Analysis of Intraday Herding Behavior
Among the Sector ETFs

Kimberly C. Gleason*
Ike Mathur**
Mark A. Peterson**

April 28, 2003

* Bentley College, Waltham, MA.
** Southern Illinois University, Carbondale, IL.

The authors thank Steve Ebner, Associate Director of New Product Development at the American Stock Exchange, for his assistance, and an anonymous referee of this journal for very helpful comments.

Correspondence Address: Ike Mathur
Department of Finance
Southern Illinois University
Carbondale, IL 62901-4626
Phone: 618-453-1421
Fax: 618-453-5626
e-mail: imathur@cba.siu.edu

Analysis of Intraday Herding Behavior
Among the Sector ETFs

Abstract

A body of literature has emerged suggesting that investors herd, or tend to make investment decisions on the basis of information provided by the trades of other market participants. In this paper, we use intraday data to examine whether traders herd during periods of extreme market movements using sector Exchange Traded Funds (ETFs). Two procedures, one based on identifying extreme up market and down market periods and the other based on incorporating a nonlinear term in a regression specification, are used to identify the possibility of the existence of herding behavior in nine sector ETFs traded on the American Stock Exchange. The results support the conclusion that investors do not herd during periods of extreme market movements using ETFs. Furthermore, we show that the market reaction to news is not symmetric for up markets and down markets.

Analysis of Intraday Herding Behavior Among the Sector ETFs

I. Introduction

The sheer volume of information and the varying degrees of sophistication of investors in financial markets suggest that there may be a tendency for some investors to mimic the actions of other investors, especially during periods when uncertainty in the markets increases. This tendency of investors to mimic the actions of other investors is called herding. Representative definitions of herding include "a group of investors trading in the same direction over a period of time" (Nofsinger and Sias, 1998) and "(when) individuals alter their private beliefs to correspond more closely with the publicly expressed opinions of others" (Cote and Sanders, 1997). The tendency of some investors to herd, or act like other investors, has important implications for financial markets because herding implies that investors may be ignoring their private information and in the process driving prices away from their fundamental values. Herding may lead to major shifts into or out of financial assets, and may lead to the formation of bubbles.

Furthermore, the tendency to herd may be strongest during periods of abnormal information flows and volatility, i.e., periods of high market stress, when investors seek the comfort of the consensus opinion. They may perceive that during these periods they will, at the minimum, achieve the average market return if they follow the herd. Second, obtaining additional reliable information during periods of market stress may be perceived as prohibitively costly. Thus, following the lead of the presumably informed aggregate trading behavior may be viewed as a low cost solution to problems resulting from acquisition of high cost information.

A large body of research has emerged indicating that a variety of market participants, ranging from equity market analysts (Desai et al, 2000; Hong et al, 2000), to institutional investors

(Nofsinger and Sias, 1999; Wermers, 1999), and investors in foreign markets (Choe et al, 1999; Chang et al, 2000; Lobao and Serra, 2002; Oehler and Chao, 2002), engage in herding behavior. However, other recent examinations of herding fail to detect it in a study on investment newsletters (Jaffe and Mahoney, 1999), and another on futures trading (Gleason et al, 2002).

While research has been done to examine herding among stock investors, investment newsletters, mutual fund managers, institutional investors, and futures traders, no evidence exists on herding behavior among exchange traded funds (ETFs), a recent innovation on the American Stock Exchange (Amex). ETFs were introduced by the Amex in 1993 and include both Standard & Poors Depository Receipts (SPDRs), with the trading symbol SPY, and nine SPDR sector ETFs. Collectively, the nine sector ETFs represent all companies in the S&P 500 index. Study of herding among sector funds is important for a number of reasons. First, previous studies (e.g., Chang, et al, 2000) have generally used daily or lower frequency data to examine herding. The use of lower frequency data may not be able to detect herding if it occurs for relatively short time periods and is masked by the aggregate nature of the data. We use intraday data, which allows us to detect herding even if it short-lived. Second, the large number of observations used in our study allows us to make more precise inferences. Third, the sector funds collectively represent the S&P 500 index, trading as SPDRs. The trades are observed as they occur, generally at one second intervals, and are not reported at more discrete time intervals as is the case with the stock market indices. Finally, some markets are represented by multiple indices. For example, the U.S. markets are represented by, among others, the Dow Jones Industrial Average, the NYSE index, the S&P 500 index, the NASDAQ index, and the Wilshire 5000 index. Herding may occur with each of these indices, but the overall effect would be diffused. Such is not the case with the ETF sector funds, where the market index is clearly defined, and there is no ambiguity regarding investors identifying aggregate market behavior. For these reasons, we use intraday data to extend the existing literature by examining whether investors herd in sector ETFs.

The remainder of the paper is organized as follows. The second section provides an overview of the characteristics of exchange traded funds. The third section provides a review of the literature on herding as well as a summary of the empirical evidence on herding. The fourth section explains the methodology and data sources. Two measures used to identify herding behavior are discussed in this section. The empirical results are provided in the fifth section. The last section concludes the paper.

II. Characteristics of ETFs

ETFs were developed by the Amex in 1993. ETFs allow investors to track the performance of a sector index by buying or selling the ETF. There are three general categories of ETFs: iShares Sector Funds, StreetTracks Sector Funds, and SPDR Sector Funds. iShares allow investors to replicate the indices of several international markets by buying the iShare of a specific country; domestic US iShares also replicate several Dow Jones sector indices and Russell indices. StreetTracks allow investors to replicate several US Morgan Stanley Sector Indices. On January 29, 1993, the Amex introduced trading on S&P 500 SPDRs (Standard and Poor Depository Receipts). SPDRs are designed to trade at 1/10 the level of the S&P 500. SPDRs represent ownership of shares in the trust that administers the SPDR, rather than ownership of the component assets in the S&P 500. The appeal of the SPDR to investors is that it allows investors to achieve instant diversification within the US equity markets, while enabling them to trade the S&P 500 index with a single security. ETFs have turned out to be tremendously popular products; by the end of 2000, $25 billion in assets were invested in SPDRs, and $70 billion in ETFs in general. Sector ETFs began trading on the Amex on December 22, 1998. SPDR sector funds allow investors to replicate portfolios of firms from specific industries, as those industries would be represented in the S&P 500 (Ebner, 2001).

In this paper we examine nine SPDR sector ETFs -- basic industries, consumer services, energy, financial, industrial, technology, consumer staples, utilities, and cyclical/transportation. The nine sector ETFs collectively represent all companies in the S&P 500 index, as does the SPDR itself. The nine sector ETFs comprise the SPDR, with the caveat that the weightings of the assets within the sector ETFs may differ from the weightings of the assets within the SPDR or the S&P 500 itself, and therefore, purchasing all sector ETFs will not necessarily fully replicate the S&P 500 at any given point in time. Sector ETFs trade daily from 9:30 am to 4 pm; SPDRs trade until 4:15 pm. The SPDR and the sector ETFs are traded like equity securities, with the exception that SPDRs and sector ETFs may be shorted on a downtick.

III. Market Microstructure and Herding Theories

Several microstructure-oriented models of information flow have emerged that may provide insights into the mechanisms through which market participants engage in herding behavior, and argue that due to the way in which news disseminates through the market, such behavior may in fact be justifiable from an economic rationality standpoint. Banerjee (1992) uses an analogy of individuals choosing between two restaurants by observing the decisions of prior customers to illustrate this concept and refers to the pattern of following an inappropriate decision by the entrant at the expense of the correct information set as a "herd externality" that leads to inefficient decisions from a social welfare perspective. The participation of early versus late traders may encourage the behavior further, in the sense that early investors will contribute to the impoundment of information into prices (Hirshleifer et al, 1994). Thus, the nature of financial markets may support herding behavior because of the importance of signaling by institutional investors (Trueman, 1988) through the establishment of herd externalities. Black (1992) argues that, in fact, it is noise in prices that encourages herding.

Herding has been examined in various contexts. Devenow and Welch (1996) outline several of the theories and applications of research in this area. They point out that one of its most well known applications has been identified in the banking industry during panics. Numerous models have been developed to identify the factors contributing to herding in this context. Diamond and Dybvig (1983) and Postlewaite and Vives (1987) provide arguments indicating that such behavior takes place in equilibrium, while others have argued that an informational component existed that may have led to bank runs (Gorton, 1985).

Literature related to managerial performance indicates that when evaluation occurs relative to the industry average, managers will seek to engage in decision making similar to others in the industry (Zwiebel, 1995). The incentive to do so may be to mask low ability through mimicking the decisions of higher ability managers. Compensation contracts for fund managers may also encourage herding behavior (Maug and Naik, 1995). Devenow and Welch (1996) also imply that frenzies of takeover activity, as well as dividend policy and the rush to adaptation of new technologies in some industries, may be linked to managerial decision herding.

These explanations of herding behavior imply that it may continue for an extended period of time. However, other theoretical arguments advanced to date indicate that even if such behavior exists, its extent may be limited because the feedback from rational investors offsets the signals provided to the market by the herders (Froot et al, 1992). In this event, herding is a short-term phenomenon. Other recent theoretical models of observational learning allowing for heterogenous preferences imply that not only may herding occur, but also confounded learning may result where market participants simply cannot act (Smith and Sorensen, 2002). Calvo and Mendoza (2000) provide a model of herding activity that implies that asymmetric information can lead emerging market investors to engage in herding.

III.a. Empirical Evidence Regarding Herding

Evidence regarding the presence of herding behavior in other contexts appears mixed. Research on herding in U.S. equity markets indicates that herding does not take place during periods of market stress, i.e., large price movements or high price volatility (Christie and Huang, 1995). Oehler and Chao (2002) find evidence of herding in the German bond market. Chang et al. (2000) find that while American and Hong Kong investors do not herd, investors in South Korea, Taiwan, and Japan do. Choe et al. (1999) provide evidence that while feedback trading and herding occurred on behalf of foreign investors prior to the Southeast Asian currency crisis, the activity declined during the crisis. Kim and Wei (2002) examine the behavior of resident and non-resident investors in the Korean market and find that non-residents tend to herd more than residents. This result substantiates the concept that herding may be related to limited information. A legitimate concern is that if investors herd during periods of high market stress, they may actually destabilize the market. However, no empirical evidence to date indicates that it does.

Graham (1999) finds that investment newsletters herd on Value Line as well as each other. The behavior has also been identified with analysts' forecasts as well (Olsen, 1996; Cote and Sanders, 1997; Trueman, 1994). Welch (2000) finds further support for the contention that analysts herd on prior analyst information and revisions. Olsen (1996) finds that herding among analysts may explain some of the bias in forecasts. He attributes herding to a level of anxiety experienced by investors due to disagreements of opinion, a characteristic of herders established in the psychology literature (Asch, 1952). Olsen further argues that the level of anxiety may be particularly high for analysts, who are evaluated on the basis of their forecasts, and finds that herding frequently takes place when the forecasting task is especially difficult. Analyst herding has been found to be particularly common in cases where the proportion of estimates close to the consensus is high (Stickel, 1990).

Because of the importance of institutional investors in financial markets, researchers are interested in examining whether herding takes place among mutual fund managers. Grinblatt, et al. (1995), utilizing a fund herding measure for individual funds, find evidence of herding activity in the mutual fund industry in that fund managers tend to buy the stocks of past winners at the same time. Wermers (1999) finds evidence of mutual fund herding as well. Institutional investors tend to move into or out of small securities based on analysts' predictions, possibly because of the relatively small amount of information available on small firms. However, the same phenomenon has not been observed for large stocks (Lakonishok et al, 1992). Nofsinger and Sias (1999) suggest that institutional herding influences prices to a greater extent than herding by individual investors. Nofsinger and Sias (1999) and Dennis and Strickland (2002) find additional evidence of herding among mutual fund managers herd. Dennis and Strickland (2002) attribute the tendency to herd to compensation schemes of mutual fund managers being tied to short-term performance. Borzenstein and Gelos (2000) find results supporting both the mutual fund and emerging market investor herding studies, namely, that emerging market mutual funds tend to herd. Finally, these results are also observed for the Portuguese mutual funds (Lobao and Serra, 2002).

The theoretical and empirical evidence on herding suggests that in equities markets herding may occur when there is a lack of information regarding financial assets. We hypothesize that with regard to ETFs, investors are able to aggregate information from the individual firms in the sector, and thus do not need to herd on the SPDR during periods of market stress. Second, the evidence suggests that investors may react to news during up markets differently from news during down markets. We hypothesize that during up markets, when news is positive, investors would be evaluating a relatively large set of investment opportunities vis a vis the positive news. As such, their actions may be spread out over time, leading to a lack of herding. On the other hand, during down markets, investors have the simpler task of evaluating the effects of news on a smaller set of stocks in their portfolios.[1] They can act quickly on the news by following the aggregate market in adjusting their portfolios, thereby creating the possibility of herding.

IV. Methodology and Data

IV.a. Methodology

During periods of normal information flow and volatility, the returns on the nine sector ETF funds should reflect the investors' reactions to information relevant to the individual sectors. However, during periods of abnormal information flows and high volatility, investors who tend to herd may be expected to not act on their information, and instead rely on the returns on the aggregate market to form their investment decisions. Thus, trading times characterized by large returns, or periods of market stress, are particularly well suited to examining herding behavior.

Given the characteristics of the Sector ETFs and the S&P 500 SPDRs, and the intraday nature of the data, a unique opportunity exists to examine potential herding activity in the equity markets using these instruments. During periods of high market stress, investors who seek to herd would observe the returns on the SPDRs and seek to achieve these market returns. Under this market scenario, we would expect the returns on the sector ETFs to converge towards those of the SPDR. Herding, thus, would result in a smaller difference between the returns on the sector ETFs and the SPDR. We use two alternative measures of dispersion to identify the difference in returns on the

1 Selling short during down markets would involve evaluating a larger set of financial assets. However, we do not consider short selling a significant issue because the number of shares that are sold short are a small proportion of

sector ETFs and the SPDR. Herding would be evidenced by a lower cross-sectional standard deviation (CSSD), and a lower or a less than proportional increase in the cross-sectional average deviation (CSAD) during periods of market stress.

The cross-sectional standard deviation (CSSD) method was used by Christie and Huang (1995) and can be expressed as

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} (R_{i,t} - R_{m,t})^2}{N - 1}} \tag{1}$$

where $R_{i,t}$ is the intraday return on Sector ETF i during time period t, and $R_{m,t}$ is the return on the SPDR during the same time period.[2]

An alternative measure of dispersion is provided by Chang et al. (2000) who define the cross-sectional absolute deviation (CSAD) as

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} | R_{i,t} - R_{m,t} | \tag{2}$$

Both of the dispersion models are used to identify any possible herding behavior. The approach taken by Christie and Huang (1995) is to argue that herding will be more prevalent during periods of market stress, which is defined in terms of extreme returns on the SPDR. Consider the following equation:

$$CSSD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t \tag{3}$$

where

$D_t^U = 1$, if the return on the SPDR for time period t lies in the extreme upper tail of the returns

---

the shares outstanding.

2 $R_{m,t}$ in equation 1 is not the average of the $R_{i,t}$'s. Thus, technically the CSSD should be referred to as the Root Mean Square Error (RMSE). However, we refer to RMSE as CSSD to relate our analysis to Christie and Huang (1995).

distribution, and = 0 otherwise.[3]

D_t^L = 1, if the return on the SPDR for time period t lies in the extreme lower tail of the returns distribution, and = 0 otherwise.[4]

If herding occurs, then $CSSD_t$ will be smaller during periods of market stress, i.e., returns on the sector ETFs would converge to the returns on the SPDR. Thus, statistically significant negative values for β_1 and β_2 would indicate the presence of herding.

Chang et al. (2000) argue that the model in Equation 3 requires defining what is meant by market stress. Under normal conditions, the conditional CAPM specifies a linear relationship between CSAD and market returns. However, if herding occurs during periods of market stress, then a nonlinear relationship will also exist. This nonlinear relationship can be modeled as follows:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{4}$$

If herding is present, then γ_2 will be significantly negative, implying that the deviation of returns on the sector ETFs from the returns on the SPDR declines during periods of stress.[5] This nonlinear component would also be observed for CSSD if herding is present during periods of market stress.

To obtain a more comprehensive analysis, we test two additional models where we swap the dependent variables in Equations 3 and 4

$$CSAD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t \tag{5}$$

$$CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{6}$$

IV.b. Data

We obtain tick by tick data from the NYSE's TAQ database for the period 1/4/1999 to 9/30/2002. Table 1 summarizes the trade and other statistics for SPDR and the nine sector ETFs.

---

3 If the criterion for extreme is set at 1%, it means that 1% of the SPDR returns observations are in upper tail.
4 If the criterion for extreme is set at 1%, it means that 1% of the SPDR returns observations are in lower tail.
5 We note that a significantly negative coefficient does not imply herding if the CAPM is non-linear.

The total number of trades for SPDR is 5,561,890 during the time period covered. Of the sector ETFs, technology, XLK, is the most actively traded over the entire time period, with 366,169 observed trades. The average trade size across all ETFs is about 2,351 shares. The average trade size of SPDRs, is 2,254 shares. The maximum trade size for SPDRs during our sample period is 9,999,900 shares. The median time to open for SPDR is 5 seconds. The largest median time to open is for XLU, the utilities sector fund, with a time of 780 seconds or 13 minutes. The median time between trades for SPDR is 1 second. The largest median time between trades is for XLV, the consumer services sector fund, with a time of 359 seconds, or about 6 minutes.

[Table 1 about here]

The 15-minute intra-day returns statistics for all 10 ETFs are summarized in Table 2. If an ETF does not trade over an interval the return is set to 0. The highest average intraday returns of 7.76E-4% are exhibited by XLV, the consumer services sector fund, while the highest volatility is exhibited by XLK, the technology sector fund. The last two rows provide information on the average intra-day CSSD and CSAD. The results indicate that CSSD is larger, and with higher volatility, than CSAD.

[Table 2 about here]

V. RESULTS

V.a. Evidence on Herding

Panel A, Table 3 summarizes the regression results for Equations 3 and 5 for returns calculated every 15 minutes.[6] The results reported in this panel use the 0.5% criterion, i.e., 0.5% of the SPDR returns observations are in the upper and in the lower tails of the SPDR returns. Based on adjusted R^2's, the equations where CSADs are used to measure the market dispersion provide a

6 The 15 minute interval is selected based on the median time to open and the median time between trades reported

better fit to capture the relationship between market dispersion and market extreme variables. The first regression in Panel A has CSSD as the dependent variable. The β_1 and β_2 coefficients for this regression are significantly positive, indicating that CSSD actually increases during periods of market stress. In other words, the returns on the sector ETFs actually diverge from SPDR returns, indicating a pattern of trading away from the market consensus. This result is contrary to what we would expect if herding behavior was present. Thus, the results are consistent with the absence of herding behavior.

[Table 3 about here]

The second regression in Panel A, Table 3 has CSAD as the dependent variable. Here too, the β_1 and β_2 coefficients are significantly positive, indicating a divergence of the sector ETF returns from the SPDR returns -- in other words, the absence of herding behavior. In summary, irrespective of the dispersion measure utilized, the results from both regressions in Panel A do not support the notion of herding behavior for the nine sector ETFs.

Panels B and C in Table 3 replicate the analysis in Panel A, except that the criterion levels are specified as 1.0% and 2.0% in Panels B and C, respectively. The adjusted R^2's become progressively higher as the criterion level is increased from 0.5% in Panel A to 1.0% in Panel B to 2.0% in Panel C. In all three cases, compared to CSSD, CSAD provides a better fit for the data. The results and the implications in Panels B and C are similar to those for Panel A.

We next turn our attention to the operational versions of the Chang et al. (2000) model. The results for this model, i.e., Equations 4 and 6, are reported in Panel D, Table 3. This model has higher explanatory power when CSAD is the dependent variable, as indicated by the adjusted R^2's of the regressions in Panel D. First, looking at the results for Equation 4 with CSSD as the dependent

---

in Table 1.

variable, we see that γ_2 is significant and positive. This result points to the absence of herding during periods of high market stress. When the analysis is replicated with CSAD as the dependent variable, we observe that γ_2 is still positive and significant. Here also, we do not observe a significantly negative coefficient, indicating that herding is not observable for the ETFs examined in this paper.[7]

Looking at the results presented in Table 3 in their entirety, the regressions, which have relatively high adjusted R^2's, indicate that herding is not a phenomenon that characterizes the ETFs analyzed. To the contrary, the results indicate that during periods of market stress, the ETF traders trade away from the market consensus as proxied by the SPDR. The results in Table 3 are similar to results reported by Christie and Huang (1995), and Chang et al (2000), who also do not find evidence of herding in US equity markets.[8]

V.b. Asymmetric Reactions to News

Chang et al. (2000) report that the market reaction to good news and bad news is not symmetric. They show that in equity markets, not only does CSAD increase with $|R_{mt}|$, but the rate of increase is higher in up markets -- defined as days when market returns are not negative -- than in the down markets -- when market returns are negative, suggesting an asymmetric reaction to good and bad macroeconomic news. Investors, more fearful of a "downside period of stress," may be more likely to herd under these circumstances (as mutual fund managers tend to herd during market crashes). We test this proposition of asymmetric reaction to good news and bad news by using the previous estimates for Equations 3 and 5, and estimating Equations 4 and 6 for up markets and down

7 We replicate Table 3 results for returns calculated at 5, 20 and 30 minute intervals also. The results are similar to the results reported in Table 3 and indicate the absence of herding. The results are available from the contact author.

8 Decimalization was introduced on January 29, 2001. After decimalization, the average trade size decreased significantly, the number of trades increased sharply, and the time between trades decreased. Given the possibility that decimalization may have affected herding, we replicated Table 3 for pre and post decimalization. The results were not

markets separately.

Panel A, Table 4 reports the results for up and down markets based on the regression coefficient estimates reported in Table 3, Panels A through C. The returns are calculated at 15 minute intervals. No evidence of asymmetric response is evident when the criterion for extreme is set at 0.5%. However, when the criterion for extreme is set at 1.0% and at 2.0%, then traders' responses to stress in up and down markets are not symmetric. The rate of increase in the dispersion measures is higher in up markets than in down markets, confirming previous conjectures on asymmetric responses to news (see, e.g., Chang et al, 2000).

Panel B, Table 4 reports the results for up markets and down markets with CSSD and CSAD as the dependent variables, when returns are calculated at 15 minute intervals. The results for CSSD do not exhibit an asymmetric response to news on behalf of traders of sector ETFs. Dispersion in returns increases proportionally during up markets and during down markets, thus not supporting the prediction of the Chang et al (2000) model. Further, as shown by the sign of the parameter estimate, γ_2, the results for CSSD are consistent with the results reported in Table 3 in that they do not support herding. That is, dispersion of sector ETF returns actually increases significantly in both up and down markets.

The evidence presented using CSAD indicates that dispersion increases during periods of stress in up markets. The dispersion during periods of stress in down markets also increases, as shown by the positive sign of the γ_2 parameter estimate, but this increase is not statistically significant. The positive sign of $\gamma_2^{up} - \gamma_2^{dn}$ in Table 4 indicates that dispersion of returns away from the SPDR is higher during periods of stress in up markets than during periods of stress in down markets, but this difference is not statistically significant.

affected by decimalization, i.e., herding was not evident before or after decimalization.

VI. Conclusions

We examine herding behavior in ETFs in this paper. Using two different measures of dispersion, and two different methods for identifying herding, we show that when we analyze up markets and down markets in aggregate, no evidence of herding is found. In fact, the results indicate that during periods of market stress, ETF traders trade away from the market consensus, as proxied by the SPDR. These results suggest that, as far as ETFs are concerned, information to traders is imparted efficiently, thereby obviating the need for traders to form their trading decisions on perceived consensus actions.

Froot et al. (1992) suggest that investors may herd if there are limited information sources available to them. Further, Lakonishok et al. (1992) provide evidence that suggests that there is a greater propensity for herding in stock of small companies compared to stocks of large companies. Lakonishok et al. (1992) argue that there is less public information and greater information asymmetry for smaller firms compared to larger firms, which leads investors to follow the decisions of other investors when investing in smaller stocks. This argument can be readily extended to sector ETFs. Each sector ETF represents multiple firms in the sector. There may be a paucity of information regarding some proportion of firms in a sector. However, investors can aggregate information on all firms in a sector when forming opinions regarding that sector. As such, there is sufficient information on sectors for investors to form informed decisions. This aggregate information on sectors leads to the observed results that herding is not present in ETF trading.

We document a weak presence of asymmetric reaction to news during periods of stress in up markets and down markets. Our results indicate that dispersion may not be similar, during periods of stress, in up and in down markets. Previous research suggests (see, e.g., McQueen et al, 1996) that there is a delayed reaction to good news, whereas market participants react more quickly to bad news. This evidence suggests that when investors respond to bad news, leading to periods of stress in down markets, they do so quickly, and thus have a greater incentive to mimic the aggregate market. In other words, market participants may fear the potential loss during a down market period of stress more than they enjoy the potential gain during an up market period of stress, and evaluate their positions relative to the market with more anxiety -- described as “myopic loss aversion” (Benartzi and Thaler, 1995). Thus, they may be more inclined to herd in down markets. This type of trading behavior leads to lower dispersion and the possibility of herding in down markets. Our results provide weak support for this hypothesis of myopic loss aversion.

REFERENCES

Asch, S. Social Psychology (Englewood Cliffs, NJ: Prentice Hall), 1952.

Banerjee, Abhijit V. "A Simple Model Of Herd Behavior," *Quarterly Journal of Economics*, 1992, 107(3), 797-818.

Benartzi, S., and R. Thaler. "Myopic Loss Aversion and the Equity Premium Puzzle," *Quarterly Journal of Economics*, 1995, 110(1), 73-94.

Black, F. "Noise," *Journal of Finance*, 41 (July) 1986, 529-544.

Borzenstein, E. R., and R. G. Gelos. "A Panic-Prone Pack? The Behavior of Emerging Market Mutual Funds," IMF Working Paper 00-198, 2000.

Calvo, G., and E. Mendoza. "Rational Herd Behavior and Globalization of Securities Markets," *Journal of International Economics*, 51 (June), 2000, 79-113.

Chang, E., J. Cheng, and A. Khorana. "An Examination of Herd Behavior in Equity Markets: An International Perspective," *Journal of Banking and Finance*, 2000, 24(10), 1651-1679.

Choe, H., B. C. Kho, and R. M. Stulz. "Do Foreign Investors Destabilize Stock Markets? The Korean Experience in 1997," *Journal of Financial Economics*, 1999, 54(2), 227-264.

Christie, William G., and Roger D. Huang. "Following The Pied Pier: Do Individual Returns Herd Around The Market?" *Financial Analyst Journal*, 1995, 51(4), 31-37.

Cote, I., and Sanders, D. "Herding Behavior: Explanations and Implications," *Behavioral Research in Accounting*, 1997, 9(1), 20-45.

Dennis, P., and D. Strickland. "Who Blinks in Volatile Markets, Individuals or Institutions?" *Journal of Finance*, 2002, 57(5), 1923-1949.

Desai, H., B. Liang, and A. K. Singh. "Do All-Stars Shine? Evaluation of Analysts Recommendations," *Financial Analysts Journal*, 2000, 56 (3), 20-29.

Devenow, Andrea, and I. Welch. "Rational Herding In Financial Economics," *European Economic Review*, 1996, 40(3-5,Apr), 603-615.

Diamond, Douglas W., and Philip H. Dybvig. "Bank Runs, Deposit Insurance, And Liquidity," *Journal of Political Economy*, 1983, 91(3), 401-419.

Ebner, S. Private Communication. American Stock Exchange, 2001.

Froot, Kenneth A., David S. Scharfstein, and Jeremy C. Stein. "Herd On The Street: Informational Inefficiencies In A Market With Short-Term Speculation," *Journal of Finance*, 1992, 47(4), 1461-1484.

Gleason, K. C., C. I. Lee, and I. Mathur. "The International Evidence on Herding Behavior in Futures Markets," Working Paper, SIUC, 2002.

Gorton, Gary. "Banking Theory And Free Banking History: A Review Essay," *Journal of Monetary Economics*, 1985, 16(2), 267-276.

Graham, J. "Herding Among Investment Newsletters: Theory and Evidence", *Journal of Finance*, 1999, 54(1), 237-268.

Grinblatt, M., S. Titman, and K. Wermers. "Momentum Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior," *American Economic Review*, 1995, 85 (5), 1088-1105.

Grossman, Sanford J., and Joseph E. Stiglitz. "Information And Competitive Price Systems," *American Economic Review*, 1976, 66(2), 246-253.

Hirshleifer, David, Avanidhar Subrahmanyam, and Sheridan Titman. "Security Analysis And Trading Patterns When Some Investors Receive Information Before Others," *Journal of Finance*, 1994, 49(5), 1665-1698.

Hong, H., T. Lim, and J. C. Stein. "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies," *Journal of Finance*, 2000, 55 (1), 265-295.

Jaffee, J. F., and J. M. Mahoney. "The Performance of Investment Newsletters," *Journal of Financial Economics*, 1999, 53(2), 289-307.

Kim, W. C., and S. J. Wei. "Foreign Portfolio Investors Before and During a Crisis," *Journal of International Economics* 56 (January), 2002, 77-96.

Lakonishok, J., A. Shleifer, and R. W. Vishny. "The Impact of Institutional Trading on Stock Prices," *Journal of Financial Economics*, 1992, 32(1), 23-44.

Lobao, J., and A.P. Serra. "Herding Behavior: Evidence from Portuguese Mutual Funds," Working Paper, Instituto de Estudos Financieros e Fiscais, Portugal, 2002.

Maug, E., and Naik, N. "Herding and Delegated Portfolio Management: The Impact of Relative Performance Evaluation on Asset Allocation," Working Paper (London Business School, London), 1995.

McQueen, G., M. A. Pinegar, and S. Thorley. "Delayed Reaction to Good News and the Cross-autocorrelation of Portfolio Returns," *Journal of Finance*, 1996, 51(3), 889-919.

Nofsinger, J.R., and R.W. Sias. "Herding and Feedback Trading by Institutional and Individual Investors," *Journal of Finance*, 1999, 54(6), 2263-2295.

Oehler, A., and G.G.C. Chao. “Institutional Herding in Bond Markets,” Working Paper, Bamberg University, Germany, 2002.

Olsen, Robert A. "Implications Of Herding Behavior For Earnings Estimation, Risk Assessment, And Stock Returns," *Financial Analysts Journal*, 1996, 52(4, Jul-Aug), 37-41.

Postlewaite, Andrew, and Xavier Vives. "Bank Runs As An Equilibrium Phenomenon," *Journal of Political Economy*, 1987, 95(3), 485-491.

Smith, L., and P. Sorensen. “Informational Herding and Optimal Experimentation,” Working Paper, University of Michigan, 2002

Stickel, Scott E. "Predicting Individual Analyst Earnings Forecasts," *Journal of Accounting Research*, 1990, 28(2), 409-417.

Trueman, Brett. "A Theory Of Noise Trading In Securities Markets," *Journal of Finance*, 1988, 43(1), 83-95.

Trueman, Brett. "Analyst Forecasts And Herding Behavior," *Review of Financial Studies*, 1994, 7(1), 97-124.

Welch, Ivo. "Herding Among Security Analysts," *Journal of Financial Economics*, 2000, 58(3), 369-396.

Wermers, R. "Mutual Fund Herding and the Impact on Stock Prices,” *Journal of Finance*, 1999, 54(2), 581-622.

Zwiebel, Jeffrey. “Corporate Conservatism and Relative Compensation,” *Journal of Political Economy*, 1995, 103(1), 1-25.

Table 1
Sample Summary

This table describes the trade statistics for the ETFs in the sample for the period 1/04/99 to 9/30/02. The ETFs represent the S&P 500 index and various S&P Sector portfolios. Data are compiled from the TAQ database for each ETF. Trades are omitted if they are coded as out of sequence or coded as having an error or correction. Trades indicated to be exchange acquisitions or distributions, trades that involve nonstandard settlement (TAQ Consolidated Trade file with Sale Condition codes A, C, D, N, O, R, and Z) are omitted as well. Trades that involve a price change (since the last trade) of 25% or more if the prior price is over $2 per share are also excluded. The ETF symbols represent the sectors as follows: SPY, S&P 500 index depository receipt, or SPDR; XLB, Basic industries; XLE, Energy; XLF, Financial; XLI, Industrial; XLK, Technology; XLP, Consumer staples; XLU, Utilities; XLV, Consumer services; XLY, Cyclical/transportation.

				Trade Size Statistics		
Symbol	Number of Trades	Median Time to Open (Seconds)	Median Time Between Trades (Seconds)	Mean	Minimum	Max.
SPY	5,561,890	5	1	2,254	100	9,999,900
XLB	47,377	481	172	3,239	100	1,370,000
XLE	92,396	509	106	3,186	100	3,000,000
XLF	145,749	532	64	5,368	100	3,600,000
XLI	29,091	787	265	2,623	100	1,200,000
XLK	366,169	346	27	2,114	100	3,340,000
XLP	59,499	522	181	2,009	100	810,700
XLU	38,664	780	207	1,920	100	1,014,800
XLV	26,746	583	359	1,679	100	500,000
XLY	28,937	615	298	4,642	100	1,930,000

Table 2
Intra-day Return and Dispersion Statistics (in percent)

This table reports the return statistics for the sample described in Table 1. The table reports the intra-day return statistics with the returns calculated every 15 minutes. The return is set to 0 if no trade occurred in a 15-minute interval. A total of 23,500 returns are calculated for each ETF (23,475 for XLI). CSSD refers to the cross-sectional standard deviation method of Christie and Huang (1995). CSAD refers to the cross-sectional absolute deviation method of Chang et al (2000).

Symbol	Mean	Standard Deviation	Minimum	Maximum
SPY	–2.80E-3	0.23	–2.14	3.83
XLB	–6.14E-4	0.39	–12.29	6.24
XLE	–1.33E-3	0.34	–4.94	5.12
XLF	–7.99E-4	0.37	–6.73	7.12
XLI	–1.95E-3	0.30	–4.17	4.05
XLK	–7.54E-3	0.45	–5.16	8.52
XLP	5.71E-4	0.36	–2.15	4.29
XLU	–3.15E-3	0.31	–4.01	5.01
XLV	7.76E-4	0.31	–4.30	7.24
XLY	5.17E-4	0.32	–3.94	6.45
CSSD	0.35	0.17	0.00	4.38
CSAD	0.29	0.15	0.00	3.69

Table 3
Regression Results of CSSD and CSAD on Market Dummy Variables and on the Absolute and Squared Returns of Market Indices

This table reports regression results using the sample described in Table 1. Returns are calculated every 15 minutes. Panels A through C report the results with the independent variables of D^U and D^L, where D^U (D^L) are dummy variables equal to 1 if the index return is in the extreme upper (lower) tail of the return distribution; 0 otherwise. If the criterion for extreme is set at 0.5% [1.0%; 2.0%] it means that 0.5% [1.0%; 2.0%] of the SPDR returns observations are in the upper and lower tails of the SPDR returns. Panel D reports the results with the independent variables equal to the absolute return on the market index and the squared market return. The return is set to 0 if no trade occurred in the interval. CSSD refers to the cross-sectional standard deviation method of Christie and Huang (1995). CSAD refers to the cross-sectional absolute deviation method of Chang et al (2000). White heteroscedastic-consistent standard errors are in parentheses. ***/**/* indicates significance of the White heteroscedastic-consistent t-statistic at the 1%/5%/10% level.

Panel A: Model: $DEPVAR = \alpha + \beta_1 D^U + \beta_2 D^L + \varepsilon$ (Criterion = 0.5%)

Dep. Variable	α	β_1	β_2	Adj. R^2
CSSD	0.00340*** (0.00001)	0.00594*** (0.00047)	0.00510*** (0.00029)	0.102
CSAD	0.00286*** (0.00001)	0.00579*** (0.00045)	0.00508*** (0.00030)	0.129

Panel B: Model: $DEPVAR = \alpha + \beta_1 D^U + \beta_2 D^L + \varepsilon$ (Criterion = 1.0%)

Dep. Variable	α	β_1	β_2	Adj. R^2
CSSD	0.00336*** (0.00001)	0.00458*** (0.00026)	0.00399*** (0.00019)	0.122
CSAD	0.00283*** (0.00001)	0.00453*** (0.00025)	0.00401*** (0.00019)	0.157

Panel C: Model: $DEPVAR = \alpha + \beta_1 D^U + \beta_2 D^L + \varepsilon$ (Criterion = 2.0%)

Dep. Variable	α	β_1	β_2	Adj. R^2
CSSD	0.00332*** (0.00001)	0.00348*** (0.00015)	0.00306*** (0.00012)	0.152
CSAD	0.00279*** (0.00001)	0.00351*** (0.00014)	0.00311*** (0.00011)	0.185

Panel D: Model: $DEPVAR = \alpha + \gamma_1 |R_m| + \gamma_2 R_m^2 + \varepsilon$

Dep. Variable	α	γ_1	γ_2	Adj. R^2
CSSD	0.00261*** (0.00002)	0.455*** (0.018)	13.8*** (2.20)	0.304
CSAD	0.00196*** (0.00001)	0.542*** (0.016)	8.27*** (2.47)	0.443

Table 4

Tests for Asymmetric Reaction in Up and Down Markets

The table reports regression results and tests of an asymmetric reaction using the sample described in Table 1. Panel A tests correspond to the regression coefficient estimates found in Table 3, Panels A through C. Panel B regressions and tests correspond to the regression equation in Table 3, Panel D. White heteroscedastic standard errors are in parentheses. ***/**/* indicates significance of the White heteroscedastic-consistent t-statistic at the 1%/5%/10% level. Differences in coefficients in Panel A are tested with an F-test with chi-square and corresponding p-values in parentheses. Differences in coefficients in far right two columns of Panel B are tested using the t-test.

Panel A: $y = \alpha + \beta_1 D^U + \beta_2 D^L + \varepsilon$

	Criterion = 0.5%				Criterion = 1.0%				Criterion = 2.0%		
	β_1	β_2	$\beta_1 - \beta_2$		β_1	β_2	$\beta_1 - \beta_2$		β_1	β_2	$\beta_1 - \beta_2$
CSSD	0.00594	0.00510	0.00084 (2.34, 0.13)		0.00458	0.00399	0.00059* (3.44, 0.06)		0.00348	0.00306	0.00042** (4.95, 0.03)
CSAD	0.00579	0.00508	0.00071 (1.72, 0.19)		0.00453	0.00401	0.00052* (2.81, 0.09)		0.00351	0.00311	0.00040** (4.64, 0.03)

Panel B: $y = \alpha + \gamma_1|R_m| + \gamma_2 R_m^2 + \varepsilon$

	Up Market			Down Market			
α	γ_1^{up}	γ_2^{up}	α	γ_1^{dn}	γ_2^{dn}	$\gamma_1^{up} - \gamma_1^{dn}$	$\gamma_2^{up} - \gamma_2^{dn}$
CSSD							
0.00261*** (0.00002)	0.465*** (0.0177)	13.4*** (2.3)	0.00260*** (0.00003)	0.442*** (0.032)	14.9*** (5.4)	0.0231 (0.0369)	−1.53 (5.85)
CSAD							
0.00195*** (0.00002)	0.548*** (0.018)	8.60*** (2.62)	0.00194*** (0.00002)	0.556*** (0.030)	4.92 (5.31)	−0.00801 (0.03493)	3.68 (5.92)