-0.946)	(146.341)	(45.319)	(6.888)	(0.306)	
	Q3	-0.058	0.974	0.808	0.178	-0.009	0.975
		(-2.215)	(77.443)	(27.544)	(4.260)	(-0.438)	
	Q4	-0.333	0.617	0.384	0.062	0.045	0.803
		(-7.259)	(28.102)	(7.505)	(0.850)	(1.231)	
	Q5	-0.457	0.501	0.188	-0.004	0.055	0.649
		(-8.795)	(20.151)	(3.249)	(-0.044)	(1.316)	
2008	Q1	0.022	1.045	0.205	-0.050	-0.085	0.993
		(1.604)	(122.959)	(12.041)	(-2.471)	(-6.235)	
	Q2	0.016	1.033	0.662	0.039	-0.118	0.991
		(1.007)	(103.577)	(33.136)	(1.637)	(-7.355)	
	Q3	-0.070	0.989	0.635	0.043	-0.082	0.966
		(-2.431)	(55.642)	(17.852)	(1.024)	(-2.879)	
	Q4	-0.219	0.664	0.283	-0.020	-0.139	0.848
		(-5.095)	(25.044)	(5.330)	(-0.317)	(-3.260)	
	Q5	-0.284	0.484	0.070	-0.038	-0.189	0.676
		(-5.252)	(14.537)	(1.048)	(-0.473)	(-3.527)	
2009	Q1	0.025	1.045	0.194	-0.009	-0.109	0.993
		(1.748)	(86.907)	(10.641)	(-0.487)	(-10.585)	
	Q2	0.045	1.024	0.644	0.062	-0.129	0.992
		(2.873)	(77.477)	(32.149)	(3.069)	(-11.431)	
	Q3	0.048	0.970	0.718	0.006	-0.150	0.977
		(1.803)	(42.961)	(20.974)	(0.186)	(-7.773)	
	Q4	0.063	0.643	0.473	-0.004	-0.173	0.923
		(1.771)	(21.237)	(10.298)	(-0.081)	(-6.694)	
	Q5	0.096	0.264	0.199	-0.006	-0.251	0.715
		(1.931)	(6.264)	(3.115)	(-0.100)	(-6.973)	
2010	Q1	0.045	0.991	0.132	0.058	0.108	0.993
		(1.944)	(99.838)	(9.099)	(3.014)	(6.736)	
	Q2	0.024	0.952	0.647	0.126	0.006	0.996
		(1.293)	(118.696)	(55.340)	(8.182)	(0.437)	
	Q3	-0.025	0.889	0.736	0.185	-0.071	0.986
		(-0.722)	(59.603)	(33.832)	(6.458)	(-2.946)	
	Q4	-0.185	0.649	0.487	0.186	0.018	0.941
		(-3.562)	(28.833)	(14.816)	(4.301)	(0.505)	
	Q5	-0.164	0.330	0.207	0.229	0.048	0.725
		(-2.304)	(10.743)	(4.609)	(3.862)	(0.971)	