RESEARCH ON THE INFLUENCE OF BEHAVIORAL FORCES THAT MOTIVATE TRADER BEHAVIOR: A PROSPECT THEORY EXEGESIS

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ABSTRACT

Although intuitively market participants construct the notion that psychological biases should influence equity values and trading activity, few studies have been able to establish this relationship empirically. These biases are not merely isolated aberrations; instead, they are persistent and systematic behavioral patterns. Unfortunately, because of the very nature of the field, studies have been more experimental than empirical in nature. Using logit regression analysis on a proprietary database of trader activity, this study sought to uncover behavioral biases that could result in less than perfectly rational investor behavior. Investors were found to behave differently during periods of extreme wealth losses as defined by periods when the market indices were significantly receding. The implications for practitioners and academicians are clear once they become aware of their predisposition to less than *satisficing* behavior.

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I. Introduction

There is an extensive body of research documenting significant market reaction to changes in market conditions. Barberis, Huang, and Santos (2001)[3] (BHS, henceforth) posited that an investor becomes less risk averse after stock prices increase because his previous gains underpin subsequent losses making him less loss averse, and more risk-seeking. Consequently he has a tendency to pay even higher prices for stocks, whereas after declines in stock prices, he becomes more concerned about further losses, exhibits a higher degree of risk aversion and becomes more loss averse. They note "after being burned by the initial loss, he is much more sensitive to additional setbacks" (p. 2). By extension, this thesis implies fewer purchases of stocks.

Shefrin (2001) presents the case of potential bankruptcy at Sony Corporation in which a co-founder led a project which had suffered heavy losses[4]. He shows that even though traditional corporate finance and accounting theory stipulate ignoring sunk costs there was a tendency for the co-founder to continue to invest in it, refusing to accept a sure loss.

Based on survey data, Thaler and Johnson (1990) (TJ) find that in the presence of prior losses, individuals who suffer initial losses were more willing to take gambles that would allow them to break even.[5] They note that subjects indicate that new losses hurt more when they occur after a loss than when they occur in isolation. This is interpreted as an indication that prior losses "sensitize people to subsequent losses of a similar magnitude" (p. 656), while prior gains are perceived as "house money" and that "losing some of the house money doesn't hurt as much as losing one's own cash." (p. 657).

There is an obvious dichotomy in the views parlayed by BHS and TJ. BHS' view implies more loss aversion (or more risk aversion in an expected utility framework) after prior losses, whereas TJ's view (like Shefrin's anecdotal evidence) implies more risk seeking or less loss aversion after similar prior losses. These opposing points of view are puzzling since both these studies rely on Prospect Theory as the underlying framework. Prospect theory suggests that after

[3] N. Barberis, M. Huang, and T. Santos, 2001, Prospect Theory and Asset Prices, *Quarterly Journal of Economics* 116, 1-53.

[4] Shefrin, H., 2001, Behavioral Corporate Finance, *Journal of Applied Corporate Finance*, Fall.

[5] Thaler, R., and E. Johnson, 1990, Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice, *Management Science*, 36, 643-660.

periods of losses, 'economic man' no longer follows the idealized behavior attributed to expected utility maximizers. This occurs because his decisions in uncertain conditions are weighted more heavily with prospective losses than prospective gains. The theory postulates that individuals make decisions under uncertainty by maximizing a value function that evaluates wealth *changes*, rather than an expected utility function that ranks choices according to the *level* of expected utility.

While, it should be noted that Prospect Theory was designed to understand single period decision making and these studies imply multi-period horizons, it seems that the main reason for the contradiction is that the reference point turns out to be crucial for risk taking. The *perceived change in wealth*, a notion that is ignored in a rational framework is crucial in the behavioral framework. Different assumptions about what reference point subjects use to evaluate outcomes can lead to very different predictions about risk taking and about the effect of prior outcomes on risky choice. BHS's study suggests that investors feel wealthy after their investments increase in value while TJ's view is based on the investors' original wealth endowment.

This study empirically investigates these decisions. It is unusual in that it uses actual trading data to check behavioral patterns rather than indirect measures like price changes and survey data. The question to be examined is whether or not traders exhibit behavior consistent with more purchases in periods of turmoil (decreases in wealth) and, correspondingly, fewer purchases after increases in wealth. It is postulated here that during periods of market turmoil, a higher level of risk aversion displayed by additional purchases reflect an attempt to return to the reference point. In terms of Prospect Theory, this tendency of more risk aversion in an expected utility framework is noted as exhibiting more 'loss aversion' or more 'risk seeking'. In contrast, fewer purchases reflect less loss aversion. Loss aversion is a greater sensitivity to losses than to gains of the same size, and is represented by a kink in the utility function. Prospect Theory generally predicts that investors prefer long-shots, avoid sure-things, buy insurance against unlikely losses, and take risky chances to win back large losses. The theory notes that those suffering from loss aversion do not measure risk consistently.

In order to test for differences in trader reactions to varying economic conditions two primary data elements are required: a measure of information and a measure of reaction. In this paper, reaction is measured by a trader's inactivity, purchases or sales of securities. The measure of information is a significant change in the value of a major index. A significant change in market returns will ensure a clearly identifiable and important event since it will directly affect the wealth of the trader.

Portfolio managers, institutional traders and investors are known to act differently when markets are "up" versus when they are "down". Wermers (1999) finds that these market participants "herd".[6] Behavioral influences like overconfidence and optimism make portfolio managers sell their winners too early to chase better opportunities.[7] Shame, avoiding regret and embarrassment, and unwillingness to admit errors make managers hold their losers.[8] Investors are prone to a mean reverting mindset; a permanent positive change will not be recognized at first. They may first under-react. Investors will rethink their position after several positive changes in information emerge, then they may over-react, a procedure Thaler (1985) terms "mental accounting".[9]

The remainder this paper is organized as follows: Section II develops the hypothesis and empirical model, Section III describes the data and their treatment; Section IV considers the empirical applications while Section V uses an alternative specification of the model; Section VI concludes and suggests implications based on the findings.

II. Hypothesis and Methodology

Prospect Theory analysis involves defining an editing phase. Here a reference point is designated to differentiate between potential gains and losses. The theory stipulates that after a period of considerable losses, sentiment changes. The process of establishing a reference point that defines a significant change in sentiment is ascertained by a significant change in a major market index like the DJIA. The DJIA is a useful index for representing short-term market movement since it concentrates on large, actively traded firms; this minimizes problems associated with non-synchronous trading (Rudd 1979).

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[6] Wermers, R., 1999, Mutual Fund Herding and the Impact on Stock Prices, *The Journal of Finance,* Volume 54, Issue 2, Page 581-622.

[7] Barber, B.M., T Odean, 2000, Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *Journal of Finance,* 55:2, p. 773-806.

[8] Shefrin, H., and M Statman, 1985, The Disposition to Sell Winners too Early and Ride Losers too Long: Theory and Evidence, *Journal of Finance*, 60:3, p 777-792.

[9] De Bondt, W., and R. Thaler, 1987, Further Evidence on Investor Overreaction and Stock Market Seasonality, *Journal of Finance,* 42:5, 57−581.

After an event that results in market turmoil, traders may feel less wealthy. Their reactions, predicated by their behavioral characteristics, may compound losses. The null hypothesis formulated is one of no direct relation between the institutional trader's probability of purchasing more securities when the market is in a downtrend and probability of selling when the market is in an uptrend. A model structure, which incorporates behavioral factors, is not consistent with expected utility maximization, for it assumes decision-makers put weight on something that is meaningless in a rational framework, but in the Prospect Theory framework, weight is placed on the perceived change in wealth relative to the reference point. The validity of Prospect Theory is investigated on a data file of volatile swings in the Dow Jones Industrial Average by employing relationships (1) and (2).

$$V(x,p:y,q) = \pi(p)v(x) + (1 - \pi)(q)v(y) \tag{1}$$

$$R = -U''(W)/U'(W) \tag{2}$$

The following hypothesis is set forth: During periods of catastrophe, when investors experience massive wealth losses as defined by an appreciable absolute change in the index, the change in the absolute risk (loss) aversion coefficient, R, is below zero if investors become less risk-averse (i.e. exhibit risk-seeking behavior), and above zero if investors become more risk-averse i.e.:

$$H_0: \Delta R < 0$$

$$H_A: \Delta R > 0 \tag{3}$$

To cast relationships (1) and (2) into testable form, a simplistic assumption is made, that investors' risk-aversion, or the lack thereof, is exemplified by his/her purchase or sale of securities. To that end, since the goal of this study is to analyze the behavior of individual investors, one way to address the problem is to review their actions under normal conditions in comparison to market turmoil ones. Risk-averse investors should avoid risk when markets are under pressure and only seek risk when markets are orderly, and the typical risk-reward trade-off is observed. Given this assumption, the hypothesis in (3) can be restated as:

(H_0): There is no difference in investors/traders' behavior during market turmoil

and the alternative,

(H_A): Investors/traders behave differently during market turmoil.

The methodology above leads into an analysis of the market turmoil and non-turmoil days under two alternatives as defined by the following equations. Here instead of inequality in the risk aversion coefficient, R we have equality between two alternatives, which is more empirically manageable. The empirical model is thus given by:

$$y = \alpha + \beta x + \varepsilon \qquad \text{on market turmoil days}$$

$$y' = \alpha' + \beta' x + \varepsilon' \qquad \text{on non-turmoil days} \tag{4}$$

Where the y's are increases, decreases or no change in security position, and the x's are the change in the value of a select market index. Equation 4 shows that the reaction of traders to the market index may be different on turmoil days. More specifically, the variables are defined as:

- y & y' : increases (buys), dummy variable is 1; decreases (sells) or no change in security position, dummy variable is zero;
- x : the percentage change in the value of a representative market index;
- α and β : coefficients for market turmoil;
- α' and β': coefficients for non-turmoil market conditions.

The null hypothesis can now be stated specifically as a test of equality of coefficients in equation 4, as follows:

H_0: $\alpha' = \alpha$

$\beta' = \beta$ and

$$(\alpha',\beta') = (\alpha,\beta) \tag{5}$$

The null hypothesis states that the coefficients are invariant between the two periods. If the null hypothesis is not true, and investors become risk seekers during market turmoil times, then as a first and necessary condition, the above coefficients will not be equal.

III. Sample and Data

The measure of information needs to be a noteworthy event that forces the trader to evaluate his position of wealth. Coval and Shumway (2004) show that proprietary traders at the CBOT evaluated their wealth position at the end of each morning and traded differently in the afternoons following morning losses.[10] It is postulated that a trader may behave similarly during days of market corrections. A market correction is typically defined as a decrease in the value of stocks, usually 10% or more over several days. The market corrections of the 1990's and early in the current millennium occurred over a more extended period. Chicago researchers Ibbotson and Associates argued in 2004, "Since 1926, the market has advanced more than two out of every three years—with an average annual gain of 22.87% in up years. Although the average annual stock market return since 1926 has been 10 percent, many individual years have seen losses.

Daily swings however achieve more notoriety. An example of the swings under consideration is Black Monday, October 19, 1987 - a 508 point (or 22.61%) loss. The largest one day point drop in history, Monday October 27, 1997 of 554.26 points (or 7.19%) was followed by the largest one day point gain of 337.17 (or 4.71%) on "Turn-around" Tuesday October 28, 1997, an event with little corresponding fundamental rationale. More recently, after the events of September 11, 2001, the stock market closed for a week. On September 17, the day the NYSE and the NASDAQ reopened after the market turmoil, the DJIA fell by 684.81 points, a 7.13% fall.

The period under consideration in this study does not cover these more recent events. The database investigated consisted of the daily closing prices of the Dow Jones Industrial Average from the period October 6, 1987 through October 30, 1992. There were only 9 days in 1987 when the index fell by more than 100 points, 3 in 1988, 4 in 1989, 3 in 1990, 8 in 1991 and 5 in 1992. There were only 36 days in this period when the Dow fell more than 50 points, and only 7 days when it fell more than 100 points. Beginning in 1996 when there were 19 such days, a 100-point fall has become more frequent. Effectively, investors have become blasé about large index swings and may tend to avoid letting behavioral biases affect their activity as frequently. Absolute capitulation is now a rarity.

Rather than considering absolute index changes like 50 or 100 point deviations, outcomes can be identified on the basis of percentage changes in the "Dow," for example 1%, 1 ½%, and 2%. More recently, the high absolute level of the Dow Jones Industrial Average has led to up and down swings of 1 – 2% points to be relatively insignificant events. However during the

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[10] Coval, J., and T. Shumway, 2004, Do Behavioral Biases Affect Prices? *Journal of Finance*, Volume 60, Issue 1, pp 1-34.

period under consideration, larger sample sizes of 146 days were found for days when the Dow fell more than 1%, 104 days when it fell more than 1.25%, 73 days at 1.5% and only 36 days when the Dow fell more than 2%. These benchmarks are arbitrarily set but are to some extent dictated by the feasibility of the data to allow statistical significance. A fairly significant sample size of 159 days was achieved during this period for a drop in the DJIA of 0.95% and greater. Since the major averages were at significantly lower nominal values and lower levels of volatility, a 0.95% fall was viewed as being an unusual event. This interval (October 6, 1987-October 30, 1992) is chosen for several reasons. Too long an interval will involve several shifts that may confound the outcome. Additionally, this period includes the effects of several days of near capitulation in the markets, days when investors really believed "the sky was falling".

Measurement of the reaction of traders is obtained through their daily purchases and sales of securities. The database under investigation is a selective one. It is made up of the changes in daily position in securities for which the brokerage has a sizeable position. Two brokerage houses are considered, the Toronto offices of First Boston (Canada) Ltd., and Merrill Lynch (Canada) Ltd. The activities of proprietary traders at these firms trading on the firm's own account, including trading as a market maker are identified. Since the period over which data were collected, significant changes have occurred with these facilities. First Boston closed its Canadian enterprise shortly after Credit Suisse purchased the American parent and remained closed for several years. Merrill has since merged with a large independent retail Canadian broker.

While the study acknowledges that there are significant weaknesses in the data, the benefits of obtaining actual versus experimental data to investigate the behavior of traders, compensate for these shortfalls. Typically, revealed preferences have more relevance over stated preferences for an analysis of the determination of economic value. When data are self-reported it is difficult to verify and can be heavily influenced by the interviewer. As a result, it is necessary to construct the modeling effort to be applicable considering the limitations of the data. We will consider the two companies separately to avoid confounding effects. Part of the data collected is highly proprietary. The researcher was forced to compile this data set under extreme secrecy conditions since many of the trades were made under restrictive circumstances. While the paucity of this data is regretful, the benefits outweigh the deficiencies. Although it is necessary to preserve the anonymity of the traders involved, the raw data points are available on request. The risk preferences of the large traders in the data file were examined after each of these events to determine their market reactions. The bid prices of these investors showed whether they still sought risk (by purchasing more securities at the market price) or averted risk otherwise.

After days when the index closed down by a predetermined percentage level, a review is made of the daily trades of the Toronto branches of the two large multinational brokerage houses (First Boston (FB) and Merrill Lynch (MER)). The focus is on sizeable positions of individual stocks, that is, stocks which comprise more than 10% of the portfolio holdings. Risk seeking behavior is displayed when traders purchased more shares of stock where positions had already been taken. Notations are made when position sizes are increased, signifying purchases. Alternatively, notations are made when position sizes decrease or remain the same, signifying sales or otherwise. Note in some cases, there are two or more securities that encompass more than 10% of the portfolio's holdings. Under these circumstances, there was more than one observation on a particular market turmoil or conversely, non-turmoil day. On several of the days, more than three stocks fitted the criteria but on most days, only one stock ended up meeting the 10% benchmark. Many of these stocks were shares of principally Canadian Corporations. However, several stocks were inter-listed on major world exchanges. The data was then subdivided into periods of market turmoil defined as days when a major market index fell by at least 0.95% and coded as one during these periods and zero during the much larger data set of non-turmoil periods.

There were some limitations on the data, for example, specific daily portfolio sizes were not given and the value of the other securities held in the portfolio was unknown. The portfolio size dilemma is difficult to solve since these companies were privately held and absolute monetary values were usually lumped under dubious categories. However, it is fair to assume that in the 1980's these companies were willing to put up sizeable capital chunks to build their presence in Canada. The causal relationship of a massive change in the price of a stock being effected may be a problem since large institutional purchases or sales may lead to others following suit. However, the fact that these traders are very small components of the market and are often price takers should alleviate that concern.

The data can be summarized in two groups. Group 1 consisted of the market turmoil data and Group 0, the non-turmoil events. The DJIA had 159 days when the index fell by 0.95% or more with a range of -22.61% to 10.15%, during the five year period under review. FB had 180 market turmoil observations and 1259 non-turmoil observations in this period. MER had 182 market turmoil observations and 1255 non-turmoil.

The S&P 500 had 154 days when the index fell by 0.95% or more with a range of -20.46% to 9.10%, similar statistics to the DOW. FB had 178 market turmoil observations and 1266 non-turmoil observations in this period. MER had 173 market turmoil observations and 1255 non-turmoil.

In the case of the S&P/TSX, there were only 74 days during the period under question where the index experienced market turmoil conditions (defined as a fall of 0.95% or more). In fact the daily range of changes during this period was -11.31% to 9.04% as compared to the DJIA whose range was -22.61% to 10.15%. However, there were 196 cases of market turmoil conditions for FB versus 1247 cases of non-turmoil conditions. MER however did not have substantially more observations, 108-market turmoil and 1339 non-turmoil.

IV. Empirical Applications

Two major models are utilized with several enhancements within each mode. Considering the scope of the data as discussed above, empirical application of the testable model in equation (4) poses some restrictions since the *y*'s are binary. Therefore application of OLS is not appropriate. The logistic regression model (Cox 1970) is conventionally used to predict the likelihood of the outcome (the odds ratio) based on the predictor variables (called covariates in logistic regression). The second model recognizes the limitations of the logistic regression model and expands the initial methodology using an alternative specification.

To investigate our research question, we specify and apply a logit model on the dataset of trader buys and sells for the initial task of determining investor's risk preferences during periods of "market turmoil" versus "non-turmoil. The logistic regression model attempts to predict the probability of the event such that:

$$\hat{p}\,(y = 1 \mid x) = \frac{e^{(\alpha + \beta x)}}{1 + e^{(\alpha + \beta x)}}$$

Or:

$$\text{logit}\,(\hat{p}) = \ln\,[\,\hat{p}/(1-\hat{p})] = (\alpha + \beta x) + e$$

Where:

- p is the probability that the event y occurs, $p(y = 1)$ given x
- $p/(1-p)$ is the "odds ratio" or the ratio of the probabilities
- ln $[p/(1-p)]$ is the actual log odds ratio, or "logit" which corresponds to the unit change of x
- x is the predicting independent variable or covariate
- α is the intercept parameter and β is the slope parameter

The logistic regression model fits the log odds through a linear function of the explanatory variables (similar to multiple regression models). [11]

Several pertinent points are summarized below.

1. For ordinary least squares (OLS) to yield best linear unbiased (BLUE) estimators, the classical regression assumptions must be met. OLS models require quantitative, continuous, unbounded dependent variables. One of the assumptions is that the variance of the dependent variable is constant across values of the independent variable (homoscedasticity). This cannot be the case with a binary variable, because of its discrete nature. The variance is given by p * (1-p). When 50 percent of the observations are 1's (p = 0.5), then the variance is .25, its maximum value. As more extreme values occur, the variance decreases. When $p = 0.10$, the variance is .1*.9 = 0.09, so as p approaches one, the variance approaches zero. Consequently while the OLS coefficients will still be unbiased they will not be efficient, invalidating hypothesis tests.
2. Logistic regression has many analogies to OLS regression: logit coefficients in the logistic regression equation correspond to slope coefficients, the standardized logit coefficients correspond to the weights of the slopes, and an adjusted r^2 statistic is available to summarize the strength of the relationship. Unlike OLS regression however, logistic regression does not assume linearity of the relationship between the independent variables (covariates) and the dependent, does not require normally distributed predictor variables or error terms, nor does it assume homoscedasticity or homogeneity of variance , and in general has less stringent requirements to ensure unbiased and efficient coefficients. It does however still assume that all observations are independent and the model is correctly specified. If the variables display

[11] Hosmer, D.W. and Lemeshow, S. (2002). *Applied Logistic Regression*. 2nd ed. Wiley: New York

multicollinearity and are linear functions of each other, the resultant large standard errors will result in inaccurate estimates of the coefficients. Another major concern in logistic regression is the omission of outliers.[12]

3. Unfortunately time series data cannot be treated as randomly selected observations from a population. Lagged dependent variables can affect the estimation since the data is likely to exhibit some degree of dependence over time. That circumvents the violations of the assumption of independence. Return data (computed as percentage change in index prices) as compared to the actual level data are generally not *serially correlated*. Therefore it is customary to treat stock price data as non-stationary and stock return data as stationary. Accordingly, using the return data can ensure the assumption of independence is not violated. After transforming the dependent into a logit variable, the logistic regression uses *Maximum Likelihood Estimation* (MLE) techniques to calculate the logit coefficients. The likelihood function is the probability that a model could generate the actual data. MLE seeks to maximize the log-likelihood function, which reflects how likely the observed values of the dependent variable may be predicted from the observed values of the independent variables. The MLE method lowers the mean square error and increases the probability of the event.
4. The structure of the error term is important in binomial choice models. By making assumptions about the probability density of the residuals, one can choose from several different binomial choice model formulations. The logistic regression model assumes a logistic distribution of errors, and the probit model assumes normal distributed errors. Since the probability p that the dependent variable takes the value of one (and by extension, the probability $(1-p)$ that it takes the value of zero) is being considered, the linear regression model poses serious inference problems. This is because for extreme values of the independent variable, the predicted value of the dependent variable will be either less than zero, or greater than one, values not appropriate for probabilities. OLS if used can give incongruent predictions. Probability must be modeled by a function that never exceeds the {0, 1} boundaries,

[12] DeMaris, A., 1992, *Logit modeling: Practical Applications*, Newbury Park, CA: Sage Publications. Series: Quantitative Applications in the Social Sciences, No. 86.

consequently the natural log of the odds or logit specification lends itself to this modeling.

5. Another basic difference between OLS and the logistic method has implications for testing. Whereas in OLS estimation the parameters are chosen which yield the smallest sum of squared errors in the fit between the model and the data, maximum likelihood estimation in logistic regression produces parameter estimates that imply the highest probability or likelihood of observing the dependent variable.[13] Another problem that can arise in using logistic regressions on rare events data (like wars, catastrophes or market turmoil) are inefficient coefficients. This can be rectified in the statistical package SAS however through weighting the likelihood function and performing maximum-likelihood logit analysis by finding the value of the coefficients that gives the maximum value of this weighted function. Weighting can therefore outperform prior correction when both a large sample is available and the functional form is mis-specified (Xie and Manski 1989). Logit and probit models are based on the same underlying threshold model. The *threshold* (Long 1997) defines the dichotomous variable and is used to divide the two portions of the y distribution, for example the probability that the event occurs is one and zero otherwise.[14]
6. Since the threshold model is based on the probability of observing the error term in a certain range, a distribution must be specified for estimation. The logistic distribution is easier to calculate since no tables are required to compute the cumulative probability; therefore its use has been more proliferate. In general the coefficents derived from logit estimation is equal to 1.6 times the coefficients obtained from using probit. The logistic distribution has a variance of $\pi^2/3$ while the probit function is based on the standard normal distribution with variance one, so in many instances the difference is only in a matter of scale. If the responses are "unordered", a logistic transformation is preferred.
7. This raises the question of whether logit modeling is preferable to probit. The fundamental theoretical difference between the two approaches concerns the

[13] Note MLE and OLS give equivalent results when the errors in the OLS model are assumed to be normally distributed.
[14] Long, J. S.,1997,. *Regression Models for Categorical and Limited Dependent Variables.* Thousand Oaks, CA: Sage.

distribution of the error term, logistic versus normal. This assumption is both the strength and the weakness of the technique. While there is typically an important difference between odds-ratios and risk-ratios, with binary logit there is no difference between the two ratios. The odds ratio provides a way of assessing the relationship between the dependent and independent variables by comparing whether the probability of a certain event is the same for two groups. A ratio of one implies the event is equally likely in both groups. A detailed comparison of logit and probit models is provided by Aldrich and Nelson (1984).

8. Logistic regression is a non-parametric technique for determining the estimates of independent variables on a dependent variable. Because it is a non-parametric technique, the tests available, are not as powerful as for OLS regression and other parametric statistical tests. This means that logistic regression will not pick up relationships between variables as comprehensively as OLS regression analysis for a given number of observations.
9. Interpretation of the coefficients is ambiguous since it gives the relationship between the independent variable and the unobservable predicted dependent one. Therefore the marginal effect is the effect of the independent variable on the probability of observing a success for the dependent variable. Since y is observable, the interpretation of the marginal effect is less ambiguous, giving a robust result. For every unit increase in the independent variable, the odds that the event will occur (Y=1) is increased by $e^{(\beta)}$.
10. There is potentially an issue with over dispersion (more variation than that allowed by the binomial distribution) of the dichotomous, discrete variable which can be dealt with using a SCALE option in SAS. Individuals' preferences underlying most economic behavior over time are likely to display substantial heterogeneity. By adjusting the covariance matrix, the condition of heterogeneity is treated. The resultant regression shows the log of the odds ratio as a linear function of the independent variables. The success of the logistic regression can be assessed by looking at the correct and incorrect classifications of the dichotomous dependent variable. In addition, goodness-of-fit tests such as the deviance are available as indicators of model appropriateness and test the significance of individual

independent variables. Another common measure of goodness of fit is the percentage of correctly classified cases. Although the logistic model can provide accurate estimates of the probability *p*, it has weaknesses. First, it is hard to determine when a satisfactory model is found, because there are few diagnostic procedures to guide the selection of variable transformations and no true test of good fit, and secondly it is difficult to interpret the coefficients of the fitted model, except in very simple situations. Hosmer and Lemeshow (1989) provide a relatively good approximation for a lack-of-fit test on logistic regressions. In fact, it is more aptly called a "badness of fit" test since the null hypothesis is rejected if this statistic is significant. While acknowledging these caveats, the option of using binomial choice models is inevitable.

Estimation of the model was performed using PROC LOGISTIC from the SAS® statistical package. The method utilizes the Fisher scoring technique, a model fit with iteratively weighted least squares. Specifically, the equation being estimated is the probability that a trader will buy (1) or sell/no change (0) as a function of the return of the market and the environment (market turmoil or not):

$$BUY\_SELL = \alpha + \beta_1 * RETURN + \beta_2 * GROUP + \beta_3 * RETURN * GROUP \qquad (6)$$

where *BUY_SELL* is a 0-1 dichotomous variable equal to 1 for a "buy" transaction and 0 for a "sell" or "no change" transaction; *RETURN* represents the percentage change in a market index and *GROUP* = 1 for market turmoil events and *GROUP* = 0 for non-turmoil events. *RETURN*GROUP* gives the interaction effects. The significance of the interaction of the two variables is measured by the change of pseudo *R*-squared of the equation with the interaction terms and the equation without the independendent variables "*GROUP*" and "*RETURN*GROUP*".

The generalized formulation above is appropriate for the full model. Allison (1999)[15], reports the following:

> "In logit and probit regression analysis, a common practice is to estimate separate models for two or more groups and then compare coefficients across groups. An equivalent method is to test for

[15] Allison, 1999, Comparing Logit and Probit Coefficients Across Groups, *Sociological Methods & Research*, Vol. 28, No. 2, November,186-208.

interactions between particular predictors and dummy (indicator) variables representing the groups."

However in this instance the groups and independent predictor are categorized similarly. The group dummy variable depends on whether or not the market index fell by a certain level, and the return predictor gives the level of the change. Accordingly the interaction effect may be dropped from the above specification without significant loss to the model. However in as much as the interaction effect in a (saturated or full) model allows directly for the measurement of the association between the variables it will be retained for this exercise.

To compute the unrestricted sum of squares, necessary to conduct a test of structural change in the separate group regressions, three logistic regression procedures are designed, one for the non-turmoil events (*GROUP* = 0), one for the market turmoil events (*GROUP* = 1), and a separate model for the complete (full) sample data set including both market turmoil and non-turmoil events.

$$BUY\_SELL = \alpha + \beta * RETURN \tag{7}$$

Following this estimation for FB, the steps were repeated for the MER data. The analysis on each brokerage house attempted to determine whether market turmoil as determined by a 0.95% fall in a market index, predicated buyer behavior. Results are presented on the estimation of Equation (6) and Equation (7) separately.

The questions that need to be addressed regarding the estimation are, how well does the model fit the data and what is the significance of the estimated coefficients? Other relevant issues are a test of the structural change in the parameters of the regressions as well as a measure of the marginal effects of the independent variables or covariates. Since the estimated coefficients themselves do not indicate the change in the probability of the event occurring given a one-unit change in the relevant explanatory variable, (the sign of the estimated coefficient indicates the direction of the change in probability only), the actual level of the change in probability, given a one-unit change in an explanatory variable, will differ based upon the initial values of all the explanatory variables and their coefficients. Thus, it is conventional to evaluate the explanatory variables at their mean values as a basis for inferring a change in probability.

The first set of results is obtained for the market as defined by the Dow Jones Industrial Average (DJIA) since changes in this index are most heavily reported in the press and its movement can lead to a significant level of trading activity. It has been viewed as a sentiment factor because of the emotion aroused by investors and in the press (Bange 2000).[16] Next, the return on the market will be measured by the S&P 500 since it is the most typically used representative of a market index. Subsequent results are given using the S&P Toronto Stock Exchange index (S&P/TSX) data since all the stocks under investigation trade on that exchange. A short covering of using the S&P/TSX to measure Canadian trader behavior is that the index is heavily weighted in the resources sector especially gold and other mining companies, whose stock returns can sometimes be negatively correlated with the market. However since the database is made up primarily of Canadian stocks it is useful to employ the S&P/TSX index as well. Table 1 presents summary statistics for the data; it is noteworthy that the sample means of the data from the two brokerage houses are relatively similar using the DJIA but not the other indices.

Table 1
Summary Statistics for the Index Return Data

Pair of Variables	Mean of the Index Returns	Standard Deviation	Minimum	Maximum
DJIA-FB	0.02346	1.3036	-22.61	10.15
DJIA-MER	0.0138	1.3084	-22.61	10.15
S&P-FB	0.2179	1.2103	-20.46	9.10
S&P-MER	-0.0033	1.1916	-20.46	9.10
S&P/TSX –FB	0.05159	1.1045	-11.31	10.15
S&P/TSX – MER	0.144	1.075	-11.31	10.15

Sensitivity analyses were performed including modeling the probability of the event ‘buy’ being zero versus one, interaction effects of the independent variables from Equation 6, and various levels of changes in the index. The most parsimonious and statistically significant results are presented. The following tables are displayed for the logistic regressions using the daily returns and trader activities when the three different indices experience a 0.95% daily fall. Table 2 reports the results of both brokerage houses for the DJIA, Table 3 for the S&P 500 and Table 4 the Canadian S&P/TSX for the First Boston (FB) and Merrill Lynch (MER) data. The

[16] Bange, M., 2000, Do the Portfolios of Small Investors Reflect Positive Feedback Trading?, *Journal of Financial and Quantitative Analysis*, Vol 35, No. 2, p 239-255.

tables are presented as (a) which reports the results for Equation (6) and (b) Equation (7). Panel A in each table gives the results of the estimation for the total set of observations while Panels B and C present results for the turmoil and stable observations respectively.

Results for the tests of structural change are also presented in these tables. The (a) tables show the tests of comparing the two separate groups of data directly within Equation (6). It accomplishes this through an odds ratio between *GROUP* =1 and *GROUP* = 0. The techniques of computing an adjusted Chow Test using the *-2 Log Likelihood* statistics and the residual sum of squares are also presented here in the spirit of non-reliance on any single statistic to show significance. In the (b) sections of the table the Chow test is also computed using the *deviance* statistic as well as Levene's test of the *Homogeneity of Variances* and Welch's test of *Equality of Means* when the variances are known *a priori* to be unequal.

Table 2a: Logistic Regressions of DJIA Returns and Group on Broker Buys/Sells: Probability modeled is buy versus sell=1

	Sample Size / No of Buys	Otherwise	LOGISTIC COEFFICIENTS STATISTICS α	β_1	β_2	β_3	Elasticity at Means (e^{β})	Pseudo or Adj R^2	LOGISTIC REGRESSION STATISTICS Pearson χ^2 Pr>ChiSq	Deviance Pr>ChiSq	-2Log Likelihood with/without	H-L/DF Pr>ChiSq
FIRST BOSTON												
PANEL A												
Total	1439		1.02*	-0.08	5.5*	1.94*	0.92	0.0907	††	††	1435	9.21/8
	1080	359	(0.07)	(0.07)	(0.99)	(0.36)					1526	0.33
PANEL B												
Turmoil	180		6.53*	1.85*	†	†	6.36	0.6045	79	46*	60	2.18/8***
	160	20	(0.99)	(0.35)					0.89	1.0	125	0.93
PANEL C												
Stable	1259		1.02*	-0.08	†	†	0.92	0.0016	284	341	1465	9.36/8
	920	339	(0.07)	(0.07)					0.64	0.027	1466	0.31

FIRST BOSTON	*Tests of Structural Change - Equality of Regressions*			
(RSS_A = 269, RSS_B = 9 RSS_C=247)	Odds Ratios Group 0 vs 1	Chow Test $\chi2$ (-2 Log L)	Pr>ChiSq	Chow Test $\chi2$ (RSS)
α (turmoil) = α (stable)	1.866 (1.716 – 2.016)*	6.7151*	0.0096	24.22*
β_1 (tumoil) = β_1 (stable)	1.174 (1.040 - 1.326)*	29.3490*	<.0001	24.24*
α, β (turmoil) = α, β (stable)	0.230 (0.129 – 0.407)*	16.9328*	<.0001	18.17*

	Sample Size / No of Buys	Otherwise	α	β_1	β_2	β_3	Elasticity at Means (e^{β})	Pseudo or Adj R^2	Pearson χ^2 Pr>ChiSq	Deviance Pr>ChiSq	-2Log Likelihood with/without	H-L/DF Pr>ChiSq
MERRILL LYNCH												
PANEL A												
Total	1437		2.59*	-0.12	7.43*	2.93*	0.88	0.1329	††	††	681	7.66/8
	1330	107	(0.12)	(0.10)	(2.14)	(0.66)					762	0.4674
PANEL B												
Turmoil	182		10.02*	2.81*	†	†	16.6	0.7848	155*	24*	29	2.6/8**
	166	16	(2.14)	(0.65)					0.0001	1.0	108	0.95
PANEL C												
Stable	1255		2.59*	-0.12	†	†	0.88	0.0025	344**	275	652	10.5/8
	1164	91	(0.12)	(0.10)					0.0394	0.85	653	0.2318

MERRILL LYNCH	*Tests of Structural Change - Equality of Regressions*			
RSS_A = 96, RSS_B = 4 RSS_C=84	Odds Ratios Group 0 vs 1	Chow Test $\chi2$ (-2 Log L)	Pr>ChiSq	Chow Test $\chi2$ (RSS)
α (turmoil) = α (stable)	2.9967 (2.8047-3.1887)*	14.9079*	0.0001	21.68*
β_1 (tumoil) = β_1 (stable)	1.550 (1.241 – 1.937)*	19.9687*	<.0001	21.70*
α, β (turmoil) = α, β (stable)	0.422 (0.189 – 0.946)*	24.7897*	<.0001	16.24*

Notes: White, heteroscedasticity-consistent standard errors are reported in parentheses.
*, **, *** denotes significance at the 1%, 5% and 10% levels respectively.
† *Group* and *Group*Return* in the MLE procedure have been set to zero since the variables are a linear combination of other variables.
†† There is more than one profile of the explanatory variables with the same profile of the aggregate variables.

Table 2b: Logistic Regressions of DJIA Returns on Broker Buys/Sells: Probability modeled is buy versus sell =1

	Sample Size		LOGISTIC COEFFICIENTS STATISTICS				LOGISTIC REGRESSION STATISTICS			
	No of Buys	Otherwise	α	β	Odds-Ratio≡ Elasticity 95% Confidence Interval	Pseudo or Adj R^2	Pearson χ^2 Pr>ChiSq	Deviance Pr>ChiSq	-2LogLikelihood with/without	H-L/DF Pr>ChiSq
FIRST BOSTON										
PANEL A										
Total	1439		1.10*	-0.02	0.978	0.0002	410	478	1617	25.77/8
	1080	359	(0.06)	(0.05)	0.890 – 1.074		0.2428	0.0016	1618	0.0011
PANEL B										
Turmoil		180	6.53*	1.85*	6.39*	0.6045	79***	46*	60	2.18/8***
	160	20	(0.99)	(0.35)	3.212 – 12.716		0.09	1.00	125	0.93
PANEL C										
Stable		1259	1.02*	-0.84*	0.92	0.0016	284	341	1465	9.36/8
	920	339	(0.07)	(0.07)	0.803 – 1.054		0.6367	0.0270	1466	0.313

FIRST BOSTON	*Tests of Equality of Regressions*		*Tests of Homogeneity of Variances*		*Tests of Equality of Means*	
$RSS_A = 269$, $RSS_B = 9$ $RSS_C=247$	Chow Test (deviance)	(Pr>ChiSq)	Levene Test F	(Pr>F)	Welch Test F	(Pr>F)
α (turmoil) = α (stable)	25.28*	<0.0001	Stable=1.25 **	.0143	Stable=0.41	1.000
β (tumoil) = β (stable)	30.56*	<0.0001	Turmoil=4.51*	.0001	Turmoil=0.021	0.994
α, β (turmoil) = α, β (stable)	32.08*	<0.0001	Total= 1.25 **	.0143	Total=0.41	1.000

	Sample Size		α	β	Odds-Ratio≡ Elasticity 95% Confidence Interval	Pseudo or Adj R^2	Pearson χ^2 Pr>ChiSq	Deviance Pr>ChiSq	-2LogLikelihood with/without	H-L/DF Pr>ChiSq
MERRILL LYNCH										
PANEL A										
Total	1437		2.56*	0.27*	1.31*	0.0263	572*	364	746	29.05/8
	1330	107	(0.10)	(0.0004)	1.129 – 1.52		0.001	0.83	762	0.0003
PANEL B										
Turmoil		182	10.02*	2.81*	16.57*	0.7848	155*	24*	29	2.6033/8**
	166	16	(2.14)	(0.65)	4.657 – 58.924		0.0001	1.0	108	0.95
PANEL C										
Stable		1255	2.59*	-0.1231	0.884	0.0025	344***	275	652	10.4978/8
	1164	91	(0.12)	(0.10)	0.721 – 1.084		0.04	0.85	653	0.2318

MERRILL LYNCH	*Tests of Equality of Regressions*		*Tests of Homogeneity of Variances*		*Tests of Equality of Means*	
$RSS_A = 96$, $RSS_B = 4$ $RSS_C=84$	Chow Test (deviance)	(Pr>ChiSq)	Levene Test F	(Pr>F)	Welch Test F	(Pr>F)
α (turmoil) = α (stable)	25.28*	<0.0001	Stable=1.67*	.0001	Stable=1.65	0.0001*
β (tumoil) = β (stable)	30.56*	<0.0001	Turmoil=11.77*	.0001	Turmoil=0.0	1.000
α, β (turmoil) = α, β (stable)	32.08*	<0.0001	Total= 1.67 *	.0001	Total=0.25	1.000

Notes: White, heteroscedasticity-consistent standard errors are reported in parentheses.
*, **, *** denotes significance at the 1%, 5% and 10% levels respectively.

Table 3a: Logistic Regressions of S&P 500 Returns and Group on Broker Buys/Sells: Probability modeled is buy versus sell =1

	Sample Size		**LOGISTIC COEFFICIENTS STATISTICS**					**LOGISTIC REGRESSION STATISTICS**				
	No of Buys	**Otherwise**	**α**	**β_1**	**β_2**	**β_3**	**Elasticity at Means (e^{β})**	**Pseudo or Adj R^2**	**Pearson χ^2 Pr>ChiSq**	**Deviance Pr>ChiSq**	**-2 Log Likelihood with/without**	**H-L/DF Pr>ChiSq**
FIRST BOSTON												
PANEL A												
Total	1444		1.01*	-0.07	0.88*	0.03	0.93	0.0215	††	††	1609	4.955/8
	1080	364	(0.07)	(0.08)	(0.36)	(0.17)					1630	0.7624
PANEL B												
Turmoil	178		1.89*	-0.04	†	†	0.96	0.0007	93	79**	133	2.07/8**
	156	22	(0.35)	(0.15)					0.69	0.95	134	0.9787
PANEL C												
Stable	1266		1.01*	-0.07	†	†	0.93	0.0009	284	337	1476	3.0125/8***
	924	342	(0.07)	(0.08)					0.79	0.09	1477	0.9336

FIRST BOSTON — ***Tests of Structural Change - Equality of Regressions***

RSS_A = 270, RSS_B = 19 RSS_C=249	Odds Ratios Group 0 vs 1	Chow Test $\chi2$ (-2 Log L)	Pr>ChiSq	Chow Test $\chi2$ (RSS)
α (turmoil) = α (stable)	1.5214 (1.3838 – 1.659)*	9.1154*	0.0025	3.57
β_1 (tumoil) = β_1 (stable)	0.939 (0.819 – 1.076)	0.0399	0.8417	3.57
α, β (turmoil) = α, β (stable)	0.435 (0.253 – 0.747)*	15.7033*	<.0001	2.68

	Sample Size		**LOGISTIC COEFFICIENTS STATISTICS**					**LOGISTIC REGRESSION STATISTICS**				
	No of Buys	**Otherwise**	**α**	**β_1**	**β_2**	**β_3**	**Elasticity at Means (e^{β})**	**Pseudo or Adj R^2**	**Pearson χ^2 Pr>ChiSq**	**Deviance Pr>ChiSq**	**-2 Log Likelihood with/without**	**H-L/DF Pr>ChiSq**
MERRILL LYNCH												
PANEL A												
Total	1430		2.56*	-0.05	0.07	-0.19	0.95	0.0044	††	††	717	6.9065/8
	1331	99	(0.12)	(0.13)	(0.82)	(0.48)			0.65	1.0	719	0.5468
PANEL B												
Turmoil	175		2.63*	-0.24	†	†	0.79	0.0079	97	45*	65	8.2036/8
	167	8	(0.81)	(0.46)					0.49	1.0	66	0.4138
PANEL C												
Stable	1259		2.56*	-0.05	†	†	0.95	0.0003	281	242*	653	10.15/8
	1164	91	(0.12)	(0.13)					0.66	0.99	654	0.2550

MERRILL LYNCH — ***Tests of Structural Change - Equality of Regressions***

RSS_A = 93, RSS_B = 8 RSS_C=84	Odds Ratios Group 0 vs 1	Chow Test $\chi2$ (-2 Log L)	Pr>ChiSq	Chow Test $\chi2$ (RSS)
α (turmoil) = α (stable)	0.7977 (0.5732 – 1.0222)	0.5795	0.4465	2.69
β_1 (tumoil) = β_1 (stable)	0.930 (0.736 – 1.176)	0.1577	0.6913	2.70
α, β (turmoil) = α, β (stable)	0.711 ().295 – 1.711)	0.0011	0.9730	2.02

Notes: White, heteroscedasticity-consistent standard errors are reported in parentheses.
*, **, *** denotes significance at the 1%, 5% and 10% levels respectively.
† *Group* and *Group*Return* in the MLE procedure have been set to zero since the variables are a linear combination of other variables.
†† There is more than one profile of the explanatory variables with the same profile of the aggregate variables.

Table 3b: Logistic Regressions of S&P 500 Returns on Broker Buys/Sells: Probability modeled is buy versus sell =1

	Sample Size No of Buys	Otherwise	LOGISTIC COEFFICIENTS STATISTICS α	β	Odds-Ratio≡ Elasticity 95% Confidence Interval	Pseudo or Adj R^2	LOGISTIC REGRESSION STATISTICS Pearson χ^2 Pr>ChiSq	Deviance Pr>ChiSq	-2LogLikelihood with/without	H-L/DF Pr>ChiSq
FIRST BOSTON										
PANEL A										
Total	1444		1.10*	-0.187*	0.829*	0.0113	366	426	1619	12.57/8
	1080	364	(0.06)	(0.06)	0.739 – 0.930		0.92	0.23	1630	0.1274
PANEL B										
Turmoil	178		1.89*	-0.036	0.965	0.0007	93	79**	133	2.07**
	156	22	(0.35)	(0.15)	0.716 – 1.3		0.6918	0.95	134	0.98
PANEL C										
Stable	1266		1.01*	-.0696	0.933	0.0009	284	337	1476	3.0125/8***
	924	342	(0.07)	(0.08)	0.804 – 1.083		0.79	0.09	1477	0.93

FIRST BOSTON	*Tests of Equality of Regressions*		*Tests of Homogeneity of Variances*		*Tests of Equality of Means*	
RSS_A = 270, RSS_B = 19 RSS_C=249	Chow Test (deviance)	(Pr>ChiSq)	Levene Test F	(Pr>F)	Welch Test F	(Pr>F)
α (turmoil) = α (stable)	25.28*	<0.0001	Stable=0.96	.6259	Stable=0.43	1.000
β (tumoil) = β (stable)	30.56*	<0.0001	Turmoil=1.23	.2715	Turmoil=0.11	0.995
α, β (turmoil) = α, β (stable)	32.08*	<0.0001	Total= 0.96	.6269	Total=0.43	1.000

	Sample Size No of Buys	Otherwise	α	β	Odds-Ratio≡ Elasticity 95% Confidence Interval	Pseudo or Adj R^2	Pearson χ^2 Pr>ChiSq	Deviance Pr>ChiSq	-2LogLikelihood with/without	H-L/DF Pr>ChiSq
MERRILL LYNCH										
PANEL A										
Total	1430		2.61*	-0.1235	0.884	0.0029	359	287*	718	7.5945/8
	1331	99	(0.11)	(0.10)	0.730 – 1.070		0.88	1.0	719	0.4740
PANEL B										
Turmoil	175		2.63*	-0.2424	0.785	0.0079	97	45*	65	8.2036/8
	167	8	(0.81)	(0.46)	0.317 – 1.944		0.49	1.0	66	0.4138
PANEL C										
Stable	1255		2.56*	-0.0509	0.95	0.0003	281	242*	653	10.1451/8
	1164	91	(0.12)	(0.13)	0.732 – 1.234		0.66	0.99	654	0.2550

MERRILL LYNCH	*Tests of Equality of Regressions*		*Tests of Homogeneity of Variances*		*Tests of Equality of Means*	
RSS_A = 93, RSS_B = 8 RSS_C=84	Chow Test (deviance)	(Pr>ChiSq)	Levene Test F	(Pr>F)	Welch Test F	(Pr>F)
α (turmoil) = α (stable)	25.28*	<0.0001	Stable=1.48*	.0001	Stable=0.41	1.000
β (tumoil) = β (stable)	30.56*	<0.0001	Turmoil=3.41*	.0006	Turmoil=0.021	0.994
α, β (turmoil) = α, β (stable)	32.08*	<0.0001	Total= 1.48 **	.0001	Total=0.41	1.000

Notes: White, heteroscedasticity-consistent standard errors are reported in parentheses.
*, **, *** denotes significance at the 1%, 5% and 10% levels respectively.

Table 4a: Logistic Regressions of S&P/TSX Returns and Group on Broker Buys/Sells: Probability modeled is buy versus sell =1

	Sample Size		LOGISTIC COEFFICIENTS STATISTICS					LOGISTIC REGRESSION STATISTICS				
	No of Buys	Otherwise	α	β_1	β_2	β_3	Elasticity at Means (e^{β})	Pseudo or Adj R^2	Pearson χ^2 Pr>ChiSq	Deviance Pr>ChiSq	-2Log Likelihood with/without	H-L/DF Pr>ChiSq
FIRST BOSTON												
PANEL A												
Total	1443		1.23*	-0.26*	0.41	0.20	0.77	0.154	††	††	1602	11.7670/8
	1085	358	(0.07)	(0.07)	(0.3)	(0.18)					1617	0.1619
PANEL B												
Turmoil	196		0.82*	-0.06	†	†	0.94	0.0011	81*	97	234	25.0865/7
	140	56	(0.29)	(0.17)					0.0098	0.0003	235	0.0007
PANEL C												
Stable	1247		1.23*	-0.26*	†	†	0.77	0.0158	329	402	1367	13.7383/8
	945	302	(0.07)	(0.07)					0.1168	0.0001	1380	0.0888

FIRST BOSTON — ***Tests of Structural Change - Equality of Regressions***

RSS_A = 268, RSS_B = 40 RSS_C=226	Odds Ratios Group 0 vs 1	Chow Test χ2 (-2 Log L)	Pr>ChiSq	Chow Test χ2 (RSS)
α (turmoil) = α (stable)	1.2112* (1.106 – 1.3164)	9.3776*	0.0022	3.61***
β_1 (tumoil) = β_1 (stable)	0.791* (0.692 – 0.904)	3.1483**	0.0760	3.6***
α, β (turmoil) = α, β (stable)	1.905* (1.261 – 2.877)	9.4672*	0.0021	2.7

	No of Buys	Otherwise	α	β_1	β_2	β_3	Elasticity at Means (e^{β})	Pseudo or Adj R^2	Pearson χ^2 Pr>ChiSq	Deviance Pr>ChiSq	-2Log Likelihood with/without	H-L/DF Pr>ChiSq
MERRILL LYNCH												
PANEL A												
Total	1447		2.68*	-0.23*	-0.70	0.27	0.80	0.0161	††	††	754	7.54/8
	1340	107	(0.12)	(0.09)	(0.44)	(0.2)					763	0.4812
PANEL B												
Turmoil	108		1.98*	0.05	†	†	1.05	0.0009	58	50	83	14.15/8
	94	14	(0.43)	(0.18)					0.40	0.70	84	0.08
PANEL C												
Stable	1339		2.68*	-0.23*	†	†	0.80	0.0095	329	271	670	5.81/8
	1246	93	(0.12)	(0.09)					0.09	0.86	675	0.67

MERRILL LYNCH — ***Tests of Structural Change - Equality of Regressions***

RSS_A = 99, RSS_B = 12 RSS_C=86	Odds Ratios Group 0 vs 1	Chow Test χ2 (-2 Log L)	Pr>ChiSq	Chow Test χ2 (RSS)
α (turmoil) = α (stable)	1.5282* (1.191 – 1.8657)	25.2802*	<.0001*	59.96*
β_1 (tumoil) = β_1 (stable)	0.830 *(0.693 – 0.995)	10.7475*	0.0132	60*
α, β (turmoil) = α, β (stable)	2.869* (1.432 – 5.747)	4.7775**	0.0288	64.97*

Notes: White, heteroscedasticity-consistent standard errors are reported in parentheses.
*, **, *** denotes significance at the 1%, 5% and 10% levels respectively.
† *Group* and *Group*Return* in the MLE procedure have been set to zero since the variables are a linear combination of other variables.
†† There is more than one profile of the explanatory variables with the same profile of the aggregate variables.

Table 4b: Logistic Regressions of S&P/TSX Returns on Broker Buys/Sells: Probability modeled is buy versus sell =1

	Sample Size No of Buys	Otherwise	LOGISTIC COEFFICIENTS STATISTICS α	β	Odds-Ratio≡ Elasticity 95% Confidence Interval	LOGISTIC REGRESSION STATISTICS Pseudo or Adj R^2	Pearson χ^2 Pr>ChiSq	Deviance Pr>ChiSq	-2LogLikelihood with/without	H-L/DF Pr>ChiSq
FIRST BOSTON										
PANEL A										
Total	1443		1.12*	-0.12**	0.88*	0.0051	423**	500	1612	18.18/8
	1085	358	(0.06)	(0.06)	0.793 - 0.987		0.047	0.0001	1617	0.02
PANEL B										
Turmoil	196		0.82*	-0.06	0.94	0.0011	81.17*	97	234	25.01/7
	140	56	(0.29)	(0.17	0.679 – 1.3		0.0098	0.0003	235	0.0007
PANEL C										
Stable	1247		1.23*	-0.26*	0.772*	0.0158	329	402	1367	13.74/8
	945	302	(0.07)	(0.07)	0.67 – 0.89		0.116	0.0001	1380	0.0888

FIRST BOSTON	*Tests of Equality of Regressions*		*Tests of Homogeneity of Variances*		*Tests of Equality of Means*	
$RSS_A = 268$, $RSS_B = 40$ RSS_C=226	Chow Test (deviance)	(Pr>ChiSq)	Levene Test F	(Pr>F)	Welch Test F	(Pr>F)
α (turmoil) = α (stable)	25.28*	<0.0001	Stable=1.68*	.0001	Stable=0.45	1.000
β (tumoil) = β (stable)	30.56*	<0.0001	Turmoil=2.58*	.0004	Turmoil=1.13	0.4132
α, β (turmoil) = α, β (stable)	32.08*	<0.0001	Total= 1.68 **	.0001	Total=0.45	1.000

	Sample Size No of Buys	Otherwise	α	β	Odds-Ratio≡ Elasticity 95% Confidence Interval	Pseudo or Adj R^2	Pearson χ^2 Pr>ChiSq	Deviance Pr>ChiSq	-2LogLikelihood with/without	H-L/DF Pr>ChiSq
MERRILL LYNCH										
PANEL A										
Total	1447		2.54*	-0.06	0.94	0.0007	445*	329	763	12.38/8
	1340	107	(0.10)	(0.09)	0.785 – 1.126		0.0005	0.7978	764	0.1351
PANEL B										
Turmoil		108	1.98*	0.04	1.043	0.0009	58	49	83	14.15/8
	94	14	(0.43)	(0.18)	0.738 – 1.476		0.40	0.70	84nm	0.0778
PANEL C										
Stable		1339	2.68*	-0.23*	0.797*	0.0095	330***	271	670	5.81
	1246	93	(0.12)	(0.09)	0.663 – 0.958		0.09	0.86	675	0.67

MERRILL LYNCH	*Tests of Equality of Regressions*		*Tests of Homogeneity of Variances*		*Tests of Equality of Means*	
$RSS_A = 99$, $RSS_B = 12$ RSS_C=86	Chow Test (deviance)	(Pr>ChiSq)	Levene Test F	(Pr>F)	Welch Test F	(Pr>F)
α (turmoil) = α (stable)	25.28*	<0.0001	Stable=1.59 *	.0001	Stable=0.41	1.000
β (tumoil) = β (stable)	30.56*	<0.0001	Turmoil=0.86	.5940	Turmoil=0.021	0.995
α, β (turmoil) = α, β (stable)	32.08*	<0.0001	Total= 1.59 *	.0001	Total=0.41	1.000

Notes: White, heteroscedasticity-consistent standard errors are reported in parentheses.
*, **, *** denotes significance at the 1%, 5% and 10% levels respectively.

The following issues are pertinent to the specification of Equations (6) and (7). It is not feasible to compute the *deviance* and *Pearson* statistics for the total observations in Equation (6). This occurs because both the *RETURN* and the *GROUP* share the same profile when the data is aggregated.[17] The dummy variable "*GROUP*" was used to differentiate the data to accommodate one single regression but has nullified the residual statistics for the total dataset. However the similar statistic *-2 log likelihood ratio* is produced, with and without the covariates to provide an adapted CHOW test. Mc Cullugh and Neder (1989) suggest using multiple measures to check for goodness/lack of fit. It is also not feasible using Equation (6) to determine the coefficients for *GROUP* and *GROUP*RETURN* individually for the turmoil and non-turmoil set of data since turmoil is defined as *GROUP* = 0 and non-turmoil *GROUP* = 1.[18]

A different issue occurs with the estimation of Equation (7). Since this specification does not test the group effect, the *deviance* statistic measures it directly here by comparing the three different regressions. Here the assessment of dummy variables or the group effect can be made using the chi-square difference, a nested technique based on an adapted Chow test. Another major benefit of this specification is to determine the confidence intervals of the odds ratios. Using this specification it is also possible to check for constant variances and means across the different sets of observations. Pertinent points regarding the statistical estimation are summarized below.

A. Tests and Interpretations of the Logistic Regression Coefficients

The initial assessment of the procedure involved tests to determine whether the independent variables are *significantly* related to the variable that measures the outcome. Accordingly the parameters of interest are calculated and interpreted. Positive (negative) signs of the estimated coefficients suggest linear increases (decreases) in the log of the odds or probability. Typically the intercept coefficient is of little interest. Many times when it is significant however it suggests missing independent variables. The slope coefficient is of greater interest and "represents the change in the logit corresponding to the change of one unit in the independent variable" (Hosmer & Lemeshow 2000 p 48). Consequently a positive slope (beta)

[17] Sigularity or near-singularity may result.

[18] Sigularity or near-singularity may result.

coefficient estimate of the market index indicates that the event (1), in this case buy, is more likely given a level of return than a (0) or sell/no changes. A negative coefficient estimate indicates that buys are less likely given a level of return. Consequently if turmoil conditions exist as measured by the change in the market index, a positive beta implies a larger probability of buying securities versus selling or no change. A positive beta for the market index is only observable with statistical significance during turmoil conditions for both brokerage houses using the DJIA; otherwise most results show a significantly negative coefficient during stable periods and for the total set of observations.

A conventional *t* statistic for the statistical significance of each estimated coefficient can be computed. Hypothesis tests for significance of the regression coefficients attempt to determine whether any omitted variables have an effect on the model. The significance levels of the group and group*return coefficients suggest that market turmoil conditions significantly affect the probability for both brokerages using the DJIA and the total FB data using the S&P500.

Measures of Marginal Effects:

Estimated coefficients are used to interpret association among explanatory variables in logistic regressions. The logistic coefficients themselves unlike with OLS are not marginal effects. The marginal effect here is the slope of the probability curve relating x to $\Pr(Y=1|x)$, holding all other variables constant. The effect is such that the model will never predict a probability greater than one, and will diminish as the probability gets closer and closer to one. These effects are evaluated by assuming a trader has a mean response for every independent variable. The mathematical basis for the marginal effects is available in Greene (1997).[19]

The marginal probability will have the same sign as the coefficient when evaluated at the means. As mentioned previously, proper interpretation of these variables depends on the difference between two logits, the effect on the margin. Marginal effects at the mean are directly built into the coefficients because of the exercise of taking logarithms. An elasticity measure gives the percentage change in the probability of a success in response to a one percentage change in the explanatory variable. Greene (2000, p. 816) notes that the elasticities vary for

[19] Greene, W., 1977, *Econometric Analysis,* Macmillan Publishing Company, New York.

every observation so it is desirable to report a summary measure by evaluating the expression at every observation and then taking the average.[20] The "Elasticity at Means" indicates the percentage change in the probability of a trader buying more of a security as a result of a one-percent change in the relevant explanatory variable (the market index return) when all variables are evaluated at their mean values. The result is meaningful when the explanatory variable of interest is roughly continuous, such as return, but not for the dummy variables. These results for both Equations (6) and (7) are the same for the turmoil and non-turmoil observations, equation (6) gives the effect of *RETURN* in isolation and equation (7) includes the confounding effects from the different groups.

Odds Ratio:

This measure of association is equivalent to the Elasticity at Means statistic. It is a test of whether the individual odds ratios are significantly different from 1 (no association) or test whether two odds ratios are different from each other. Some view it as a measure of relative risk (Rothman and Greenland 1998)[21]. These non-parametric tests use the chi square statistic. If the statistic is large relative to the degrees of freedom then the model does not significantly describe the data. Analysis using the odds ratios illustrates the change in the probability of the dependent variable for a unit change in the independent variable depending on the starting or reference point. The Elasticity at Means and the Odds ratio show significant levels for the turmoil data using the DJIA. However interestingly, it also shows significance for the total MER data in the scenario using the DJIA as a dependent variable.

The tables show statistical significance using the DJIA for both brokerages. This is probably because the effect from the turmoil data is lending an undue influence on the total data, especially since it does not show up in the non-turmoil data. Significant results are also seen for the total observations at FB using the S&P500 and S&P/TSX as well as the stable results at FB and MER using the S&P/TSX. This is probably a result of the negative correlation of mining stocks at the S&P/TSX and the total market index at S&P500.

The estimation of the odds ratio using Equation (6) is useful in determining the interaction effects. If there is an interaction effect between a risk factor and another variable, the

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[20] Greene, W. H., 2000, *Econometric Analysis,* 4th edition, Upper Saddle River, New Jersey: Prentice-Hall.

[21] Rothman, K. J. and Greenland, S., 1998, *Modern Epidemiology*, 2nd ed. Lippincott-Raven, Philadelphia.

estimate of the odds ratio of the risk factor will vary. This interaction is seen in two ways. The first is by comparing the estimates for the total observations under specifications Equation (6) and (7). If they are different it implies the only variables that do not exist in the other specification are significant. In all cases there are differences suggesting that the group effect and the group*return interaction effect are important. A direct test is on the odds ratio comparing *GROUP* =0 with *GROUP*=1 which is presented as an adapted (since it is also nested) Chow test in the (b) sections of all the tables and is based on Hosmer & Lemeshow (2000, pg 75).

Odds Ratios and 95% Confidence Intervals:

The interval provides additional information about the parameter. It is useful to measure the likelihood that the odds ratio 1 is found within the interval, in which case the model does not significantly describe the data. The only consistently statistically suitable odds ratio statistics are for the turmoil observations. The tables that use the DJIA data show the odds of buying over selling during the turmoil observations are six times that of the stable observations for FB and 16 times for MER. For the stable and total observations, the probabilities are statistically equally likely that the trader will buy or sell except in the case as mentioned previously for MER. The number 1 occurs in the confidence intervals for all the remaining regressions except for MER in the stable observations of the S&P/TSX data. The tables show similar results as reported for the individual ratios noted above but with a 95% confidence interval. This lends some support to the postulation that the buy actions of traders are inversely related to the returns on the S&P/TSX.

B. Overall Tests of the Logistic Regressions

Significance of the Model, Influence or Goodness of Fit Statistics:

In OLS regressions r^2, the coefficient of determination can be used to measure overall fit of the model. Several analogous measures of fit have been suggested for logit models but none of them supports a straightforward interpretation as r^2. The adjusted or pseudo R^2 of logistic methods can be calculated using a variety of methods and are all based on comparisons of the predicted values from the fitted model to those from a model using an intercept only. Ljungqvist and Wilhelm Jr. (2005), in their study of "weather" as providing a behavioral bias use "probit" regressions and consider a "pseudo R^2 of 23.5%" in conjunction with a significant Pearson chi-square statistic as providing evidence of a "good" model. Unfortunately low R^2 values are the norm in logistic regression, a fact difficult to reconcile with the relatively higher r^2 common in OLS regressions. Consequently it is important to review R^2 in conjunction with other measures to determine "goodness of fit". Aldrich and Nelson's (1984) pseudo or adjusted R^2 measure suggests significant support only for the model during times of turmoil using the DJIA on the data from both brokerage houses. The R^2 squared for the turmoil set of observations is roughly 60% at FB and 78% at MER while it is negligible for the stable set.

The residual sum of squares in logistic regressions is not as useful as in OLS since the deviation of each observation from 1 will not be considerable since a probability deviation from 1 will give a negligible result. These are calculated for all the market indices for both brokerage houses and are seen to have only fractional remainders of the sum of the two separate sets from the total set. In logit regressions the equivalent measures of sum of squared residuals are the *deviance residuals* and the *likelihood ratio*. The statistic will follow a $\chi2$ distribution rather than an F, can be calculated and used in an adapted Chow test. Another measure of discrepancy between observed and fitted values analogous to the residual sum of squared errors in OLS is the *Pearson residuals*. The test statistics are the *Pearson χ^2 statistic* which is the sum of the *Pearson residuals* and the *deviance*, the sum of squared *deviance residuals*. This *Likelihood Ratio Goodness of Fit statistic* (LR) is also based on the comparison of the restricted and unrestricted maximum of the log likelihood function. These tests are described in Mc Cullagh & Nelder (1989) and follow an asymptotic chi-square distribution with degrees of freedom equal to $(m\text{-}1)*(k+1)$, where m is the number of sub-samples and k is the number of independent variables in the model. The *Pearson* statistic on the other hand is a true goodness of fit test since a significant statistic suggests a good fit.

Since the *deviance* test statistic determines whether a given logit model is worse than a perfectly fitted (saturated or full) model, it is more appropriately known as a "badness of fit" test since non-significant residual deviances or residuals are considered good fit. A "smaller" *deviance* value given a particular sample size would indicate that the fitted model describes the data as a whole well whereas a "large" value would suggest otherwise. Thus, the *deviance* can also be used directly to test the goodness of fit of the model. The *deviance* statistic gives support for the model during turmoil conditions for both brokerages using the DJIA. It also gives some support for the actions during turmoil conditions at FB using the S&P 500. Surprisingly it also shows statistical significance at MER for all observations and conditions using the S&P 500.

The log-likelihood statistic is adjusted to present the *-2 Log Likelihood test* which determines the difference between the model with intercept only and the one with all the covariates. The results presented include the total statistic which measures all the covariates and the difference from the model with only the intercept. A good fitting model will have a very significant difference between the two statistics. The absolute value of the statistic is heavily dependent on the number of observations in the sample. As noted in the appendix, for logistic regressions, the Chow test can be adapted using the chi-square value produced by subtracting the *–2 Log Likelihood* for the two nested models. It has one degree of freedom. Meaningful differences are prevalent for both brokerage house turmoil observations using the DJIA.

A third measure of standardized residuals is provided by the Hosmer-Lemeshow (H-L) Goodness-of-Fit Test (also know as the *Lackfit* test). Some studies suggest that the *deviance* statistic is not distributed as chi-square when there are a small number of observed values (less than 400). The Hosmer-Lemeshow fit test is designed to correct for the small sample size (especially when there are continuous predictors). This provides a chi-square-based test that assesses how well the data under analysis perform under the null hypothesis that the model fits the data. Again, when this test is *not significant* then the model being tested is a good fit to the data because this means the parsimonious model is not significantly worse than the well-fitting saturated model. Mc Cullagh & Neder (1989) caution against using a single statistic to draw conclusions about goodness of fit, so several are be presented with a conclusion based on the significance levels of more than one of them. Using the DJIA for the turmoil data, the results show consistently for both brokerage houses that the model is a good fit (or not a bad fit) to model the probability that a broker will buy securities during a down market versus sell/no change. There is also support at FB using the S&P 500 for the turmoil and stable observations separately.

Tests of Structural Change and Equality of Regressions:

Most statistical tests rely on the assumption of static parameters of the model (or the covariances of the data have remained constant over the sample observations). However during periods of unusual circumstances it is likely this is an unrealistic assumption and that the model can be improved by accounting for structural changes that may have caused the model parameters to change. A typical test for structural stability is Chow's (1960)[22] Breakpoint Test. This test divides the data into two sub-samples. It then estimates the same equation for each sub-sample separately, to see whether there are significant differences in the estimated equations. A significant difference indicates a structural change in the relationship. The Chow test for ordinary linear squares regression is an *F* test that involves computing the residual sum of squares of the regression. In logistic regression, the analogy to this residual is the *deviance*. The test consists of determining the significance probability of the *deviance* for a given degrees of freedom. If this probability is small, then the null hypothesis of no significant change in the data prior to and after the structural change is rejected, suggesting evidence of a structural change in the data. Toyoda (1974)[23] shows that the Chow test "is well behaved even under heteroscedasticity as long as at least one of two sample sizes is very large".

There are still some studies that believe that the Chow tests can provide wrong conclusions in the presence of heteroscedastic disturbances. Additionally it is not conceptually feasible to use the *deviance* in the same manner as the residual sum of squares in OLS. This is because a very large denominator (which is comprised predominantly of the number of observations) will produce a large statistic that may seem to be statistically significant even if the deviance is small. Consequently, this statistic has to be adapted somewhat for a logistic equation. Instead it is more suitable to divide the data into groups depending on the different characteristics, for example turmoil observation versus stable observation and then checking for similarities between the two groups. When the two different methods give the same indications, the result is a robust test for the structural equality of logistic regression parameters, a Chow test that is chi square distributed.

Another definition of the 'Chow test' equivalent to pooling the data, estimating the fully interacted model, and then testing the hypothesis that the group 1 coefficients are significantly

[22] Chow, G., 1960, Tests of Equality Between Sets of Coefficients in Two Linear Regressions, *Econometrica,* vol. 28, 591-605.

[23] Toyoda, T., 1974, Use of the Chow Test under Heteroscedasticity, *Econometrica*, Vol. 42, No. 3, May, pp. 601-608.

different to the coefficients estimated in group 0, is a preferential method for testing for parameter consistency. This is an odds ratio test on Equation (6).[24]

The tests show significant results for both brokerage houses using DJIA as a predictor, for FB only using S&P 500 as a predictor, but only the intercepts show significant differences for the use of S&P/TSX as a predictor. Consequently, the null hypothesis that the regression slopes, intercepts and total regression for the market turmoil and non-turmoil observations are equal is rejected and supported by all three versions of the Chow test and the odds ratio variation. This statistic shows statistically significant structural break points occurred principally for the loss of the DJIA index greater than the 0.95% point

In Tables 2(a) and (b) the most striking results from the regressions on Equations (6) and (7) is that the chi square of the return and standard errors are highly significant for the market turmoil data set but not the non-turmoil nor total observation data using the DJIA. It is also significant for Merrill's total set of observations possibly because the effect in the turmoil observation is strong. Using S&P 500 as a predictor the only significant result is for First Boston (FB)'s total set of observations. The results for the stable set of observations of FB are significant at the 1% and 5% for MER when the S&P/TSX is used. This may imply that since the S&P/TSX is heavily weighted with natural resources it may exhibit a negative correlation with the returns of the general market and consequently show different characteristics than the DJIA or S&P 500.

Test of Homogeneity of Variances and Tests of Equality of Means:

The test of Homogeneity of Variances, the Levene test and the Test of Equality of Means if the variances are known *a priori* to be unequal, the Welch test, are typically not measured for logistic regressions since the dichotomous dependable variable is not normally distributed. However there are benefits to computing these statistics to understand the characteristics of the data. The Levene tests show convincingly using the DJIA and various other sets of observations using the S&P500 and the S&P/TSX that the variances are not homogeneous. Given the lack of homogeneity, the Welch tests show there are virtually no differences in the means.[25]

[24] This Type 3 analysis of effects is reported as part of the logistic procedure in SAS.
[25] The procedure in SAS automatically drops groups in the Levene test for homogeneity of BUY_SELL variances across different return groups. In addition, groups are dropped from Welch's ANOVA of return effect for BUY_SELL for no observed variability.

Consequently, there are no observed differences in these tests between the stable and total observations. There is however a noticeable difference in these tests in the turmoil observation for all three parts. The null hypothesis of homogeneous variances can be decisively rejected when the DJIA is used for both brokerage houses and FB only with the S&P/TSX. Given that this is the case in these parts, the Welch test is not meaningful. However using S&P500, the null hypothesis that the means are equal once tests show that the variances are not equal, can be rejected.

It is noteworthy that the coefficients derived for the variables using logit/probit procedures only have meaning relative to each other, therefore the absolute magnitude of the coefficients is not interpretable like it is in ordinary least squares regression models. The model represents the association of the dependent variable, which represents the probability of a particular choice being made, and the independent variable. Therefore, the regression parameters represent the change in the buys/sells associated with a unit change in the incremental return of the market, and do not necessarily represent causal effects. Hence, the model represents a convenient way to explain relationships or predict the propensity to buy or sell given the known inputs or extreme change in the market conditions.

The results reported from the different brokerage houses indicate robustness of the effects because of their similar conclusions. Arguably, the more experienced traders at various brokerage houses may be less prone to behavioral biases. The differential experience levels can account for significantly different trader behavior. An exercise for future exploration can include a test of statistically significant difference between the two brokerage houses.

C. Implication of these Results

The results using the DJIA consistently lend support to the null hypothesis that during observations of market turmoil, investors trade differently while the other two indices lend some support. The exercise affirms behavioral biases suggesting that perceptions and sentiment may heavily influence trading patterns. This observation leads to an extension of the methodology of this study. It may also be useful to investigate how the above results change with the inclusion of another indicator of investors' risk preferences, sentiment.

V. Alternative Empirical Specifications

Evidence suggests that stock market returns can be predicted by a compendium of financial and macroeconomic variables manifested across stock markets and over different time horizons. Studies of US equity returns have reported that fundamental variables, such as earnings yield, cash flow yield, book-to-market ratio and size, have predictive power (e.g. Basu (1977), Fama and French (1992), Lakonishok, Shliefer and Vishny (1994). Fama and French (1993) argue that a three-factor asset-pricing model is the appropriate benchmark against which anomalies should be measured. In other words, other factors are priced as risk.

In as much as interpretations and robustness of the results are heavily influenced by the type of distributions and sample sizes, the results may be improved through an alternative specification of the model. The results so far indicate that traders in Toronto significantly base their trading decisions on the daily changes in the DJIA. This thesis now attempts to follow Fama and French (1993)'s multifactor approach to Merton's (1973) ICAPM to determine whether other factors like the return on DJIA, change in Consumer Sentiment and Trader Activity contribute to changes in the market index as a whole as defined by the S&P 500. The result is a multi-factor model as suggested by Fama and French (1996). The framework will however be limited to a behavioral one.

Since there are many more non-turmoil observations than market turmoil, the data can be combined into one sample with the different types of observations being assigned dummy variables. The resulting model specifies these different observations as independent variables.

$$\textit{Model:} \quad RETURN = \alpha + \beta_1 \, (BUY\_SELL) + \beta_2 \, GROUP + \varepsilon \qquad (8)$$

Since the previous section noted that the results based on the DJIA showed a high correlation between trader behavior and market returns it is a good candidate for inclusion in an extension of the methodology. In this specification of the model, the dependent variable is the market return. The dummy variable *GROUP* is defined as 1 for the group of market turmoil observations, and 0 for the non-turmoil ones. The other independent variable is as defined as the brokerage data from the previous section, the *BUY_SELL* responses of the traders. This methodology serves a two-fold purpose, since the number of market turmoil observations is far less than the non-turmoil ones, it eliminates biases that may be caused by inferences made from extreme differences in sample size. Secondly, it allows for testing of sub-hypotheses that check for the effect of several behavioral factors. Since the return of the market is the new dependent variable, sub-hypotheses include whether the lagged returns of the DJIA or other behavioral factors like the traders' buy or sell activities and investor sentiment are parsimonious predictors. Adding lags may also enhance the plausibility of the assumption of normalcy in the error term, with mean zero and constant variance.

Since the dependent variable is no longer binary a logit or probit specification is no longer necessary and predictive tendencies can be discerned using OLS. Lakonishok and Smidt (1988), in a test for seasonal patterns in rates of return on 90 years of data, also specified the predicted variable as the return on the market. An *F*-test is conducted on the joint significance of the regression coefficients. The general model is presented as follows:

$$\textit{Model:} \qquad RETURN = \alpha + \beta_1\,(x_1, x_2, x_3) + \beta_2\,GROUP + \varepsilon \qquad (9)$$

Where x_1, x_2, x_3 may be any independent variables that can determine buy/sell activity for example sentiment, bankruptcies, volume of stock traded, buys or sells. The dummy variable (*GROUP*) will again be one during market turmoil and zero otherwise. The caveat here is the interpretation. Is the market return predicted by these behavioral factors, or does market return predict consumer behavior? It may be argued that the DJIA is a behavioral factor since it has the capacity to create either euphoria or fear. Lagged endogenous and/or exogenous variables are typically introduced in order to reduce the autocorrelation and endogenous regressors problems. The lagged return is especially useful since anecdotally and empirically it has been noted that based on mean reversion of returns, traders first over-react and then eventually pull back (Shefrin 2001). Therefore, it can also be used as a behavioral factor in this multi-factor model. Hence, an alternate index like the S&P 500 can be classified as the market return as is the norm in empirical studies.

The test would be therefore on whether or not the β's are significantly different from zero. If they are, this supports the hypothesis that investor behavior is different because of behavioral factors as well as market conditions (turmoil versus non-turmoil). A major advantage of this specification is the assumptions of ordinary least squares are no longer violated and more robust statistics can be computed. [26]

A. ***Lagged DJIA, Consumer Sentiment & Trader Activity as Predictors of the Market Return (S&P500)***

There is a large difference in sample sizes among the market turmoil and non-turmoil observations. Consequently, the implications may be skewed if the data is tested separately. Therefore, by aggregating the data one large sample can be tested with the observations from the turmoil and non-turmoil environments being categorized using dummy variables. Since the model no longer involves estimating a discrete choice dependent variable, the estimation is no longer constrained to calculating probabilities. Hence, the model can be estimated using ordinary least squares achieving the benefits of coefficients with special meanings; however, it is important to determine that the assumptions of normality and equal variances are not violated. In regression models, when the data are time-series in nature, there is a possibility that the error terms follow an autoregressive process. An autoregressive error model corrects for serial correlation. Since ordinary least-squares regression assumes constant error variance, heteroscedasticity problems cause the OLS estimates to be inefficient. Another problem that arises is the OLS forecast error variance is inaccurate since the predicted forecast variance is based on the average variance instead of the variability at the end of the series. Therefore, the estimation will be adjusted for heteroscedasticity and serial correlation in this section. [27]

The specification of this model suffers from a drawback. The DJIA is serially correlated with the S&P 500. Even though it is not an extremely large component of this market, the results may be compromised. Using a lagged return of the S&P 500 should solve this problem. Additionally, the lagged return will check for evidence of herding. Herding occurs when a group of investors trades the same stock in the same direction over time, while feedback trading occurs when lagged returns act as the common signal that the investors follow.

$$RETURN = \alpha + \beta_1 (RETURN_{t-1}) + \beta_2 (SENT) + \beta_3 (SENT_{t-1}) + \beta_4\, BUY\_SELL_{\,1} + \beta_5\, GROUP + \varepsilon \quad (10)$$

---

[26] Unfortunately the endogeneity issue remains.
[27] The estimation procedure in SAS, PROC AUTOREG accounts for changing variance and as a member of the family of GARCH models provides a means of estimating and correcting for the changing variability of the data. The GARCH process assumes that the errors, although uncorrelated, are not independent and models the conditional error variance as a function of the past realizations of the series.

The variables are defined as follows:

$RETURN_i$ = return on S&P 500

α = intercept

β_1 = coefficient estimate of the impact of the lagged S&P return

$RETURN_{t-1}$ = the one-day lagged return on the S&P 500

β_2 = coefficient estimate of the impact of change in sentiment

SENT = change in sentiment, as measured by the change in the consumer sentiment index

β_3 = coefficient impact of the one period lagged change in sentiment

$SENT_{t-1}$ = lagged change in sentiment

β_4 = coefficient impact of trader activity

BUY_SELL = dummy variable defined as one for trader "buys" and zero otherwise

β_5 = coefficient impact of "market turmoil" versus "non-turmoil" condition

GROUP = dummy variable defined as one for market turmoil observations and zero otherwise

ε = Error term

All the variables have been defined before except for the sentiment data.[28] During the period under investigation, this index was only collected quarterly. Therefore, it was essentially the same over a three-month period. The results are also treated for heteroscedasticity. Another confounding effect as mentioned before is, while investors may over-react one day, they may re-think their behavior and compensate the following day, eventually leading to mean-reversion. Since the behavioral bias of over-reaction is not being investigated in this thesis the DJIA can be removed from this specification and replaced with a lag of the S&P 500. Table 3-4a presents results using DJIA and its lag and the specification reported in Table 3-4b utilizes the S&P500 and its lag to verify that the results produced by the two indices are similar. Intuitively the specification in equation (9) using the DJIA in lieu of the S&P500 undoubtedly leads to high predictive capacity based on the results from the first set of equations that show that the DJIA

[28] The measure of sentiment used here is the Index of Consumer Confidence (ICC). The monthly Index of Consumer Confidence is constructed from responses to four attitudinal questions posed to a random sample of Canadian households. The Index has been accumulated monthly since December 2001 but quarterly since 1971.

was a good predictor of the brokers' buy/sell or change decisions during this time frame. Table 5a reports regression results for the estimated models on FB and then MER using S&P 500 and its lagged return.

$$\hat{RETURN} = 0.058 + 0.20RETURN_{t-1} + 0.001SENT + 0.003SENT_{t-1} + 0.2315BUY\_SELL - 1.8209GROUP$$

(0.058)* (0.0228)* (0.004) (.004) (.06)* (0.10)*

$$\hat{RETURN} = 0.072 + 0.1978RETURN_{t-1} - 0.001SENT + 0.003SENT_{t-1} + 0.1683BUY\_SELL - 1.7613GROUP$$

(0.1018)* (0.0230)* (0.004) (.004) (0.11)* (0.0990)*

Table 5a: Regression Statistics

FIRST BOSTON			
Total R-square Corrected for heteroscedasticity		0.3594	
Durbin Watson		1.9381	
Total R-square		0.7502	
Test of the Model (Pr > F = <.0001)		7.45*	
Tests of Structural Change	Chow Test	42.28*	Break Point 173
MERRILL LYNCH			
Total R-square Corrected for heteroscedasticity		0.3520	
Durbin Watson		1.9337	
Total R-square		0.7486	
Test of the Model (Pr > F = <.0001)		6.35*	
Tests of Structural Change	Chow Test	32.25*	Break Point 175

Table 5b reports regression results for the estimated models on FB and then MER using the DJIA and its lag.

$$\hat{RETURN} = 0.037 + 0.2827RETURN_{t-1} - 0.002SENT + 0.001SENT_{t-1} + 0.1704BUY\_SELL - 1.2754GROUP$$

(0.054)* (0.0238)* (0.004) (.004) (.06)* (0.09)*

$$\hat{RETURN} = -0.27 + 0.2652RETURN_{t-1} - 0.0015SENT + 0.001SENT_{t-1} + 0.4826BUY\_SELL - 1.3167GROUP$$

(0.0967)* (0.0233)* (0.004) (.004) (0.10)* (0.0920)*

Table 5b: Regression Statistics

FIRST BOSTON			
Total R-square Corrected for heteroscedasticity		0.3144	
Durbin Watson		1.9061	
Total R-square		0.7740	
Test of the Model (Pr > F = <.0001)		8.47*	
Tests of Structural Change	Chow Test	35.37*	Break Point 173
MERRILL LYNCH			
Total R-square Corrected for heteroscedasticity		0.3280	
Durbin Watson		1.9051	
Total R-square		0.7688	
Test of the Model (Pr > F = <.0001)		8.22*	
Tests of Structural Change	Chow Test	32.25*	Break Point 175

B. Consumer Sentiment & Trader Activity as Predictors of the Market Return (S&P500)

Since the DJIA and S&P500 produce similar results the analysis using the DJIA will be dropped henceforth. The previous model can provide a reference point to see how much predictive power is lost by removing the lagged S&P 500 as a regressor.

The new model to be estimated therefore is:

$$RETURN = \alpha + \beta_1 (SENT) + \beta_2 (SENT_{t-1}) + \beta_3\, BUY\_SELL + \beta_4\, GROUP + \varepsilon \quad (11)$$

The variables are defined as previously described but excludes the lagged S&P 500. Table 6 reports regression results for the specification in Equation (10) for the estimated models on FB and then MER.

$$\hat{RETURN} = 0.12 + - 0.002\, SENT + 0.002\, SENT_{t-1} + 0.1523\, BUY\_SELL - 1.8142\, GROUP$$

(0.056)* (0.004) (0.004) (.06)* (0.0843)*

$$\hat{RETURN} = -0.26 -0.002\, SENT + 0.002\, SENT_{t-1} + 0.5374\, BUY\_SELL - 1.839\, GROUP$$

(0.1009)* (0.004) (0.004) (0.1037)* (0.0833)*

Table 6: Regression Statistics

FIRST BOSTON			
Total R-square Corrected for heteroscedasticity		0.2442	
Durbin Watson		1.2781	
Total R-square		0.2702	
Test of the Model (Pr > F = <.0001)		23.88*	
Tests of Structural Change	Chow Test	44.07*	Break Point 178
MERRILL LYNCH			
Total R-square Corrected for heteroscedasticity		0.2672	
Durbin Watson		1.3247	
Total R-square		0.3374	
Test of the Model (Pr > F = <.0001)		32.84	
Tests of Structural Change	Chow Test	28.62*	Break Point 175

C. ***Implication of these Results***

From Tables 5 and 6 we can see that the behavioral factors lagged *S&P500*, lagged *DJIA* and the *BUY_SELL* dummy variables are significant in this multi-factor model. During turmoil times when the *GROUP* dummy is 1, return is shown to be significantly negative since it outweighs the coefficient for *BUY_SELL*. Sentiment is not a significantly priced factor. This is probably reflective of the fact that during the period under consideration in this paper the Canadian Consumer Sentiment data was aggregated only quarterly. Consequently, much of the daily effects may have been lost by dated information. In an analysis of *r* squared it did show some small contribution to the general strength of the regression. Therefore, a further exercise could be to utilize a better measure of consumer sentiment than this quarterly data. It is noteworthy that the lagged value of the *S&P500* and the *DJIA* are significantly priced risk factors, lending support to herding behavior.

It is useful here to test whether the power of the specification is greatly reduced by removing all explanatory factors except for the buy-sell dummy variable. While this specification may be nonsensical since it is presumptuous to believe that the trader activity of two small brokerage houses can significantly affect the return on the market, the spirit of the argument is motivated by a study by Hirshleifer & Shumway (2003).[29] This study seeks exogenous factors like the sunshine effect, rain and snow conditions to determine the probability that stock market returns in New York are positive. They determine that the sunshine effect

[29] Hirshleifer, David & Shumway, Tyler, 2003, Good Day Sunshine: Stock Returns and the Weather, *The Journal of Finance,* 58 (3), 1009-1032.

consistently predicts positive daily returns, and investors can improve their Sharpe ratios by trading on morning weather conditions. They conclude that after accounting for transactions costs, the benefit of this information is greatly diminished but "sunshine is just one of the many influences on mood". The implications of this study make reconciliation with fully rational efficient markets difficult and suggest that a traders' reference point (i.e. whether he has experienced wealth losses or not) plays an important role in market returns. Consequently, if it is assumed that investors' buy/sell decisions are exogenous to the daily return of a market index and are one of the priced factors that can successfully be used in "assessing the information processing ability of financial markets" (Roll 1992)[30], then the above specification is useful. It is noteworthy however that this specification is entirely different to the original specification in this thesis, which suggests that the buy/sell decisions depend on the state of the market. The resultant estimation gives the following equation and Table 7a reports the results:

$$\hat{RETURN} = \underset{(0.0554)^*}{0.12} + \underset{(.06)^*}{0.15}\ BUY\_SELL - \underset{(0.0842)^*}{1.8137}\ GROUP \qquad FB$$

$$\hat{RETURN} = \underset{(0.10)^*}{-0.26} + \underset{(.10)^*}{0.538}\ BUY\_SELL - \underset{(0.0801)^*}{1.839}\ GROUP \qquad MER$$

Table 7a

FIRST BOSTON			
Total R-square Corrected for heteroscedasticity		0.2439	
Durbin Watson		1.2769	
Total R-square		0.2439	
Test of the Model (Pr > F = <.0001)		232*	
Tests of Structural Change	Chow Test	59.20*	Break Point 178
MERRILL LYNCH			
Total R-square Corrected for heteroscedasticity		0.2670	
Durbin Watson		1.3234	
Total R-square		0.2670	
Test of the Model (Pr > F = <.0001)		262*	
Tests of Structural Change	Chow Test	70.84*	Break Point 175

[30] Roll, R. W., 1992, Weather, in Peter Newman, Murray Milgate, and John Eatwell, ed.: *The New Palgrave Dictionary of Money and Finance,* Macmillan Press: London, 3, 789–790.

Table 7b reintroduces the DJIA and its lag since it was a better contributing factor in the initial logit specification.

$$\hat{RETURN} = 0.12 + 0.22\ BUY\_SELL - 2.2815\ GROUP \qquad FB$$
$$(0.0560)^* \quad (.0651)^* \quad (0.0867)^*$$

$$\hat{RETURN} = 0.06 + 0.242\ BUY\_SELL - 2.2138 GROUP \qquad MER$$
$$(0.10)^* \quad (.11)^* \quad (0.0860)^*$$

Table 7b

FIRST BOSTON			
Total R-square Corrected for heteroscedasticity		0.3248	
Durbin Watson		1.4943	
Total R-square		0.3248	
Test of the Model (Pr > F = <.0001)		347*	
Tests of Structural Change	Chow Test	81.97*	Break Point 173
MERRILL LYNCH			
Total R-square Corrected for heteroscedasticity		0.3182	
Durbin Watson		1.4996	
Total R-square		0.3182	
Test of the Model (Pr > F = <.0001)		336*	
Tests of Structural Change	Chow Test	16.76*	Break Point 175

These results are fairly similar but the serial correlation problem remains.

D. ***Interpreting the Results***

The results are consistent with the initial specification presented in this thesis. Even though it is not practical to model the return on a major index as being predicated by the buy/sell activities of two small brokerage houses, the relatively high *r* squared and the significance of the coefficients show that they are highly correlated. Additionally structural change as measured by the Chow statistic is statistically significant at the point where the turmoil versus non-turmoil break in observations occurred.

While we expect that institutional investors will generally sell when markets are down and buy during up markets since there is an expectation that their mutual fund clients and other investors would require redemptions, the activity does not have to be repeated in the brokers' "own" accounts. Several considerations may play a role here, traders/brokers may buy since they see value or they see potential for arbitrage profits during periods when markets deviated from normal trading patterns according to Merton's (1987) zero arbitrage risk-return relation. Unfortunately the data cannot clarify these ambiguities. However, during times of extreme wealth altering conditions these considerations may play less of a role in investor behavior.

There is an ongoing argument regarding market anomalies. One theory suggests that anomalies exist and are currently being exploited as sources of alpha (the constant) in the regression, while some note that anomalies disappear over time. Therefore it is useful to incorporate a multi-factor model to search for factors that compensate investors for risk as suggested by Fama and French (1993).

E. Limitations and Robustness of this Methodology

This methodology, while it can not formulate utility functions, places loss aversion as opposed to risk aversion as defined in rational expectations theory, as being prevalent during periods of extreme wealth altering circumstances or "market turmoil". A limitation of this methodology occurs because we are unable to obtain risk preferences or risk aversion directly, which is a necessary component of prospect theory.[31] A detailed survey of the literature showing attempts to measure risk aversion directly in included in Starmer (2000).[32] Therefore, we can assume that risk aversion or loss aversion is reflected in the buy/sell decision.

Since the coefficients in the sample of non-turmoil data as well as the total sample of both market turmoil and non-turmoil data were found to be insignificant (equations 6 and 7), suggesting other variables may be more important, it is necessary to check for robustness of the econometrics and the specification of the model.

F. Potential Extensions

Checks of robustness may include tests for heteroscedasticity, with arbitrary within-year correlation (cluster by year) and arbitrary between firm correlation (cluster by brokerage). Another question that can be asked is, can some set of other independent variables that determine buy/sell activity be able to predict the buying or selling (no change) behavior? Subsequently, an

[31] Benartzi, Shlomo & Thaler, Richard H, 1995, Myopic Loss Aversion Myopic Loss Aversion and the Equity Premium Puzzle, *The Quarterly Journal of Economics,* vol. 110(1), 73-92.

[32] Starmer, C, 2000, Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk, *Journal of Economic Literature, Vol. XXXVIII* (*June*), 332–382.

expanded version of the full model with additional independent variables can be considered. Similarly, tests can be conducted as to whether year or brokerage fixed effects in the regressions affect the results. Whether results are sensitive to variations in the cutoff values for small and large trades can also be investigated. The regression can be repeated for each year in the sample, and for various other sub-samples including cut-offs for "market turmoil" definitions.

Special situations that bear further investigation include events that occur when the market increased by specified percentage levels. This is an attempt to formalize Mr. Greenspan's observation of "Irrational Exuberance". There is also a possibility that the changes in positions (i.e. bought or sold) are not accurate since the data only details the change in percentage of the security in the portfolio. Thus, the portfolio as a whole may have gone down in value more than the security in question, or vice versa. An additional test can then be performed on the data under a "binary dependent" variables approach.

VI Conclusions

A logit specification was employed to predict the probability that traders at the Toronto branches of two large multinational brokers would buy securities during periods of wealth reducing periods. This specification was chosen in lieu of OLS because of non-normality concerns, heteroscedasticity and the constraints that predicted values were constrain between zero and one. Alternative specifications using OLS were also employed to check for robustness of the effect.

Consistent with Thaler & Johnson's (1990) survey and Shefrin's (2001) anecdotal account, but in contrast to Barberis, Huang and Santos (2001), the probability of traders buying stock after a period of wealth losses as defined by a substantial fall in the returns of a major index increases. From the perspective of expected utility theory, behavioral biases should have no explanatory power. However, empirical investigation of the buy/sell actions of institutional traders at the Toronto branches of two large brokerage houses show that the traders seem to be able to withstand significant losses to their portfolios until they reach some threshold of intolerance, or reflection point in the jargon of Prospect Theory. At this threshold point, they reacted differently.

Anecdotal evidence suggests that individual investors evaluate their portfolio performance at the end of every quarter and react or make changes to the portfolio, after reviewing its efficacy. The performance of professional traders is also evaluated against some benchmark at the end of every quarter. This study seeks answers from a more frequent assessment period, daily evaluation of a trader's portfolio. Evidence supporting different behavior under market turmoil conditions was found especially for the use of the DJIA as a predictor of traders' purchases, sales and no change in their market making and proprietary accounts. If trader behavior can be connected to consumer behavior and assuming traders make changes to their portfolios based on these characteristics, then it would be feasible to investigate aggregate behavior at an economy wide level. A definitive characterization of trader behavior and the applicability for generalization remains a meaningful challenge for future research.

Bibliography

Arkes, H.R. & Blumer, C., (1985), The Psychology of Sunk Cost, *Organizational Behavior and Decision Processes*, 35, 124 – 140.

Baker and Wurgler, (2003) Investor sentiment and the cross-section of stock returns, *NBER Working Paper 10449* November 2003

Barber and Odean, (2000), Trading is hazardous to your wealth: The common stock performance of individual investors, *Journal of Finance*, 55, 773-806.

Barber, B and T. Odean (2001), Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261-292.

Barberis, N. and M. Huang (2001), Mental accounting, loss aversion, and individual stock returns , *Journal of Finance* 56, 1247-1292.

Barberis, N., A. Shleifer, and R. Vishny, (1998), A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Barberis, N., M. Huang and T. Santos (2001), Prospect theory and asset prices, *Quarterly Journal of Economics* 116, 1-53

Benartzi, S. and R.H. Thaler (2001), Naive diversification strategies in defined contribution savings plans, *American Economic Review* 91, 79-98.

Biais, B. and R. Shadur (2000), Darwinian selection does not eliminate irrational traders, *European Economic Review* 44, 469-490.

Bleichrodt, Han, Jose Luis Pinto, & Peter P. Wakker (2001), Making Descriptive Use of Prospect Theory to Improve the Prescriptive Use of Expected Utility, *Management Science* 47, 1498-1514.

Campbell, J. Y., A. W. Lo and A. C. MacKinlay (1997). *The Econometrics of Financial Markets*. Princeton, NJ: Princeton University Press.

Chordia, T., A. Subramanyam and V.R. Anshuman, (2001), Trading activity and expected stock Returns, *Journal of Financial Economics*, 59, 3-32.

Coval, J.D., and T. Shumway (2002), Do Behavioral Biases Affect Prices? Paper Presented at the *2001 Western Finance Association*.

Coval, J.D., D. Hirshleifer and T. Shumway (2002), Can Individual Investors Beat the Market? *Working Paper*

Daniel, K., D. Hirshleirfer, and A. Subrahmanyam, (1998), Investor psychology and security market under- and over-reactions, *Journal of Finance*, 53, 1839-1886.

Daniel, K., D. Hirshleirfer, and A. Subrahmanyam, (2001), Overconfidence, Arbitrage and equilibrium asset pricing, *Journal of Finance*, 56, 921-965

De Bondt, W., and R. Thaler (1987), Further evidence on investor overreaction and stock market seasonality, *Journal of Finance* 42:557−581.

DeLong, J. B., Shleifer, A., Summers, L. H. and Waldmann, R. J. (1990), Noise trader risk in financial markets. *Journal of Political Economy* 98(4): 703-738.

Ding, Charoenwong and Seetoh, (2004), Prospect Theory, Analyst Forecasts, and Stock Returns*,* *Journal of Multinational Financial Management* Volume 14, December 2004, 425-442

Fama, Eugene F., (1998), Market Efficiency, Long-Term Returns, and Behavioral Finance*,* *Journal of Financial Economics*, 49, 283-306.

Fama, E. & French, K. (1992), The cross-section of expected stock returns, *Journal of Finance*, vol. 47, pp. 427-67.

Fama, Eugene and Kenneth French, (1993), Common risk factors in the returns of stocks and bonds, *Journal of Financial Economics* 33, 3-55.

Fiegenbaum, A. (1990), Prospect Theory and the Risk-Return Association, An Empirical Examination in 85 industries, *Journal of Economic Behavior and Organizations*, 14, 187 – 203.

Gervais and Odean, (2001), Learning to be overconfident, *Review of Financial Studies*, 14, 1-27

Grinblatt, Mark and Matti Keloharju, (2001), What Makes Investors Trade? *The Journal of Finance*, April 2001, Vol. 56 No. 2, pp. 589-616.

Hirshleifer, David (2001) Investor Psychology and Asset Pricing, *Journal of Finance*, August 2001, Vol. 56 No. 4, pp. 1533-1597.

Hong, H. and J. C. Stein, (1999), A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance*, 54, December 1999, 2143-2184.

Kahneman and A. Tversky, (1979) Prospect Theory: An Analysis of Decision under Risk, *Econometrica* (47):262-291

Keim and R. Stambaugh, (1986) Predicting Returns in the Stock and Bond Markets, *Journal of Financial Economics*, (17): 357-390

Kogan, L., Ross, S., Wang, J. and Westerfield, M. (2003), The Price Impact and Survival of Irrational Traders, *NBER Working Paper Series, Working Paper 9434,* January 2003

Kyle, A.S., Ou-Yang, H., and Xiong, W., (2004), Prospect Theory and Liquidation Decisions, *Journal of Economic Theory, September 15, 2004*

Lakonishok, J., A. Shleifer, and R. W. Vishny (1994). Contrarian Investment, Extrapolation and Risk, *The Journal of Finance*, 49(5): 1541–1578.

Lakonishok, J and Smidt, S., Are seasonal anomalies real? A ninety-year perspective *Review of Financial Studies*, 1988, vol. 1, no. 4, pp. 403-425(23)

Levy and H. Markowitz, (1979), Approximating Expected Utility by a Function of Mean and Variance, *The American Economic Review*, June 1979 (69):308-317

Ljungqvist, A. and W.J. Wilhelm, (2005), Does Prospect Theory Explain IPO Market Behavior? *Journal of Finance*, Forthcoming August 2005.

Locke, Peter and Steven Mann, (1999), Do professional traders Exhibit Loss Realization Aversion? *Texas Christian University, Working Paper*

Loughran and Ritter, (2000), Uniformly least powerful tests of market efficiency, *Journal of Financial Economics*, 55, 361-389.

Malkiel, Burton G., (2003), The Efficient Market Hypothesis and Its Critics, *Journal of Economic Perspectives,* Vol 17, No. 1: 59 – 82

Marsh and Merton, (1986), Dividend Variability and Variance Bound Tests for the Rationality of Stock Prices, *American Economic Review*, June 1986:483-497

Miller, E., (1977), Risk, Uncertainty and Divergence of Opinion *Journal of Finance*, Volume 32, Issue 4 (Sep., 1977), 1151-1168

Mullainathan, S & Richard Thaler, (2000), Behavioral Economics, *MIT Department of Economics Working Paper No. 00-27*

Newman, D.P, (1980), Prospect Theory: Implications for Information Evaluation, *Accounting Organizations and Society*, 1980(5): 217-230

Nofsinger, J.R., and R. W. Sias, (1999), Herding and Feedback Trading by Institutional and Individual Investors, *Journal of Finance* 54, no. 6: 2263-2295.

Odean, Terrance,(1998), Are Investors Reluctant to Realize their Losses, *Journal of Finance* 53, 1775-1798.

Odean, Terrance, (1998), Do Investors Trade Too Much? *American Economic Review*1989, 1279-1298

Pratt, J., (1964), Risk Aversion in the Small and in Large. *Econometrica.,* 32: 122-136.

Goldfeld, S.M. and Quandt, R.E. (1976), *Studies in Nonlinear Estimation*, Cambridge, MA: Ballinger Publishing Company

Rubinstein, Mark (2001), Rational Markets: Yes or No? The Affirmative Case, *Financial Analysts Journal*, May/June, 15-29

Rudd, A. T., (1979), The Revised Dow Jones Industrial Average: New Wine In Old Bottles? *Financial Analysts Journal,* November-December, 57-63.

Savage, L. J. (1954). “The Sure-Thing Principle.” In Leonard J. Savage, *The Foundations of Statistics*. New York: John Wiley, pp. 21–26.

Shefrin, Hersh, (2005), A Behavioral Approach to Asset Pricing, *Academic Press (Elsevier) Advanced Finance Series*

Shefrin, Hersh and Meir Statman. (1985), The Disposition to Sell Winners Too Early and Ride Losers too Long. *Journal of Finance*. 40, pp. 777-792.

Shefrin and Statman, (1994), Behavioral capital asset pricing theory, *Journal of Financial and Quantitative Analysis*, 29, 323-349.

Shefrin, Hersch and Meir Statman, (2000), Behavioral Portfolio Theory, *Journal of Financial and Quantitative Analysis,* June 2000, Vol. 35 No. 2, pp. 127-152.

Shleifer, A. and Vishny, R. W., (1997), The limits of arbitrage, *Journal of Finance* 52: 35-55

Shiller, Robert, (2000), Irrational Exuberance, Princeton University Press

Simon, Herbert. (1955). A Behavioral Model of Rational Choice. *Quarterly Journal of Economics*.,pp. 99-118.

Sinha, Tapen, (1994), Prospect Theory and the Risk Return Association: Another Look, *Journal of Economic Behavior and Organization*, 1994, v24 (2), 225-231

Slovic, Paul, (2000), The Perception of Risk, London; Sterling, VA: Earthscan Publications

Soane, Emma, (2001), Knowing the Risks: Theory and Practice in Financial Market Trading, *Human Relations*, Vol 54, Issue 7

Subramanyam, K. (1996), The pricing of discretionary accruals, *Journal of Accounting and Economics*, 1996, 22, 249-281.

Thaler, Richard, (1985), Mental accounting and consumer choice, *Marketing Science* 4, 199–214.

Thaler, R., Tversky, Kahneman & Schwartz, (1997), The Effect of Myopia and Loss Aversion on Risk Taking: An Experiment Test, *The Quarterly Journal of Economics*, May 1997: 647 - 661

Tversky and D. Kahneman, (1992), Advances in Prospect Theory: Cumulative Representation of Uncertainty, *Journal of Risk and Uncertainty* 1992(5): 292-323

Varian, H., (1985), Divergence of opinion in complete markets: A note, *Journal of Finance*, 1985, 40

Vriend, Nicolaas J., (1996), Rational Behavior and Economic Theory, *Journal of Economic Behavior and Organization*, 1996, v29 (2, Mar), 263-285

Willman, Paul, Mark Fenton, O'Creevy, Nigel Nicholson, Emma Soane, (2001), Traders, Managers and Loss Aversion in Investment Banking, *Journal of Accounting, Organization and Society* (January 2001).

Xie, Yu, and Charles F. Manski, (1989), The Logit Model and Response-Based Samples, *Sociological Methods and Research,* 17(3): 283–302.