



IMF Working Paper

Herd Behavior in Financial Markets: A Review

Sushil Bikhchandani and Sunil Sharma

IMF Working Paper

IMF Institute

Herd Behavior in Financial Markets: A Review

Prepared by Sushil Bikhchandani and Sunil Sharma¹

Authorized for distribution by Eric V. Clifton

March 2000

Abstract

<p>The views expressed in this Working Paper are those of the author(s) and do not necessarily represent those of the IMF or IMF policy. Working Papers describe research in progress by the author(s) and are published to elicit comments and to further debate.</p>
--

Policymakers often express concern that herding by financial market participants destabilizes markets and increases the fragility of the financial system. This paper provides an overview of the recent theoretical and empirical research on herd behavior in financial markets. It addresses the following questions: What precisely do we mean by herding? What could be the causes of herd behavior? What success have existing studies had in identifying such behavior? And what effect does herding have on financial markets?

JEL Classification Numbers: G1, G2, F4

Keywords: herd behavior, momentum strategies, financial markets

Author's E-Mail Address: sushil.bikhchandani@anderson.ucla.edu; ssharma@imf.org

¹ Sushil Bikhchandani is on the faculty of the Anderson Graduate School of Management, UCLA and Sunil Sharma is a staff member of the IMF Institute. Many people provided useful comments and in particular the authors would like to thank Ralph Chami, David Hirshleifer, Mohsin Khan, Laura Kodres, Ashoka Mody, Peter Montiel, Mahmood Pradhan, Tony Richards, Ivo Welch, Russ Wermers, and Chorng-Huey Wong.

Contents	Page
I. Introduction	3
II. Causes of Rational Herd Behavior	5
A. Information-based Herding and Cascades	5
Application to Financial Markets.....	9
B. Reputation-based Herding.....	10
C. Compensation-based Herding	12
III. Implications for Empirical Tests.....	13
IV. The Empirical Evidence	14
A. Herding in the Stock Market.....	14
Drawbacks with the LSV Measure of Herding.....	18
A Modification of the LSV Measure of Herding.....	19
Other Measures of Herding.....	20
B. Herding in Other Financial Markets.....	21
C. Herding Among Investment Analysts and News Letters	23
D. Herding in Emerging Stock Markets	25
V. Concluding Remarks.....	27
VI. References.....	29

I. INTRODUCTION

“Men, it has been well said, think in herds; it will be seen that they go mad in herds, while they only recover their senses slowly, and one by one.”

Charles MacKay

“The reaction of one man can be forecast by no known mathematics; the reaction of a billion is something else again.”

Isaac Asimov

In the aftermath of the recent financial crises, “herd” has become a pejorative term in the financial lexicon. Investors and fund managers have been portrayed as herds that charge into risky ventures without adequate information and appreciation of the risk-reward trade-offs and, at the first sign of trouble, flee to safer havens. Some policymakers express concern that herding by market participants exacerbates volatility, destabilizes markets and increases the fragility of the financial system.² This raises the following questions: why is it surprising that profit-maximizing investors, increasingly with similar information sets, react similarly at more or less the same time? Is such behavior part of market discipline in relatively transparent markets, or is it due to other factors?

For an investor to imitate others, she must be aware of and be influenced by others' actions. Intuitively, an individual can be said to herd if she would have made an investment without knowing other investors' decisions, but does not make that investment when she finds that others have decided not to do so. Alternatively, she herds when knowledge that others are investing changes her decision from not investing to making the investment.

There are several reasons for a profit/utility maximizing investor to be influenced (into reversing her planned decision) after observing others. First, others may know something about the return on the investment and their actions reveal this information. Second, and this is relevant only for money managers who invest on behalf of others, the incentives provided by the compensation scheme and terms of employment may be such that imitation is rewarded. A third reason for imitation is that individuals may have an intrinsic preference for conformity.

² See, for example, Eichengreen and Mathieson et.al. (1998) for a discussion of the role herding may have played in amplifying the volatility of capital flows associated with the Asian crisis; Council on Foreign Relations (1999), Folkerts-Landau and Garber (1999) and Furman and Stiglitz (1999) for a discussion in the context of the international financial architecture; and Eichengreen and Mussa et.al. (1998) for a discussion in the context of capital account liberalization.

According to the definition of herd behavior given above, herding results from an obvious intent by investors to copy the behavior of other investors. This should be distinguished from “spurious herding” where groups facing similar decision problems and information sets take similar decisions. Such spurious herding is an efficient outcome whereas “intentional” herding, as explained in Section II, need not be efficient. But it needs pointing out, that empirically distinguishing “spurious herding” from “intentional” herding is easier said than done and may even be impossible, since typically, a multitude of factors have the potential to affect an investment decision.

Fundamentals-driven spurious herding out of equities could arise if, for example, interest rates suddenly rise and stocks become less attractive investments. Investors under the changed circumstances may want to hold a smaller percentage of stocks in their portfolio. This is not herding according to the definition above because investors are not reversing their decision after observing others. Instead, they are reacting to commonly known public information, which is the rise in interest rates.

Spurious herding may also arise if the opportunity sets of different investors differ. Suppose there are two groups of investors who invest in a country’s stock market—domestic (D) and foreign (F) investors. Due to restrictions on capital account convertibility in this country, type D individuals invest only in S_d , the domestic stock market, and in B_d , the domestic bond market. Type F individuals invest in S_d , B_d , and also in S_f , a foreign country’s stock market and B_f , the foreign bond market. If, in the foreign country, interest rates decrease or there is greater pessimism regarding firms’ earning expectations, then type F investors may increase the share of S_d and B_d in their portfolio, buying both from type D investors. Consequently, in the domestic markets S_d and B_d , type F investors *appear* to be part of a buying “herd” whereas type D investors *appear* to be part of a selling “herd.” However, the investment decisions of types F and D investors are individual decisions and may not be influenced by others’ actions. Moreover, this behavior is efficient under the capital convertibility constraints imposed on type D investors.

It is worth pointing out that direct payoff externalities (i.e., externalities by which an agent’s action affects the utility payoffs or the production possibilities of other agents) are not an important cause of herd behavior in financial markets. Direct payoff externalities are significant in bank-runs or formation of markets, topics that are outside the scope of this paper. See Diamond and Dybvig (1983) for more on herd behavior caused by direct payoff externalities.

Other causes of herding include behavior that is not fully rational (and Bayesian). Recent papers on this topic include DeLong, Shleifer, Summers, and Waldman (1990), Froot,

Scharfstein, and Stein (1992), and Lux and Marchesi (1999).³ In this review, we do not discuss models of herd behavior by individuals who are not fully rational except to note that one type of herd behavior – use of momentum investment strategies – has been documented (see, for example, Grinblatt, Titman and Wermers (1995), Froot et. al. (1998), Choe et.al. (1999), Kim and Wei (1999a, 1999b)). A momentum investment strategy is the tendency of an investor to buy and sell stocks based on past returns of the stocks, i.e., to buy recent winners and sell recent losers. This form of herd behavior is not rational under the efficient markets hypothesis since market prices are assumed to reflect all available information. Such “momentum investment” or “positive-feedback” strategies can exacerbate price movements and add to volatility. Of course, one could argue that it takes time for market participants to completely digest and act on new information and hence market prices fully incorporate new information only over time. If this is the case, then positive-feedback strategies may be rational and participants who follow such strategies can be seen as exploiting the persistence of returns over some time period.

In this paper we provide an overview of the recent theoretical and empirical research on *rational* herd behavior in financial markets. Specifically, we examine what precisely is meant by herding, what could be the causes of rational herd behavior, what success existing studies have had in identifying it, and what effect such behavior has on financial markets.⁴

II. CAUSES OF RATIONAL HERD BEHAVIOR

There are several potential reasons for rational herd behavior in financial markets. The most important of these are imperfect information, concern for reputation, and compensation structures. We describe each of these below.

A. Information-based Herding and Cascades

The basic models in Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992), and Welch (1992) assume that the investment opportunity is available to all individuals at the same price, i.e., the supply is perfectly elastic. This may be a reasonable assumption for foreign direct investment in countries with fixed exchange rates. However, these theories are not an adequate model of financial markets where the investment decisions of early individuals are reflected in the subsequent price of the investment. Later, we discuss how the basic insights from these models are modified when applied to a model of the stock market (Avery and Zemsky 1998).

³ See Shleifer and Summers (1990) for an exposition of the noise trader approach to finance. This approach rests on two assumptions: (i) some of the investors are not fully rational (the noise traders), and (ii) arbitrage is risky and hence limited.

⁴ See Devenow and Welch (1995) for an earlier survey on this topic.

Suppose that individuals face similar investment decisions under uncertainty and have private (but imperfect) information about the correct course of action. In the context considered here, the private information may be the conclusions of an investor's research effort. Alternatively, all information relevant to the investment is public but there is uncertainty about the quality of this information. For example, has the government doctored the economic data just released? Is the government really committed to economic reform? etc. An individual's assessment of the quality of publicly available information is privately known to her.

Individuals can observe each other's actions but not the private information or signals that each player receives. If individuals have some view about the appropriate course of action then inferences about a player's private information can be made from the actions chosen. In such a framework herd behavior could arise---behavior which is *fragile*, in that it may break easily with the arrival of a little new information, and *idiosyncratic*, in that random events combined with the choices of the first few players determine the type of behavior on which individuals herd. A simple example illustrates the main features.

Suppose that several investors decide in sequence whether to invest in an individual stock (or an industry or a country). Each investor's compensation is proportional to the payoff on her investment. Let V denote the payoff to investing for each investor. V is either +1 or -1 with equal probability. The order in which the investors decide is exogenously specified. Each investor observes a private signal (either Good, G or Bad, B) about the payoff of the investment. If $V=+1$, then the probability that the signal is G is equal to p and that the signal is B is $1-p$, where $0.5 < p < 1$. Similarly, if $V=-1$ then the signal realization is B with probability p (G with probability $1-p$). The investors' signals are independent conditional on the true value. Apart from her own private signal, each investor observes the decisions (but not the private signals) of her predecessors. Applying Bayes' rule, the posterior probability of $V=+1$ after observing a G is

$$\begin{aligned} \text{Prob}[V = +1 | G] &= \frac{\text{Prob}[G | V = +1] \cdot \text{Prob}[V = +1]}{\text{Prob}[G | V = +1] \cdot \text{Prob}[V = +1] + \text{Prob}[G | V = -1] \cdot \text{Prob}[V = -1]} \\ &= \frac{p \times 0.5}{p \times 0.5 + (1 - p) \times 0.5} = p > 0.5 \end{aligned}$$

Therefore, the first investor, Angela, will follow her signal: if she observes G then she invests, if she observes B then she does not invest. Bob, the second investor, knows this and can figure out Angela's signal from her action. If his signal is G and he observed Angela invest then he too will invest. If he observes G and sees Angela not invest then another application of Bayes' rule implies that his posterior probability that $V=+1$ is 0.5 (it is as if Bob observed two signals, a G and B) and he flips a coin. Thus if Angela invests and Bob does not then Claire will infer that Angela saw G and Bob saw B . If instead Angela and Bob both invest, then Claire, the third investor, will infer that Angela saw G and Bob is more likely to have seen G than B . The remaining two cases where Angela does not invest and Bob does or does not invest are symmetric.

Suppose that Angela and Bob both invest. Claire concludes that Angela and probably also Bob observed good signals. Another application of Bayes' rule shows that Claire will invest even if her signal is B. David learns nothing about Claire's signal realization from her decision to invest. David is in exactly the same position that Claire was and he too will invest regardless of his own signal realization. And so will Emma, Frank, Greta, Harry, etc. An *invest cascade* is said to have started with Claire. Similarly, if Angela and Bob both do not invest then a *reject cascade* starts with Claire.

If, on the other hand, Angela and Bob take opposite actions then Claire knows that one of them saw the signal G and the other saw signal B. Her prior belief (before observing her signal) is that $V=+1$ and $V=-1$ are equally likely and she, being exactly in the position that Angela found herself in, follows her signal.

In general, an individual will be in an "invest cascade" ("reject cascade") if and only if the number of predecessors who invest exceeds (lags) the number of predecessors who do not invest by two or more. The probability that a cascade starts after the first few individuals is very high. Even if the signal is arbitrarily noisy (i.e., p arbitrarily close to 0.5) a cascade starts after the first four (eight) individuals with probability greater than 0.93 (0.996). Especially for noisy signals, the probability that the cascade is incorrect (i.e., a reject cascade when $V=+1$ or an invest cascade when $V=-1$) is significant. For instance, when $p=0.55$ the probability that the eventual cascade is incorrect is 0.434, which is only slightly less than 0.45, the probability of an individual taking the incorrect action without the benefit of observing predecessors. The information available with the investors, if aggregated properly, would yield a much more accurate forecast of the true value. For instance, if there are a hundred individuals and the second through the tenth individuals ignore the information content of their predecessors' actions and instead follow their private signals then better information is available to the eleventh through the hundredth individuals. These individuals 11 through 100 will tend to herd on a decision which is much more likely to be correct than if, instead, individuals 2 through 10 rationally took into account the information revealed by their predecessors' actions.

Once an individual enters a cascade, her action and the actions of all subsequent individuals are uninformative about their signal realizations. When an individual takes an action that is uninformative to others, it creates a negative externality.⁵ If an early individual were to make the socially optimal choice of following the private signal instead of acting in her self-interest and obeying a cascade, the action of that individual would add to the public pool of knowledge, to the benefit of followers. Such altruistic behavior by a number of individuals would ultimately lead to almost perfectly accurate decisions. Instead,

⁵ Observe that this externality is distinct from the direct payoff externality referred to in footnote 5. The actions of one individual do not change the underlying payoffs of other individuals but they do influence the beliefs of others.

individuals, acting in their own self-interest, rationally take uninformative imitative actions. Thus, the information externality leads to an inefficient outcome.

Furthermore, the type of cascade depends not just on how many Good and Bad signals arrive, but the order in which they arrive. For example, if signals arrive in the order GGBB..., then all individuals invest, because Claire begins an invest cascade. If, instead, the same set of signals arrive in the order BBGG..., no individual invests, because Claire begins a reject cascade. And if the signals arrive as GBBG..., then with probability one-half Bob invests and Claire begins an invest cascade. Thus, whether individuals on the whole invest or reject is *path-dependent* and *idiosyncratic*.

If predecessors' signal realizations were observable instead of their actions, later individuals would have almost perfect information about the value of investing and would tend to take the correct action. The fundamental reason the outcome with observable actions is so different from the observable-signals benchmark is that once a cascade starts, public information stops accumulating. An early preponderance towards investing or rejecting causes all subsequent individuals to ignore their private signals, which thus never join the public pool of knowledge. Nor does the public pool of knowledge have to be very informative to cause individuals to disregard their private signals. As soon as the public information becomes even slightly more informative than the signal of a single participant, individuals defer to the actions of predecessors and a cascade begins. Consequently, a cascade is not robust to small shocks. Several possible kinds of shocks could dislodge a cascade: for example, the arrival of better informed individuals, the release of new public information, and shifts in the underlying value of investing versus not investing. Indeed, when participants know that they are in a cascade, they also know that the cascade is based on little information relative to the information of private individuals. Thus, a key prediction of the theory is that behavior in cascades is *fragile* with respect to small shocks.

Thus information-based cascades are born quickly, idiosyncratically, and shatter easily. This conclusion is robust to relaxing many of assumptions in the example. For instance, Chari and Kehoe (1999) show that information cascades persist in a model with endogenous timing of decisions by individuals, continuous action space, and the possibility of information sharing among investors. Calvo and Mendoza (1998) investigate a model in which individuals may invest in N different countries. There is a fixed cost of collecting information about returns to investment in country A. The payoff to individuals from collecting this information decreases as N , the number of countries (investment opportunities), increases. For sufficiently large N , the number of investors who are informed about country A decreases significantly and investors herd in their decisions regarding country A. For more on the robustness of informational herding, see Bikhchandani, Hirshleifer, and Welch (1998) and the references therein.

Application to Financial Markets

In the preceding discussion, the price for taking an action is fixed *ex ante* and remains so. This assumption is relaxed in Avery and Zemsky (1998)⁶.

In the simple example just considered, the price of the investment was normalized to zero and remained fixed throughout. Suppose instead that after every buy or sell decision by an investor, the price of a stock adjusts to take into account the information revealed by this decision. (We ignore bid-ask spreads to simplify the exposition.) In a setting with competitive market-makers, the stock price will always be the expected value of the investment conditional on all publicly available information. Therefore, an investor who has only publicly available information (including the actions of predecessors) will be just indifferent between buying or selling. Further, the action of any privately informed investor will reveal his or her information. That is, an information cascade never starts. This is easy to see in the simple example, modified to allow for flexible prices. Recall that V , the true value of the investment, is either $+1$ or -1 with equal probability and investors get a private signal that is correct with probability $p \in (0.5, 1)$. The initial price of the investment is 0. If Angela, the first investor, buys then the stock price increases to $2p-1$, the expected value of the stock price conditional on Angela observing G . As before Bob knows that Angela bought and therefore she must have observed a signal realization G . If Bob's private signal realization is B then his posterior expected value of V is 0 which is less than $2p-1$, the price of the investment. If, instead, Bob observes G then his posterior expected value of V is $[2p-1]/[p^2+(1-p)^2]$ which is greater than $2p-1$. Hence, Bob follows his private signal – invest if private information is good and do not invest if private information is bad. If instead Angela did not buy, then Bob faces a price $1-2p$ and once again a simple calculation shows that he will follow his signal. Every subsequent investor follows his or her own private information precisely because the price adjusts in a manner that based only on publicly available information, (s)he is exactly indifferent between buying or selling; as the investor's private information tips the balance it (the investor's private information) is revealed by the investor's action. Consequently, herd behavior will not arise when the price adjusts to reflect available information. Under these assumptions, the stock-market is informationally efficient. The stock-market is informationally efficient. The price reflects fundamentals and there is no mispricing.

Next, Avery and Zemsky add another dimension to the underlying uncertainty in the basic model considered in the previous paragraph. Suppose that there are two types of investors H and L . Type H have very accurate information (p_H close to 1) and type L have very noisy information (p_L close to 0.5). Further, suppose that the proportion of the two types of investors in the population is not common knowledge among market participants. In particular, this proportion is not known to the market-makers. Hence, although at any point

⁶ See also Lee (1995).

in time the stock-market price reflects all public information, the price does not reveal the private information of all previous investors. A sequence of identical decisions may arise naturally in a well-informed market (one in which most of the investors are of type H) because most the investors have the same (very informative) private signal realization. Further, a sequence of identical decisions is also natural in a poorly informed market (one in which most of the investors are of type L) because of herding by type L investors who mistakenly believe that most of the other investors are of type H. Thus, informationally inefficient herd behavior may occur and can lead to price bubbles and mispricing when the accuracy (or lack thereof) of the information with market participants is not common knowledge. Traders may mimic the behavior of an initial group of investors in the erroneous belief that this group knows something.

Thus, when the uncertainty is only about the value of the underlying investment, the stock-market price is informationally efficient and herd behavior will not occur. However, when there is an additional dimension to the uncertainty, namely uncertainty about the accuracy of the information possessed by market participants, a one-dimensional stock price is no longer efficient and herd behavior can arise, even when investors are rational.

Derivative securities add multiple dimensions to stock prices. They aid in the market price discovery process by providing a link between the prices in the cash market today and the prices expected to prevail in the cash market in the future. Futures and forward markets offer forecasts of future prices to the general public. Options markets provide valuable information on the expected volatility of prices and hence about the risk of holding the underlying spot asset. Avery and Zemsky conjecture that allowing derivatives may make herding and price bubbles less pronounced as multidimensional stock prices are better equipped to reveal multidimensional uncertainty.

B. Reputation-based Herding

Scharfstein and Stein (1990) provide another theory of herding. The basic idea is that if an investment manager and her employer are uncertain of the manager's ability to pick the right stocks, conformity with other investment professionals preserves the fog – that is, the uncertainty regarding the ability of the manager to manage the portfolio. This benefits the manager and if other investment professionals are in a similar situation then herding occurs.

Consider the decisions of two investment managers, I_1 and I_2 , faced with an identical investment opportunity. Each manager I_i , $i = 1, 2$, may be of high ability or low ability, and their type or ability level is chosen independently. A high ability manager receives informative signals about the return from an investment, whereas a low ability manager's signal is pure noise. Neither the manager I_i nor her employer E_i knows whether the manager I_i is of low or high ability. Each manager and her employer have an identical prior belief about the manager's type. This belief is updated after the decisions of the two managers and the return from the investment (which is observed whether or not an investment is made) are observed. The price of the investment remains fixed throughout.

If both managers are of high ability then they observe the same signal realization (Good or Bad) from an informative signal distribution (but neither manager observes the other's signal realization). If both managers are of low ability then they observe independent draws of a signal (either G or B) from a distribution that is pure noise. If one manager is of high ability and the other of low ability, then they observe independent draws from the informative signal distribution and the noisy signal distribution respectively. The informative and noisy signal distributions are such that the *ex ante* probability of observing G is the same with either distribution.⁷ Thus, after observing her signal realization a manager does not update her prior beliefs about her own type.

I_1 makes her investment decisions first and then I_2 . I_1 's decision is based only on her signal realization (which may either be information or pure noise – I_1 does not know which it is). I_2 's decision is based on her own signal realization and on I_1 's decision. In the final period, the investments pay off and the two investors are rewarded based on an *ex post* assessment of their abilities.

This game has a herding equilibrium in which I_1 follows her own signal and I_2 imitates I_1 regardless of her own (I_2 's) signal. The intuition behind this result is that since I_2 is uncertain about her own ability, she dare not take a decision contrary to I_1 's decision and risk being considered dumb (in case her conflicting decision turns out to be incorrect). Thus, it is better for I_2 to imitate I_1 even if her own information tells her otherwise. If the common decision turns out to be incorrect it will be attributed to an unlucky draw of the same signal realization from an informative distribution, thus increasing the posterior beliefs of her employer that I_2 is of high ability.⁸ I_1 is happy to go along with this arrangement as she too is unsure of her own abilities – I_2 's imitation also provides I_1 with cover.

If there are several managers deciding in sequence everyone imitates the decision of the first manager. Eventually there will be a preponderance of G signals (B signals) if the investment is profitable (unprofitable). However, this private information will not be revealed since the first manager's decision is imitated by all subsequent managers without regard to their information. Thus, the herding is inefficient. Moreover, it is idiosyncratic because it is predicated on the first individual's signal realization and fragile since the herd behavior is based on very little information. Many of the implications of this theory are similar to that of informational herding with rigid prices.⁹

⁷ The noisy signal is, of course, uncorrelated with and the informative signal is positively correlated with the return on the investment.

⁸ Observe that the signals of two informed managers are positively correlated whereas the signals of two uninformed managers are uncorrelated. Hence, identical actions (even incorrect actions) by the two managers makes it more likely that they are both informed.

⁹ See also Trueman (1994), who shows that there may exist reputation-based incentives for investment analysts to herd in their predictions.

As in the papers by Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992), here too it is assumed that the investment opportunity is available to all individuals at the same price. The extent to which prices in a well-functioning market mitigate the inefficiencies in Scharfstein and Stein's model is not clear.

C. Compensation-based Herding

If an investor's (i.e., an agent's) compensation depends on how her performance compares to other investors' performance, then this distorts the agent's incentives and she ends up with an inefficient portfolio (see Brennan (1993) and Roll (1992)). It may also lead to herd behavior.

Maug and Naik (1996) consider a risk-averse investor (the agent) whose compensation increases with her own performance and decreases in the performance of another investor (the benchmark). Both the agent and her benchmark have imperfect, private information about stock returns. The benchmark investor makes her investment decisions first and the agent chooses her portfolio after observing the benchmark's actions. Then, as argued in Section A on information-based herding, the agent has an incentive to imitate the benchmark in that her optimal investment portfolio moves closer to the benchmark's portfolio after the agent observes the benchmark's actions. Further, the compensation scheme provides an additional reason to imitate the benchmark. The fact that her compensation decreases if she under-performs the benchmark causes the agent to skew her investments even more towards the benchmark's portfolio than if she were trading on her own account only. It is optimal for the principal (the employer of the agent) to write such a relative performance contract when there is moral hazard (encourage the agent to gather information, for example) or adverse selection (separate good portfolio managers from bad). Any other efficient contract (i.e., any contract that maximizes a weighted sum of the principal's and the agent's utility) will also link the agent's compensation to the benchmark's performance. Thus herding may be constrained efficient (the constraints being imposed by moral hazard or adverse selection). However, the compensation scheme selected by an employer would seek to maximize the employer's profits rather than society's welfare. Thus herding may be constrained efficient (the constraints being imposed by moral hazard or adverse selection).

The constrained efficiency of benchmark-based compensation in Maug and Naik (1996) is due to their assumption of a single risky asset. Admati and Pfleiderer (1997) analyze a multiple (risky) assets model of delegated portfolio management in which the agent investor has private information about stock returns. They find that commonly observed benchmark-based compensation contracts for the agent are inefficient, inconsistent with optimal risk sharing, and ineffective in overcoming moral hazard and adverse selection problems. Unlike in a single risky asset model, a benchmark-adjusted return is not a sufficient statistic for the agent's private information in a multiple risky assets model. Hence the sharp difference in results from these two types of models.

III. IMPLICATIONS FOR EMPIRICAL TESTS

A stock bought by an individual is sold by another. Therefore, all market participants cannot be part of a “buying herd” or a “selling herd” in a two-sided market. To examine herd behavior, one needs to find a group of participants that trade actively and act similarly. Such a group is more likely to herd if it is sufficiently homogenous (each member faces a similar decision problem), and each member can observe the trades of other members of the group. Also, such a homogenous group cannot be too large relative to the size of the market because in a large group (say one that holds 80 percent of the outstanding stock) both buyers and sellers are likely to be adequately represented.

Intentional herding may be inefficient and is usually characterized by fragility and idiosyncrasy. It leads to excess volatility and systemic risk. Therefore, it is important to distinguish between true (intentional) and spurious (unintentional) herding. How can this be done empirically? Further, the causes of investor herding are crucial for determining policy responses for mitigating herd behavior. How does one empirically distinguish between informational, reputation-based, and compensation-based herding? One approach would be to examine whether the assumptions underlying some of the theories of herd behavior are satisfied.

It is unlikely that investors observe each other’s holdings of an individual stock soon enough to change their own portfolios.¹⁰ Thus there is little possibility of intentional herding at the level of individual stocks. One is more likely to find herding at the level of investments in a group of stocks (stocks of firms in an industry or in a country) after the impact of fundamentals has been factored out.

One probably cannot distinguish between informational cascades and reputation-based herding directly from the analysis of a data set as it is difficult to discern the motive behind a trade that is not driven by fundamentals. However, it should be possible to separate out reactions to public information (unintentional herding) by explicitly allowing for changes in fundamentals. If after factoring out the effect of fundamentals, one still finds herding in the data (i.e., a correlation in the positions taken by different managers), then informational cascades or reputation-based herding may be the cause. Further differentiation among the causes of herding is possible by analyzing the incentives created for the fund manager by the compensation structure.

¹⁰ Of course, there is some information leakage through brokers about the trading patterns of various funds and investors. And “snapshots” of quarterly holdings are marketed by many companies. Still, it is difficult to get reliable information on daily, weekly or even monthly changes in stock portfolios.

IV. THE EMPIRICAL EVIDENCE

The empirical studies, by and large, do not examine or test a particular model of herd behavior—exceptions are Wermers (1999) and Graham (1999). Rather, the approach generally used is a purely statistical one, to gauge whether clustering of decisions, irrespective of the underlying reasons for such behavior, is taking place in certain securities markets. Hence, there is a lack of a direct link between the theoretical discussion of herd behavior and the empirical specifications used to test for herding. Also, many studies do not differentiate between “true” and “spurious” herding, and it is not clear to what extent the statistical analysis is merely picking up common responses of participants to publicly available information. While some researchers attempt to correct for fundamentals, it is hard to do so for two reasons: first, it is difficult to pinpoint what constitutes “fundamentals,” and second, in many cases it is difficult to measure and quantify them.

A. Herding in the Stock Market

Several papers use a statistical measure of herding due to Lakonishok, Shleifer, and Vishny (hereafter LSV) (1992). It defines and measures herding as the average tendency of a group of money managers to buy (sell) particular stocks at the same time, relative to what could be expected if money managers traded independently. While it is called a herding measure, it really assesses the correlation in trading patterns for a particular group of traders and their tendency to buy and sell the same set of stocks. Herding clearly leads to correlated trading, but the reverse need not be true.

The LSV measure is based on trades conducted by a subset of market participants over a period of time. This subset usually consists of a homogenous group of fund managers whose behavior is of interest. Let $B(i,t)$ [$S(i,t)$] be the number of investors in this subset who buy [sell] stock i in quarter t and $H(i,t)$ be the measure of herding in stock i for quarter t . The measure of herding used by LSV is defined as follows:

$$H(i,t) = |p(i,t) - p(t)| - AF(i,t)$$

where $p(i,t) = B(i,t) / [B(i,t) + S(i,t)]$, and $p(t)$ is the average of $p(i,t)$ over all stocks i that were traded by at least one of the fund managers in the group. The adjustment factor is

$$AF(i,t) = E \left[|p(i,t) - p(t)| \right],$$

where the expectation is calculated under the null hypothesis— $B(i,t)$ follows a binomial distribution with parameter $p(t)$

Under the null hypothesis of no herding the probability of a randomly chosen money manager being a net buyer of stock i is $p(t)$ and therefore the expected value of $|p(i,t) - p(t)|$ is $AF(i,t)$. If $N(i,t) = B(i,t) + S(i,t)$ is large then under the null hypothesis $AF(i,t)$ will be close to

zero since $p(i,t)$ tends to $p(t)$ as the number of active traders increases. The adjustment factor is included in the herding measure to take care of the bias in $|p(i,t) - p(t)|$ for stock-quarters which are not traded by a large number of participants. For small $N(i,t)$, $AF(i,t)$ will generally be positive. Values of $H(i,t)$ significantly different from zero are interpreted as evidence of herd behavior.

LSV (1992) use the investment behavior of 769 U.S. tax-exempt equity funds managed by 341 different money managers to empirically test for herd behavior. Most of the fund sponsors are corporate pension plans with the rest consisting of endowments and state/municipal pension plans. Since some managers ran multiple funds the unit of analysis is the money manager. Their panel data set covering the period 1985-1989 consists of the number of shares of each stock held by each fund at the end of each quarter. The funds considered managed a total of \$124 billion, which was 18 percent of the total actively managed holdings of pension plans.

LSV conclude that money managers in their sample do not exhibit significant herding. There is some evidence of such behavior being relatively more prevalent in stocks of small companies compared to those of large company stocks (where most institutional trades are concentrated). LSV's explanation is that there is less public information on small stocks and hence money managers pay relatively greater attention to the actions of other players in making their own investment decisions regarding small stocks. LSV's examination of herding conditional on past stock performance, of herding within certain industry groups and between industries, and of herding among subsets of money managers differentiated by size of assets under management reveals no evidence of herd behavior. However, as LSV caution, the impact of herding is difficult to evaluate without precise knowledge of the demand elasticities for stocks. It is possible that even mild herding behavior could have large price effects.

Grinblatt, Titman, and Wermers (GTW) (1995) use data on portfolio changes of 274 mutual funds between end-1974 and end-1984 to examine herd behavior among fund managers and the relation of such behavior to momentum investment strategies and performance. Using the LSV measure of herding, $H(i,t)$, GTW find little evidence of (economically significant) herding in their sample. The average value of $H(i,t)$ for their sample is 2.5 and is similar to that found by LSV for pension funds, 2.7. That is, if 100 funds were trading the average stock-quarter pair, then 2.5 more funds traded on the same side of the market than would be expected if portfolio managers made their decisions independently of one another. Disaggregating by past performance of stocks, GTW find that the funds in their sample exhibit greater herding in buying past winners than in selling past losers. Herding on the sell side, though positive, is less pronounced and only weakly related to past performance.¹¹ This is consistent with some of their other findings, namely, that the average

¹¹ Note that short-selling constraints on most mutual funds might prevent them from herding on the sell-side. On this point see Wylie (1997).

mutual fund is a momentum investor in that it buys past winners but does not systematically divest past losers. And such behavior leads to some herding in stocks that have performed well but there is no evidence of herding out of stocks that have earned poor returns in the immediate past.¹²

LSV and GTW test for herding at the stock level and find little evidence of it. What they rule out is unintentional herding and not intentional herding as we do not expect to find herding at the level of individual stocks. Nevertheless, their results are surprising as we would expect investors to react to public information such as forecasts of analysts and earnings announcements by firms.

There are two reasons why the extent of herding may be understated. First, the types of mutual funds considered is too heterogeneous; and second, for many stock-quarter pairs the trading may be too low for observing any significant herding. GTW (1995) attempt to address such biases. Differentiating funds according to their stated investment strategies—aggressive growth funds, balanced funds, growth funds, growth-income funds, income funds—they find even less evidence of herding than in the total sample. However, when they restrict attention to quarters where at least a certain number of trades take place they find greater evidence of herding behavior.

To evaluate fund performance in the context of herding, GTW develop a measure of “herding by an individual fund” to assess to what extent a particular fund runs with the crowd or against it. They find that fund performance is significantly correlated with the tendency of a fund to herd. However, this correlation is explained by the fact that a tendency to herd is highly correlated with the tendency to pursue momentum strategies and buy past winners. The relation between a fund’s tendency to run with the pack and its performance dissipates once GTW control for the tendency of funds to get into stocks that have performed well in the recent past.

Wermers (1999) using the LSV measure and data on quarterly equity holdings of virtually all mutual funds that were in existence between 1975 and 1994 finds that for the average stock there is some evidence of herding by mutual funds.¹³ For Wermers sample the average level of herding (i.e., of $H(i,t)$) computed over all stocks and quarters for the two decades covered is 3.4. While statistically significant this value for $H(i,t)$ is only slightly

¹²They also show that the previous quarter’s returns had a greater effect on portfolio choice of managers than returns posted in the more distant past. Further, for all objective categories and the total sample of funds, most momentum-investing behavior was accounted for by a move into well-performing large capitalization stocks.

¹³The data set in Wermers (1999) is a superset of that used in GTW (1995) and includes information for the period 1985-1994. To study herd behavior, Wermers restricts attention to stock trading where at least 5 different funds were active in a particular quarter.

larger than that reported by LSV (1992) suggesting that there is somewhat greater herding among mutual funds than among pension funds. An analysis of trading behavior when a larger number of funds are active in a stock shows that herding by mutual funds does not increase with trading activity and actually falls off as the number of active funds increases. This is due to the fact that stocks traded by a large number of funds tend to be large capitalization stocks and herding in these is generally lower.

An examination of herding levels among funds with different investment objectives—aggressive growth, growth, growth-income, balanced/income, international/other—shows that growth oriented funds have a greater tendency to herd than income-oriented funds. This could be because growth-oriented funds trade and hold a larger proportion of growth stocks, many of which are small caps on whom public information is harder to obtain and analyze and as a consequence there is greater scope for herding behavior. It is noteworthy that the average herding measure for all funds is not significantly lower, and in many cases is higher, than that calculated for sub-groups with different investment styles. This suggests that herds form across sub-groups as much as within sub-groups of funds or that it merely reflects the fact that many funds use a common investment strategy.¹⁴

Differentiating by market capitalization, Wermers finds that there is, in fact, greater herding in small growth stocks. Also, contrary to GTW's finding reported earlier that herding is more noticeable on the buy-side of the market, Wermers shows that, for all funds taken together, herds form much more often on the sell-side of the market than on the buy-side and this is especially pronounced for smaller stocks. The clearest picture of herding emerges in the sale of small stocks by growth-oriented funds and international funds. This is consistent with herding theories based on agency problems and those on information differentials among market participants.

Following up on Grinblatt, Titman and Wermers (1995), who show that positive-feedback strategies are widely used by mutual fund managers, Wermers (1999) finds that herding levels are somewhat higher among stocks that have large positive or negative returns in prior quarters. Herding on the buy-side is strongest in stocks having high prior-quarter returns and sell-side herding is most evident for stocks with low prior-quarter returns. He also finds that positive-feedback investment strategies are more likely to involve the buying of past winners than the sale of past losers. Window-dressing explanations while consistent with selling losers does not seem to be an important determinant of herding behavior since there is not much variation in the sell-side herding levels across quarters.

¹⁴It is also possible that the analysis is picking up trading by funds belonging to the same fund family but with different investment objectives. However, Wermers shows that when the fund family rather than the individual fund is used as the unit of measurement, herding levels though lower are not significantly diminished.

To assess whether a sudden increase in buying and selling of stocks by mutual funds could be driven by new cash inflows and widespread redemptions, Wermers correlates average buying and selling herding measures with various measures of present and lagged cash inflows. He concludes that such flows do not have much effect on the tendency of mutual funds to herd into stocks. He also shows that minor portfolio adjustments in the same direction by many funds does not underlie the observed results and that restricting the analysis to trades that exceed 0.1 percent of total net assets for the trading fund reveals even higher levels of herding.

What is the impact of herding by investors into or out of particular stocks? Wermers results suggest that stocks bought by herds, on average, have higher contemporaneous returns as well as higher returns in the following six months than stocks sold by herds. This difference is most pronounced in contemporaneous returns for small stocks but a modest differential is also observed for large stocks.¹⁵ Wermers argues that since this return differential is not temporary but persists over some time period the observed herding may be “rational” and a stabilizing force that speeds the incorporation of new information into prices.

Drawbacks with the LSV Measure of Herding

The LSV (1992) measure of herding is deficient in two respects: First, the measure only uses the number of investors on the two sides of the market, without regard to the amount of stock they buy or sell, to assess the extent of herding in a particular stock. Consider a situation in which the buyers and sellers are similar in number but that the buyers collectively demand a substantial amount of the stock while the sellers only put a relatively small amount on the market. In such situations, even though herding into the stock exists, the LSV measure would not pick it up.

Second, it is not possible to identify intertemporal trading patterns using the LSV measure. For example, the LSV measure could be used to test whether herding in a particular stock persists over time, that is evaluate whether $E[H(i, t) | H(i, t - k)] = E[H(i, t)]$, but it cannot inform us whether it is the same funds that continue to herd.

In addition, in applying the LSV measure the choice of investment category i and the time interval t over which trading data are observed is very important. For example, Fund managers might not observe, either instantaneously or with short lags, holdings of other managers at the level of individual stocks. The evidence provided by Shiller and Pound (1989) is mixed. If indeed holdings of other investment entities can only be observed with a (considerable) lag then intentional herding cannot arise because what cannot be observed cannot be imitated. Managers may be able to observe actions at a more aggregate level—

¹⁵Given the quarterly data window, it is not possible to determine whether within quarter feedback strategies or herding itself is responsible for the contemporaneous return differential.

stocks in specific industries, sectors, or countries. Therefore, there may be a better chance of detecting herding at this level.

Furthermore, the frequency with which fund managers trade in a stock is crucial for selecting the time interval t . If the average time between trades of a stock is a quarter or more, then one may use quarterly (or shorter time period) data to look for herd behavior. If, on the other hand, the average time between trades of a stock is a month or less, then a quarter is too long a time-period for discerning herd behavior. The market for large company stock is much more liquid than that for small company stock. Hence, the appropriate window of observation, t , is likely to be relatively smaller for large company stock.

A Modification of the LSV Measure of Herding

Wermers (1995) develops a new measure of herding that captures both the direction and intensity of trading by investors. This new measure, which he calls a portfolio-change measure (PCM) of correlated trading, overcomes the first drawback listed above. Intuitively, herding is measured by the extent to which portfolio-weights assigned to the various stocks by different money managers move in the same direction. The intensity of beliefs is captured by the percent change of the fraction accounted for by a stock in a fund portfolio. The cross-correlation PCM of lag τ between portfolio I and J is defined as follows:

$$\hat{\rho}_{t,\tau}^{I,J} \equiv \frac{\left(\frac{1}{N_t}\right) \sum_{n=1}^{N_t} (\Delta \tilde{\omega}_{n,t}^I) (\Delta \tilde{\omega}_{n,t-\tau}^J)}{\hat{\sigma}^{I,J}(\tau)}$$

where

$\Delta \tilde{\omega}_{n,t}^I$ = the change in portfolio I 's weight of n during the period (quarter) $[t-1, t]$,

$\Delta \tilde{\omega}_{n,t}^J$ = the change in portfolio J 's weight of n during the period $[t-\tau-1, t-\tau]$,

N_t = number of stocks in the intersection of the set of tradable securities in portfolio I during period $[t-1, t]$ and the set of tradable securities in portfolio J during period $[t-\tau-1, t-\tau]$,

and

$$\hat{\sigma}^{I,J}(\tau) = \frac{1}{T} \sum_t \left\{ \frac{1}{N_t} \left[\sum_n (\Delta \tilde{\omega}_{n,t}^I)^2 \sum_n (\Delta \tilde{\omega}_{n,t-\tau}^J)^2 \right]^{1/2} \right\}$$

is the time-series average of the product of the cross-sectional standard-deviations.

Wermers (1995) finds a significant level of herding by mutual funds using the PCM measure. The data set is the same as that in Wermers (1999). To measure herding in the aggregate Wermers (1995) randomly splits his sample of mutual funds into two groups and then uses the PCM measure of correlated trading to compare the revisions of the net asset value weighted portfolios of the two groups. For each quarter, the PCM measure is calculated across all stocks; an average across all quarters is the measure of herding for a given random split. A set of 10 randomizations of the 274 mutual funds in the sample into two groups of

137 funds is conducted and the mean PCM for this set turns out to be 0.1855 and statistically significant.

In contrast to $H(i,t)$, the herding measure of LSV (1992), the PCM measure of herding increases as the number of funds trading a particular stock increases, showing that when the number of funds active in a particular stock rises, it also results in a greater proportion of them trading on the same side of the market. Wermers shows that for his sample the PCM measure of herding when “at least five funds are active in a particular stock” is about half that obtained when the calculation is restricted to quarters in which “at least 25 funds are active in a particular stock.”¹⁶

The PCM measure also has some drawbacks. While one should weight the buy or sell decision by the amount traded, doing this introduces another bias since larger fund managers tend to get a higher weight. Also, Wermers’ statistic which looks at changes in fractional weights of stocks in portfolios may yield spurious herding as weights of stocks that increase (decrease) in price tend to go up, even without any buying (selling). Taking the average of beginning and end-quarter prices to determine portfolio weights may correct for it as Wermers claims but that depends on exactly how it is done. Further, the justification for using net asset values as weights in constructing the PCM measure is not clear.

Other Measures of Herding

Another strand of the literature looks at whether the returns on individual stocks cluster more tightly around the market return during large price changes. The rationale is that if during periods of market stress individual stocks have a tendency to become more tightly clustered around the market, then this is evidence that during such periods markets are less discriminating of individual stocks and treat all stocks similarly. Trading intervals characterized by large swings in average prices are examined because the expectation is that herds are more likely to form in periods of market stress when individuals are more likely to suppress their own beliefs in favor of the market consensus.

Christie and Huang (1995), using daily returns on U.S. equities, show that under their measure of cross-sectional dispersion, there is relatively *higher* dispersion around the market return at times of large price movements. This is interpreted as evidence against herding. They also check whether the failure to detect herding may be due to returns clustering around the returns of firms that share common characteristics rather than around the average return of all market participants. Using industry specific averages, they still obtain the same results.

¹⁶The high correlation between the number of funds trading a particular stock and the stock’s market capitalization leads him to suggest that there is greater herding in large-cap stocks. This could be a result of sample selection since the mutual funds considered mainly trade in large-cap stocks and hence the sample may not be very informative about the small-cap market.

However, as Richards (1999) points out, the Christie and Huang test (and a related test by Chang et.al. (1998)) looks for evidence of a specific form of herding and that too only in the asset-specific component of returns. It does not allow for other forms of herding that may show up in the common component of returns, for example, when prices of all assets in a class (or market or country) change in the same direction. Hence, the Christie and Huang test should be regarded as a gauge of a particular form of herding and the absence of evidence against this form of herding should not be construed as showing that other types of herding do not exist.

B. Herding in Other Financial Markets

Unlike the above papers (which use quarterly data on equity portfolios), Kodres and Pritsker (1996) analyze daily trading data on futures contracts to detect herd behavior. The data cover the period August 1992 to August 1994 and were obtained from the Commodity Futures Trading Commission (CFTC) which has a end-of-day reporting requirement for “large” traders defined as those who own futures contracts above certain threshold levels. Such information is monitored by the CFTC to ensure that players do not attempt to manipulate the markets. These positions are not publicly known, although traders can see each other trade on the exchange floor.¹⁷

The futures contracts in the data set are for Treasury securities (91-day bill, 5-year note, 10-year note, 30 year bond), the S&P 500 index, and foreign exchange (3-month Euro dollar, British pound, Canadian dollar, Deutsche mark, Japanese yen, Swiss franc). The data are truncated in the sense that traders’ whose positions are smaller than the critical threshold that triggers the reporting requirement do not appear in the data set. In fact, a participant may be continuously present in the market but only intermittently so in the data set. Also, the average open interest held by the large traders during the sample period varies from 40 percent for Swiss francs to 72 percent for 5-year Treasury notes. Except in the 3-month Eurodollar and 5- and 10-yr Treasury notes, in all other securities the open interest held by smaller traders exceeds 40 percent. To the extent that information gathering is more costly for small traders, informational cascades are more likely to form among them. An analysis that uses data on “large” trader reporting requirements neglects the behavior of “small” traders (who collectively may make up a substantial fraction of the market) and hence underestimates herding behavior.

Large participants are classified into the following categories: broker-dealer, commercial bank, foreign bank, hedge fund, insurance company, mutual fund, pension fund, and savings

¹⁷Note that since positions reported to the CFTC are not made available to other market participants the possibility of (intentional) herding is decreased. If trading becomes computerized, observability may be decreased or increased depending on how the computer program is set-up.

and loan association. This enables testing for herd behavior among institutions belonging to the same category. However, note that an institution may have several traders, one trading as a pension fund, another as a mutual fund etc. If so, then such traders, to the extent that they talk to each other, share the parent institution's research and other information, are more likely to "herd." Therefore, while one may expect that institutions in the same categories with similar objectives would be natural groups within which to examine herding, it is possible that much of the observed herd behavior takes place across institutional categories by traders affiliated to the same institution. Since traders are not identified by institution in the data, it is not possible to examine such behavior or correct for it in assessing herding across different firms.

Kodres and Pritsker (1996) focus on looking at directional changes in positions (irrespective of magnitudes) and first conduct a simple correlation analysis of changes in positions for each pair of participants in the same institutional category. This is done for 29 combinations of institutional types and contracts for which there were at least 40 large traders during the sample period. An absence of herding among large traders would imply that correlation coefficients be statistically indistinguishable from zero. In only 5 out of the 29 type-contract pairs are the correlation coefficients different from zero at a 5 percent significance level. This analysis suggests that broker-dealers and hedge funds with positions in foreign currency contracts were most likely to change their positions at the same time.

Next, a probit model is used to investigate whether some large participants are more likely to buy or sell when other participants are doing the same. Each category of traders is randomly divided into two subgroups with the first subgroup being half as big as the second one. The second subgroup is the "herd." For each member of the first sub-group, a probit regression is run to determine to what extent the probability of a buy trade depends on the proportion of buys relative to total trades in the second sub-group. The estimated parameters are used to test whether the first subgroup follows the second.¹⁸ Herding is detected in 13 of the 29 participant type-contract pairs analyzed. The results suggest that herding is most likely by broker-dealers and foreign banks with positions in foreign currency (Deutsche mark, Japanese yen) and broker-dealer, pension funds and hedge funds with positions in the S & P 500 Index futures contracts. It is less likely in futures on US government paper.¹⁹ However, the probit analog of R^2 for the regressions is low—generally below 0.10—suggesting that imitation of the second sub-group by members of the first sub-group accounted for a small part of the variation in their positions.

¹⁸To ensure some precision in the estimated parameters, Kodres and Pritsker (1996) perform the regressions for only those participants that altered their positions on at least 30 days while remaining in the sample.

¹⁹An examination by contract type but without regard to institutional categories showed herding in all contracts except those for the 5-year Treasury note, 30-year Treasury note and the Eurodollar.

These results need to be interpreted with caution. Although Kodres and Pritsker (1996) attempt to examine herding intensity by including the net number of contracts bought or sold in their probit analysis, they do not distinguish between intentional and unintentional herding. Also, as the authors themselves note, observed changes in futures trading could be offset by changes in underlying cash positions and hence herding observed when the analysis is restricted to certain futures contracts may not show up if a portfolio-wide perspective is taken. Further, data censoring forces the authors to restrict their analysis to “large” participants whose positions are greater than certain thresholds—smaller participants are not included in the analysis. And even for large participants the analysis examines those participants who make frequent position changes. It is possible that in markets where small participants account for a sizable fraction of the open interest, herding takes place and is an important feature of the market. Of course, whether such herding by smaller participants can have dramatic implications for prices and trading volumes can only be answered in the context of a specific market and a particular environment.

C. Herding Among Investment Analysts and News Letters

Another strand of the literature, rather than examining the clustering of decisions to trade in particular financial instruments, looks at herd behavior among investment analysts and news letters.²⁰ This setting, where actions (i.e. recommendations) of other newsletters are easily observable, provides a potentially fertile ground for herd behavior. While this is another way to shed empirical light on the usefulness of different models of herd behavior, it leaves open the question to what extent herding by analysts in recommending certain investments is actually followed by investors herding into those investments. Recently, there has been some skepticism about the “independence” of research findings of investment banks and other researchers about the prospects of firms who are their clients or would-be clients. It is difficult to ascertain to what extent traders and other decision makers are swayed by newsletter recommendations. Nevertheless, the literature on herding by analysts provides some insights into the various motives that could lead to herd behavior.

Following Scharfstein and Stein (1990), Graham (1999) builds a reputational model of herd behavior among investment news letters. In Graham’s model the likelihood of herding

(i) decreases with the analysts ability—a low ability analyst has greater incentive to hide in the herd than a high ability analyst;

²⁰ Using the LSV measure to examine stock recommendations by newsletters followed by the *Hulbert Financial Digest* over the period 1980-1996, Jaffee and Mahoney (1998) find weak evidence of herding among newsletters in their sample. The value for the herding measure in their study is of the same order of magnitude as that found for money managers by LSV (1992).

- (ii) increases with the analysts initial reputation—analysts with high reputations (and presumably salaries), are more conservative in bucking the consensus and herd to protect their current status and pay levels; those with lesser reputations have “less to lose” and hence more likely to act on their private information;
- (iii) increases with the strength of prior public information (and if it is consistent with the leader’s action)—when aggregate public information is strongly held (i.e. the prior distribution has a relatively smaller variance), and reinforced by the actions of the market leader, an individual analyst is less likely to take an opposing view based on private information;
- (iv) increases with the level of correlation across informative signals.

The data used by Graham (1999) covers the 1980–1992 period and contains 5293 recommendations made by 237 newsletters. Given its stature and accessibility, the *Value Line Investment Survey* is used as the market leader and the benchmark against which analysts compare their advice. An announcement is a recommendation by a newsletter to increase or decrease portfolio equity weights—the question being to examine whether a newsletter changes its equity weight recommendation in the same direction as that recommended by *Value Line*. The dependent variable in the empirical analysis is defined to take the value one when a newsletter makes the same directional recommendation for equity weights as *Value Line*, and to take the value zero otherwise.

The main result in Graham (1999) is that the precision of private information (i.e. ability of the analyst) is the key factor in determining whether a newsletter herds on *Value Line*. He also shows that herding is more likely if the reputation of the newsletter is high, prior information is strongly held and informative signals are highly correlated. These results seem to hold even after allowing for the possibility that newsletters may be recommending momentum-investment strategies. Graham’s paper, one of the few attempts to directly test a model of herd behavior, provides evidence which is consistent with information cascades and reputational models of herd behavior.

Welch (1999) uses Zacks Historical Recommendation Database to examine herding among security analysts, which he defines as the influence exerted on an analyst by the prevailing consensus and recent revisions by other analysts. The data set used consists of about 50,000 recommendations issued by 226 brokers over the period 1989-1994. A recommendation consists of categorizing a particular stock into a (i) strong buy, (ii) buy, (iii) hold, (iv) sell, or (v) strong sell, and the data includes only those stocks that had at least 16 recommendations over the time period considered. Welch’s null hypothesis is that for each recommendation the transition from one category to another is generated by “no herding.” He then uses a parsimonious parametric specification of how this transition is affected by the prevailing consensus and recent revisions by analysts, to examine whether herding does or does not occur.

His results suggest that the prevailing consensus as well as the two most recent revisions by other analysts influence recommendations by analysts. The revisions by others have a stronger influence if they are more recent and if they turn out to be good predictors of

security returns *ex post*. The effect of the prevailing consensus, however, does not depend on whether it is a good predictor of subsequent stock movements. Welch interprets this as evidence that the influence of recent revisions by other analysts stems from a desire to exploit short-lived information about fundamentals, while herding towards the consensus is less likely to be caused by information about fundamentals. He also finds that herding towards the consensus is much stronger in market up-turns and hence booming markets aggregate less information and therefore could be more “fragile” than market downturns.

Both the above studies can be seen as providing conservative estimates of herding by analysts. The reason is that they use the available universe of stocks to examine herd behavior without, for example, distinguishing between large- and small-cap stocks. Investors typically have much more information on the heavily followed large cap-stocks, which typically also have longer track records. Smaller stocks are followed by fewer analysts, information on them is much harder to obtain, and the market consensus, if it exists, is likely to be less firmly grounded in reality. It is possible that herding among analysts is much stronger in small stocks than in larger cap stocks. Similarly, it may be that herding by newsletters is much more likely in emerging market financial instruments than in those available in developed markets.

D. Herding in Emerging Stock Markets

In the aftermath of the recent crises in emerging markets, considerable attention has focussed on the question of whether herding by international investors leads to excessive volatility in the flow of capital to developing countries. Much of the research has focussed on Korea and we suspect this is due to the availability of micro-level data that is needed to shed light on questions relating to the trading strategy of investors. The studies cited below provide evidence of herding in the Korean stock market.²¹

Kim and Wei (1999a), using data spanning December 1996-June 1998, investigate the trading strategies of investors in the Korean stock market. The data, provided by an affiliate of the Korean Stock Exchange (KSE), reports the end-of-month investor holdings for each stock listed on the KSE and contains information on whether the investor is Korean or foreign, resident or non-resident, an individual or an institution, and whether for a particular

²¹ Note that in Korea, like many emerging markets, other cross-border capital flows (bank loans, bonds, trade credits, foreign direct investment) significantly dwarf cross-border equity flows. To make a judgement on the volatility of capital flows, it is important to examine the non-equity transactions of foreign investors. See, for example, Kinoshita and Mody (1999), for an empirical examination of the relative importance of privately-held information obtained through direct production experience in an emerging market country and information inferred from observing competitors, in the making of foreign investment location decisions by Japanese firms.

month the (individual and collective) investment ceilings on foreign ownership of a particular stock are binding. Employing the LSV (1992) measure of herding, the authors conclude:

- (i) non-resident institutional investors used positive feed-back trading strategies before the crisis; after the crisis broke out in November 1997, there was even greater use of momentum strategies by such investors;
- (ii) resident institutional investors were contrarian traders before the crisis but became positive-feedback traders during the crisis;
- (iii) non-resident investors did herd significantly more than resident ones; herding measures for individual investors were significantly higher than for institutional investors; herding may have increased during the crisis period but this increase was not statistically significant;
- (iv) herds of non-resident institutional investors formed more easily for the 19 Korean stocks that are regularly reported in the Wall Street Journal and for stocks that show extreme returns in the previous month; and the greater pessimism of the Western press relative to its Korean counterpart was reflected in greater net selling of Korean stocks by non-resident compared to resident investors.

In another paper, Kim and Wei (1999b) use the above mentioned data set to examine whether there are systematic differences between the trading strategies adopted by funds registered in offshore financial centers and those domiciled in the United States and the United Kingdom. Their results suggest that although offshore funds trade more frequently they do not as a group engage in positive-feedback trading. However, the funds domiciled in the US and the UK do use momentum strategies and have higher LSV herding statistics compared to the other funds. The authors conclude, that based on available data for Korean crisis, funds based in offshore financial centers cannot be singled out for being particularly prone to herding.

Choe, Kho and Stulz (1999) using daily transactions data from the KSE broadly come to the same conclusions. The main difference seems to be that whereas Kim and Wei (1999a) find increased herding after the outbreak of the crisis, Choe et.al find that the extent of herding may have been lower. In part, the difference could be due to different data frequencies and sample periods. Classifying investors into three categories—domestic individual investors, domestic institutional investors and foreign investors—Choe et. al. examine the behavior of foreign investors in the Korean stock market before the Korean crisis (November 30, 1996 – September 30, 1997) and during the height of the crisis (October 1, 1997 – December 31, 1997).²²

²² Their data set does not allow them to differentiate between individual and institutional foreign investors. Also, as the authors acknowledge, since buy and sell trades are not associated with an investor ID (only with nationality and type of investor) in their data, the computation of herding measures for foreign investors assuming “each buy and sell trade is assumed to be done by a different foreign investor” may lead to an upward bias in their results. Another limitation is that it is difficult, if not impossible, to ascertain whether Korean investors are using foreign entities to trade on the KSE.

Using the LSV measure of herding, Choe et. al. (1999) reveal there was significant herding into Korean stocks; also, prior to the crisis foreign investors used positive-feedback trading strategies, buying (selling) stocks on days when the Korean stock market index had risen (fallen) on the previous day.²³ During the crisis period itself, they find some decline in herding and that foreign investors were less likely to use momentum strategies.

Choe et. al. also contend that foreign investors were not a destabilizing influence in the Korean market over their sample period. Their evidence suggests that there were no abnormal returns in short (intraday) time intervals around large foreign trades and that, even for horizons of a few days, there was little price momentum around days when there were large trades by foreign investors.

V. CONCLUDING REMARKS

Most of the studies examining the empirical evidence on herding and its effects have been done in the context of developed countries. In these countries the evidence suggests that investment managers do not exhibit significant herd behavior and that the tendency to herd is highly correlated with a manager's tendency to pursue momentum investment strategies. Whether such positive-feedback or momentum strategies are efficient, depends on how fast new information is incorporated into market prices.

More empirical work needs to be done on emerging markets where, as the evidence suggests, one is likely to find a greater tendency to herd. In these markets, where the environment is relatively opaque because of weak reporting requirements, lower accounting standards, lax enforcement of regulations, and costly information acquisition, information cascades and reputational herding are more likely to arise. Also, since information is likely to be revealed and absorbed more slowly, momentum investment strategies could be potentially more profitable.

The statistical measures used in empirical studies need to be further refined to distinguish true herd behavior from the reactions of participants to public announcements or commonly available information. It should be emphasized that "adjusting for changes in fundamentals" is easier said than done and that it is difficult to adequately capture both the direction and intensity of herding in a particular security or market. Further, a large repricing of a security may take place with only little trading and hence there may be very few observed changes in portfolio holdings.

²³ The daily LSV herding measures for foreign investors—values in the range 21-25 pre-crisis and 16-26 during the crisis, depending on stock size and past-weeks return—are significantly higher compared to those obtained by Wermers (1999) in his quarterly analysis of US institutional investors. They are also higher than the range of 6-16 obtained for non-resident investors by Kim and Wei (1999).

Even equipped with more sophisticated measures, examination of herd behavior is likely to remain difficult since the requisite data will not be available. Anonymity is important for the existence, functioning and liquidity of markets and it may not be appropriate to require the players to reveal proprietary information on their investment strategies.

There is always an information asymmetry between any borrower and lender, and some element of an agency problem when owners of funds delegate investment decisions to professional managers. Hence, there will always be some possibility of informational cascades and of reputation and compensation based herding. Disclosure rules, timely provision of data and better designed compensation contracts may make markets and institutions more transparent. And the development of futures and forward markets may bring information about market expectations into the public domain. However, in a relatively transparent environment, changes in the situation of economic units is likely to bring forth similar responses from many, if not most, profit-maximizing investors, but this behavior would reflect the reaction to publicly available information in well-functioning markets. Greater transparency makes it more likely that prices will closely track fundamentals; it does not necessarily imply that transparency will reduce price volatility.

VI. REFERENCES

- Admati, Anat and Paul Pfleiderer, 1997, "Does it All Add Up? Benchmarks and the Compensation of Active Portfolio Managers," *Journal of Business*, 70, pp. 323-350.
- Avery, Christopher and Peter Zemsky, 1998, "Multidimensional Uncertainty and Herd Behavior in Financial Markets," *American Economic Review*, 88, pp. 724-748.
- Banerjee, Abhijit, 1992, "A Simple Model of Herd Behavior," *Quarterly Journal of Economics*, 107, pp. 797-818.
- Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch, 1992, "A Theory of Fads, Fashion, Custom and Cultural Change as Informational Cascades," *Journal of Political Economy*, 100, pp. 992-1026.
- Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch, 1998, "Learning from the Behavior of Others: Conformity, Fads and Informational Cascades," *Journal of Economic Perspectives*, 12, pp. 151-170.
- Brennan, Michael, 1993, "Agency and Asset Prices," Finance Working Paper No. 6-93, UCLA.
- Calvo, Guillermo and Enrique Mendoza, 1998, "Rational Herd Behavior and Globalization of Securities Markets," mimeo, University of Maryland.
- Chari, V.V. and Patrick Kehoe, 1999, "Financial Crises as Herds," mimeo, Federal Reserve Bank of Minneapolis.
- Choe, Hyuk, Bong-Chan Kho, and Rene M. Stulz, 1999, "Do foreign investors destabilize stock markets? The Korean experience in 1997," mimeo, Ohio State University.
- Chang, Eric, Joseph Cheng, and Ajay Khurana, 1998, "An Examination of Herd Behavior in Equity Markets: An Empirical Perspective," (unpublished paper; Georgia Institute of Technology).
- Christie, William G., and Roger D. Huang, 1995, "Following the Pied Piper: Do Individual Returns Herd Around the Market?," *Financial Analysts Journal*, (July-August), pp. 31-37.
- Council on Foreign Relations, (1999), *Safeguarding Prosperity in a Global Financial System: The Future International Financial Architecture*, Report of an Independent Task Force, Co-chairs: Carla A. Hills and Peter G. Peterson, Project Director: Morris Goldstein, (Washington: Institute for International Economics).

- Devenow, Andrea and Ivo Welch, 1996, "Rational Herding in Financial Economics," *European Economic Review*, 40, pp. 603-615.
- DeLong, J. Bradford, Andrei Schleifer, Lawrence Summers, and Robert Waldman, 1990, "Positive Feedback Investment Strategies and Destabilizing Rational Speculation," *Journal of Finance*, 45, pp. 379-395.
- Diamond, Douglas and Phillip Dybvig, 1983, "Bank Runs, Deposit Insurance, and Liquidity," *Journal of Political Economy*, 91, pp. 401-409.
- Eichengreen, Barry, Donald Mathieson, Bankim Chadha, Anne Jansen, Laura Kodres and Sunil Sharma, 1998, *Hedge Funds and Financial Market Dynamics*, Occasional Paper No. 166, (Washington: International Monetary Fund).
- Eichengreen, Barry, Michael Mussa, Giovanni Dell'Ariccia, Enrica Detragiache, Gian Maria Milesi-Ferretti, and Andrew Tweedie, 1998, *Capital Account Liberalization: Theoretical and Practical Aspects*, Occasional Paper No. 172, (Washington: International Monetary Fund).
- Folkerts-Landau, David and Peter M. Garber, 1999, "The New Financial Architecture: A Threat to the Markets?" *Deutsche Bank Global Markets Research*, Vol. 2 No.2, April.
- Froot, Kenneth, Paul G. J. O'Connell and Mark Seasholes, 1998, "The Portfolio Flows of International Investors," NBER Working Paper No. 6687, (Cambridge, Massachusetts: NBER).
- Froot, Kenneth, David Scharfstein, and Jeremy Stein, 1992, "Herd on the Street: Informational Efficiencies in a Market with Short-Term Speculation," *Journal of Finance*, 47, pp. 1461-1484.
- Furman, Jason and Joseph E. Stiglitz, 1998, "Economic Crises: Evidence and Insights from East Asia," *Brookings Papers on Economic Activity*, 2, pp. 1-136.
- Graham, John R., 1999, "Herding among Investment Newsletters: Theory and Evidence," *Journal of Finance*, 54, pp. 237-268.
- Grinblatt, Mark, Sheridan Titman and Russ Wermers, 1995, "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior," *American Economic Review*, December, Vol. 85 No. 5, pp.1088-1105.
- Jaffe, Jeffrey F. and James M. Mahoney, 1998, "The Performance of Investment Newsletters," Federal Reserve Bank of New York, Staff Report No. 48, October.
- Kim, Woochan and Shang-Jin Wei, 1999, "Foreign Portfolio Investors Before and During a Crisis," NBER Working Paper No. 6968, (Cambridge, Massachusetts: NBER).

- Kim, Woochan and Shang-Jin Wei, 1999, "Offshore Investment Funds: Monsters in Emerging Markets," Working Paper No. 7133, (Cambridge, Massachusetts: NBER).
- Kinoshita, Yuko and Ashoka Mody, 1999, "Private Information for Foreign Investment in Emerging Economies," mimeo, The World Bank.
- Kodres, Laura and Matthew Pritsker, 1996, "Directionally-Similar Position Taking and Herding By Large Futures Market Participants," mimeo, International Monetary Fund.
- Lakonishok, Josef, Andrei Shleifer and Robert W. Vishny, 1992, "The Impact of Institutional Trading on Stock Prices," *Journal of Financial Economics*, 32, pp. 23-43.
- Lee, In Ho, 1995, "Market Crashes and Information Avalanches," mimeo, University of Southampton, U.K.
- Lux, Thomas and Michele Marchesi, 1999, "Scaling and Criticality in a Stochastic Multi-agent Model of a Financial Market," *Nature*, Vol. 397, February 11, pp. 498-500.
- Maug, Ernst and Narayan Naik, 1996, "Herding and Delegated Portfolio Management," mimeo, London Business School.
- Richards, Anthony, 1999, "Idiosyncratic Risk: An Empirical Analysis, with Implications for the Risk of Relative-Value Trading Strategies," IMF Working Paper WP/99/148, (Washington: International Monetary Fund).
- Roll, Richard, 1992, "A Mean/Variance Analysis of Tracking Error," *Journal of Portfolio Management*, summer, 13-22.
- Scharfstein, David and Jeremy Stein, 1990, "Herd Behavior and Investment," *American Economic Review*, 80, 465-479.
- Shiller, Robert and John Pound, 1989, "Survey Evidence on Diffusion of Interest and Information among Investors," *Journal of Economic Behavior and Organization*, 2, pp. 47-66.
- Shleifer, Andrei and Lawrence Summers, 1990, "The Noise Trader Approach to Finance," *Journal of Economic Perspectives*, 4, pp. 19-34.
- Trueman, Brett, 1994, "Analyst Forecasts and Herding Behavior," *Review of Financial Studies*, 7, 97-124.
- Welch, Ivo, 1992, "Sequential Sales, Learning and Cascades," *Journal of Finance*, 47, pp. 695-732.

Welch, Ivo, 1999, "Herding Among Security Analysts," forthcoming *Journal of Financial Economics*.

Wermers, Russ, 1995, "Herding, Trade Reversals, and Cascading by Institutional Investors," mimeo, University of Colorado, Boulder.

Wermers, Russ, 1999, "Mutual Fund Herding and the Impact on Stock Prices," *Journal of Finance*, 54, pp. 581-622.

Wylie, Samuel, 1997, "Tests of the Accuracy of Measures of Herding Using UK data," Working Paper, Dartmouth University.