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Herd Behavior in Financial Markets

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This paper provides an overview of the recent theoretical and empirical research on herd behavior in financial markets. It looks at what precisely is meant by herding, the causes of herd behavior, the success of existing studies in identifying the phenomenon, and the effect that herding has on financial markets. [JEL G1, G2, F4]

> "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 (1841)

In the aftermath of several widespread financial crises, "herd" has again become a pejorative term in the financial lexicon. Investors and fund managers are 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 observers express concern that herding by market participants exacerbates volatility, destabilizes markets, and increases

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the fragility of the financial system.[1] This raises questions about why it is surprising that profit-maximizing investors, increasingly with similar information sets, react similarly at more or less the same time? And 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 a 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]

When investors are influenced by others' decisions, they may herd on an investment decision that is wrong for all of them. Suppose that 100 investors each have their own assessments, possibly different, about the profitability of investing in an emerging market. For concreteness, suppose that 20 of the investors believe that this investment is worthwhile and the remaining 80 believe that it is not. Every investor knows only her own estimate of the profitability of this investment; she does not know the assessments of others' or which way a majority of them are leaning. If these investors pooled their knowledge and assessments, they would collectively decide that investing in the emerging market is not a good idea. But they do not share their information and assessments with each other. Moreover, these 100 investors do not take their investment decisions at the same time. Suppose that the first few investors who decide are among the 20 optimistic investors and they make a decision to enter the emerging market. Then several of the 80 pessimistic investors may revise their beliefs and also decide to invest. This, in turn, could have a snowballing effect, and lead to most of the 100 individuals investing in the emerging market. Later, when the unprofitability of the decision becomes clear, these investors exit the market.

The above example illustrates several aspects of *information cascades* or herd behavior arising from informational differences. First, the actions (and the

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[1]See, for example, Morris and Shin (1999), Persaud (2000) and Shiller (1990) for an analysis of how the interaction of herding and institutional risk management strategies may amplify volatility; Eichengreen and others (1998) for the role hedge funds may have played in 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; Eichengreen and others (1998) for a discussion of herd behavior in the context of capital account liberalization.

[2]Externalities due to direct payoff or utility interactions (i.e., externalities by which an agent's action affects the utility 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 in the 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.

assessments) of investors who decide early may be crucial in determining which way the majority will decide. Second, the decision that investors herd on may well be incorrect. Third, if investors take a wrong decision, then with experience and/or the arrival of new information, they are likely to eventually reverse their decision starting a herd in the opposite direction. This, in turn, increases volatility in the market.

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 I, 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.

Other causes of intentional 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 in the literature (see, for example, Grinblatt, Titman and Wermers (1995); Froot and others (2001); Choe

[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.

and others (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, that is, 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.[4]

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 are possible causes of rational herd behavior, what success existing studies have had in identifying it, and what effect such behavior has on financial markets.[5] In Section I, we discuss how imperfect information, concern for reputation, and compensation structures can cause herding.

Intentional herding may be inefficient and is usually characterized by fragility and idiosyncrasy. It can lead to excess volatility and systemic risk.[6] Therefore, it is important to distinguish between true (intentional) and spurious (unintentional) herding. Furthermore, 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.

A financial asset bought by one market player must be sold by another. Therefore, all market participants cannot be part of a "buying herd" or a "selling herd." 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.

It is unlikely that investors observe each other's holdings of an individual stock soon enough to change their own portfolios.[7] There is therefore little

[4]For a fascinating interpretation of structural, cultural and psychological factors that may be responsible for recent U.S. stock market valuations, see Shiller (2000). Also, see Flood and Hodrick (1986), West (1988) and Campbell et al (2000) for a discussion of the empirical literature on asset price volatility. For a fundamentals based explanation of some famous bubbles, see Garber (2001).

[5]See Devenow and Welch (1995) for an earlier survey of theoretical models.

[6]By this we mean that volatility is likely to be higher compared to market situations in which herd behavior is not prevalent.

[7]Of course, there is some information leakage through brokers about the trading patterns of various funds and investors. And many companies market "snapshots" of quarterly holdings. Still, it is difficult to get reliable information on daily, weekly or even monthly changes in stock portfolios.

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.

Manski (2000) provides an accessible survey of the state of empirical research on social interactions, and the difficulty of drawing inferences about the nature of an interaction process from observations on its outcomes. He argues that structural analysis of markets remains a subtle inferential problem and econometric methods do not—indeed cannot—resolve the basic identification problem. The data commonly brought to bear to study such interactions has only limited power to distinguish among alternative plausible hypotheses. Observations on market transactions and their prices can reveal only so much about the factors determining the choices of market participants. And given the data currently available, analysis of social interactions requires strong assumptions that diminish the credibility of the conclusions about behavior.

One cannot distinguish between different causes of herd behavior directly from the analysis of a data set on asset holdings and price changes since it is difficult, if not impossible, to discern the motive behind a trade that is not driven by "fundamentals." However, though difficult, it may be possible to separate out reactions to public information (unintentional herding) by explicitly allowing for changes in fundamentals. If after factoring out such effects, one still finds herding in the data (i.e., a correlation in the positions taken by different managers), then informational cascades, reputation-based herding, or the compensation systems for the portfolio managers may be the cause. In the absence of richer data sets—especially lack of data on the subjective expectations of market participants—further differentiation among the causes of herd behavior will prove difficult.

Keeping these issues in mind, we discuss the empirical literature in Section II. Much of the work does not test the validity of specific models or causes of herd behavior. The empirical specifications do not naturally arise from the theoretical models discussed, and generally a purely statistical approach is used to examine to what extent there is a clustering of decisions, after an attempt has been made to account for changes in "fundamentals" and publicly available information.

I. 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.

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, that is, 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 equity (or bond) 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).

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, an investor's private information may be the conclusions of her 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? An individual's assessment of the quality of publicly available information is only privately known to her.

Individuals can observe each other's actions but not the private information or signals that each player receives. (Even if individuals communicate their private information to each other, the idea that "actions speak louder than words" provides justification for this assumption.) 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. We show below that herd behavior may arise in this setting. Moreover, such behavior is *fragile*, in that it may break easily with the arrival of a little new information; and it is *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 ideas.

Suppose that several investors decide in sequence whether to invest in an individual stock (or an industry or a country). For each investor, let V denote the payoff to investing relative to the next best project. V is either +1 or –1 with equal probability. (The payoff from the next best project is normalized to zero). The order in which the investors decide is exogenously specified. Each investor observes a private signal (either a good signal, G, or a bad one, 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.

It is worth noting the following implication of the symmetry of the signals. Suppose that a total of M good signals and N bad signals are observed. Then repeated application of Bayes' rules implies that, if $M > N$, the posterior distribution of V is the same as if a total of $M - N$ signals were observed, all of them good. Alternatively, if $M < N$, the posterior is same as if a total of $N - M$ signals were observed, all of them bad. And if $M = N$ then the posterior is the same as the prior, that is, V is either +1 or –1 with equal probability. This observation makes the remainder of this section easier to follow.

Applying Bayes' rule, the posterior probability of $V = +1$ after observing a G is

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

A similar calculation using Bayes' rule implies that the posterior probability of $V = +1$ after observing a B is

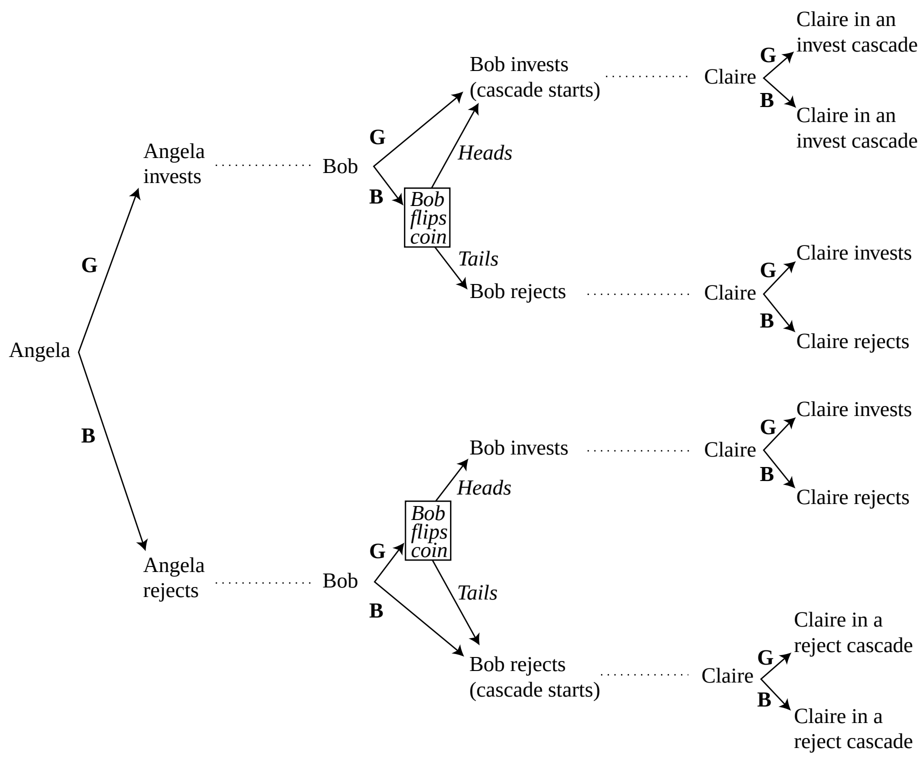
$$Prob[V = +1 \mid B] = \frac{(1 - p) \times 0.5}{p \times 0.5 + (1 - p) \times 0.5} = 1 - p < 0.5$$

As a result, 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 observes Angela invest then he too will invest. If, instead, Bob's signal is B and he observes Angela 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); therefore, Bob is indifferent between investing and rejecting and he flips a coin to decide. Thus, if Angela invests and Bob rejects, then Claire, the third investor, will infer that Angela saw G and Bob saw B. If instead Angela and Bob both invest, then Claire will infer that Angela saw G and Bob is more likely to have seen G than B. The remaining two cases where Angela rejects and Bob either invests or rejects 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 should always invest *regardless of her private information*. Even if Angela's signal is B, her posterior probability that $V = +1$ exceeds 0.5. This is so, because Claire's B signal and Angela's G signal (which Claire infers from Angela's decision to invest) cancel each other and, Claire reasons, that since Bob invested he is more likely to have observed G rather than B. Thus, David, the fourth investor, learns nothing about Claire's signal realization from her (rational and optimal) 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. Figure 1 summarizes the preceding discussion.

Figure 1.



In general the following is true:

Proposition: *An individual will be in an "invest cascade" ("reject cascade") if and only if the number of predecessors who invest is greater (less) than the number of predecessors who do not invest by two or more.*

To summarize, an invest cascade, say, starts with the first individual who finds that the number of predecessors who invested exceeds the predecessors who rejected by two. This individual and all subsequent individuals, acting rationally, will then invest regardless of what their private signal tells them about the value of the investment. Once a cascade starts, an individual's action does not reflect her private information. Consequently, once a cascade starts, the private information of subsequent investors is never included in the public pool of knowledge.

The probability that a cascade will start 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 private information available to investors, if it were to become public, would yield a much more accurate forecast of the true value of the investment. Imagine that all investors are altruistic in that they care as much about other investors as they do about themselves. For concreteness, suppose that each individual's payoff, instead of being the return on his/her own investment decision, is the average return on the investment decisions of all individuals. Suppose now that Angela and Bob both decide to invest, and Claire observes a B signal. Claire infers that Angela and Bob each observed G.[8] If Claire cared only about the return on her own investment decision then, as argued earlier, she would rationally ignore her signal and invest (since her posterior probability that $V = +1$ is $p > 0.5$). But an altruistic Claire cares equally about the decisions of all subsequent individuals and would like them to know of her signal; the only way Claire can communicate her signal is by rejecting the investment. Hence, she faces a choice of increasing her payoff (which is the average return on the investment decisions of all individuals) either (i) by adding to the pool of public knowledge by rejecting or (ii) by taking the best investment decision based on currently available information, that is, by investing. Her decision will be to reject if there are at least two subsequent individuals and the signals are not exceedingly accurate (i.e., p is not very close to one). Similarly, if after observing Angela and Bob invest, Claire observes a G signal then there is no conflict between (i) and (ii) above: investing communicates her private information and is also the best investment decision based on her current information. David, and all later individuals, face a similar choice between conveying information and taking the best current period decision.

A cascade will eventually start under altruistic behavior, but much later, only after a substantial number of individuals' private information has been revealed through their actions. For instance, if there are a hundred individuals and the second through the tenth individuals altruistically follow their private signals in taking actions, then much better information is available (when compared with the selfish-individuals scenario) to the eleventh through the hundredth individuals. Individuals 11 through 100 will tend to herd on a decision, which is much more likely to be correct than under the selfish-individuals scenario, where a cascade might start with the third individual. The outcome under altruistic behavior is efficient in that all private information available is being used Pareto optimally (within the constraint that individuals cannot observe the private information of others). Or to put it differently, if selfish individuals were to follow strategies of altruistic individuals then the sum of payoffs of all (selfish) individuals would be strictly greater.[9]

Although the altruistic-individuals scenario is unrealistic, contrasting it to the selfish-individuals scenario highlights the fact that when an individual takes an

[8] After observing Angela invest, Bob will not be indifferent between investing and rejecting if he were to see the signal B; he would strictly prefer to reject in order to convey his information. That is, altruistic Bob always follows his signal.

[9] Alternatively, a benevolent social planner with the authority to direct each (selfish) individual's strategy choices (but without the ability to observe their private signals) could do no better.

action that is uninformative to others, it creates a negative externality.[10] This information or herding externality leads to an inefficient outcome. Like all externalities, the herding externality, too, disappears if individuals internalize the utility function of others, that is, if individuals are altruistic.

Let us revert back to the original model with a sequence of selfish individuals who observe their predecessors' actions. In that model, 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 (a) *path-dependent* in that it matters whether the first four signal realizations are GGBB or BBGG and (b) *idiosyncratic* in that small differences in initial events can make a big difference to the behavior of a large number of individuals.

If the signals received by predecessors (instead of actions taken) were observable, later decision makers 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 knowledge pool. Also, this public knowledge pool does not 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 in which the sequence of decision makers is endogenously determined, the action space instead of being discrete is a continuum, and there is the possibility of information sharing among investors. Calvo and Mendoza (2000) 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

[10]Observe that this externality is distinct from the direct payoff externality referred to in footnote 3. The actions of one individual do not change the underlying payoffs of other individuals but they do influence the beliefs of others.

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 investing in country A.

Herd behavior is therefore robust to relaxing our assumptions that investors take decisions in an exogenous linear order and that information acquisition is costless. Others have shown that herd behavior persists even under imperfect observability of predecessors' actions[11] or with some heterogeneity among investors.[12] For more on the robustness of informational herding, see Bikhchandani, Hirshleifer, and Welch (1998) and the references therein.

Application to Stock Markets

In the preceding discussion, the price for taking an action is fixed ex ante and remains so. This assumption is inappropriate for a model of herd behavior in the stock market, as the investment decisions of early investors are likely to be reflected in the subsequent price of the asset. The assumption of fixed prices is relaxed in Avery and Zemsky (1998).[13]

In the simple framework considered in the previous section, 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, $0.5 < p < 1$. 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 invested 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 infor-

[11]For instance, only a summary statistic of predecessor's actions, such as the aggregate investment in the last year, may be observable to future investors.

[12]Such as differences in the accuracy of investors' information or in the payoffs they obtain from the investment.

[13]See also Lee (1995).

mation precisely because the price adjusts in such a manner that, based only on publicly available information, a person is exactly indifferent between buying and selling. If a person's private information tips the balance in favor of buying or selling, this private information is revealed by the individual'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 price reflects fundamentals and there is no mispricing.

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 investors 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 in time the price in the stock market reflects all public information, the price does not reveal the private information of all previous investors. A clustering of identical decisions may arise naturally in a well informed market (one in which most of the investors are of type H) because most of the investors have the same (very informative) private signal realization. Further, a clustering 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 in forward markets. 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 the availability of derivatives may make herding and price bubbles less pronounced, since multidimensional stock prices are better equipped to reveal multidimensional uncertainty.

Reputation-Based Herding

Scharfstein and Stein (1990); Trueman (1994); Zweibel (1995); Prendergast and Stole (1996); and Graham (1999); provide another theory of herding based on the reputational concerns of fund managers or analysts. Reputation or, more broadly, career concerns arise because of uncertainty about the ability or skill of a particular manager. The basic idea (in Scharfstein and Stein) 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 employer has 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.[14] 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 does so. I_1's decision is based only on her signal realization (which may either be informative 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.[15] 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.

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

[15]Observe that the signals of two informed managers are positively correlated whereas the signals of two uninformed managers are uncorrelated. Hence, an identical action (even incorrect ones) by the two managers makes it more likely that they are both informed.

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 because all subsequent managers, without regard to their information, imitate the first manager's decision. 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.

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 the movement of prices in a well-functioning market mitigate the inefficiencies in Scharfstein and Stein's model is not clear.

Compensation-Based Herding

If an investment manager's (i.e., an agent's) compensation depends on how her performance compares with that of other similar professionals, 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 a benchmark (which may be the performance of a separate group of investors or the return of an appropriate index). 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 the section on information-based herding above, 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. Furthermore, the compensation scheme provides an additional reason to imitate the benchmark. The fact that her compensation decreases if she underperforms 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[16] or adverse selection.[17] 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

[16]For example, the agent may not be hard-working and the principal is unable to observe how much effort the agent puts in to researching her investment options. A relative performance contract in which the bonus paid to the agent depends on how well she does relative to the benchmark would provide the right incentives to the agent.

[17]For example, a potential agent may be an incompetent portfolio manager, no matter how hard she works, but the principal cannot gauge her skill level. A relative performance contract would dissuade an incompetent agent from taking up a job as a portfolio manager.

compensation scheme selected by an employer would seek to maximize the employer's profits rather than society's welfare.

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.

II. 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. Thus, there is 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 to quantify them.

Herding in the Stock Market

Several papers use a statistical measure of herding put forward by Lakonishok, Shleifer, and Vishny (hereafter referred to as LSV) (1992). They define and measure 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

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

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 mangers 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 1985–89 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 examinations 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, reveal 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 (hereafter referred to as 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.[18] This is consistent with some of their other findings, namely, that the average 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.[19]

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 because 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 volumes 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 to buy past winners. The relationship 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) uses the LSV measure and data on quarterly equity holdings of virtually all mutual funds that were in existence between 1975 and 1994 and finds that for the average stock there is some evidence of herding by mutual funds.[20] 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 larger than that reported by LSV (1992) suggesting that there is somewhat greater herding among mutual funds than

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

[19]They 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 mutual fund categories" and the total sample of funds, momentum-investing behavior generally constituted a move into well-performing large capitalization stocks.

[20]The 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.

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 subgroups with different investment styles. This suggests that herds form across subgroups as much as within subgroups of funds or that it merely reflects the fact that many funds use a common investment strategy.[21]

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, Wermer 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 GTW (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.

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.

[21]It 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.

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.[22] 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.[23]

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 the buyers collectively demand a substantial amount of the stock while the sellers only put a relatively small amount in 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, IMF 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—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.

[22]Given 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.

[23]Nofsinger and Sias (1999) in their examination of herding by institutional investors find no evidence of return reversal over a two-year period, and show that stocks purchased by institutional investors outperform those they sell. They suggest that this could be due to the use of momentum investment strategies, or because institutional investors are better informed and better able to predict short-term performance than other investors.

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:

$$\hat{\rho}^{I,J}_{t,\tau} \equiv \frac{\left(1/N_t\right)\sum_{n=1}^{N_t}\left(\Delta\tilde{\omega}^{I}_{n,t}\right)\left(\Delta\tilde{\omega}^{J}_{n,t-\tau}\right)}{\hat{\sigma}^{I,J}(\tau)} \tag{5}$$

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

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

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."[24]

[24]The high correlation between the number of funds trading a particular stock and the stock's market capitalization leads him to suggests 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.

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, Wermer's 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.

However, as Richards (1999) points out, the Christie and Huang test (and a related test by Chang and others, 1998) looks for evidence of a particular 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. The Christie and Huang test should, therefore, be regarded as a gauge of a particular form of herding and the absence of evidence against this form of herding should, therefore, not be construed as showing that other types of herding do not exist.

In a recent paper, Nofsinger and Sias (1999) adopt a different approach to examine the relative importance of herding by institutional and individual investors. They use monthly data on stock returns from the Center for Research in Security Prices (CRSP), and annual data on the fraction of outstanding shares held by institutional investors for all firms listed on the New York Stock Exchange from Standard and Poors' *Security Owners' Stock Guides*. Their methodology can be described as follows: For each year (1977–85) they first partition firms into deciles based on the fraction of shares held by institutional investors. Then, for each initial institutional ownership decile, they further partition the firms into deciles based on the change in the fraction of shares owned by institutional investors over the following year. Finally, they reaggregate the firms based on their change in ownership decile rank and create 10 portfolios of stocks that have similar institutional ownership at the beginning of each year (with October being the origin) but large differences in the change in institutional ownership over the year. They show that there is a strong positive relation between annual changes in institutional ownership and returns over the herding interval (in their case a year). Furthermore this result holds across capitalization, that is, for small and large stocks. The authors interpret this as evidence of intrayear positive feedback trading by institutional investors and that institutional herding has a larger effect on stock returns than herding by individuals.

There are two major drawbacks to the Nofsinger and Sias analysis. First, the window of observation, one full year, is too large. Admittedly, this is a restriction imposed by their data. In any case, a monthly or quarterly window would have been more suitable for judging the extent of herding. Second, as the authors recognize, the use of changes in the fraction of shares held by institutions to measure herding is problematic. A substantial increase in this fraction need not reflect herding, but merely a large position by one or two institutions. Institutional ownership could grow for other reasons as well—some institutional investors face minimum capitalization restrictions, and thus a firm may become more widely held by institutions as it becomes larger.

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 an 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.[25]

The futures contracts in the data set are for interest rates (3-month Euro dollar, 91-day Treasury bill, 5-year note, 10-year note, 30-year treasury bond), the S&P 500 index, and foreign exchange (British pound, Canadian dollar, German 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-year treasury notes, in all other securities the open interest held by smaller traders exceeds 40 percent. To the extent that information

[25]Note 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.

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 thus 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 and loan association. This enables testing for herd behavior among institutions belonging to the same category. However, note that an exchange-clearing member may have several traders, one trading for a pension fund, another for a mutual fund, and so on. If so, then such traders, to the extent that they talk to each other, share the exchange-clearing member'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 with the same clearing member. Because 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 institution 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 subgroup, 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 subgroup. The estimated parameters are used to test whether the first subgroup follows the second.[26] 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 (German 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 U.S. government paper.[27] However, the probit analog of R^2 for the regressions is low—generally below 0.10—suggesting that imitation of the second

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

[27]An 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.

subgroup by members of the first subgroup accounted for a small part of the variation in their positions.

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, therefore, herding observed when the analysis is restricted to certain futures contracts may not show up if a portfolio-wide perspective is taken. Furthermore, 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.

Herding Among Investment Analysts and Newsletters

One branch of the literature on herding, rather than examining the clustering of decisions to trade in particular financial instruments, looks at herd behavior among investment analysts and newsletters.[28] In a setting where actions (i.e., recommendations) of other newsletters are easily observable, there is potentially fertile ground for herd behavior. While this setting is another way to shed empirical light on the usefulness of different models of herd behavior, it leaves open the question of 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.[29] 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 newsletters. 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;

[28]Using the LSV measure to examine stock recommendations by newsletters followed by the *Hulbert Financial Digest* over the period 1980–96, 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).

[29]See, for example, Michaely and Womack (1999).

(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—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; and
(iv) increases with the level of correlation across informative signals.

The data used by Graham (1999) covers the period 1980–92 period and contains 5,293 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 a value of one when a newsletter makes the same directional recommendation for equity weights as *Value Line*, and to take a value of 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.

Chevalier and Ellison (1999) (for mutual fund managers) and Hong, Kubik, and Solomon (2000) (for sell-side security analysts) also examine whether reputational and career concerns induce herding. The former article uses *Morningstar* data for fund managers of growth and growth and income funds over the period 1992–95; and the latter uses data from the Institutional Brokers Estimate System (I/B/E/S) database over the period 1983–96 on estimates by 8,421 analysts covering 4,527 firms. Their results show that poorly performing employees are generally less likely to be promoted and more likely to be fired. However, conditional upon performance, inexperienced employees are more likely to suffer career setbacks than their older colleagues when they make relatively bold predictions. There is some evidence that "going out on a limb" and being wrong when you are young and inexperienced is costly in career terms, while bucking the consensus and being right does not significantly add to career prospects. They find that such incentives make inexperienced asset managers/analysts take less risks and herd more than their experienced counterparts. This is in contrast to the Graham (1999) result that analysts with high reputations are more likely to herd.

Welch (2000) 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 1989–94. A recommendation consists of categorizing a particular stock into one of the following: strong buy, buy, hold, sell, or 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 toward the consensus is less likely to be caused by information about fundamentals. He also finds that herding toward the consensus is much stronger in market upturns and, thus, booming markets aggregate less information and, therefore, could be more "fragile" than market downturns.

The above studies may 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. Fewer analysts follow smaller stocks, 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.

Herding in Emerging Stock Markets

In the aftermath of the recent crises in emerging markets, considerable attention has focused 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 focused on Korea and we suspect this is due to the availability of microlevel data that is needed to shed light on questions relating to the trading strategy of investors.[30]

Kim and Wei (1999a), using data for December 1996 to June 1998, investigate the trading strategies of investors in the Korean stock market. The data set,

[30]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.

provided by an affiliate of the Korean Stock Exchange (KSE), reports the end-of-month investor holdings for each stock listed on the KSE. It contains information on whether the investor is Korean or foreign, resident or nonresident, an individual or an institution, and whether for a particular 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) nonresident institutional investors used positive feedback 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; and

(iv) herds of nonresident 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 nonresident 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 United States and the United Kingdom do use momentum strategies and have higher LSV herding statistics compared with the other funds. The authors conclude that, based on available data for the Korean crisis, funds based in offshore financial centers cannot be singled out for being particularly prone to herding.

Choe, Kho, and Stulz (1999 (hereafter referred to as CKS)), 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, CKS 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—CKS 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).[31]

[31]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, CKS (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. The daily herding measures for foreign investors—values in the range 21–25 precrisis and 16–26 during the crisis, depending on stock size and on past-weeks return—are significantly higher compared with those obtained by Wermers (1999) in his quarterly analysis of U.S. institutional investors. They are also higher than the range of 6–16 obtained for nonresident investors by Kim and Wei (1999). During the crisis period itself, they find some decline in herding and that foreign investors were less likely to use momentum strategies.

CKS 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.

The study by Borensztein and Gelos (2000) does not focus on a particular country, but instead uses a data set collected by Emerging Markets Funds Research, Inc., on the monthly geographic asset allocations of 467 funds active in developing countries over the period 1996:1–1999:3. These funds, classified as global, emerging market, regional, and single-country funds, are domiciled mostly in developed countries and offshore banking centers. For many of the markets, the size of these funds is not insignificant and represents between 4 percent and 7 percent of the market capitalization.[32]

Borensztein and Gelos obtain an average LSV herding measure of 7.2 for all funds—in the lower part of the range reported by Kim and Wei (1999) for nonresident institutional investors in Korea. There is little variation in this average across regions and over crisis and noncrisis periods. Also, in line with Kim and Wei they find that offshore funds tend to herd less than other funds. An interesting finding is that herding is more prevalent in larger markets, which is consistent with the hypothesis that the funds in the sample prefer to adjust their portfolios more often in relatively liquid markets. The authors also present some evidence that suggests that increased herding measures are associated with higher stock return volatility, but caution against pushing this conclusion too far.

III. 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-

[32]Since the data set contains information on monthly asset holdings of the funds, *flows* to individual countries have to be calculated by making some assumptions on changes in stock valuations. This is a limitation of the data and is discussed by the authors.

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, because 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. Furthermore, 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.

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. Therefore, 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.

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