

Mutual Fund Herding and Price Discovery – Evidence from an Emerging
Market

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Abstract

In this paper, we directly investigate the impact of mutual funds' herding behavior on the price discovery process by using a VAR test procedure, which simultaneously and sequentially tests the multiple hypotheses of the return dynamics. Results show that mutual funds' herding contains information in the sense that stocks that mutual funds herd tend to adjust information faster than stocks that mutual funds do not herd. This implies that mutual fund managers herd on new information about the firms' future prospects and will expedite the incorporation of information into stock prices. Furthermore, we also find that mutual funds' herd buying contains more information than their herd selling behavior. Finally, we evidence that without herding mutual fund managers may still exhibit their private information via their act of trading.

Keywords: mutual fund herding, price discovery, VAR test, buy-herd, sell-herd, return dynamics

I. Introduction

Recently, the institutional investors' herding behavior has drawn much attention in finance literature. Since institutional investors' trading pattern may have significant impact on the price and volatility of securities market, institutional investors' herding is important for understanding the influence of institutional trading on securities markets and on the speed and process of information transmitted into market prices.

Many recent studies evidence the herding behavior of institutional investors. For example, Lakonishok, Shleifer and Vishny (1992) show that pension fund managers either engage in positive-feedback trading or trading in herds, and especially for the smaller sized stocks. Grinblatt, Titman and Wermers (1995) document the herding pattern of mutual funds. They also find that most of mutual funds use positive-feedback trading strategies to select stocks. In addition, Graham (1999) evidences that analysts who publish investment newsletters have a tendency to herd. Brown, Wei and Wermers (2007) document the tendency of mutual fund managers to follow analyst recommendation revisions in their stock trading and, thus, mutual funds herding could be a result of analysts herding on their recommendation revisions. Furthermore, Nofsinger and Sias (1999), Wermers (1999) and Sias (2004) all find evidence of the herding behavior among institutional investors.

Basically, there are four rationales explaining why institutional investors herd in their trade. First, due to the risk of acting differently from other managers, fund managers may tend to ignore their private information and trade with the crowd (e.g., Scharfstein and Stein (1990)). Second, managers may trade in the same direction as the better-informed managers do by inferring information from their prior trades (e.g., Bikhchandani, Hirshleifer, and Welch (1992)). Third, managers may trade the same stocks by receiving correlated private information, which may due to the fact that they are

making trading decisions based on similar indicators (e.g., Hirshleifer et al. (1994)). Finally, most of the fund managers may be reluctant to trade on stocks with certain characteristics, such as stocks with lower liquidity or stocks that are less risky (e.g., Falkenstein (1996)).

While the institutional herding can be based on little or no information (e.g., Scharfstein and Stein (1990); Bikhchandani et al. (1992)), it can also be informational and helps expediting the price discovery to information if institutions herd buy under-priced and herd sell over-priced stocks (e.g., Hirshleifer et al. (1994); Nofsinger and Sias (1999); Wermers (1999)).

Moreover, Sias (2004) finds that institutional herding primarily results from institutions inferring information from each other. In a more recent study, Puckett and Yan (2007) also evidence that institutional herding tend to help impound new information into security prices more efficiently. All of the above literature provides evidence that institutional herding tends to be information-based and help drive the security prices closer to their fundamental values.

In addition to documenting the herding behavior of institutional traders, recently more studies focus on the impact of institutional traders herding behavior on prices and volatility of securities markets. For example, Scharfstein and Stein (1990) evidence that institution's herd is a destabilizing factor to stock market, while Hirshleifer et al. (1994) argue that mutual funds herding need not be destabilizing and actually could be stabilizing prices if funds herd buy underpriced and herd sell overpriced stocks.

Wermers (1999) investigates the impact of mutual fund herding on stock prices and documents that stocks that herds buy outperform stocks that herds sell. Wermers infers this result being “consistent with theories where managers herding on new information

about the future prospects of firms and help to speed up the incorporation of this new information into prices.” (Wermers (1999), p. 618)

While the result of Wermers (1999) is insightful for understanding the performance of stocks that are bought by herds and those that are not, he does not directly examine the effect of mutual funds’ herding behavior on the speed of price-adjustment process. Thus, his finding regarding the performance of herded and non-herded stocks simply indicates that stocks that are herded by mutual funds on average perform better than stocks that are not herded by mutual funds. The result of stock performance does not imply anything regarding the price discovery process and, thus, cannot be inferred to the speed of incorporation of new information into prices.

To our knowledge, there has been no study in the existing literature that directly explores the impact of institutional herding on the security price discovery process. The purpose of this paper is to fill this gap and attempts to directly investigate the effect of institutional herding on the speed of stock price discovery by looking at the return dynamics between the stocks that institutions herd versus those that they do not herd.

Specifically, we use a VAR test methodology, which simultaneously and sequentially tests the multiple hypotheses of the return dynamics, to examine the speed of price discovery between returns of stocks that mutual funds herd and those that mutual funds do not herd. Our result shows that returns of stocks that mutual funds herd, either buy-herd or sell-herd, tend to lead those that mutual funds do not herd. This is consistent with the implication from Wermers’ (1999) result.

However, unlike Wermers (1999) who only indirectly infers that phenomenon, we directly test it and find that stocks that mutual funds herd tend to adjust information faster than stocks that mutual funds do not herd. In other words, our finding suggests that

mutual funds' herding behavior tends to speed up the security price discovery process. This result also implies that mutual funds' herding is rational and informational in the sense that mutual fund managers herd on new information about the firms' future prospects and will bring security prices closer to their fundamental values and, thus, will speed up the security price discovery process.

Furthermore, by segregating mutual funds' herding into buy-herd and sell-herd, we further find that stocks that mutual funds buy in herd tend to lead stocks that mutual funds sell in herd. The result indicates that the above finding regarding mutual funds' herding on the speed of price discovery process is mainly attributed to mutual funds' buy-herd rather than their sell-herd behavior. This asymmetric result implies that mutual funds' buy-herd behavior contains more information than their sell-herd behavior. This finding is also consistent with what has been found by Puckett and Yan (2007) that institutional buy-herd tends to be more information-based while institutional sell-herd tends to be motivated by non-informational and behavioral considerations.

We also examine the possibility that the above asymmetric result between buy-herd and sell-herd may be caused by the effect of mutual fund investors' redemption. That is, when investors redeem their shares from the fund, fund managers are forced to sell stocks from their portfolios more often because of the redemption. This can be quite significant when the market keeps sliding and causes panics among investors. As a result, the mutual fund sell-herd will contain less or no information.

However, when we divide the sample funds into open-end and closed-end funds and repeat the analysis, we find similar asymmetric results in both open-end and closed-end funds. Thus, it implies that the redemption effect is not the major cause for the above buy-herd versus sell-herd asymmetric results.

In addition, by further dividing sample stocks into those mutual funds trade but do not herd and those mutual funds do not even trade, we find that returns of stocks that mutual funds trade but do not herd tend to lead those that mutual funds do not trade. This indicates that not only mutual funds' herding will speed up the price discovery process, but mutual funds' trading behavior per se reveals some information. This implies that mutual fund managers play an informational leading role in terms of expediting the price discovery process in their trading behavior.

However, from the above results that returns of stocks that mutual funds herd lead those that mutual funds do not herd, the information content and the effect on the speed of price discovery of mutual funds' herding is more significant than that of mutual funds' trading behavior. That is, mutual funds herding provides significant and more incremental information than mutual funds trading.

The remainder of the paper is organized as follows. Section II describes the data, the herding measures and the statistical methodology that we use. Empirical findings and analyses are presented in Section III. And, finally we conclude our paper in Section IV.

II. Data and Methodology

A. Data

We include both open-end and closed-end equity funds in this study. Since there may exist redemption pressure on the open-end funds during the time when market is declining, fund managers may herd out of stocks simply because of the redemption pressure. Therefore, in addition to the analysis based on all mutual funds in our sample, we further analyze the effect of herding by the open-end and closed-end funds separately

on the speed of price discovery process to see whether the extent and significance of the effect from herding on price discovery will be different on these two types of funds.

Since the shareholding data of Taiwan's mutual funds was not published until May, 1993, our sample period of mutual funds starts from May, 1993 and ends at December, 2006. Our sample stocks include all of the shares listed in Taiwan Stock Exchange and Taiwan's OTC market during the above sample period. However, in order to avoid the result being contaminated by the non-trading effect, we exclude stocks with one or more non-trading days in our sample period. Thus, all of the stocks included in our sample are traded in every trading day in the sample period. Both the returns of individual stocks and the mutual funds' shareholdings data are obtained from Taiwan Economic Journal (TEJ) database.

In order to investigate the effect of mutual fund's herding behavior on the stock price-adjustment process, we first examine the significance of herding by mutual funds for each of our sampled individual stocks. In specific, we use the herding measures developed by Lakonishok et al. (1992) and Wermers (1999), which will be discussed in next subsection, to test the significance of herding for each individual stock.

Next, we segregate all of the sample stocks into two portfolios: one with stocks that are traded and significantly herded by mutual funds and another with stocks that are traded but not herded by mutual funds. These are the two basic portfolios that will be used to test for the difference in the speed of price discovery between herded and non-herded stocks. We then can infer the effect of mutual funds' herding on the price discovery process from the test result. If the prices of stocks that are herded by mutual funds adjust to information faster than the prices of stocks that are not herded by mutual funds, then it implies that mutual fund herding helps expediting the incorporation of new

information into stock prices. That is, mutual funds' herding expedites the stock price discovery process.

A basic data description is summarized in Table 1. In Table 1, we report the number of stocks in each of the herding and non-herding categories and other between-category-comparison figures for all sample funds, open-end funds and closed-end funds, respectively.

First of all, from the first row of Table 1, it is obvious that number of stocks that are herded by open-end funds is much more than number of stocks that are herded by closed-end funds. There are a total of 438 stocks that have been herded by open-end funds, while there are only 66 stocks that have been herded by closed-end funds. The number of stocks being herded by open-end funds is about 7 times more than that being herded by closed-end funds. This suggests that open-end fund managers exhibit more herding behavior in their trading than closed-end fund managers.

In terms of the percentage relative to the total number of stocks in our sample, row seven shows that there are 46% of the stocks have been herded by open-end funds while there are only 6% of the stocks that have been herded by closed-end funds. This is also true in terms of the percentage relative to the number of stocks that have been traded, which is shown in row eight in Table 1 where 48% of the traded stocks has been herded by open-end funds while only 9% of the traded stocks has been herded by closed-end funds. Again, it shows that open-end fund managers are engaged in more herding behavior than closed-end fund managers.

Secondly, by comparing different columns in row five we find that there are more stocks not have been traded by closed-end funds than by open-end funds. For example, there are 84 stocks that open-end funds have not traded while there are 279 stocks that

closed-end funds have never traded during the sample period. This pattern implies that open-end funds are more active and more diversified in their trading.

Thirdly, the last row of Table 1 shows the ratio of the number of stocks that mutual funds buy in herds (buy-herd) to the number of stocks that mutual funds sell in herds (sell-herd). For all of the fund categories, the ratio is from about 1.5 to 1.7, which indicates that buy-herd is about one and a half times more than sell-herd. This implies that mutual funds buy in herds more often and more active than they sell in herds. This finding is different from what Lakonishok et al. (1992) find for the US market where mutual fund managers are equally likely to herd either when they are on the buy side or on the sell side.

B. The Herding Measures

In order to identify the mutual funds' herding and the stocks that mutual funds herd, we use the measure of herding developed by Lakonishok et al. (1992). Specifically, the measure of herding by funds into (or out of) stock i during month t can be expressed as:

$$H(i,t) = \left| \frac{B(i,t)}{B(i,t) + S(i,t)} - P(t) \right| - AF(i,t), \quad (1)$$

where $B(i,t)$ is the number of funds buying stock i during month t ;

$S(i,t)$ is the number of funds selling stock i during month t ;

$$P(t) = \frac{\sum_{i=1}^n B(i,t)}{\sum_{i=1}^n B(i,t) + \sum_{i=1}^n S(i,t)}, \text{ which is the proportion of all mutual funds trading}$$

stock-month i, t that are buyers;

$AF(i,t) = E[\left| \frac{B(i,t)}{B(i,t) + S(i,t)} - P(t) \right|]$, which is an adjustment factor representing the expected value of $\left| \frac{B(i,t)}{B(i,t) + S(i,t)} - P(t) \right|$ under the null hypothesis that no herding exists.¹

Equation (1) represents the difference between the probability of stock i being bought by all mutual funds and the average probability of any stock being bought by mutual funds in a certain month. Thus, the extent of the difference indicates the tendency of mutual funds to herd in trading a given stock more often than would be expected by funds trading independently and randomly.

Equation (1) defines the measure for mutual funds' herding in trading a given stock. However, it does not provide information regarding whether funds buy or sell a given stock in herd. In order to measure the extent of "buy herding" or "sell herding", we follow the measures developed by Wermers (1999) and segregate stocks by whether they have a higher or lower proportion of buyers than the average stock during a certain month. The measures of "buy herding" and "sell herding" are described as in the equation (2) and (3), respectively:²

$$BH(i,t) = H(i,t) \left| \frac{B(i,t)}{B(i,t) + S(i,t)} - P(t) \right| > P(t) \quad (2)$$

¹ Since $B(i,t)$ follows a binomial distribution in t , $AF(i,t)$ is the expected value of the binomial distribution function:

$$E\left| \frac{B(i,t)}{B(i,t) + S(i,t)} - P(t) \right| = \sum_{B(i,t)=0}^N \left| \frac{B(i,t)}{B(i,t) + S(i,t)} - P(t) \right| * \binom{N}{B(i,t)} * (P(t))^{B(i,t)} * (1-P(t))^{N-B(i,t)}$$

where $P(t)$ is the average value of $\frac{B(i,t)}{B(i,t) + S(i,t)}$ under the null hypothesis that no herding exists.

Therefore, $AF(i,t)$ can be calculated using the above equation.

² In order to obtain the values of $H(i,t)$ in equation (2) and (3), we need to recalculate the adjustment factor $AF(i,t)$.

$$SH(i,t) = H(i,t) \left| \frac{B(i,t)}{B(i,t) + S(i,t)} < P(t) \right. \quad (3)$$

By breaking the funds' herding measure into buy and sell herding, we are able to investigate separately the effects mutual funds' buy herding and sell herding on the stock price discovery process.

C. Methodology

To understand the effect of mutual fund herding on the stock price discovery process or the speed of price adjustment process, we need an empirical framework and method to identify the dynamic relations among returns of the stocks with different extent of herding. The empirical methodology that we use for identifying such dynamic relations is VAR (Vector Auto-regression) test, which was originally proposed by Chen and Lee (1990). VAR test adopts a systematic multiple hypotheses testing method to determine a specific causal relation. The advantage of using VAR test is that it avoids the potential bias induced by restricting the causal relation to a single alternative hypothesis, such as the traditional pair-wise Granger Causality hypothesis testing.

In order to identify the directions of the dynamic relations between returns of stocks that mutual funds herd and those that mutual funds do not herd, we need to systematically test each of the following statistical hypotheses:

H1: $r_1 \wedge r_2$ (r_1 and r_2 are independent),

H2: $r_1 \leftrightarrow r_2$ (r_1 and r_2 are contemporaneously related),

H3: $r_1 \lhd \ntriangleright r_2$ (There is no unidirectional relation from r_2 to r_1),

H3*: $r_1 \not\lhd \not\ntriangleright r_2$ (There is no unidirectional relation from r_1 to r_2),

H4: $r_1 \leftrightarrow r_2$ (There is a feedback relation between r_1 and r_2),

where r_1 and r_2 are the returns of stocks that mutual funds herd and those that mutual funds do not herd. The procedure of VAR test is to examine all of the above five hypotheses in a systematic way before a conclusion of dynamic relationship between stock returns can be drawn.

Before the sequential inference procedure of the VAR test, we need to first define the above five basic hypotheses in terms of the parametric constraints on the VAR structure. Essentially, the VAR test includes the following steps: (1) identifying the appropriate VAR specification for the stock return series, (2) estimating the parameters of the VAR structure, (3) testing for the hypotheses by employing the likelihood ratio test, and (4) implementing the sequential inference procedure for identifying the return dynamic relation to be one of the above five relations.

The identification procedure applies the method developed by Tiao and Box (1981) and Tiao and Tsay (1983), whereas the maximum likelihood estimation method is developed by Hillmer and Tiao (1979). The degree of freedom in the likelihood ratio test is equal to the difference in the constraints between the maintained and restricted hypotheses. The test statistic is compared with chi-square table to determine the significance of the dynamic relations.

The inference procedure is based on the principle that a maintained hypothesis should not be rejected until there is sufficient evidence against it. The procedure conducts a total of six tests, where each test involves a pair of the above hypotheses. The procedure is described as follows:

Step 1: implementing test (a): H3 vs. H4, and test (b): H3* vs. H4, which examines

the unidirectional relation vs. the feedback one.

Step 2: testing (c): H_2 vs. H_3 , and test (d): H_2 vs. H_3^* , which examines the contemporaneous relation vs. the unidirectional one.

Step 3: conducting test (e): H_2 vs. H_4 , which investigates the contemporaneous relation vs. the feedback one.

Step 4: performing test (f): H_1 vs. H_2 , which examines the independency vs. the contemporaneous relation.

From this inference procedure, there are a total of twelve possible outcomes, M_1, \dots, M_{12} :

M1: reject H_3 in test (a) and reject H_3^* in test (b);

M2: reject H_3 in test (a) and not reject H_3^* in test (b);

M3: not reject H_3 in test (a) and reject H_3^* in test (b);

M4: not reject H_3 in test (a) and not reject H_3^* in test (b);

M5: reject H_2 in test (c) and not reject H_2 in test (d);

M6: not reject H_2 in test (c) and reject H_2 in test (d);

M7: reject H_2 in test (c) and reject H_2 in test (d);

M8: not reject H_2 in test (c) and not reject H_2 in test (d);

M9: reject H_2 ;

M10: not reject H_2 ;

M11: reject H_1 ;

M12: not reject H_1 .

Table 2 summarizes the inference process. Outcomes M1, M2 and M3, leading to the conclusions of $r_1 \Leftrightarrow r_2$, $r_1 \Leftarrow r_2$, and $r_1 \Rightarrow r_2$, respectively, will stop the test at step 1.

However, outcome M4 will lead to further testing (c) and (d) in step 2, which involves outcomes M5 through M8. The realization of outcome M5 indicates $r_1 \Rightarrow r_2$, whereas outcome M6 implies $r_1 \Leftarrow r_2$. M5 and M6 will stop the procedure at the end of step 2. When outcome M7 is realized, we need to conduct test (e), which leads to either outcome M9 or outcome M10. Outcome M9 will result in the relation that $r_1 \Leftrightarrow r_2$ and stop the procedure. Either outcome M8 in step 2 or outcome M10 in step 3 leads to test (f) in step 4. Finally, outcomes M11 and M12 will conclude that $r_1 \Leftrightarrow r_2$ and $r_1 \wedge r_2$, respectively.

III. Empirical Results

Before exploring the dynamic return patterns and the price-adjustment process for stocks with different extent of mutual fund herding, we first examine the stationarity of the stock portfolio return series. We use the Augmented Dickey Fuller (ADF) test developed by Dickey and Fuller (1979) to investigate whether both of the herded and non-herded portfolio return series are stationary. The test result shows that both of these two return series are stationary with ADF t-statistic significantly rejecting the null hypothesis of series being having unit-root at one percent level.³

After ensuring the stationarity of the return series, we proceed to investigate the return dynamic pattern between the herded and non-herded portfolios. As we stated in above sections, our purpose is to examine whether mutual funds' herding helps to speed up the incorporation of information into prices. To do this we employ a sequential causal relation test procedure, the VAR test, to identify the bi-variate return causal effect between herded and non-herded portfolios. This approach enables us to understand the

³ For the interest of brevity, the detailed result of the ADF test is not reported here.

difference in the speed of price discovery to information between stocks that are traded in herds and those that are traded by mutual funds but without herds.

In Wermers' (1999) study, he finds that stocks that mutual funds herd buy outperform stocks that they sell. He infers this result as an evidence of mutual funds' herding being facilitating the speed of price adjustment. However, although Wermers' result may shed some lights on the performance of stocks being herded, his finding has no direct implication for the impact of mutual funds' herding behavior on the speed of price-adjustment. One way to directly investigate the effect of herd on the speed of price-adjustment is to examine the difference in the speed of price-adjustment between stocks that are herded and those that are not herded by mutual funds. We use the VAR test procedure to carry out this task.

In the following sections, we first test the return dynamics between stocks that mutual funds herd and those that mutual funds do not herd. Then, we further segregate stocks into more herding-related categories. Specifically, first we divide the stocks that mutual funds herd into two groups: one that mutual funds buy in herd and another that they sell in herd. We then investigate whether there exist different return dynamic patterns and different speeds of price discovery between stocks that mutual funds buy in herd and those that mutual funds sell in herd. If mutual funds herding behavior contains information, we should observe that stocks that mutual funds herd incorporate new information faster than stocks that mutual funds do not herd. In terms of our test result, we should see that returns of stocks that mutual funds herd will lead those that mutual funds do not herd.

Next, we compare the speed of price discovery between stocks that mutual funds herd and those that mutual funds do not trade at all. In this way we are able to

investigate whether mutual funds' herding does expedite the information incorporation into stock returns comparing to stocks that mutual funds do not trade. If mutual fund managers trade in herd due to their private information, we should observe that returns of stocks that mutual funds herd will not only lead those that mutual funds do not herd but will also lead those stocks that mutual funds do not trade.

Finally, we investigate the difference in the speed of price adjustment between stocks that mutual funds trade but do not herd and stocks that mutual funds do not trade. In this design, we try to understand whether mutual funds' trading itself, but not their herding, may contain information thus expedite the price adjustment process. It is possible that mutual fund managers trade stocks based on information and thus stocks that mutual funds trade may exhibit faster speed of price adjustment.

A. Herded versus Non-herded Portfolios

Table 3 reports the test result for the return adjustment dynamics of herded versus non-herded portfolios. The second to the fourth columns of the table exhibit the test statistics of various dynamic hypotheses for all of the funds, open-end funds and closed-end funds, respectively. The first six rows of the table report the test statistics for different pairs of the sequential hypothesis tests. And the last row shows the final test result for the dynamic relation between returns of the herded versus non-herded portfolios.

It is obvious from the result of Table 3 that returns of herded portfolios tend to lead returns of non-herded portfolios for all of the funds and for both open-end funds and closed-end funds. In other words, stocks that are herded by either open-end funds or closed-end funds tend to exhibit faster speed of price adjustment than stocks that are not

herded by either of the funds. This result strongly suggests that mutual funds' herding behavior will speed up the incorporation of new information into prices and, thus, expedites the price discovery process.

Many recent studies have paid attention to the role that mutual fund herding plays in the market stabilization. Specifically, some argue that mutual funds' behavior of buying or selling in herds may destabilize the market since mutual funds herding is based on little of no information (e.g., Scharfstein and Stein (1990) and Bikhchandani et al. (1992)). While in a more recent study, Walter and Weber (2006) find no evidence of mutual fund herding in either stabilizing or destabilizing the market.

However, other studies find that mutual funds herding does not necessarily increase market volatility and destabilize the market if mutual fund managers trade together because they receive correlated private information or they infer private information from the prior trades of better-informed managers (Hirshleifer et al. (1994), Wermers (1999), Sias (2004), Puckett and Yan (2007)). Thus, if mutual fund managers herd in trade due to either of the above rationales, mutual funds herding not only will not destabilize the market but it will actually stabilize the market and lead to a more efficient market environment by expediting the process of information incorporated into stock prices.

The above result of return dynamics between herded and non-herded portfolios indicates that stocks that mutual fund herd in their trading tend to exhibit faster speed of price discovery than stocks that mutual funds do not herd. This evidence is consistent with argument by Wermers (1999) and Hirshleifer et al. (1994) that, instead of being a destabilizing factor, mutual funds' herding actually tend to stabilize the market. The result also implies that mutual fund managers may herd in trade due to similar private information they receive from analyzing the same indicators or due to the fact that they

tend to follow the trades of better-informed managers and trade in the same direction.

B. Comparisons between More Specific Portfolios

The above result evidences the impact of mutual funds herding on return dynamics and price discovery process for stocks that mutual funds herd. Another question of interest is whether there exist different return dynamic patterns and thus exhibit different speeds of price adjustment between stocks that mutual funds buy in herd and those that mutual funds sell in herd. In order to perform this analysis, we segregate the stocks that are herded by mutual funds into two portfolios: one that mutual funds buy in herd, called “buy-herd”, and another that mutual funds sell in herd, called “sell-herd”. The related test results are reported in Table 4.

Basically, Table 4 exhibits the same unidirectional return dynamic pattern as that shown in Table 3. The difference is that now in Table 4 we are comparing between the buy-herd and the sell-herd stock portfolios. The result shows that for all of the fund categories, returns of stocks that funds buy in herd tend to lead those that funds sell in herd.

In Table 4, all of the unidirectional relations are valid under the one-percent significance level, signifying that stocks that mutual funds buy in herd reflect information into prices much faster than those that mutual funds sell in herd. Therefore, it implies that mutual funds’ herding when they buy stocks contains more information than their herding when they sell stocks. This is interesting because, without any other information, we would expect that the behavior of mutual funds’ buy-herd and sell-herd play exactly the same role and exhibit no different pattern in terms of expediting the incorporation of information into prices.

One possible explanation is that due to investors' redemption, especially during the periods of the downturn market, fund managers may be forced to sell out securities in their portfolios. Thus, such a security selling behavior may contain less or no information and resulting in the asymmetric pattern that funds buy-herd tends to contain more information and impound information faster into security prices than funds sell-herd does.

However, if that is the case, then we should observe no such pattern in closed-end funds because closed-end funds have no redemption pressure from investors. But, on the contrary, in Table 4 we do see that similar pattern also occurs in the closed-end funds sample. Therefore, it implies that redemption pressure is not the major cause for that asymmetric pattern. In other words, it suggests that mutual funds sell-herd tend to be not driven by the information and, thus, it does not impound information into security prices faster than mutual funds buy-herd. This result is consistent with the finding by Puckett and Yan (2007) who evidence that institutions sell herds tend to be motivated by behavioral considerations.

Next, in order for our results not to be biased toward the stocks that mutual funds trade, we now include stocks that mutual funds do not trade during our sample period. The purpose is to examine whether the above findings are still valid when comparing either herded or non-herded stocks with stocks that mutual funds do not even invest.

First, we compare the price-adjustment process between stocks that mutual funds herd and those that mutual funds have not traded at all. If mutual funds' herding does contain more information, we should observe that stocks that mutual funds herd will exhibit faster price adjustment process than stocks that mutual funds do not trade. The results are shown in Table 5.

From Table 5, we are not surprised to find that, except for the result of closed-end funds where it shows a feedback relation between herded and non-trade portfolios, returns of stocks that mutual funds trade and herd tend to lead those that mutual funds do not trade. This result reinforces the findings in tables 3 and 4 that mutual funds' herding does contain information and thus will speed up the price discovery process.

Finally, there is one more question that we are interested in. The above results shed lights on the effect of mutual funds' herding, especially mutual funds' buy-herding, on the stock price adjustment process. In addition to the effect of mutual funds' herding on the speed of price adjustment, we also would like to know whether mutual funds' trading, but without herding, may still play a role in expediting the price discovery process. In other words, we try to investigate whether fund managers' trading behavior *per se* contains information. To do this, we compare the returns behavior between stocks that mutual funds trade but not herd and stocks that mutual funds do not trade. The test results are shown in Table 6.

It is obvious from the results in Table 6 that basically the return dynamic relations exhibited here are the same as those in Table 5 where the herd and non-trade portfolios are compared. The results in Table 6 indicate that returns of non-herd portfolios lead returns of non-trade portfolios in the price adjustment process. This implies that, even without herding, mutual fund managers tend to exhibit their private information in their act of trading. Thus the stocks that they trade may incorporate new information faster than those that they do not trade. This finding is consistent with Sias and Starks (1997), who provide some evidence that institutional trading reflects information and increases the speed of stock price adjustment. Furthermore, this finding also sheds more lights on the role that institutional investors play in the market stabilization process.

IV. Conclusions

In this paper, we directly investigate the impact of mutual funds' herding behavior on the price discovery process by using a VAR test procedure, which simultaneously and sequentially tests the multiple hypotheses of the return dynamics. Consistent with Wermers' (1999) implication, we find that mutual funds' herding contains information and may expedite the price discovery process. Specifically, we find that stocks that mutual funds herd tend to adjust information faster than stocks that mutual funds do not herd. This implies that mutual funds' herding is rational and informational in the sense that mutual fund managers herd on new information about the firms' future prospects and will bring stock prices closer to their fundamental values and, thus, it will speed up the incorporation of information into stock prices

Furthermore, we also find that mutual funds' buying in herd contains more information than mutual funds' selling in herd. This indicates that the above finding regarding mutual funds' herding on the speed of price discovery process is mainly attributed to mutual funds' buy-herd rather than their sell-herd behavior.

Finally, we examine the information content of mutual funds' trading behavior. We evidence that without herding mutual funds' trading itself also contains information. That is, mutual fund managers may exhibit their private information via their act of trading. However, mutual funds herding impound information into security prices faster than mutual funds trading per se. This suggests that mutual funds herding provides significant more incremental information than mutual funds trading. Therefore, we evidence that mutual funds herding drives security prices closer to their fundamental values and expedites the price discovery process.

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Table 1
Data Summary

This table reports the number of stocks in each of the herding and non-herding categories for all funds, open-end funds and closed-end funds. There are a total of 1036 stocks in our sample after excluding stocks with one or more non-trading days in the sample period. Herd (Non-herd) represents the stocks being (not being) herded by funds. Buy-herd (Sell-herd) represents the stocks being herded on the buy- (sell-) side. Non-trade represents the stocks that have not been traded by funds in the sample period.

	All Funds	Open-end Funds	Closed-end Funds
1. Herd	425	438	66
2. Buy-herd	293	302	43
3. Sell-herd	185	176	26
4. Non-herd	487	514	691
5. Non-trade	124	84	279
6. Total no. of stocks (1+2+5)	1036	1036	1036
7. Herd/Total (1/6)	0.41	0.46	0.06
8. Herd/Trade (1/(1+2))	0.47	0.48	0.09
9. Buy-herd/Sell-herd (3/4)	1.58	1.72	1.65

Table 2
Summary of VAR Test Procedure and Inference Process

Test outcome	Resulted Dynamic Relation between X_1 and X_2
M_1, M_2, M_3	$X_1 \leftrightarrow X_2, X_1 \leftarrow X_2, X_1 \rightarrow X_2$
M_4	Step 2
M_5, M_6	$X_1 \rightarrow X_2, X_1 \leftarrow X_2$
M_7	Step 3
M_8	Step 4
M_9	$X_1 \leftrightarrow X_2$
M_{10}	Step 4
M_{11}, M_{12}	$X_1 \leftrightarrow X_2, X_1 \wedge X_2$

Table 3
Herd vs. Non-herd Portfolios

Let r_1 and r_2 represent returns of herd and non-herd portfolios, respectively, then the various hypotheses of the dynamic relations are as follows:

- H1: $r_1 \wedge r_2$ (r_1 and r_2 are independent),
- H2: $r_1 \leftrightarrow r_2$ (r_1 and r_2 are contemporaneously related),
- H3: $r_1 \not\rightarrow r_2$ (There is no unidirectional relation from r_2 to r_1),
- H3*: $r_1 \not\leftarrow r_2$ (There is no unidirectional relation from r_1 to r_2),
- H4: $r_1 \leftrightarrow r_2$ (There is a feedback relation between r_1 and r_2)

	All Funds	Open-end Funds	Closed-end Funds
H3-H4	3.63	4.08	1.65
H3*-H4	4160.10***	4209.64***	3416.21***
H2-H3	5.05	5.40	4.78
H2-H3*	1.43	5.16	3.38
H2-H4	8.68	9.48***	6.43
H1-H2	4154.81***	4204.13***	3413.62***
Dynamic relation	Herd \Rightarrow Non-herd	Herd \Rightarrow Non-herd	Herd \Rightarrow Non-herd

*** denotes significance at the 1% level.

'X \Rightarrow Y' denotes a significant unidirectional relation from X to Y.

Table 4
Buy-herd vs. Sell-herd Portfolios

Let r_1 and r_2 represent returns of herd and non-herd portfolios, respectively, then the various hypotheses of the dynamic relations are as follows:

- H1: $r_1 \wedge r_2$ (r_1 and r_2 are independent),
- H2: $r_1 \leftrightarrow r_2$ (r_1 and r_2 are contemporaneously related),
- H3: $r_1 \not\rightarrow r_2$ (There is no unidirectional relation from r_2 to r_1),
- H3*: $r_1 \not\leftarrow r_2$ (There is no unidirectional relation from r_1 to r_2),
- H4: $r_1 \leftrightarrow r_2$ (There is a feedback relation between r_1 and r_2)

	All Funds	Open-end Funds	Closed-end Funds
H3-H4	3.06	4.56	2.57
H3*-H4	4578.96***	5127.39***	1548.25***
H2-H3	4.75	1.34	8.35***
H2-H3*	1.15	1.48	4.34
H2-H4	7.81	5.91	10.91***
H1-H2	4576.50***	5126.83***	1541.38***
Dynamic relation	Buy-herd⇒Sell-herd	Buy-herd⇒Sell-herd	Buy-herd⇒Sell-herd

*** denotes significance at the 1% level.

‘X⇒Y’ denotes a significant unidirectional relation from X to Y.

Table 5
Herd vs. Non-trade Portfolios

Let r_1 and r_2 represent returns of herd and non-herd portfolios, respectively, then the various hypotheses of the dynamic relations are as follows:

- H1: $r_1 \wedge r_2$ (r_1 and r_2 are independent),
- H2: $r_1 \leftrightarrow r_2$ (r_1 and r_2 are contemporaneously related),
- H3: $r_1 \not\rightarrow r_2$ (There is no unidirectional relation from r_2 to r_1),
- H3*: $r_1 \not\leftarrow r_2$ (There is no unidirectional relation from r_1 to r_2),
- H4: $r_1 \leftrightarrow r_2$ (There is a feedback relation between r_1 and r_2)

	All Funds	Open-end Funds	Closed-end Funds
H3-H4	8.05	8.43	10.18***
H3*-H4	732.69***	740.78***	1900.44***
H2-H3	7.81	7.68	6.14
H2-H3*	6.83	4.66	4.11
H2-H4	15.86	16.12	16.32***
H1-H2	729.50***	737.40***	1898.32***
Dynamic relation	Herd \Rightarrow Non-trade	Herd \Rightarrow Non-trade	Herd \leftrightarrow Non-trade

*** denotes significance at the 1% level.

' $X \Rightarrow Y$ ' denotes a unidirectional relation from X to Y ; ' $X \leftrightarrow Y$ ' denotes a feedback relation between X and Y .

Table 6
Non-herd vs. Non-trade Portfolios

Let r_1 and r_2 represent returns of herd and non-herd portfolios, respectively, then the various hypotheses of the dynamic relations are as follows:

- H1: $r_1 \wedge r_2$ (r_1 and r_2 are independent),
- H2: $r_1 \leftrightarrow r_2$ (r_1 and r_2 are contemporaneously related),
- H3: $r_1 \not\rightarrow r_2$ (There is no unidirectional relation from r_2 to r_1),
- H3*: $r_1 \not\leftarrow r_2$ (There is no unidirectional relation from r_1 to r_2),
- H4: $r_1 \leftrightarrow r_2$ (There is a feedback relation between r_1 and r_2)

	All Funds	Open-end Funds	Closed-end Funds
H3-H4	4.82	4.95	11.93***
H3*-H4	571.16***	582.29***	2883.39***
H2-H3	6.92	6.48	14.88***
H2-H3*	5.43	5.86	5.57
H2-H4	11.73	11.43	26.82***
H1-H2	569.13***	580.14***	2880.94***
Dynamic relation	Non-herd \Rightarrow Non-trade	Non-herd \Rightarrow Non-trade	Non-herd \leftrightarrow Non-trade

*** denotes significance at the 1% level.

' $X \Rightarrow Y$ ' denotes a unidirectional relation from X to Y ; ' $X \leftrightarrow Y$ ' denotes a feedback relation between X and Y .