Overreaction diamonds: Precursors and aftershocks for significant price changes

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Overreactions and other behavioral effects in stock prices can best be examined by adjusting for the changes in fundamentals. We perform this by subtracting the relative price changes in the net asset value (NAV) from that of market price (MP) daily for 134,406 data points of closed end funds trading in US markets. We examine the days before and after a significant rise or fall in price deviation and MP return and find evidence of overreaction in the days after the change. Prior to a spike in deviation we find a gradual two or three day decline (and analogously in the other direction). Overall, there is a characteristic diamond pattern, revealing a symmetry in deviations before and after the significant change. Much of the statistical significance and the patterns disappear when the subtraction of NAV return is eliminated, suggesting that the frequent changes in fundamentals mask behavioral effects. A second study subdivides the data depending on whether the NAV or market price is responsible for the spike in the relative difference. In a majority of spikes, it is the change in market price rather than NAV that is dominant. Among those spikes for which there is little or no change in NAV, the results are similar to the overall study. Furthermore, the upward spikes are preceded by one or two days of declining market price while NAV rises slightly or is relatively unchanged. This suggests that a cause of the spike may be due to over-positioning of traders in the opposite direction in anticipation.

Keywords: Overreaction; Price deviation; Diamond pattern; Over-positioning; Market dynamics; Financial markets; Behavioral finance; Closed-end funds

1 Introduction

During the past few decades, there has been an intense debate about the dynamics of stock prices. The prevalent theory has been the Efficient Market Hypothesis (EMH), which stipulates that stock prices move in accordance with the change in valuation. Since all participants quickly gain access to the same public information, there is a unique valuation about which the stock fluctuates randomly due to the presence of traders who are less informed. Thus, according to EMH, there is a unique price at each given moment that represents the value. Since a large number of traders are aware of this value, and eager to exploit any deviations from it, these deviations are not only temporary, but also random. If the deviations were biased in a particular way, the knowledgeable traders, argue the EMH theorists, would be aware of the bias and seek to exploit it, thereby eliminating it. The existence of systematic patterns in prices thus argues against the underlying assumptions of EMH.

In recent years, a new set of ideas, known as Behavioral Finance (BF), has gradually provided an alternative to EMH by stipulating that systematic biases exist in market dynamics. One aspect of this is that even experts are subject to the behavioral biases. Even if portfolio managers were not subject to these biases, they often do not have the latitude to reduce their exposure to stocks, or even a particular sector. For example, a manager may believe that almost all of the technology stocks are overvalued at a particular time. However, his fund prospectus may require that at least 95% of the assets be invested and that it be sector neutral (so that the percentage of technology stocks in his portfolio must match that of the S&P). The decision to buy the mutual fund itself is made by a less informed individual, but the manager can only mitigate that decision by an insignificant amount. To aggravate matters, any rise in the overvalued sector automatically increases their percentage ratio in the S&P, thereby forcing the manager to buy even more of the stocks that he believed to be overvalued.

Of course, EMH theorists would say that while a particular set of managers may be in this situation, there will be a large amount of capital, for example in hedge funds, that will take advantage of this by using short selling. However, there are many restrictions on short selling. Ultimately, these issues involve the quantities of assets and the behavior of investors controlling them. Hence the question of whether these assets are adequate to restore efficiency needs to be decided by an examination of the data. If the basic ideas of EMH are essentially correct, then the data would not exhibit any systematic biases, since the more informed traders would recognize and exploit them, thereby eliminating the effect.

A number of studies have shown systematic bias by examining either a long or short time horizon, as discussed below in the literature survey. A key idea in these studies involves comparing the return on a stock with the expected return based upon the overall market. In examining returns, there is an error or noise term specific to the stock or the sector, as discussed in classical finance (see Bodie et al. (2005)). Essentially, this means that many factors can be expected to influence a particular stock. The randomness involved in these firm specific changes adds a significant amount of noise to any data analysis. For a given stock, if one has a reliable model for changes in valuation which could be subtracted from the trading price return, then this "noise" arising from the random events that alter valuation could be removed. This would leave behind either random fluctuations (as EMH would assert) or particular patterns reflecting systematic bias (as BF would assert). The difficulty here, for most stocks, is that there is no unique way to quantify changes in valuation. Data analysis utilizing a particular scheme for computing the valuation on a day-to-day basis would leave open the question of whether a different valuation procedure would lead to the same conclusions.

In order to circumvent these issues we consider a class of stocks, namely closed-end funds, for which the valuation is available based upon the underlying assets. Closed-end funds have been studied in numerous papers (see Anderson and Born (2002) for survey), and are similar to other companies in that they are initiated by the pooling of a sum of money for a particular type of investment. For example, suppose that $300 million is raised for investment in the German stock market and the shares are priced (initially arbitrarily) at $15, yielding 20 million shares. Once the fund is launched and the $300 million is used to purchase German stocks, these investments will rise and fall along with the trading prices of those German stocks. The net asset value (NAV) is defined as the total value of the investments assets net of liabilities divided by the total number of shares and is computed daily. In our example, this would be $15 initially, but would change with the German market subsequently. Meanwhile, once the initial public offering is concluded, the shares trade on the NYSE as any other stock. This means of course that there is no requirement that they trade at, or even near, the NAV. If they trade below the NAV, the stock is said to be trading at a discount, and analogously for a premium. Precisely, one defines the premium as

$$\text{Premium} = (\text{Trading Price -NAV})/\text{NAV}.$$

The theoretical value of a closed-end fund is clearly related to its NAV. The NAV, plus or minus some percentage that varies very slowly in time, can be regarded as fundamental value.

The major difference between the closed-end investment companies and most other companies is that the former is simpler, and its value is easier to establish. The advantage of using closed-end funds is that unlike typical corporations, the firm's value is readily determined because the majority of assets are carried at fair market value rather than at historic cost. If the fund were liquidated at any point, the amount rendered for each share would be the NAV minus a small amount for the cost of the transactions. This is not only a theoretical possibility but also a reality for several funds that have been liquidated in this way.

The fact that NAV is explicitly determined on a regular basis provides an opportunity to examine relative price changes and their relationship with valuation. Any inefficiency that is discovered in markets is usually labeled as an "anomaly", suggesting that it is an unusual aberration from the norm of efficient markets. Studies of closed-end funds that demonstrate inefficiency are often classified in this way, suggesting that similar phenomena do not occur with other stocks. An examination of some features of the closed-end fund data suggests that the trading volume, ownership and exchange under which they are traded are similar to most other stocks. In particular, the daily trading volume in many closed-end funds is highly significant, usually in tens of thousands of shares, as with many mid-cap stocks. An examination of securities filings for closed-end funds shows ownership by a spectrum of institutions as well as individual investors. A large majority of these are traded on the NYSE, so that the same rules apply. Given these similarities in trading volume, ownership and rules of trading (exchange mechanism), there is little to suggest that the short term price dynamics of closed-end funds would be significantly different from other stocks.

The vast majority of the studies of closed-end funds have focused on the long term issues. Many of the closed-end funds have traded at discounts for prolonged times (Anderson and Born (2002), Chapter 6.). Various explanations have been advanced to account for this phenomenon, such as the structure of the fund, and the possibility that they will issue more shares, etc [1]. In some cases the discount may be compatible with EMH. For example, there may be a tax liability in the closed-end fund. However, it is more difficult for EMH to justify systematic changes in the discount or premium that occur on a short term basis, which is our main interest in this paper.

If the EMH were valid, the discount or premium would either be zero for all time, or slowly changing. Hence, the existence of a chronic discount or premium that may be due to tax related issues, for example, will not be relevant for our study. Moreover, even if there were some fundamental reason for an abrupt change in the discount or premium, it would not address the issue that we study in this paper, namely, the precursors and aftershocks of this change.

In many cases, a premium or discount widens over a time period of weeks or months with relatively little change in the NAV. In the case of a large premium, the phenomenon appears to have the characteristics of a classical bubble. Sometimes, the origin of the bubble is due to a large interest in a particular country for which there are only a few ways to invest (Bosner-Neal et al. (1990)). However, similar bubbles occur even when this is not the case. For example, the premium for the Spain Fund (SNF) grew to 50% in January of 2005, while the NAV was gradually declining, even though an exchange traded fund (EWP) could be purchased within 1% of its net asset value. Near the end of the Spain Fund bubble there were several days on which the trading price rose by several percent while the NAV was almost unchanged. The bubble burst as the trading price dropped by 19.32% on one day, again with little change in the NAV.

Utilizing 52 closed-end funds we begin by considering the set of days ("events") in which there is a significant deviation between the relative change in the market price and that of the NAV (see Section 2 for precise definition). This could occur in several ways; either there is a large change in the NAV and little corresponding change in the trading price, or there is a large change in the price without much change in the NAV. Alternatively, there could be a moderate change for both in opposite directions. For example, suppose there is a 1% increase in NAV on a given day (Day 0). If there is a 5% increase in the price, then we would have a 4% deviation. [Obviously, there is a strong relation between deviation and premium so that a positive deviation on Day 0 corresponds to a decrease in discount or an increase in premium. If the change in discount or premium

[1] Value based managers often say that some stocks (particularly those that are not in the limelight) are chronically undervalued. However, since there is no unique calculation to assess the value of a typical industrial corporation, the studies that can be done (e.g., using price-to-earnings ratios) are not as precise or convincing as the studies of closed-end funds.

is zero, then the deviation is zero as well.]

We allow for the possibility that the excess change in price (on Day 0) could be due to some fundamental reason, such as a share buyback offer. The question is, what do we expect for the following day (Day 1)? If there were no systematic biases, then we would expect that the deviation of the following day would be zero. [Note that although there is a tiny drift term in both the NAV and the market price, the expected difference in drift will be zero. See main diagonal of Table 1.] If, on the other hand, we were to obtain a large sample of such events (Day 0), and find that, on average, there is a decrease in the difference between the relative change in the market price and that of NAV on Day 1, then this would be evidence of a systematic bias. Often the terminology "overreaction" is used when there is a change on a subsequent day in the opposite direction of the original day, and the term "underreaction" refers to subsequent change in the same direction.

Using this procedure, we do not need to make a determination as to which market, say the closed-end fund in the NYSE, or the German market in the example above, is more efficient, and which market is overreacting. In many cases, we expect that it is the NAV representing the trading in a larger market that will be more efficient and less volatile. This is confirmed by a study by Pontiff (1997) that showed a set of closed-end funds that were 64% more volatile than the underlying index. For example, the NAV of a fund investing in Japan is determined by a huge trading volume compared with the volume of the closed-end fund that invests in Japan. Consequently, one would expect, from the perspective of either EMH or BF, that the volatility would be greater in the smaller market, namely the closed-end fund. From this perspective, we have also examined statistically the change in market price for subsets of data in which the NAV exhibits a change that is within a particular range. Consistent with the study of Pontiff, our data suggests that a relatively small fraction of the events are characterized by large relative changes in NAV accompanied by small relative changes in the trading price. Most of the deviations occur with a relatively small change in the NAV that triggers a large change in trading price.

A subset of our data set consists of closed-end funds whose assets are abroad, e.g., Spain Fund, Germany Fund, although the fund itself trades on the New York Stock Exchange (NYSE). The Asian and European markets end their trading day well before the close of the NYSE, so an investor can easily augment the NAV of the Fund from the previous day with the changes that have occurred in the current day. For example, if the latest NAV reported for the Spain Fund is \$ 10.00 and the Spain stocks have increased by 2% in terms of dollors, then the NAV at the end of the day is expected to be about \$ 10.20. A more precise estimate can be obtained by determining the positions of the fund and pricing the securities according to the latest available data (including currency changes). Although trading in US stocks may provide some additional information on the NAV the next day, studies have shown that for most of these foreign funds, the correlation is small (Anderson et al. (2001)). Hence, the results we obtain are not likely to be an artifact of time lag in markets. Nevertheless, the patterns we find are also present in the subset of closed end funds with assets in the US.

In both sets of statistical results (i.e., those involving deviations between MP return and NAV return, as well as deviations in MP return when there is little change in NAV) we have found that there is evidence of an overreaction, i.e., on Day 1 there is a statistically significant change in the deviation that is in the opposite direction. Hence, a drop in the deviation on Day 0 is followed by a rise on Day 1, and analogously for a rise in the deviation. We have found overreaction for the market price returns as well. Unlike some of the studies on prices alone, these predictable changes on Day 1 are very substantial. Even more surprising, however, is the price movement in the opposite direction on the day prior to Day 0. In other words, a rise of the deviation on Day 0 is preceded by a dip. The key features of our results are displayed in Figure 1, in which the characteristic diamond pattern displays the gradual decline in deviations before the spike, and the decline after the spike. The opposite is true for a significant decline in deviations on Day 0. Figure 1 shows a symmetry between the upward and downward spikes, for low and medium threshold levels. But, more surprisingly, there is also an approximate symmetry between the days before and the days after the significant change (see Figure 1).

The presence of a decline <u>before</u> a sharp rise, from the perspective of EMH, is even more surprising than a subsequent decline. After all, one can attribute the decline after a sharp rise to an imperfect price adjustment process that has a time scale of a few days. However, the decline before a sharp rise indicates that there is a precursor of the deviation that is part of the cause. In the absence of an infinite amount of capital that is immediately available for arbitrage, one can explain this phenomenon as follows. On the day before the sharp rise there is an anticipation of negative news and, consequently, underinvestment on the part of the speculative traders. When the news is better than expected (e.g., a small rise in NAV instead of a sharp drop), there is an imbalance of cash/asset as the underinvested are rushing to buy. This initial and rapid price rise fuels further momentum buying that leads to a price at the end of Day 0 that is considerably higher than the previous day.

In other words, the overreaction happens because too many traders are caught short or underinvested, and there is a subsequent stampede to buy. The situation is analogous for downward spike on Day 0.

The perspective outlined above differs significantly from the EMH in that it invokes the concept of the finiteness of assets (see Caginalp and Balenovich (1999)), rather than infinite arbitrage capital that is central to EMH. In order to examine the possible underlying causes we partition the data in Section 3 into four parts. We find that a majority of the spike events we consider are the result of market price returns rather than relative changes in NAV. In a second study, we consider those spikes which occur while NAV is relatively unchanged. The data show that for upward spikes there is a gradual rise in the NAV accompanied by a gradual decline in the market price (see Figure 5). This is consistent with the concept (see Hypothesis 3) that traders with finite assets have been “caught short” or “underinvested” in anticipation of an event that turns out to be more positive than expected.

To the best of our knowledge, this is the first study to consider a precursor to significant short term changes. Another novel feature is the subtraction of the relative changes in fundamentals, thereby eliminating much of the noise that encumbers statistical testing.

Review of prior literature:

The existence of an abnormal price reversal following a large price movement has been considered as evidence for the overreaction hypothesis. Several types of studies have discussed the existence and degree of overreaction or underreaction in the stock markets. While some of them consider overreaction or underreaction associated with momentum and reversal strategies over relatively long term, others examine it at the time of an extreme price change. The latter studies focus on daily market price adjustments to new information.

Madura and Richie (2004) define underreaction as positive (negative) cumulative abnormal returns following large positive (negative) price changes, whereas they consider overreaction as reversals of returns. Poterba and Summers (1988) discuss the presence of transition periods when stock prices deviate from their fundamental values in illogical ways. Rosenberg et al. (1985) and Zarovin (1989) find evidence that stock prices overreact in the short run. They conclude that the stock market is inefficient since arbitrageurs who detect the market’s tendency to overreact could earn huge returns by buying losers and selling winners.

Most of the latter studies define events as stock price changes in excess of $M\%$ (in either direction). A winner (loser) stock is a stock experiencing a one-day return at least $M\%$ ($-M\%$). Bremer and Sweeney (1991) and Akhigbe et al. (2002) used 10% trigger value to identify events. Bremer and Sweeney (1991) examine the reversal of large price decreases for Fortune 500 firms. They find significant positive three day abnormal returns following the drop date, upon examining the period between 1962 and 1986. They conclude that such a slow recovery is inconsistent with the notion that market prices fully and quickly reflect relevant information. They suggest that this is incompatible with market efficiency. Moreover, they consider that one of the potential explanations for these remarkably large returns is market illiquidity. Akhigbe et al. (2002) find a greater degree of overreaction within extreme positive price movements in technology stocks than within non-tech stocks, based on their subsequent stock price behavior, during the 1998-2000 period. Moreover, they detect a greater degree of underreaction within extreme negative changes in technology stocks than in non-tech stocks. They observe that the market is overoptimistic while evaluating technology stock prices in reaction to favorable and unfavorable information relative to a matched sample of non-technology firms.

Sturm (2003) hypothesizes that post-event price behavior following large one-day price shocks is related to pre-event price and firm fundamental characteristics. He suggests that these characteristics proxy for investor confidence. The relationship between pre-event long term returns and post-event short-term returns are tested, for companies from the 2002 Fortune 500 index. He finds presence of a price shock effect whereby post-event reversals are smaller for larger price shocks. More recently, Madura and Richie (2004) find substantial overreaction of Exchange-Traded Funds (ETFs) during normal trading hours and after hours, giving opportunities for feedback traders. Their sample includes observation of daily opening and closing prices for AMEX-traded ETFs during the 1998-2002 period. The degree of overreaction is also more evident for international ETFs. They use three M values such as 5, 6 and 7, where $trigger > M\%$ for winners and $trigger < -M\%$ for losers.

Financial markets are dynamic. Experimental economics has shown that even when there is no change or uncertainty in the expected payout of an asset, there is robust trading with dramatic changes (see Porter and Smith (1994)), as there is always some uncertainty in the anticipation of the actions of other traders. For the closed-end funds we study, there is, of course, a stream of news that constantly readjusts the value of the fund. This is reflected in the NAV of the fund. However, the anticipation of strategies of other traders' actions and the inflow of information are also part of the market. As traders have access to faster and faster means of acquiring and processing information, it becomes possible to react on a more rapid time scale. While rapid dissemination of information could be a stabilizing force in the markets, the positive feedback strategies involved in trying to trade quickly on news or price movements could provide a destabilizing force that is often characterized by overreaction.

Moreover, studies involving long term behavior of prices (e.g., one or more years) tend to average over large disturbances, thereby hiding abnormal events. Hence, focusing on significantly large short term price changes can provide researchers with a tool to study these phenomena, and help decide the issues in an empirical manner. Of course, a large price change in itself does not necessarily indicate any abnormal investor reaction. A world event may drastically change the valuation of a closed-end fund, for example. However, by subtracting out the NAV return of the fund, we can study changes that are predominantly exclusive of the changes in valuation. The closed-end funds comprise many stocks so that private information, etc., cannot provide an explanation for the rapid changes between the trading price return of the stock and the NAV return.

Possible theoretical reasons for overreaction or underreaction:

1. People tend to place too much emphasis on the strength of new information (see Griffin and Tversky (1992)). Investors overreact to new information rather than placing it within the context of existing information and accurately recomputing expected values. There may be overreaction to rumors or to facts (Madura and Richie (2004)).

2. Attribution theory. Weiner (2000) gives a property of causal reasoning such that if an outcome is attributable to a non-stable cause, the future expectation will be either uncertain or different from the immediate past. Particularly, Sturm (2003) suggest that if the price shock is attributed to a non-stable cause, the future outcome will either be uncertain or different from the price shock, leading to a reversal.

3. Stock price behavior is affected by feedback traders who trade based on recent price movements rather than fundamental factors (see Caginalp et al. (2000) and Cutler et al. (1990)).

4. Affect and representativeness theories. As noted by Sturm (2003), if a particular market or sector is moving up rapidly, there is a positive image about it. Investors tend to flock to a particular investment, thereby increasing the price as they provide *a posteriori* arguments to justify the ever higher price. For example, when the Spain Fund traded at a steep premium of about 100%, the justification for it was that it was difficult to buy Spanish stocks in the US in any other way. Yet if the potential for Spanish stocks is so great, why wouldn't the stocks already reflect that information?

5. Reference points in investments. Investors are often keenly aware of prices at which major turning points occurred. For example, if a closed-end fund touched $20 and then retreated quickly, there is a general feeling of regret on the part of investors who wish they had sold at that point. The next time the stock reaches that point, it may be amply justified by the NAV; yet selling to avoid regret may be a cause of a larger deviation from NAV at that point. In other words, the selling near $20 causes the price to lag behind the upward move in the NAV. This would be a negative deviation, as we define in the next section.

Moreover, Caginalp et al. (2000) examine the relationship between momentum, fundamental value and overreaction based on a series of experiments to test the predictions of a momentum model using a dynamical systems approach.

The remainder of the paper is organized as follows. In Section 2, we present our deviation model. In Section 3, the deviation model is handled with partition. Section 4 concludes the paper. The Appendix includes the corresponding statistical tables for the models.

2 The deviation model (DM)

In this section we examine the relative change in the market price to the relative change in the net asset value (NAV) price. Let P_t denote the market price at time t, and V_t denote the NAV price at time t. We define the deviation between the relative changes of these two quantities from day t to day $t+k$ (with k nonnegative) by

$$D_{t+k} = (P_{t+k} - P_t)/P_t - (V_{t+k} - V_t)/V_t. \qquad (1)$$

2.1 Basic formalism

In Table 1, we consider the D_{t+k} in terms of the relative changes to the NAV and the market price. For example, if there is a small decrease in NAV but a large decrease in market price, then D_{t+k} is negative, and we say that the market price exhibits negative sentiment relative to the NAV. That is, there is a relative pessimism among investors.

Before examining the statistics, we need to verify that the deviation formulation (1) introduced above is not biased. This is immediate from the definitions, and is summarized below in Proposition 1.

Proposition 1. *Let A be any array of market price returns and B be any array of NAV returns such that $A = B$. That is, $A(i)$ is an entry in the first column, $B(j)$ is an entry in the first row, and D_{t+k} is the corresponding deviation, in Table 1. Then, the double sum of all the possible deviation outcomes is zero, independent of the chosen threshold level.*

$$\sum_{i=1}^{n}\sum_{j=1}^{n} D_{t+k} = \sum_{i=1}^{n}\sum_{j=1}^{n}(A(i) - B(j)) = 0 \qquad (2)$$

Also,

$$\sum_{i \neq j}^{n} D_{t+k} = \sum_{i \neq j}^{n}(A(i) - B(j)) = 0 \qquad (3)$$

With a model that is not biased *a priori*, we can now determine if the deviations before and after days of significant change have zero mean, as would be predicted by the efficient market hypothesis, or whether there is a systematic tendency in the deviations.

2.2 Sample selection and descriptive statistics

To assess and analyze the overreaction or underreaction behavior of 52 closed-end funds (CEFs), we used both Market Price (MP) and Net Asset Value (NAV) with 134,406 data points of daily closing prices from CEFs comprising 20 Specialized Equity Funds (SEFs), 15 General Equity Funds (GEFs) and 17 World Equity Funds (WEFs) during April 1, 1998-March 31, 2006.

Events are defined as abnormal deviations having threshold levels ($L < threshold \leqslant U$) for positive deviations where threshold is deviation in percent, $L > 0$ is the lower bound and $U > 0$ is the upper bound. Similarly, events for negative deviations are defined as abnormal deviations having threshold level ($-U \leqslant threshold < -L$).

We group the threshold levels for large deviations into four groups for positive events
Group 1. low ($2.5 < threshold \leqslant 5$),
Group 2. medium ($5 < threshold \leqslant 7.5$),
Group 3. high ($7.5 < threshold \leqslant 10$), and
Group 4. very high ($10 < threshold \leqslant 50$),
and four groups for negative events
Group 1. low ($-5 \leqslant threshold < -2.5$),
Group 2. medium ($-7.5 \leqslant threshold < -5$),
Group 3. high ($-10 \leqslant threshold < -7.5$), and
Group 4. very high ($-50 \leqslant threshold < -10$).

Overreaction to minor changes (particularly recent ones) in valuation is emerging as a key concept in behavioral finance. In terms of our definitions, we examine the set of deviations between the market price returns and NAV returns (Day 0), and determine whether the following day (Day 1) is in the same or opposite direction.

Hypothesis 1 (Overreaction). If there is a positive deviation on Day 0, there is a greater probability that there will be a negative deviation on Day 1. Similarly, a negative deviation on Day 0 is likely to be followed by a positive deviation on Day 1.

Hypothesis 2 (Underreaction). If there is a positive deviation on Day 0, there is a greater probability that there will be a positive deviation on Day 1. Similarly, a negative deviation on Day 0 is likely to be followed by a negative deviation on Day 1.

In both cases the null hypothesis (of the EMH) is that the mean of relative changes on Day 1 is zero.

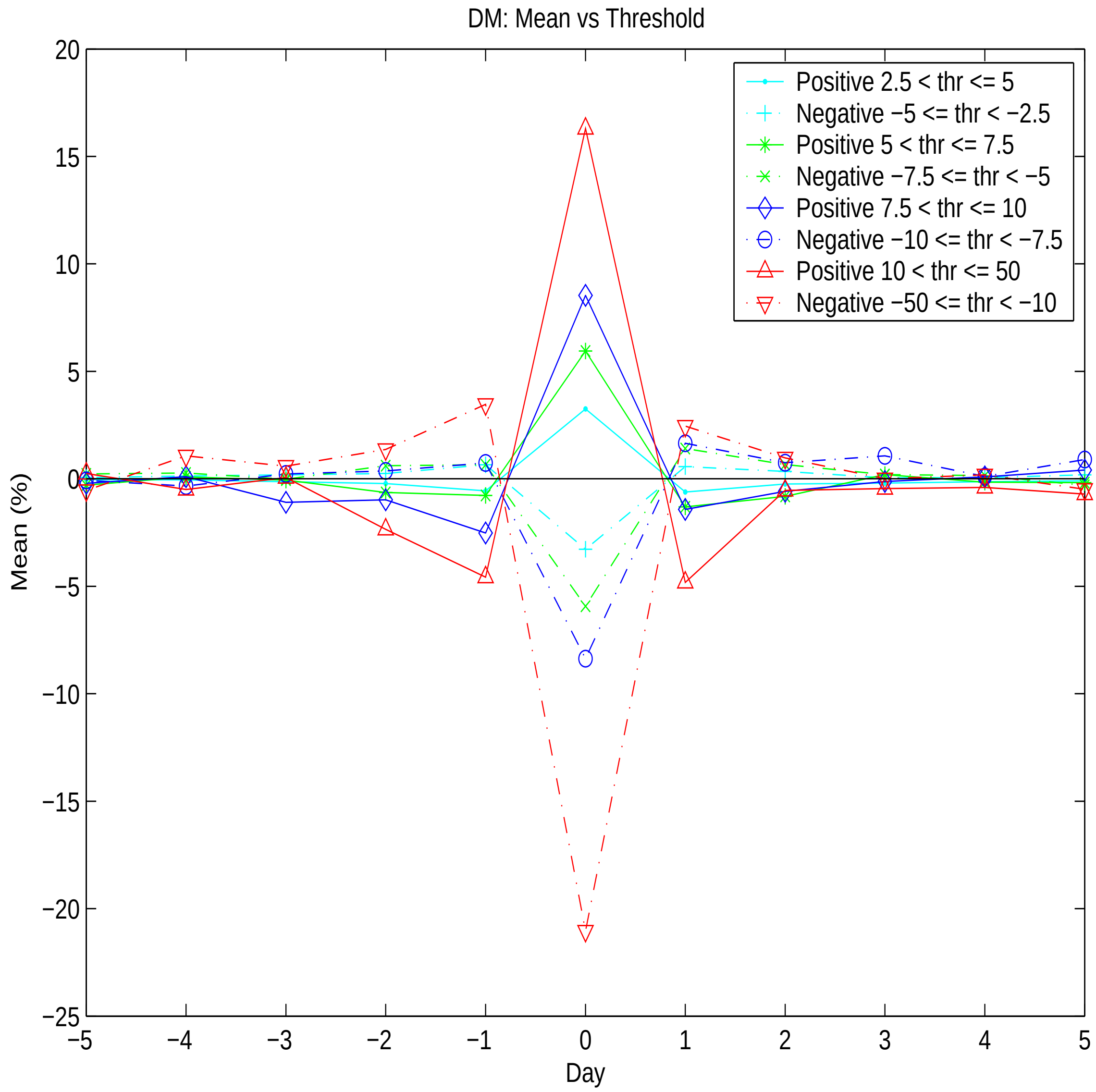

Figure 1: Mean deviation versus threshold ranges on 11-day window.

Table 1: **Basic formalism.** Interpretation of market price (MP) changes using deviation operations. MP exhibits positive or negative reaction relative to the NAV.

		NAV			
	Deviation	*Large Decrease*	*Small Decrease*	*Small Increase*	*Large Increase*
MP	*Large Decrease*	*neutral*	*more negative*	*highly negative*	*highly negative*
	Small Decrease	*positive*	*neutral*	*highly negative*	*highly negative*
	Small Increase	*highly positive*	*highly positive*	*neutral*	*negative*
	Large Increase	*highly positive*	*highly positive*	*more positive*	*neutral*

Note that the drift term (average increase of a stock per day) is present in both of the quantities (market price and NAV) so that the subtraction eliminates this term.

2.3 Results for the deviation model

Figure 1 shows the mean deviation versus threshold ranges for positive and negative events on 11-day window. Prior to a spike in deviations we find a gradual two or three day decline (and analogously in the other direction). This suggests that a cause of the spike may be due to positioning of traders in the opposite direction. Overall, there is a characteristic diamond pattern, revealing a symmetry in the deviations before and after the significant change. Figure 1 suggests overreaction for both directions because of the reversals during the post-event days. In addition, the magnitude of the reversal increases as the degree of shock increases. Moreover, the magnitudes on pre- and post-day are very similar for the low threshold levels, revealing another component of symmetry. Furthermore, the magnitude of the negative deviation is higher than that of positive deviation, only for the very high threshold level, on Day 0. This indicates that the effect of unfavorable information is higher than that of favorable information for this level, in the short term.

Figure 2 shows the average percentage of positive deviations with respect to the large positive and negative deviations on Day 0. It provides evidence of overreaction for both directions and all threshold levels. On Day 1, the percentages of positive deviations are less than 36%, indicating the reversal, for all positive threshold levels. In the negative direction the percentages of positive deviations are greater than 60%, indicating the reversal for the low, medium and high threshold levels on Day 1. During the two pre- and post-day, the percentages of positive deviations are less than 50% for the large positive deviators. In the negative direction during the two pre- and post-day, the percentages of positive deviations are greater than 50% for the low and medium threshold levels.

Figure 3 shows that there is a decline before a sharp rise in MP return in the low threshold level. Then there is reversal both in deviation and MP return. We obtained similar results for all large positive deviators (see Duran (2006)). Figure 4 illustrates that there is one day rise before a sharp dip in MP return in the low threshold level. Then, there is reversal in MP return on Day 1. We obtained similar results for the first three threshold levels. The

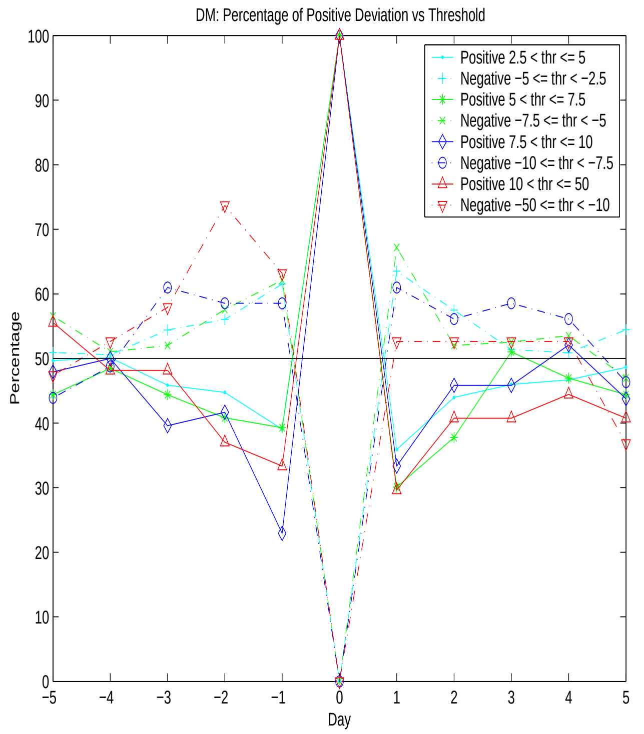

Figure 2: Percentages of positive deviations on 11-day window.

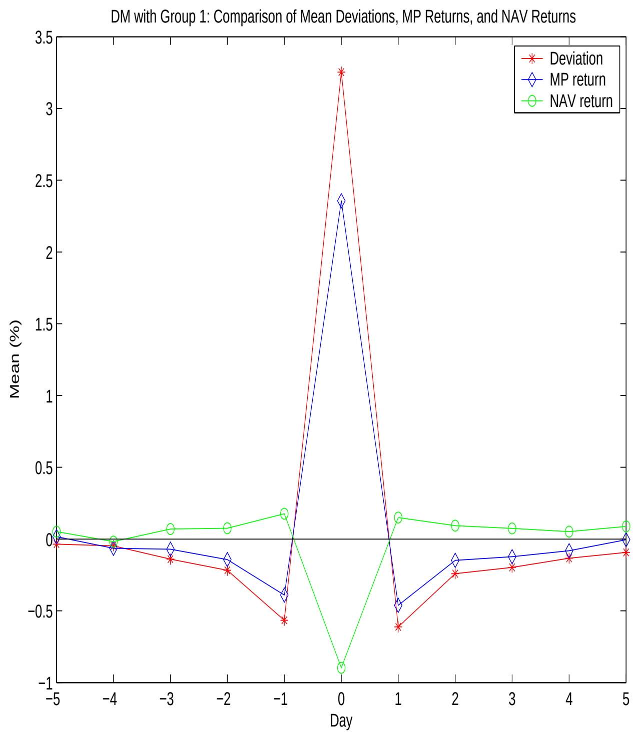

Figure 3: Relative optimism on Day 0 and the upper diamond pattern in the low threshold level.

reversal of a very large dip is slower because of the price effect.

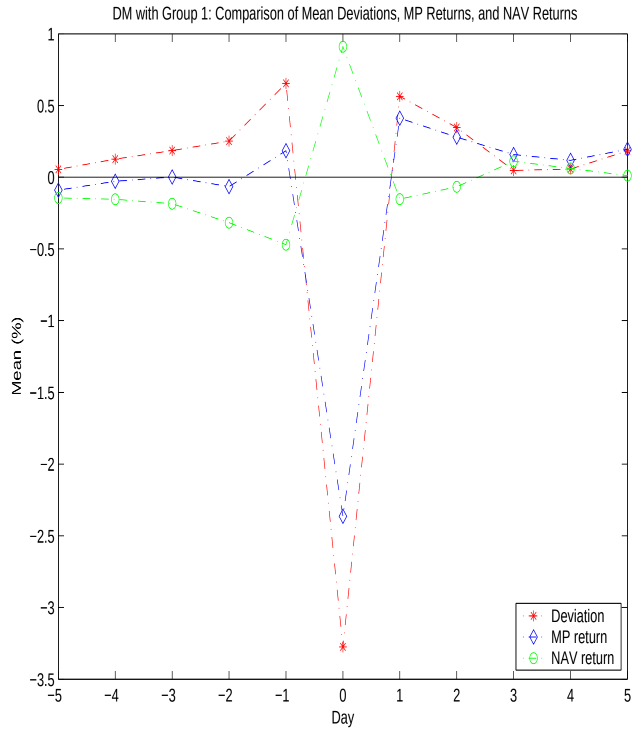

Figure 4: Precursor, relative pessimism on Day 0, and the post-event reversal in the low threshold level.

2.3.1 Low thresholds

In Table 2, the average deviation on Day 0 is 3.25% for the 1947 large positive events, after statistically significant three pre-day pessimism in the low threshold level. During the first five post-event days, there is reversal. In other words, MP returns exhibit statistically significant pessimism relative to the percentage changes in NAV for this period.

In Table 3, after a four-day significant pre-day rise, the average deviation on Day 0 is −3.28%, close to that of positive events in magnitude, for the 1954 large negative events in the low threshold level. During the first two post-event days, there is statistically significant reversal. That is, MP returns show positive sentiment relative to the NAV returns for this period, while it is negative sentiment on Day 0.

2.3.2 Medium thresholds

In Table 4, the average deviation on Day 0 is 5.95%, following two significant drops for the 196 large positive events in the medium threshold level. There is statistically significant two post-day reversal.

In Table 5, after two-day significant rise in relative optimism, the average deviation on Day 0 is −5.93%, close to that of positive events in magnitude for the 198 large negative events in the medium threshold level. During the first two post-event days, there is statistically significant reversal.

2.3.3 High thresholds

In Table 6, the average deviation on Day 0 is 8.54% following two-day significant drop for the 48 large positive events in the high threshold level. Then, there is a statistically significant one day reversal. In other words, the relative positive sentiment on Day 0 is replaced by the negative sentiment subsequently.

In Table 7, the average deviation on Day 0 is −8.37% for the 41 large negative events in the high threshold level. On Day 1 and Day 3, statistically significant reversal takes place.

2.3.4 Very high thresholds

In Table 8, the average deviation on Day 0 is 16.29% following two-day significant relative pessimism for the 27 large positive events in the very high threshold level. There is then a one day statistically significant reversal.

In Table 9, the average deviation on Day 0 is −21.04%, larger than that of positive events in magnitude, for the 19 large negative events in the very high threshold level. During the first four post-day, there is limited significant behavior due to the small sample size. Also, there may be price shock effects making the post-event reversals smaller in magnitude for the negative very high threshold levels. This suggests that the size of the threshold level on Day 0 affects the investor sentiment during the post-event days.

The statistically significant results thereby confirm Hypothesis 1, and reject both the null hypothesis and Hypothesis 2. In summary, any significant deviation between the market price and the net asset value is characterized by both a precursor and an aftershock in the opposite direction. This occurs for each of the threshold levels for the deviation on Day 0.

3 The deviation model with partition

In Section 2, we examined the spikes in the difference of daily MP returns and NAV returns. Now, we analyze the data by decomposing events into spikes in MP returns versus spikes in NAV returns. Partitioning in this way provides more detailed information.

The EMH involves another assumption, namely, that there is effectively an infinite amount of investment capital that can be used for arbitrage. An alternative set of ideas that explicitly utilizes the finiteness of assets of different groups has been the foundation of a mathematical approach to behavioral finance (see Caginalp and Balenovich (1999) and references therein). This uses a price equation in which the transition between cash and asset can depend on other factors beyond valuation such as momentum trading (i.e., buying due to rising prices). Using models of this type, Caginalp et al. (2000) were able to resolve some key issues in asset market experiments in which bubbles have been observed. One of the predictions of the differential equations has been that a larger bubble results if there is a larger total cash to asset ratio. Our current study allows us to test an important feature of this approach, namely the impact of finite assets, against the null hypothesis of EMH which stipulates infinite capital for arbitrage.

Hypothesis 3. Consider the subset of "events," (i.e., there is a significant deviation on Day 0) for which relatively little change occurs for NAV (as defined by BP1 in Section 3.1). Then on Day (-1) there is a deviation in the opposite direction.

There is no reason for Day (-1) to deviate from zero, according to the default hypothesis of the EMH. However, the asset flow approach in Caginalp and Balenovich (1999) stipulates that a cause of a significant change is the excess of cash that can be used to buy stock. If investors have an excess of cash due to net selling on Day (-1) there will be a significant rebound on Day 0.

3.1 Positive deviation with partition

Definition Let Ω_{RO} be the set of events for large positive deviations on Day 0. Then, a partition of Ω_{RO} is a collection $P_{RO} = \{BP_1, BP_2, BP_3, BP_4\}$ of nonempty subsets of Ω_{RO}, where BP_is are the blocks of the partition. They satisfy the following properties:

1. The blocks are pairwise disjoint
2. All of the Ω_{RO} is the union of the blocks.

In particular, we define "relatively unchanged" to mean that the change in one quantity is less than one-fifth of the other.

1. BP_1 = {Large positive deviations | MP return spikes up while NAV is relatively unchanged on Day 0}.
2. BP_2 = {Large positive deviations | both MP return and NAV return are changed and the magnitude of MP return on Day 0 is greater}.
3. BP_3 = {Large positive deviations | both MP return and NAV return are changed and the magnitude of NAV return on Day 0 is greater}.
4. BP_4 = {Large positive deviations | NAV return spikes down while MP is relatively unchanged on Day 0}.

The vast majority of large positive deviations are influenced by large MP returns. The corresponding percentages of BP1, BP2, BP3 and BP4 are (26.86, 41.60, 22.60, 8.94) for the low threshold level, and (36.73, 40.31, 14.29, 8.67) for the medium threshold level. That is, the percentages of large positive deviations influenced by large MP returns are 68.46% and 77.04% in the low and medium threshold levels, respectively.

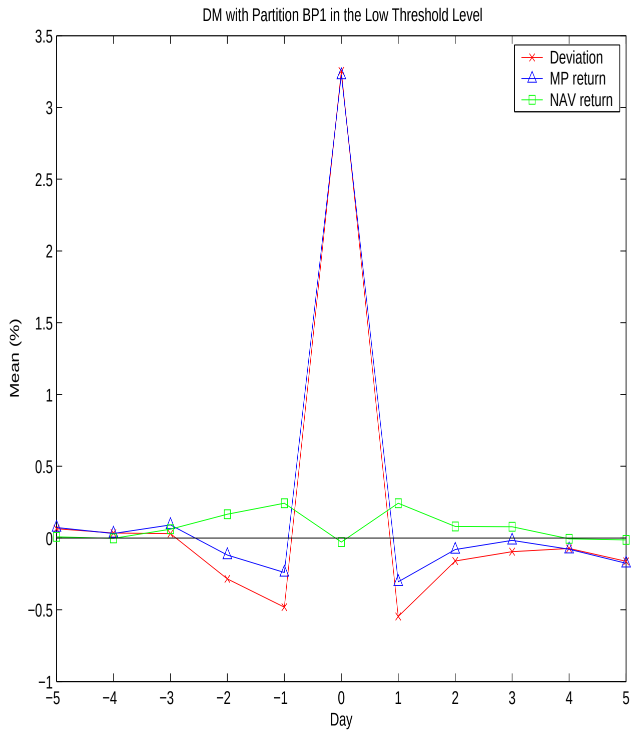

Figure 5: The comparison of daily MP returns, NAV returns, and the deviations shows overreaction upper diamond patterns for both deviation and MP return.

Figure 5 and Figure 6 compare daily MP returns, NAV returns, and the deviations in the positive low threshold level for the block of partition BP1 and in the positive medium threshold level for the block of partition BP2, respectively. Even numbered tables from 10 to 40 represent the average deviations, MP returns, NAV returns, and reversals associated with large positive deviators of Day 0. The statistically significant results with the partitions BP1 and BP2 in the low and medium threshold levels and the partitions BP3 and BP4 in the low threshold level support Hypothesis 1, where the number of events is sufficiently large ($n \geq 30$). These subsets have also statistically significant reversals in MP returns on Day 1. There are post-event reversals in the deviations for the other partitions also, but the number of events is small.

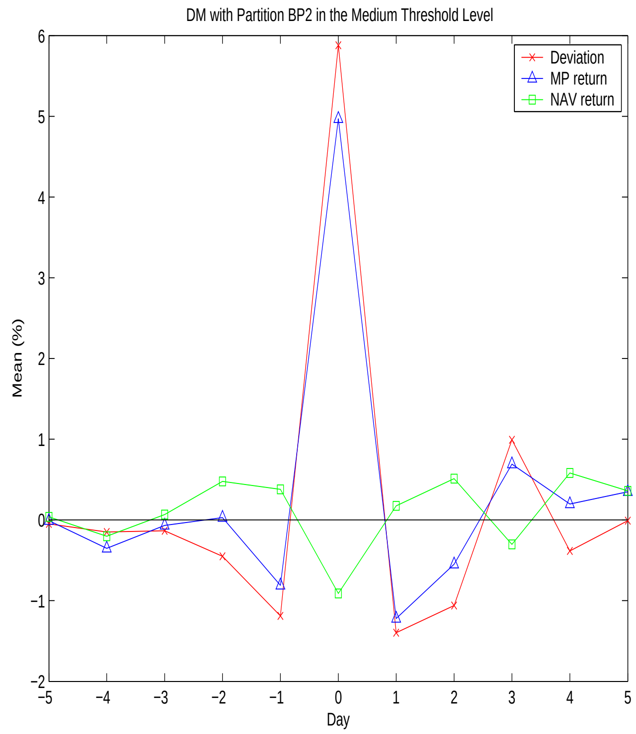

Figure 6: Comparison of daily MP returns, NAV returns, and the deviations in the positive medium threshold level.

Moreover, the subsets BP_1 in the low threshold level and BP_2 in the low and medium threshold levels confirm Hypothesis 3. All BP_is in the low threshold levels and BP_2 in the medium threshold level have a statistically significant drop in MP return on Day (-1).

3.2 Negative deviation with partition

Definition Let Ω_{RP} be the set of events for large negative deviations on Day 0. Then, a partition of Ω_{RP} is a collection $P_{RP} = \{BN_1, BN_2, BN_3, BN_4\}$ of nonempty subsets of Ω_{RP}, where BN_is are the blocks of the partition. They satisfy the following properties:

1. The blocks are pairwise disjoint
2. All of the Ω_{RP} is the union of the blocks.

In particular,

1. $BN_1 = \{$Large negative deviations | MP return spikes down while NAV is relatively unchanged on Day 0$\}$.
2. $BN_2 = \{$Large negative deviations | both MP return and NAV return are changed and the magnitude of MP return on Day 0 is greater$\}$.
3. $BN_3 = \{$Large negative deviations | both MP return and NAV return are changed and the magnitude of NAV return on Day 0 is greater$\}$.
4. $BN_4 = \{$Large negative deviations | NAV return spikes up while MP is relatively unchanged on Day 0$\}$.

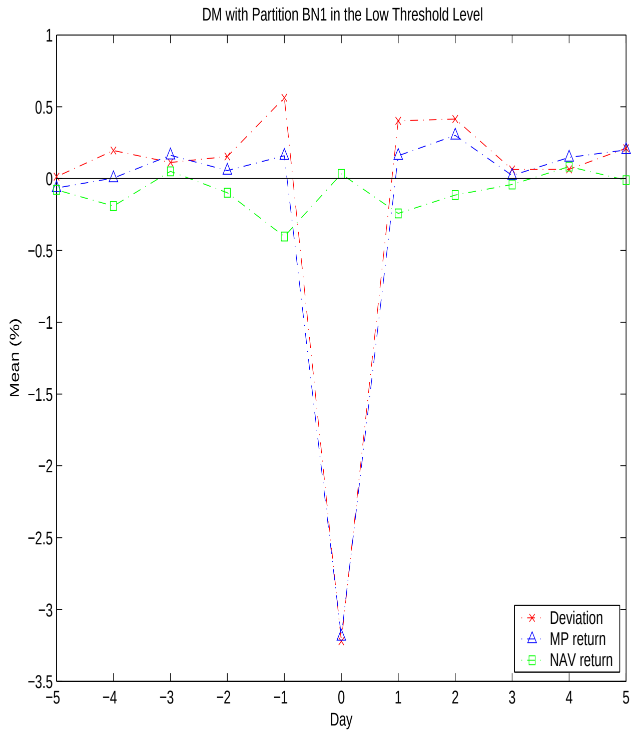

Figure 7: Comparison of daily MP returns, NAV returns, and the deviations in the negative low threshold level.

The distributions of large negative deviations for BN1, BN2, BN3 and BN4 are (23.90%, 42.94%, 24.36%, 8.80%) in the low threshold level and (37.88%, 41.41%, 15.15%, 5.56%) in the medium threshold level. In other words, the percentages of large negative deviations influenced by large MP returns are 66.84% and 79.19% in the low and medium threshold levels, respectively.

The other results are also similar to the positive deviations of the previous section and are displayed in Figure 7 and odd numbered tables from 11 to 41. The statistically significant results with the partitions again confirm Hypothesis 1. Moreover, the results for the subsets BN_1 in the low threshold level and BN_2 in the low and medium threshold levels confirm Hypothesis 3.

Furthermore, as the influence of NAV return on Day 0 increases (from BN_1 to BN_4), the magnitude of reversal in the MP return on Day 1 increases in the low threshold level. In summary, a detailed examination of the deviations between market price and net asset value shows that the largest part occurs when there is relatively little change in NAV but a significant change in MP. Within this subset we find similar precursor and aftershock behavior.

4 Conclusion

The issues of overreaction and underreaction are central to the debate on behavioral finance, but are often difficult to establish statistically through data analysis. We have performed a study in which the relative change in the fundamental value is subtracted from that of the trading price, so that the difference provides a clearer picture of the underlying dynamics of trading price. In particular, we found that for a set of closed-end funds over a long period, any significant deviation between the market price return and the fundamental value return on a particular day is likely to be followed by a reversal the next day. More surprisingly, however, was the discovery that prior to such "event" days, there is a tendency to move gradually in the opposite direction during the previous two or three days. This precursor for the significant changes is also very different from the results one would expect from the efficient market hypothesis. There is no reason for the spike from a traditional finance perspective. However, with different groups interacting and maneuvering to find an edge, it seems that if one group is positioned, for example, as a short in anticipation of negative news, a small amount of good news is reason to buy aggressively to cover the short. The aggressive buying then pushes the price far above the levels justified by the change in fundamentals.

Within the framework of EMH, a market price is a highly stable equilibrium value that is established by traders having common information. However, another viewpoint incorporated into the asset flow theory in Caginalp and Balenovich (1999) is that there are two or more large groups that have widely differing assessments of value. At a particular time, the market receives either a small amount of new information, or a small amount of additional traders. The traders are aware of other viewpoints as the information or resources arrive. However, there is uncertainty created by the strategies (and resources) of others. Consequently, there is a price movement that can be far in excess of any new information. As discussed in the asset flow references, overreaction (Hypothesis 1) is a natural consequence of this approach within a particular time scale that must be established by the data. While overreaction can have several other explanations, it is difficult to justify within the context of EMH.

The statistics have confirmed our viewpoint that the random changes in fundamentals obscure most of the behavioral effects in price movements. When the same tests are done without subtracting the net asset value, much of the statistical significance disappears. This is at the heart of the debate between behavioral finance and the efficient market advocates. The latter argue that overreactions and underreactions should not be systematically distinguishable. Augmenting earlier studies (Akhigbe et al. (2002), Madura and Richie (2004) and Sturm (2003)) we find that our "event" criteria, described as a deviation between market price return and net asset value return, stipulate sufficient conditions for overreaction. The magnitude of the overreaction we find is quite significant even for the lower threshold levels (i.e., when the deviation is only a few percent). The presence of a precursor to such events is even more difficult to explain from an efficient market perspective. There is also remarkable symmetry between the pre-event and post-event days, as well as for the positive and negative deviations.

Closed-end funds provide a good avenue to test ideas of market dynamics. As noted earlier, their valuation is unambiguously calculated since their assets are based on current security values. In some ways the situation is similar to options trading. The value of an option is related to the trading price of the underlying stock, and one can examine the efficiency of the option price relative to the stock price, without making an *a priori* assumption on the efficiency of the stock price. In a similar way, one can examine the efficiency of the closed-end fund relative to the net asset value. A previous study by Pontiff (1997) had shown that the volatility of the closed-end fund is much greater than the volatility of the underlying index. Our study confirms this from a different perspective, and it is consistent with the concept of finite assets (rather than infinite capital for arbitrage) that underlies Hypothesis 3. In other words, if one compares a large, widely followed market such as Japan with a relatively small closed- end fund investing in Japan, then the assumption of infinite arbitrage capital is much less likely to be valid for the closed-end fund. The reason for this is not so much due to a closed-end fund's structure, but rather to its size, visibility and trading volume. After all, if there is a trading volume of tens of thousands in a particular closed-end fund, the potential profit on deviations of a few percent is too small for all but the tiniest hedge funds. Thus one would expect the closed-end fund to be more volatile than the underlying assets, even from the EMH perspective. However, one would expect the level of deviations to be much smaller and less systematic than we have found.

A large part of the patterns disappear when the relative change in NAV is not subtracted from the relative change in market price. This may explain why many data studies of markets show fairly small deviations from efficiency. As noted earlier, the valuation is influenced by many factors that can be regarded, from the perspective of traders, as stochastic. Hence any effort to show systematic behavioral bias that does not account for these changes in valuation encounters a great deal of "noise" so that obtaining statistical significance is difficult. It has been noted by Black (1986), an EMH advocate, that "noise makes it very difficult to test either practical or academic theories about the way economic or financial markets work." He adds that a reasonable definition of efficiency is that the market price is "more than half of value and less than twice value." The methodology we have used helps overcome this obstacle of "noise" in understanding market dynamics.

One aspect of our study focuses on those events in which there is relatively little change in NAV during the occurrence of a significant relative change (e.g., increase) in market price. A new phenomenon discovered in our analysis is that there is a dip during the two or three days prior to the upward spike. It would be difficult to concoct any explanation of this based upon the EMH, or any of the prevalent ideas in finance. However, this phenomenon is perfectly consistent with the asset flow approach in which the classical price theory is augmented with the concepts of finiteness of assets and trading decisions based upon momentum as well as valuation.

A key challenge to behavioral finance has been the development of a paradigm– such as the risk/reward criterion of classical finance– on which a quantitative theory can be developed. This is more difficult than the paradigm for classical finance since the latter is essentially a default theory based on an idealization. A necessary first step then is the establishment of key phenomena that can be used to develop a theory. One of the main arguments of efficient market theorists has been the absence of obvious systematic biases in market prices. Early statistical studies indicated that prices were close to a random walk. While subsequent studies have shown some short term biases, they have often been dismissed as too small to be profitable. The omnipresence of random events that influence valuation as well as the wealth of traders tends to introduce a sufficient amount of noise into the system that makes it difficult to uncover deterministic influences in price dynamics.

Both parts of our study eliminate the randomness inherent in valuation. In particular, one of the data sets comprises significant relative changes in market price that occur in the absence of much change in valuation. This has allowed us to examine the remaining influences on price dynamics, and identify patterns in prices that can be used to test the validity of new theories and methodologies in behavioral finance.

Acknowledgements

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Appendix

Tables for the deviation model (DM) and the DM with partition

Eight tables for the DM in Section 2 and thirty two tables for the DM with partition in Section 3 are included. We do not use the assumption of normality (see Roman (2004), p. 240-244) in most cases.

Let $\overline{x}$ be sample mean and s be the sample's standard deviation. We use t-statistic, $t = \frac{\overline{x}-\mu}{s/\sqrt{n}}$ with $(n-1)$ degrees of freedom, when the number of observations (n) is less than 30 where the expected mean μ is zero as stated earlier in the null hypothesis. When the sample size is sufficiently large (for example $n \geq 30$), $\overline{x}$ and $z \approx \frac{\overline{x}-\mu}{s/\sqrt{n}}$ have approximately normal distributions (see Mendenhall et al. (2003), p. 246-248 and 363-367).

The values in the tables are represented in the form of two decimal digits after rounding. Statistical significance is denoted by stars at the 0.01 (***), 0.05 (**), and 0.1 (*) levels using a 1-tailed test for significance in all tables.

Tables for the DM

Table 2: **Positive low threshold level for the DM.** Average deviations, in percent, associated with 1947 large positive deviators of Day 0 for $2.5 < threshold \leqslant 5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.05	-0.14	-0.22	-0.57	3.25	-0.61	-0.24	-0.20	-0.13
$Z-$Statistic	-0.84	-2.86	-3.88	-11.34	228.99	-11.94	-4.74	-3.97	-2.71
Significance		***	***	***	***	***	***	***	***
Percentage > 0	50.13	45.87	44.74	39.03	100.00	35.90	43.97	45.97	46.69
Variance	6.03	4.70	6.14	4.84	0.39	5.11	5.04	4.82	4.71

Table 3: **Negative low threshold level for the DM.** Average deviations, in percent, associated with 1954 large negative deviators of Day 0 for $-5 \leqslant threshold < -2.5$ during 1998-2006

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.13	0.19	0.25	0.66	-3.28	0.56	0.35	0.05	0.06
$Z-$Statistic	2.40	3.44	5.02	11.72	-229.40	11.50	7.09	0.92	1.11
Significance	***	***	***	***	***	***	***		
Percentage > 0	50.56	54.40	56.04	61.51	0.00	63.51	57.47	51.38	50.87
Variance	5.27	5.73	4.91	6.10	0.40	4.71	4.67	5.26	5.06

Table 4: **Positive medium threshold level for the DM.** Average deviations, in percent, associated with 196 large positive deviators of Day 0 for $5 < threshold \leqslant 7.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.09	-0.06	-0.64	-0.77	5.95	-1.31	-0.81	0.19	-0.16
$Z-$Statistic	0.46	-0.27	-2.90	-3.57	120.30	-6.67	-3.94	0.62	-0.68
Significance			***	***	***	***	***		
Percentage > 0	48.47	44.39	40.82	39.29	100.00	30.10	37.76	51.02	46.94
Variance	7.26	9.11	9.44	9.18	0.48	7.54	8.36	19.29	11.08

Table 5: **Negative medium threshold level for the DM.** Average deviations associated with 198 large negative deviators of Day 0 for $-7.5 \leqslant threshold < -5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.27	-0.01	0.61	0.66	-5.93	1.41	0.66	0.19	0.15
$Z-$Statistic	1.30	-0.06	1.70	2.03	-128.16	5.83	2.99	0.73	0.69
Significance	*		**	**	***	***	***		
Percentage > 0	51.01	52.02	57.58	62.12	0.00	67.17	52.02	52.53	53.54
Variance	8.72	10.51	25.13	20.73	0.43	11.56	9.78	14.27	9.68

Table 6: **Positive high threshold level for the DM.** Average deviations associated with 48 large positive deviators of Day 0 for $7.5 < threshold \leqslant 10$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.10	-1.10	-0.98	-2.52	8.54	-1.42	-0.58	-0.13	0.09
$Z-$Statistic	0.21	-1.22	-1.95	-3.81	78.19	-2.58	-1.43	-0.26	0.17
Significance			**	***	***	***	*		
Percentage > 0	50.00	39.58	41.67	22.92	100.00	33.33	45.83	45.83	52.08
Variance	11.48	38.88	11.99	21.03	0.57	14.63	7.87	12.13	13.56

Table 7: **Negative high threshold level for the DM.** Average deviations associated with 41 large negative deviators of Day 0 for $-10 \leqslant threshold < -7.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.34	0.22	0.37	0.74	-8.37	1.65	0.75	1.10	0.11
Z−Statistic	-0.60	0.43	0.73	1.19	-81.14	2.62	1.33	1.85	0.26
Significance					***	***	*	**	
Percentage > 0	48.78	60.98	58.54	58.54	0.00	60.98	56.10	58.54	56.10
Variance	13.47	11.38	10.27	15.98	0.44	16.29	13.03	13.59	7.58

Table 8: **Positive very high threshold level for the DM.** Average deviations associated with 27 large positive deviators of Day 0 for $10 < threshold \leqslant 50$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.50	0.05	-2.36	-4.57	16.29	-4.82	-0.54	-0.45	-0.40
T−Statistic	-0.68	0.10	-1.70	-2.28	11.41	-2.45	-0.82	-0.69	-0.55
Significance			*	**	***	**			
Percentage > 0	48.15	48.15	37.04	33.33	100.00	29.63	40.74	40.74	44.44
Variance	14.30	7.49	51.98	108.16	55.07	104.65	11.95	11.78	13.92

Table 9: **Negative very high threshold level for the DM.** Average deviations associated with 19 large negative deviators of Day 0 for $-50 \leqslant threshold < -10$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	1.10	0.59	1.37	3.46	-21.04	2.46	0.97	0.01	0.18
T−Statistic	0.97	0.76	2.69	0.95	-7.43	0.88	0.82	0.01	0.18
Significance			***		***				
Percentage > 0	52.63	57.89	73.68	63.16	0	52.63	52.63	52.63	52.63
Variance	23.04	11.31	4.92	250.86	152.22	146.79	26.76	8.29	20.12

Tables for the DM with partition

Table 10: **The DM with partition BP1 in the low threshold level.** Average deviations, MP returns, and NAV returns, in percent, associated with 523 large positive deviators of Day 0 for $2.5 < threshold \leqslant 5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.04	0.03	-0.29	-0.48	3.25	-0.55	-0.16	-0.10	-0.07
Significance			***	***	***	***	**		
Mean MP Return	0.03	0.09	-0.12	-0.24	3.23	-0.31	-0.08	-0.02	-0.09
Significance				***	***	***			
Mean NAV Return	-0.01	0.06	0.17	0.24	-0.03	0.24	0.08	0.08	-0.01
Significance			***	***	***	***	*	*	

Table 11: **The DM with partition BN1 in the low threshold level.** Average deviations, in percent, associated with 467 large negative deviators of Day 0 for $-5 \leqslant threshold < -2.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.20	0.11	0.15	0.56	-3.22	0.40	0.42	0.06	0.06
Significance	*		*	***	***	***	***		
Mean MP Return	0.00	0.16	0.06	0.16	-3.19	0.16	0.30	0.02	0.15
Significance		*		**	***	*	***		*
Mean NAV Return	-0.19	0.05	-0.10	-0.40	0.03	-0.24	-0.11	-0.04	0.08
Significance	***		*	***	***	***	**		

Table 12: **The DM with partition BP1 in the medium threshold level.** Average deviations, in percent, associated with 72 large positive deviators of Day 0 for $5 < threshold \leqslant 7.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.21	-0.17	-0.31	0.30	5.96	−1.28	-0.15	0.40	-0.63
Significance					***	***		*	***
Mean MP Return	-0.25	-0.25	-0.24	0.27	6.01	-0.20	-0.13	0.40	-0.34
Significance					***			*	
Mean NAV Return	−0.46	-0.09	0.07	-0.03	0.05	1.08	0.02	-0.00	0.29
Significance	**					***			*

Table 13: **The DM with partition BN1 in the medium threshold level.** Average deviations, in percent, associated with 75 large negative deviators of Day 0 for $-7.5 \leqslant threshold < -5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.06	0.22	1.55	-0.25	−5.80	1.54	0.38	0.10	0.16
Significance			***		***	***	*		
Mean MP Return	-0.06	0.18	1.26	-0.22	−5.61	0.46	0.42	0.45	0.55
Significance			**		***	**	*	*	**
Mean NAV Return	-0.12	-0.04	-0.29	0.04	0.19	−1.08	0.04	0.34	0.39
Significance			*		***	***		**	**

Table 14: **The DM with partition BP1 in the high threshold level.** Average deviations, in percent, associated with 21 large positive deviators of Day 0 for $7.5 < threshold \leqslant 10$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.46	-2.63	-1.01	-1.26	8.59	-1.51	-0.25	-0.72	-0.05
Significance		*			***	*			
Mean MP Return	0.16	-2.87	-0.73	-1.28	8.28	0.15	0.64	-0.90	-0.21
Significance		*			***			*	
Mean NAV Return	-0.30	-0.25	0.28	-0.03	−0.31	1.66	0.89	-0.18	-0.16
Significance					**	***	**		

Table 15: **The DM with partition BN1 in the high threshold level.** Average deviations, in percent, associated with 24 large negative deviators of Day 0 for $-10 \leqslant threshold < -7.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.18	0.42	0.26	-0.04	−8.43	2.09	0.81	1.60	-0.48
Significance					***	**		***	
Mean MP Return	-0.51	-0.11	-0.08	-0.42	−8.48	0.26	0.11	1.20	−0.94
Significance					***			**	**
Mean NAV Return	−0.69	−0.54	-0.33	-0.38	-0.04	−1.83	−0.70	-0.46	-0.46
Significance	***	**				***	**	*	*

Table 16: **The DM with partition BP1 in the very high threshold level.** Average deviations, in percent, associated with 4 large positive deviators of Day 0 for $10 < threshold \leqslant 50$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	1.30	1.50	-10.5	0.24	12.69	-1.05	−4.60	0.64	-0.42
Significance					***		***		
Mean MP Return	0.38	2.31	-10.20	0.56	12.60	1.92	-2.30	-0.14	-0.39
Significance					***				
Mean NAV Return	-0.87	0.81	0.31	0.32	-0.10	2.97	2.30	-0.78	0.02
Significance						*			

Table 17: **The DM with partition BN1 in the very high threshold level.** Average deviations, in percent, associated with 10 large negative deviators of Day 0 for $-50 \leqslant threshold < -10$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.52	1.21	1.32	-1.64	-16.14	1.85	2.10	1.30	-0.46
Significance			**		***			*	
Mean MP Return	1.80	0.63	0.40	0.82	-16.27	1.29	2.60	0.45	-0.80
Significance	**				***		*		
Mean NAV Return	1.20	-0.58	-0.92	2.46	-0.13	-0.55	0.53	-0.82	-0.34
Significance			*						

Table 18: **The DM with partition BP2 in the low threshold level.** Average deviations, in percent, associated with 810 large positive deviators of Day 0 for $2.5 < threshold \leqslant 5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.05	-0.34	-0.19	-0.60	3.30	-0.52	-0.19	-0.25	-0.13
Significance		***	**	***	***	***	**	***	**
Mean MP Return	-0.05	-0.19	-0.12	-0.36	3.31	-0.30	-0.06	-0.19	-0.10
Significance		***	*	***	***	***		**	*
Mean NAV Return	-0.00	0.15	0.08	0.24	0.01	0.21	0.12	0.06	0.04
Significance		***		***		***	***		

Table 19: **The DM with partition BN2 in the low threshold level.** Average deviations, in percent, associated with 839 large negative deviators of Day 0 for $-5 \leqslant threshold < -2.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.12	0.22	0.24	0.53	-3.34	0.59	0.36	0.13	0.08
Significance	*	***	***	***	***	***	***	**	
Mean MP Return	-0.06	0.10	-0.08	-0.04	-3.42	0.32	0.40	0.23	0.12
Significance		*			***	***	***	***	*
Mean NAV Return	-0.18	-0.12	-0.33	-0.56	-0.08	-0.28	0.04	0.11	0.05
Significance	***	**	***	***	*	***		**	

Table 20: **The DM with partition BP2 in the medium threshold level.** Average deviations, in percent, associated with 79 large positive deviators of Day 0 for $5 < threshold \leqslant 7.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.15	-0.13	-0.45	-1.19	5.88	-1.40	-1.10	0.99	-0.38
Significance				***	***	***	***	***	
Mean MP Return	-0.35	-0.07	0.03	-0.81	4.97	-1.22	-0.55	0.69	0.20
Significance				***	***	***	*	**	
Mean NAV Return	-0.20	0.07	0.48	0.38	-0.91	0.18	0.51	-0.30	0.58
Significance			**	**	***		**	*	***

Table 21: **The DM with partition BN2 in the medium threshold level.** Average deviations, in percent, associated with 82 large negative deviators of Day 0 for $-7.5 \leqslant threshold < -5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.51	0.13	-0.07	1.12	-6.04	1.59	0.64	0.15	0.47
Significance	**			***	***	***	**		*
Mean MP Return	0.23	-0.39	-0.42	0.39	-5.39	0.78	0.49	0.53	0.32
Significance			*		***	**	*	*	
Mean NAV Return	-0.28	-0.52	-0.36	-0.73	0.65	-0.81	-0.14	0.38	-0.15
Significance	*	**	**	***	***	***		**	

Table 22: **The DM with partition BP2 in the high threshold level.** Average deviations, in percent, associated with 17 large positive deviators of Day 0 for $7.5 < threshold \leqslant 10$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.65	-0.04	-1.26	-3.31	8.63	-2.08	-1.00	1.10	-0.21
Significance			*	***	***	***	*		
Mean MP Return	-0.46	0.55	-1.49	-2.70	6.76	-0.88	-1.10	0.36	0.20
Significance			*	**	***	*	*		
Mean NAV Return	0.19	0.59	-0.23	0.61	-1.87	1.20	-0.10	-0.69	0.41
Significance		*			***	**		*	

Table 23: **The DM with partition BN2 in the high threshold level.** Average deviations, in percent, associated with 11 large negative deviators of Day 0 for $-10 \leqslant threshold < -7.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.84	0.00	1.34	2.15	-8.35	1.25	1.00	1.10	1.30
Significance				**	***				*
Mean MP Return	-0.67	-0.49	-0.48	-0.28	-7.96	-0.12	-0.29	0.28	0.83
Significance					***				
Mean NAV Return	0.17	-0.49	-1.82	-2.43	0.39	-1.37	-1.30	-0.80	-0.49
Significance			**	***		*	*		

Table 24: **The DM with partition BP2 in the very high threshold level.** Average deviations, in percent, associated with 7 large positive deviators of Day 0 for $10 < threshold \leqslant 50$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.36	-0.99	-1.75	-2.77	16.57	-5.63	0.39	-0.72	-2.60
Significance				*	***	*			
Mean MP Return	-0.88	-0.13	-3.05	-2.95	13.71	-1.85	0.03	-0.49	-1.60
Significance			*	*	***	*			
Mean NAV Return	-0.52	0.86	-1.30	-0.18	-2.86	3.78	-0.36	0.23	1.10
Significance			**		**	*			

Table 25: **The DM with partition BN2 in the very high threshold level.** Average deviations, in percent, associated with 2 large negative deviators of Day 0 for $-50 \leqslant threshold < -10$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	2.60	0.74	2.28	2.50	-13.81	8.27	1.20	-2.60	-2.80
Significance				*	*	***			
Mean MP Return	2.70	1.48	3.39	3.53	-9.75	4.40	2.10	-0.44	-0.70
Significance				*	*	*			
Mean NAV Return	0.10	0.73	1.10	1.03	4.06	-3.87	0.86	2.10	2.10
Significance					*	*			

Table 26: **The DM with partition BP3 in the low threshold level.** Average deviations, in percent, associated with 440 large positive deviators of Day 0 for $2.5 < threshold \leqslant 5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.23	-0.07	-0.20	-0.65	3.23	-0.81	-0.32	-0.15	-0.19
Significance	*		**	***	***	***	***	*	*
Mean MP Return	-0.21	-0.13	-0.13	-0.58	0.48	-0.78	-0.26	-0.09	-0.08
Significance	*	*		***	***	***	**		
Mean NAV Return	0.03	-0.06	0.07	0.07	-2.76	0.03	0.05	0.06	0.11
Significance					***				

Table 27: **DM with partition BN3 in the low threshold level.** Average deviations, in percent, associated with 476 large negative deviators of Day 0 for $-5 \leqslant threshold < -2.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.08	0.19	0.45	0.91	-3.28	0.56	0.36	-0.07	0.02
Significance		**	***	***	***	***	***		
Mean MP Return	-0.03	-0.27	-0.03	0.60	-0.51	0.58	0.10	0.19	0.08
Significance		***		***	***	***		**	
Mean NAV Return	-0.11	-0.46	-0.48	-0.32	2.77	0.02	-0.26	0.26	0.06
Significance		***	***	***	***		***	**	

Table 28: **DM with partition BP3 in the medium threshold level.** Average deviations, in percent, associated with 28 large positive deviators of Day 0 for $5 < threshold \leqslant 7.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.28	0.38	-1.60	-1.96	6.18	-0.90	-1.80	-2.60	1.70
Significance			***	***	***	**	***	*	*
Mean MP Return	-0.36	0.52	-1.62	-3.01	1.31	-0.81	-1.40	-0.88	0.08
Significance			***	***	***	**	***		
Mean NAV Return	-0.65	0.15	-0.02	-1.05	-4.87	0.08	0.38	1.70	-1.60
Significance	**			**	***				*

Table 29: **DM with partition BN3 in the medium threshold level.** Average deviations, in percent, associated with 30 large negative deviators of Day 0 for $-7.5 \leqslant threshold < -5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.10	-0.67	1.26	1.77	-5.99	1.14	0.90	-0.28	0.32
Significance			***	***	***	**			
Mean MP Return	-0.31	-0.53	0.85	0.96	-1.83	0.95	0.31	0.44	0.56
Significance			*	*	***	**			*
Mean NAV Return	-0.20	0.14	-0.41	-0.81	4.16	-0.19	-0.59	0.72	0.24
Significance				**	***			*	

Table 30: **DM with partition BP3 in the high threshold level.** Average deviations, in percent, associated with 6 large positive deviators of Day 0 for $7.5 < threshold \leqslant 10$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.57	-0.11	-0.57	-4.57	8.19	-0.73	-0.01	-1.30	2.90
Significance				*	***				*
Mean MP Return	-0.16	0.96	-0.76	-3.56	3.18	0.25	0.66	-0.41	2.30
Significance				*	***				
Mean NAV Return	-0.72	1.07	-0.19	1.01	-5.01	0.98	0.67	0.93	-0.61
Significance		*			***	*			

Table 31: **DM with partition BN3 in the high threshold level.** Average deviations, in percent, associated with 4 large negative deviators of Day 0 for $-10 \leqslant threshold < -7.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-3.80	0.15	-1.04	-0.25	-8.31	-0.11	-0.34	-1.20	0.74
Significance					***				
Mean MP Return	-0.94	-1.34	-2.07	-0.49	-2.29	-0.18	0.97	0.36	0.41
Significance			*		***		*		
Mean NAV Return	2.90	-1.49	-1.04	-0.24	6.02	-0.07	1.30	1.60	-0.32
Significance		*			***		**		

Table 32: **DM with partition BP3 in the very high threshold level.** Average deviations, in percent, associated with 9 large positive deviators of Day 0 for $10 < threshold \leqslant 50$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-1.90	-0.35	−0.98	-6.16	19.00	-7.46	0.03	-0.83	0.21
Significance			**		***	*			
Mean MP Return	−1.60	-0.18	-0.46	-1.04	1.96	-0.40	0.34	-0.32	1.50
Significance	**				**				**
Mean NAV Return	0.32	0.17	0.52	5.11	−17.04	7.06	0.32	0.52	1.30
Significance					***	*			**

Table 33: **DM with partition BN3 in the very high threshold level.** Average deviations, in percent, associated with 2 large negative deviators of Day 0 for $-50 \leqslant threshold < -10$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	5.60	−2.64	4.44	15.50	−17.66	−3.51	-0.92	-3.70	9.00
Significance					*				
Mean MP Return	10.00	−2.47	2.60	18.80	−5.67	−3.51	-0.80	-4.40	4.70
Significance					***				
Mean NAV Return	4.50	0.16	−1.83	3.37	11.99	0.00	0.12	-0.71	-4.40
Significance	*		**	*					

Table 34: **The DM with partition BP4 in the low threshold level.** Average deviations, in percent, associated with 174 large deviators of Day 0 for $2.5 < threshold \leqslant 5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.19	0.10	-0.19	−0.46	3.07	−0.74	−0.55	−0.36	-0.17
Significance			*	***	***	***	***	**	
Mean MP Return	-0.06	0.16	−0.37	−0.48	0.06	−0.86	−0.46	-0.19	-0.02
Significance			***	***	***	***	***		
Mean NAV Return	−0.25	0.06	-0.19	-0.03	−3.01	-0.12	0.08	0.17	0.15
Significance	**		*		***				

Table 35: **The DM with partition BN4 in the low threshold level.** Average deviations, in percent, associated with 172 large deviators of Day 0 for $-5 \leqslant threshold < -2.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.08	0.24	-0.00	0.82	−3.08	0.89	0.05	-0.05	0.05
Significance		*		***	***	***			
Mean MP Return	0.05	-0.17	−0.42	0.19	−0.08	1.09	0.12	0.09	0.11
Significance			***		***	***			
Mean NAV Return	-0.04	−0.41	−0.41	−0.63	2.99	0.21	0.06	0.13	0.06
Significance		***	***	***	***	*			

Table 36: **The DM with partition BP4 in the medium threshold level.** Average deviations, in percent, associated with 17 large deviators of Day 0 for $5 < threshold \leqslant 7.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.35	0.05	−1.30	−1.44	5.83	−1.72	-0.83	0.23	-0.18
Significance			*	**	***	***			
Mean MP Return	-0.22	-1.28	-0.73	−2.09	0.17	-0.91	-0.97	-0.40	−1.20
Significance		*		***	*				**
Mean NAV Return	-0.57	-1.33	0.56	-0.65	−5.66	0.81	-0.14	-0.63	-1.00
Significance					***				*

Table 37: **The DM with partition BN4 in the medium threshold level.** Average deviations, in percent, associated with 11 large deviators of Day 0 for $-7.5 \leqslant threshold < -5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.87	-0.87	-2.59	0.34	-5.92	-0.12	2.10	2.50	-2.70
Significance					***		***		
Mean MP Return	1.10	-0.84	1.21	0.62	-0.11	-0.43	1.80	3.60	-1.40
Significance							**		*
Mean NAV Return	0.21	0.03	3.80	0.28	5.81	-0.31	-0.36	1.20	1.40
Significance					***				

Table 38: **The DM with partition BP4 in the high threshold level.** Average deviations, in percent, associated with 4 large deviators of Day 0 for $7.5 < threshold \leqslant 10$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.69	0.96	-0.24	-2.74	8.37	0.81	-1.20	-0.22	-2.20
Significance				*	***	**			**
Mean MP Return	0.32	0.85	1.02	-2.34	0.00	0.62	-0.50	-0.14	-2.20
Significance		*							**
Mean NAV Return	-0.38	-0.11	1.26	0.40	-8.37	-0.19	0.72	0.08	-0.01
Significance			*		***		*		

Table 39: **The DM with partition BN4 in the high threshold level.** Average deviations, in percent, associated with 2 large deviators of Day 0 for $-10 \leqslant threshold < -7.5$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	3.10	-0.77	-0.88	4.39	-7.84	2.11	0.82	-1.20	-0.71
Significance					***				
Mean MP Return	2.90	1.33	0.61	5.52	-1.03	1.71	0.43	-0.97	-2.10
Significance	**	**							
Mean NAV Return	-0.22	2.10	1.48	1.13	6.81	-0.39	-0.39	0.23	-1.40
Significance					**				**

Table 40: **The DM with partition BP4 in the very high threshold level.** Average deviations, in percent, associated with 7 large deviators of Day 0 for $10 < threshold \leqslant 50$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	0.15	0.79	-0.09	-7.09	14.60	-2.78	0.12	-0.33	1.10
Significance		*		*	***				
Mean MP Return	-0.24	0.18	0.05	-2.97	0.40	-2.93	-0.61	-0.74	1.00
Significance				*					
Mean NAV Return	-0.39	-0.61	0.14	4.11	-14.20	-0.14	-0.73	-0.41	-0.05
Significance					***				

Table 41: **The DM with partition BN4 in the very high threshold level.** Average deviations, in percent, associated with 5 large deviators of Day 0 for $-50 \leqslant threshold < -10$ during 1998-2006.

Day	-4	-3	-2	-1	0	1	2	3	4
Mean Deviation	-0.26	0.56	-0.11	9.26	-35.08	3.74	-0.56	-0.00	-0.88
Significance					***				
Mean MP Return	-0.94	-0.17	0.34	0.43	0.13	-6.81	0.86	-0.30	-0.32
Significance							*		
Mean NAV Return	-0.68	-0.73	0.45	-8.83	35.21	-10.60	1.40	-0.29	0.56
Significance					***	*		**	

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