Chapter 36 Social Interactions and Investing

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ABSTRACT

How do social interactions affect investment behavior? Answering such a question touches on vast and diverse research in the field of financial economics. This chapter provides an overview of published work. The emphasis is on recent empirical papers covering correlated trading (herding), the effects of neighbors/colleagues, information diffusion, and the link between social capital and financial development. The final section discusses the difficulty of identifying a causal link between social interactions and investment behavior. Papers employing identification strategies are rare. The chapter provides examples of four strategies currently being used: (1) laboratory experiments; (2) field experiments; (3) instrumental variable approaches; and (4) exploitation of market structures.

INTRODUCTION

How do social interactions affect investment behavior? Answering this question touches on vast and diverse research in the field of financial economics. Investment decisions may be influenced by observing the decisions of others to the point that some individuals may ignore their own private information. Individuals' preferences may depend on the actions and choices of others. Wealth and consumption may be measured relative to the wealth and consumption of others in the community. Social interactions can have positive or negative effects on investor welfare. Individuals may be more likely to save for retirement if their colleagues join savings plans. Alternatively, individuals may follow others into underperforming assets.

The voluminous literature includes theoretical models, laboratory experiments, field experiments, and empirical studies. This chapter begins by briefly covering the well-developed theory literature on herding, information cascades, and preferences. It then moves quickly to its main focus—a discussion of recent empirical work on herd behavior and correlated trading. The intent of this chapter is not to give short shrift to the theoretical literature but rather to focus on the abundant empirical studies about the effects of neighbors, colleagues, information diffusion, and social capital on investment decisions.

This chapter ends with an analysis of the challenges faced by empiricists when studying social interactions and investment behavior. Take, for example, a hypothetical study of herding behavior. Financial economists may notice that investment managers in New York City are net buyers of IBM stock in the month of April 1996. Expanding the study in the time-series dimension, financial economists may notice that in most months, NYC investment managers (as a group) are either net buyers or net sellers of IBM stock. The finding that investment managers tend to buy or sell together is evidence of herd behavior. Gathering more months of data allows financial economists to be increasingly confident in a statistical sense that NYC fund managers herd.

Ultimately, financial economists are interested in asset prices. Therefore, many papers test whether a time series of net buys is correlated with a time series of stock returns. Suppose that in the aforementioned hypothetical study, a positive (time-series) correlation is found between the NYC fund managers' trade imbalances (buys-minus-sells) of IBM stock and the stock's returns. How should financial economists interpret this positive correlation? Note that a group of investors' buys-minus-sells has a number of names in the literature including: trading imbalances, order imbalances, net trades, net buys, and many more. The words "order imbalances" typically refer to executed orders and are thus the same as trading imbalances.

Many papers interpret a positive correlation between trading imbalances and stock returns as evidence that herd behavior "moves" stocks prices. When studying monthly data, can one make such a causal statement? Does net buying "push" prices higher and net selling "push" prices lower? Beyond contemporaneous effects, there might be a positive correlation between the trading imbalances and lagged stock returns (called "positive feedback trading").

Researchers might also find a positive correlation between trading imbalances and future returns (evidence of informed trading if the returns do not later reverse themselves).

Why do NYC mutual fund managers tend to trade a given stock in the same direction? There may be several reasons. For example, managers may be benchmarked against their peers. The managers may be hedging against price rises of scarce local resources. Or, they may have similar information from local news, discussions with local companies, or from talking amongst themselves. Finally, fund managers might simply be following a rule of thumb such as “buy last month’s winners." Ascribing a causal link between trading imbalances and returns turns out to be very difficult.

To answer the questions posed in this introduction, the chapter has the following structure. The first section reviews herding and information cascades. This is followed by a discussion of preferences, relative wealth, and indirect effects that may cause investors to trade together. The next section covers the large empirical literature on correlated trading (also known as herding). The next three sections review work on neighbors/colleagues, information diffusion, and social capital respectively. The difficulties of making causal links between social interactions and investment behavior are discussed next. The relatively few papers that address these causation issues are reviewed in this section. The final section provides a summary and conclusion.

HERDING AND INFORMATION CASCADES

Investors choose portfolios as part of their savings plans for future consumption. Traditional asset pricing models assume investors only evaluate risks and expected returns when choosing optimal portfolios. They hope to grow their wealth while at the same time being wary of economic downturns especially around the time of retirement. In traditional and frictionless markets, all investors know each stock’s expected return. Investors also know the covariance matrix of stock returns. In frictionless markets, investors can freely analyze and trade all assets. There is little benefit to observing the actions of others.

What happens when information cannot be freely traded or when an investor's utility function depends on the choices and actions of others? To help answer these questions, there is a large, well-developed, and now 20-year old literature on herding and information cascades. The literature is so well developed that numerous, thorough, and easily accessible review articles exist, including Devenow and Welch (1996), Bikhchandani, Hirshleifer, and Welch (1998), Bikhchandani and Sharma (2001), and Hirshleifer and Teoh (2003). The review articles cover the well-known papers in this area including Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992), and Welch (1992).

Theory Models

Hirshleifer and Teoh (2003) provide a useful taxonomy of different behaviors along with definitions and reviews of relevant papers. As shown in Figure 36.1, the Hirshleifer and Teoh taxonomy outlines four nested levels of observational hierarchy. The most inclusive category ("A: Herding/Dispersing") simply allows for convergence or divergence of behavior brought about by the interactions of individuals. The most restrictive category ("D: Informational Cascades") is one in which an individual is so prone to observing the actions of others that he ignores his own private information.

(Insert Figure 36.1 about here)

Additional factors such as payoff externalities may lead to herding behavior. Mobile phones became increasingly valuable throughout the 1990s as more people purchased them. Suppose all individuals initially receive the same marginal value from buying the first mobile phone. As more people buy phones, the marginal value of owning a phone increases, and more individuals rationally choose to purchase the phones—a form of herd behavior.

Reputational concerns may induce economic agents to engage in similar behaviors. Scharfstein and Stein (1990) study herd behavior of firm managers who are concerned about their reputations in the labor market. Researchers have applied a similar idea of reputation to studying stock analyst recommendations. If being seen as different from the average analyst is not highly valued, analysts have an incentive to produce forecasts and recommendations with low dispersion as noted by Chevalier and Ellison (1999), Graham (1999), and Hong, Kubik, and Solomon (2000).

Recently, two working papers by Ozsoylev (2006, 2007) extend the traditional rational expectations framework in which investors glean information from publically observable prices. In Ozsoylev's frameworks, an investor may obtain additional information by observing the demands of certain other investors. The author presents a series of directed graphs that define different social networks (i.e., who can observe the actions of whom). The graphs link different social networks to asset prices. One conclusion is that when information is initially private and disperse, social interactions can impair information aggregation.

Experimental Results

Experimental economics lends itself particularly well to studying information cascades. Researchers can precisely control an individual's information set. Anderson and Holt (1997) conduct an experiment in which individuals sequentially and privately see a colored marble that has been drawn from one of two urns. An individual makes a private decision about from which urn he or she thinks the marble comes. An announcer conveys the decision to other participants. Individuals are rewarded for choosing the correct urn. Individuals who get to choose later have the "advantage" of hearing the decisions of earlier individuals. Anderson and Holt (p. 859) report "some decision sequences result in reverse cascades, where initial misrepresentative signals start a chain of incorrect decisions that is not broken by more representative signals received later." The authors find that cascades occur approximately 75 percent of the time with normal cascades being twice as prevalent as reverse cascades.

Celen and Kariv (2004) extend experimental results by distinguishing between herd behavior (a series of individuals make identical decisions) and informational cascades (agents make identical decisions while ignoring their own private signals). The authors employ a cutoff elicitation technique to obtain subjects' beliefs and experimentally distinguish between the two behaviors. They find herds develop 36 percent of the time with 97 percent of the herds being correct. Cascades happen 35 percent of the time, far in excess of what Celen and Kariv's model predicted.

Cipriani and Guarino (2005) study a financial/laboratory market in which subjects receive private information about an asset's value and sequentially trade with a market maker. Theory predicts herds should not form and the author's results concur. Interestingly, subjects ignore their private information and refuse to trade in some cases.

Empirical Results

There are many empirical studies of herd behavior. One of the first is by Lakonishok, Shleifer, and Vishny (1992), who study the holdings of 769 tax exempt funds. Quarterly changes in holdings represent the net trades of a given fund and can be measured on a stock-by-stock basis. Suppose 50 percent of holdings increase on average. The authors find that 52.7 percent of the managers in their study change their holdings in one direction while 47.3 percent change their holdings in the opposite direction. While the imbalance may seem small (i.e., only 2.7 percentage points away from 50 percent), the funds in their sample hold $124 billion or about 18 percent of the total actively-managed holdings of all pension funds. When their imbalance measure is in its upper 20 percent, abnormal stock returns are 1.81 percent. When the imbalance measure is in its lower 20 percent, abnormal stock returns are -0.31 percent. The authors interpret the positive relation between net trades and stock returns as evidence that herding “moves” stock prices. Understanding whether the observed relation between trades and returns is causal remains one of the most challenging areas of financial economics.

A later section of this paper reviews studies of correlated trading (herding) in more depth. Interpretations of the positive relation between the herd behavior and stock price movements will also be discussed. A particular focus of this chapter is the difficulty inherent in assigning causality from trades to price movements.

PREFERENCES, RELATIVE WEALTH, AND INDIRECT EFFECTS

Rather than be directly influenced by observing the actions of others, investors may be indirectly influenced. Habit formation models, for example, introduce the possibility that investors care about current consumption relative to levels of past consumption. Such assumptions differ from traditional models that assume investors care only about the level and variance of their own consumption and do not consider consumption relative to past levels.

Able’s (1990) “catching up with the Joneses” preferences assume an investor’s current utility depends on his or her current consumption relative to a lagged cross-sectional average level of consumption. Consuming the same (real dollar) amount of goods no longer provides the same level of utility if others have been consuming increasing amounts. Stated differently, owning a Porsche near San Francisco may have had low utility in the late 1990s. Why? The dot.com bubble offered many people the opportunity to own similar (or better) cars. Note that Able’s external habit model lends itself easily to thinking about how the actions of others may indirectly affect an investor’s decisions, i.e., others’ past consumption raises the overall level of habit. Internal habit models, such as Constantinides (1990), do not necessary help in thinking about social interactions. This is because an investor compares current consumption to his or her own level of past consumption (habit).

Habit formation models have become increasingly popular in macro asset pricing as economists seek to reconcile smooth levels of aggregate consumption with high observed stock returns and high levels of stock price volatility. Consider a group of investors who have consumed similar (real) dollar amounts over the past 20 years. In the coming year, the marginal value of consuming one more dollar of goods can fluctuate wildly if the level of planned consumption moves closer to, or farther from, these investors' habit level. Campbell and Cochrane (1999) use habit formation and fluctuating marginal values to model a number of asset market features.

Scarce local resources may also cause an individual’s investment choices to be influenced by the choices of other members of his community. DeMarzo, Kaniel, and Kremer (2004) present a rational general equilibrium model in which competition for scarce local resources induces concern about relative wealth in a community. For example, an investor who plans to retire in Switzerland cares very much about the costs of health care and services in Switzerland and less about health care costs in other areas. If Swiss resources are scarce, the investor recognizes competition will exist in the future and alters his portfolio today. The community effects give investors the incentive to herd and choose similar portfolios. Another implication of the DeMarzo et al. framework is that small groups of traders with behavioral biases can have large effects on asset prices by influencing the community to trade in a similar direction.

DeMarzo, Kaniel, and Kremer (2008) further explore the link between relative wealth concerns and financial bubbles. Even when agents care only about their own consumption, community effects can influence asset prices. As the authors explain, in standard asset pricing models, trading against price distortions is both profitable and helps eliminate the distortions. In their paper, agents are sensitive to the wealth of others in their community. Trading against the crowd increases the relative wealth risk. Thus, investors may be reluctant to sell overpriced assets and buy underpriced assets. The net result is that asset price bubbles can form. Rational investors are reluctant to trade against such bubbles.

CORRELATED TRADING

For every share of stock bought, a share is sold. This "adding-up constraint" ensures that any market-wide trade imbalance measure (buys-minus-sells) is zero, for any stock, over any time period. Consider the trades of one well-defined investor group such as mutual funds. Over a set period of time such as a day, week, month, or quarter, shares bought of a given stock need not equal shares sold because *other* investor groups are also involved in the trades. Focusing again on a well-defined investor group, non-zero trade imbalances are evidence of possible herding behavior. Thus, any empirical study that consistently measures non-zero trading imbalances can be thought of as a study that finds evidence of herd behavior. Technically, adding-up constraints apply to shares. Many herding measures are concerned with the number of investors buying or selling together. If all investors trade the same number of shares, counting share imbalances is equivalent to counting investor imbalances. Even when investors do not trade the same number of shares, share imbalances are typically highly correlated with imbalances based on the number of investors.

The adding-up constraint mentioned in the previous paragraph allows financial economists to comment on the behavior of at least two groups of market participants. If mutual funds are found to have been net buyers of IBM stock during April 1996, then the group of investors labeled "non-mutual funds" represent net sellers over the same time period. If mutual funds are found to be herding, "non-mutual funds" are also likely to be herding.

As previously mentioned, there is a wealth of empirical herding studies that directly follow the work of Lakonishok et al. (1992). Many use the same herding measure (henceforth called the "LSV herding measure"). For a well-specified investor group trading stock *i* over a period of time *t,* the LSV measure is shown below. If there is no herding, the measure should be zero. Note that *t* can be almost any length of time such as a day, week, month, or quarter.

$$LSV_{i,t} = \left|p_{i,t} - \overline{p}_{i,t}\right| - E\left|p_{i,t} - \overline{p}_{i,t}\right| \qquad (1)$$

where

$$p_{i,t} = \frac{Buys_{i,t}}{Buys_{i,t} + Sells_{i,t}} \tag{2}$$

Typically, "$Buys_{i,t}$" is the number of investors who increase their ownership in stock *i* over time period *t* and "$Sells_{i,t}$" is the number of investors who decrease their ownership in stock *i* over time period *t.* The term "$\overline{p}_{i,t}$" is included to account for times when the investor group experiences buying or selling across all stocks (e.g., times of large mutual fund inflows that cause most managers to buy). As a proxy for $\overline{p}_{i,t}$ many researchers use the proportion of all stock trades by the investor group that are purchases during time period *t*. The final term of the expression is an adjustment factor because noise in datasets causes the first term to be non-zero, even if the numbers of buyers and sellers are equal on average. Papers often report average *LSV* measures. These measures average $LSV_{i,t}$ across all stocks and time periods.

In general, empirical studies find low levels of institutional herding (the fraction of institutional investors who buy together is close to half). However, a small imbalance can represent millions of dollars of excess buying or selling. In addition to studies of institutional trading, the last decade has seen an increase in studies of individual investor herding. Many measures of individual herding are much larger than measures of institutional herding. Table 36.1 provides a meta-analysis of different LSV herding measures. Versions of the table originally appeared in working drafts of Feng and Seasholes (2004). The accompanying table notes are important in understanding the measures and where to find them in the original papers. While LSV measures are typically low, there is large dispersion across studies.

(Insert 36.1Table 1 about here)

Finally, many studies cover both positive feedback trading (buying past winners and selling past losers) and herding. If an investor group is found to engage in positive feedback trading on average, financial economists should expect to find herding behavior. This mechanical link stems from the fact that there is only one price history per stock. Consider an investor group who buys based on past positive stock returns. If recent returns are positive, then group members, on average, should be buying today, i.e., herding.

Institutional Trading

Grinblatt, Titman, and Wermers (1995) study 10 years of mutual fund trades. The authors focus on both positive feedback trading and herding. Grinblatt et al. (p. 1099) find a LSV herding measure of 2.5 meaning that “if 100 funds traded [a] stock-quarter, 2.5 more funds traded on the same side of the market than would be expected [by random].” The mutual funds exhibit more herding when buying past winners than past losers. Evidence of herding increases dramatically when the sample is limited to stock quarters with at least five or ten trades. The authors conclude by noting a link between the degree to which a fund engages in positive feedback trading and the fund’s performance.

Sias and Starks (1997) test the relations between levels of institutional ownership and stock return autocorrelation. They find that both an individual stock’s return autocorrelation and a portfolio’s return autocorrelation increase with institutional ownership. They focus more on stock holding levels rather than trades. Holding levels are the sum of all past buys minus the sum of all past sells. As such, institutions with similarly high levels of holdings in the same stock most likely engaged in similar average levels of buying in the past.

Wermers (1999) finds high levels of herding in small stocks and in the trades of growth-oriented funds. His 20-year sample starts in 1975 and ends in 1994. A portfolio comprised of stocks with the highest levels of buy-side herding has significantly positive abnormal returns in both the current and next quarter. A portfolio comprised of stocks with the most sell-side herding has significantly negative returns in the current quarter and the following three quarters. Because returns over future quarters appear permanent (i.e., they do not reverse themselves), Wermers concludes that fund trading helps to speed the adjustment of stock prices toward fundamental values.

Nofsinger and Sias (1999) also study positive feedback trading and herding. Their results are consistent with those in other papers. Stocks with a high degree of herding from buying (selling) have significantly positive (negative) returns over the same period. The authors obtain data on the number of shares owned by institutions. Institutional fractional ownership is simply the number of shares owned divided by number of shares outstanding. The authors then define individual fractional ownership as one minus institutional fractional ownership. Nofsinger and Sias (p. 2293) conclude that “returns are strongly [positively and contemporaneously] correlated with changes in institutional ownership.” Due to the adding up constraint imposed in this paper, the conclusion could just as easily be drawn that returns are strongly negative and contemporaneously correlated with changes in individual ownership.

Sias (2004) attempts to disentangle positive feedback and herding effects by decomposing the fraction of institutional buying over adjacent quarters. As mentioned at the start of this section, if institutions follow positive feedback trading strategies, a financial economist is likely to (mechanically) find positive herding measures. Here, Sias employs linear regressions. The left-hand side variable is the fraction of institutions with increasing positions in a given quarter. The two right hand side variables are the fraction of institutions with increasing positions last quarter (institutions following their own trades) and returns in the previous quarter (feedback trading/following the trades of others). Sias compiles trade data for five trader types: banks, insurance companies, mutual funds, independent advisors, and unclassified. Having five investor groups means that the adding-up constraint does not mechanically link the trading of any two groups. Of course, the net trades of all five groups must still sum to zero over a given period. Sias concludes that institutions follow their own trades and this effect can explain much of the observed herding behavior.

Individual Herding

Choe, Kho, and Stulz (1999) provide one of the first papers to document high levels of correlated trading (herding) among individual investors. While the focus of the paper is the behavior of foreign institutions during the Asian financial crises, they also measure individual trading imbalances.

When studying trade-level data, researchers should avoid double counting some individuals' trades. Suppose a financial economist is constructing a daily herding measure. Simply counting the number of buy and sell trades will overstate herding. This is because some individuals may break up a single trade into parts that are executed throughout the day. Stated differently, if an individual breaks up a 1,000-share buy order into ten 100-share orders, it might look like herd behavior (really a type of "self-herding") because there is now a plethora of buy orders. To protect against mis-measuring herding, all trades by the same individual should be aggregated over each time period/security combination.

Table 36.1 shows the result of controlling for possible self-herding. When Choe et al. (1999) treat each purchase as coming from a distinct investor, the average LSV herding measure for foreign investors becomes greater than 0.20 (indicating that approximately 70 percent of trades are in the same direction). When foreign investors are first grouped into 658 classes based on country of residence and all trades within a class are aggregated by stock and day, the average LSV herding measure shifts to a more reasonable 0.0365 level.

The Asian financial crisis provides the setting for a Korean study by Kim and Wei (2002) that includes individual herding results. The authors calculate the LSV herding measure for both foreign institutions and foreign individuals. They calculate the measures during three time periods: December 1996 to May 1997 (tranquil period), June 1997 to October 1997 (pre-crisis period), and November 1997 to June 1998 (crisis period). The authors find strong evidence of herd behavior among foreign investors before the crisis. Surprisingly, the levels of herding fall during the crisis period. Kim and Wei conclude that foreigners did not destabilize prices.

Feng and Seasholes (2004) focus exclusively on correlated trading by individual investors. The authors study brokerage account data from the People's Republic of China (PRC). They aggregate trades at the "fund account-level" effectively combining all trades by the same individual even if the individual controls different stock accounts. They use an institutional feature of brokerage offices in the PRC to help identify sources of correlated trading. Because this is one of the few papers to focus on the identification issues, further discussion occurs in a later section of this chapter.

Kumar and Lee (2006) provide a complete description of individual trading imbalances among retail (individual) investors in the United States. The authors study 62,387 households who collectively make an average of 1,244 trades per day between 1991 and 1996. Kumar and Lee form a buys-minus-sells measure for each stock-month. Their measure is defined as dollars bought minus dollars sold, all divided by dollars bought plus dollars sold. There is evidence of market-wide buy-minus-sell imbalances. More importantly, the buys-minus-sells index helps explain the returns of stocks in the smallest size quintile.

Andrade, Chang, and Seasholes (2008) test a multi-asset version of the Grossman and Miller (1988) model. If individual trades are non-informational and the market's risk-bearing capacity is limited, the model predicts the trades can induce temporary price reversals. Buys push prices up today but these movements reverse themselves in the coming days, weeks, or months. The model also shows that trading in one stock can affect the prices of other stocks due to liquidity supplier hedging activities. The authors use data from individuals in Taiwan. The magnitude and duration of price reversals are stunning. Each week, the authors sort stocks into quintiles based on net buying. The week zero return difference between stocks bought (quintile 1) and stocks sold (quintile 5) is 2.37 percent. The prices then converge over the following ten weeks. There are 52 basis points of convergence in the first week alone (a figure which compounds to more than 26 percent of temporary return predictability per annum).

Kaniel, Saar, and Titman (2008) do not study herd behavior per se, but the authors do study individual trades on the New York Stock Exchange (NYSE). They consistently find non-zero trade imbalances indicating individuals typically buy or sell together (herding). Interestingly, their results regarding individual trade imbalances and stock returns are different than results reported in other papers. Individual trades on the NYSE act to provide liquidity to others who demand immediacy. As prices are falling, Kaniel et al. show individuals tend to be net buyers. As prices rise, individuals tend to be net sellers. The amount of return predictability following intense individual trading is enormous. In the 20 days (trading month) following intense individual buying, market-adjusted returns are +0.80 percent on average. In the 20 days after intense individual selling, market-adjusted returns are -0.33 percent on average.

Dorn, Huberman, and Sengmueller (2008) study more than 37,000 retail clients from one of Germany's largest discount brokers. The authors differentiate between speculative trades and other trades. They also differentiate between market orders and (executed) limit orders. Dorn et al. use the LSV herding throughout the paper. Individuals in Germany are found to herd at daily, weekly, monthly, and quarterly frequencies.

Barber, Odean, and Zhu (2009) study 66,456 households from a large discount broker and 665,553 investors from a large retail broker. Individuals are net buyers of stocks at the same time (a cross-sectional, herding-related result). In the time-series dimension, stocks with positive trade imbalances one month are likely to have positive trade imbalances in future months. In fact, the persistence can last up to 24 months. Interestingly, the authors find that individuals tend to buy stocks with strong past returns (positive feedback trading). The result is surprising because earlier studies find that institutions engage in positive feedback trading. Adding-up constraints imply that not all investors can be positive feedback traders.

NEIGHBORS AND COLLEAGUES

Recently, a series of papers investigated the roles of neighbors and colleagues in economic decisions. Focusing on neighbors and/or colleagues is a natural way to study social interactions. Duflo and Saez (2002) study individuals' decisions to enroll in a tax deferred savings plan. The individuals in the study are university employees. The authors ask whether the decisions of colleagues in the same department affect others' enrollment decisions and the choices of vendors (once enrolled). Staff at the university's eleven libraries has participation rates that vary from 14 percent to 73 percent even though salary and tenure are relatively similar across groups. The range of participation rates suggests that colleagues influence investment behavior.

Duflo and Saez (2002) recognize that many decisions within a group are correlated for reasons that have nothing to do with individuals simply imitating the actions of others. For example, a group of investors may be of similar ages and thus have similar spending and savings needs. The authors attack these issues by studying 12,500 university employees. The individuals are organized into departments and share the same savings plan and the same program inputs. The authors get around the worry that individuals with similar traits choose to be in the same department by studying average participation rates across departments. They find that when a department's participation increases by 1 percent, an individual's participation rate increases by 0.2 percent. When the share of the contribution allocated to one vendor increases by 1 percent, an individual's share increases 0.5 percent. Duflo and Saez end the paper with this still-unanswered query: Does the observed behavior stem from learning or from a desire to conform to a social norm?

Duflo and Saez (2003) follow their earlier work by conducting a randomized experiment within a population of university employees. This, experiment (p. 815) allows the authors to "shed light on the role of information and social interactions in employees' decisions to enroll in a Tax Deferred Account."

The Duflo and Saez (2003) study uses the following research design. The authors send invitations for an investment fair to a randomly selected group of university employees. The employees are chosen from a randomly selected subset of the university's departments. The research design (called a "classical encouragement design") allows the authors to study the effect of the invitations on investment fair attendance. Treated individuals are five times more likely to attend the fair. The research design also allows for measuring the causal effects of fair attendance (and social effects) on the decision to enroll in a savings plan. Individuals from treated departments are significantly more likely to enroll than those from untreated departments. There is no significant difference in enrollment when looking within a department.

Hong, Kubik, and Stein (2004) find suggestive evidence that individuals who interact more with their neighbors or who attend church are more likely to participate in the stock market. They study 7,500 households from a 1992 University of Michigan survey. The authors are well aware that some readers worry that their social variables (like church attendance) do not detect the effect of social interaction per se, but rather individual personality traits. Clearly, unobserved community-wide effects are worries as well.

Hong, Kubik, and Stein (2005) study the investment decisions of mutual fund managers in the same city. According to Hong et al. (p. 2802), their key result is that "a given manager's purchases of a stock (as a fraction of her total portfolio) increase by roughly 0.13 percentage points when other managers from different fund families in the same city increase their purchases of the same stock by 1 percentage point." While suggestive of social behavior affecting investment choices, the study relies on limited data. There are eight quarters of holdings data and thus seven periods to observe changes in holdings (net trades). Furthermore, 69.4 percent of all assets are held by funds in one of three cities (New York, Boston, and Los Angeles).

Brown, Ivkovic, Smith, and Weisbenner (2008) are acutely aware of the endogeneity issues that affect the ability to answer the question of whether social interactions affect investment behavior. Brown et al. (p. 1511) explain that “because individuals are not randomly assigned to communities, the observed correlation between the stock ownership of an individual and his community could reflect numerous unobservable influences that induce a spurious correlation even after controlling for observable characteristics.” The authors implement an instrumental variable strategy.

The research design in Brown et al. (2008) begins by identifying “native” individuals whom they define as people who live in the same community throughout their panel and who still reside in their birth state. They then create an instrument for the average ownership within a community by measuring the lagged ownership of “nonnative” neighbors (those born in different communities and different states). The results are striking. A 10-percentage point increase in the average ownership of one’s community leads to a 4-percentage point increase in the likelihood that an individual will own stocks.

Bodnaruk (2009) attempts to identify community effects by examining Swedish investors who move from one location to another. In this study of portfolio composition, he takes as given that investors tilt their portfolios towards local stocks. After moving, holdings of stocks that were originally considered local fall by 26.76 percentage on average (the stocks are no longer considered local after the move.) Also after moving, investors begin to tilt their portfolios towards stocks located near their new home. It is difficult to determine whether these portfolio shifts are the result of different public/local news or whether they result from private conversations with members of the new community.

A recent working paper by Knupfer (2008) studies the relation between an individual’s social interactions and the propensity to tilt a portfolio towards local stocks. He finds more social investors have stronger local biases than do less social investors.

INFORMATION DIFFUSION

There is a small and under-developed literature on information diffusion. Trying to measure how information diffuses from one investor to another seems like a natural topic for financial economists interested in social interactions. Shiller and Pound (1989) use a questionnaire to survey institutional and individual investors. They find that direct interpersonal communication is very important in one's investment/decision-making process. Unfortunately, there have been relatively few papers since that provide further understanding of information diffusion.

The difficulty in measuring information diffusion arises because investors' information sets are unobservable. At present, there is almost no way to ascertain the information to which an investor has been exposed. A financial economist cannot know what information an investor has retained. Laboratory experiments present a possible setting for studying information sets. Unfortunately, studying diffusion may not be feasible in a laboratory because of the difficulty in setting up and funding a large scale experiment. If possible, the experimental design should allow a researcher to "place information" in part of the population and then measure how that information moves throughout the rest of the population.

In an early "diffusion" paper, Boness and Jen (1970, p.282) describe "a dynamic adjustment mechanism in the stock market. Adjustments are made at market clearing prices by traders in response to new information on their individual holdings of stocks." In reality, the model is an econometric specification containing simultaneous equations. There are exogenously determined values of information relevant to stock prices and predetermined behavioral patterns of investors perceiving and adjusting to new information..

Hong and Stein (1999, p. 2145) assume "private information diffuses gradually across the [population]" in their study of stock price momentum and reversals. They do not study information diffusion per se. Papers such as Hong, Lim, and Stein (2000) and Doukas and McKnight (2005) test whether stock price momentum is the result of slow information diffusion.

These papers do not test for slow information diffusion. To carry out their tests, the latter two sets of authors use residual analyst coverage as a proxy for the rate of information diffusion.

Finally, Ivkovic and Weisbenner (2007) study the relation between a household's stock purchases and purchases made by neighbors. The authors use the 1991 to 1996 Barber and Odean dataset of trades from a large discount broker. A ten percentage point increase in neighbors' purchases of stocks from a given industry is associated with a two percentage point increase of a household's purchases of stocks from the same industry. The authors use the term "information diffusion" to refer loosely to indicate a correlation between a household's investments and the investments of neighbors. Results could stem from word-of-mouth effects, similarities in preferences, or common reactions to news. Disentangling these is difficult.

SOCIAL CAPITAL

The link between investment decisions and social capital is another emerging area of research. Social capital is defined by DiPasquale and Glaeser (1999, p. 355) as "the social links among citizens". Guiso, Sapienza, and Zingales (2004, p. 528) define it as "the advantages and opportunities accruing to people through membership in certain communities." One can think of social capital as an incentive to improve the quality of one's community. Investing in a public good can build social capital.

DiPasquale and Glaeser (1999) document that U.S. homeowners invest more in social capital than do non-homeowners. As DiPasquale and Glaeser (p. 356) point out, "homeownership is an endogenous variable that is correlated with other individual characteristics that may determine good citizenship." The authors use the average homeownership rate of an individual's income quartile as an instrument for homeownership. They find the instrument increases the effect of homeownership on measures of citizenship.

Guiso et al. (2004) study the role of social capital in a country's capital development. The empirical work measures differences in the level of social capital across Italy. Guiso et al. (p.

526) find that “in high-social-capital areas households are more likely to use checks, invest less in cash and more in stock, have higher access to institutional credit, and make less use of informal credit.” The primary measures of social capital are voter turnout/participation in referenda and blood donation. Participation in referenda is highest in northern Italy (south of the Alps) and lowest in southern Italy (especially in Calabria and Sicilia).

Many papers reviewed in this chapter combine work from the fields of social psychology and financial economics. In general, there is little work that combines techniques from the fields of sociology and financial economics. Explaining why financial economists do not see more papers that overlap with sociology is a question worth considering. Presumably, there are differences between the goals of the two fields.

Wikipedia (http://en.wikipedia.org/wiki/Economics) defines economics as “the social science that studies the production, distribution, and consumption of goods and services … A definition that captures much of modern economics was articulated by Lionel Robbins in a 1932 essay: “the science which studies human behaviour as a relationship between ends and scarce means which have alternative uses.” Wikipedia (http://en.wikipedia.org/wiki/Sociology) defines sociology as “a branch of the social sciences that uses systematic methods of empirical investigation and critical analysis to develop and refine a body of knowledge about human social structure and activity, sometimes with the goal of applying such knowledge to the pursuit of social welfare. Its subject matter ranges from the micro level of face-to-face interaction to the macro level of societies at large.”

The above definitions appear to have substantial overlap especially in the area of social welfare. Undoubtedly, work that spans sociology and financial economics remains an area with great potential. Hertz (1998), who provides an ethnographic study of trading behavior on the Shanghai stock exchange, provides a rare example that combines the fields. Ethnography typically relies on interviews and in-depth case studies. Case studies are rare in top finance journals.

CAUSALITY AND IDENTIFICATION

This chapter highlights difficulties in making a causal link between social interactions and investment behavior. Does more social interaction affect investment behavior? Or do individuals simultaneously "choose" their preferred levels of social behavior and their investments? Stated differently, the second question asks whether there are unobserved factors that determine an individual's propensity to engage in both social behavior and investing. These unobserved factors may include physiological similarities and differences among individuals. For example, individuals who have similar levels of risk aversion may choose to live near each other and may hold similar portfolios. The factors may also include community-wide effects such as recent plant closures or other shocks to a community's wealth.

Over the past decade, financial economists have been increasingly interested in answering the question of whether social interactions affect investment behavior. Successfully answering such a question requires independent variation in the level of individuals' social interaction. Finding such independent variation is difficult.

Experimental economics offers hope. A researcher can create controlled settings that should allow him or her to independently vary a subject's level of social interaction. Laboratory research has the advantage of being able to run experiments multiple times; thus, experiments can generate independent data samples. The trouble with implementing laboratory experiments comes from recreating the investment choices faced by individuals. The world's stock markets are enormous (approximately US $30 trillion in capitalization). Bond, currency, commodity, and real estate markets are also large. A fund manager faced with a US$ 10 million investment may behave differently than a laboratory subject faced with a US$ 10 choice.

Field experiments, such as the one conducted by Duflo and Saez (2003), offer financial economists hope in their quest to identify causal effects. The department structure found in most universities allows the authors to "treat" some departments and not others. Within a department, the authors' research design allows them to randomly "treat" some individuals and not others. Random treatment allows the researchers to create independent variation in a key variable.

Instrumental variables also offer hope in the quest to identify causal relations between social interactions and investment decisions. Brown et al. (2008) use social security numbers to determine (estimate) individuals' birth states. They can then divide investors into those who are "native" (live in the same community throughout the sample period and live in the same state since birth) and those who are "nonnative" (born in a different community and state).

The authors' goal is to test for causation running from community effects to investment behavior. To run such a test, they need a variable (the instrument) which affects the decision to own stocks only through community effects and not through other possible channels. According to Brown et al. (2008, p. 1511), their instrument is based on "the average ownership of the birth states of 'nonnative' neighbors." In addition Brown et al. (p.1509) also control for "individual and community fixed effects, a broad set of time-varying individual and community controls, and state-year effects." The authors conclude that neighbors matter. The more likely one's neighbors are to participate in the stock market, the more likely an individual is to participate as well.

Exploiting Market Structures

Exploiting existing market structures also allows financial economists to isolate possible reasons behind herding. This identification strategy is sometimes known as a "natural experiment." The word "experiment" implies a researcher can vary key parameters. Because researchers rarely have this ability, this section refrains from using this terminology.

Feng and Seasholes (2004) question an implied finding in many herding papers that herd behavior *affects* stocks prices. The authors first present a rational expectations equilibrium model in which investment choices (trades) and stock returns are simultaneously determined.

The model is based on insights and assumptions from Brennan and Cao (1997). Investors are assumed to have better information about locally-headquartered firms than they do about remotely-headquartered firms. Upon receiving new information, investors with less information (diffuse priors) about a firm's prospects update beliefs more heavily than those with more information (narrow priors). In equilibrium, when investors have different priors, public news causes some to be buyers and others to be sellers. Thus, good news about a firm leads to four simultaneous effects: (1) all investors update their beliefs (positively) about the stock's future dividends; (2) the stock price goes up; (3) less informed investors are net buyers; and (4) more informed investors are net sellers. That is, local investors are net sellers of local stocks on days the stock prices go up. Distant investors are net buyers of the same stocks on the same days. Related predictions exist on days stock prices go down.

Feng and Seasholes (2004) exploit a feature of the PRC stock market—investors can only place trades at the branch office where they opened their account. Because telephone and computer trades are rare at the time of their study, the rule implies that investors must physically travel to a specific brokerage office in order to trade. Brokerage offices in the PRC are large open rooms.

(Insert Figure 36.2 about here)

The layout shown in Figure 36.2 appears to offer an ideal set-up for encouraging correlated trading (herd behavior). Investors can freely discuss stocks while viewing price updates on large, electronic displays. Many investors such as day traders, retirees, and non-working spouses spend hours each day at brokerage offices in the PRC.

(Insert Figure 36.3 about here)

Feng and Seasholes (2004) use brokerage office location to help categorize investors by their information sets. Their data come from four offices in the Shanghai municipality (labeled A, B, C, and D in Figure 36.3) and three offices in Guandong province (labeled E, F, and G). Brokerage offices within a province are separated by kilometers. Shanghai and Guangdong are about 1,650 kilometers apart. PRC brokerage system rules allow Feng and Seasholes to test the following hypotheses:

1. If individuals are influenced by those directly around them, then financial economists should measure non-zero buys-minus-sells imbalances within a branch office.
2. If herds develop within a branch office, there is no a priori reason for seeing similarly signed imbalances for the same stock on the same day across offices. Hence, trading imbalances for a given stock should be uncorrelated across offices.
3. If individuals are influenced by province-level effects, then researchers should see high correlations of trading imbalances for the same stocks on the same days across offices within the same province.
4. If individuals' priors are built up from local news or discussions with workers at local companies, then correlations should be high for trading imbalances for the same stock on the same day across offices within the same province.
5. If a stock is headquartered in the same province as a brokerage office, individuals/locals should be net sellers on days when the stock price goes up, and net buyers on days when the stock price goes down.
6. If the stock is headquartered in a distant province, individuals should be net buyers on days when the stock price goes up, and net sellers on days the stock price goes down.
7. If the decision to buy or sell a given stock is related to market-wide effects (news), then there may be a common component across the isolated investor groups (branch offices).

Feng and Seasholes (2004) focus on a sample of high-volume stocks that are headquartered in Guangdong province and are listed on the Shenzhen Stock Exchange (also in Guangdong province). For a given stock, net trades are positively correlated across brokerage offices in Guangdong province. Net trades are positively correlated across brokerage offices in Shanghai municipality. Most importantly, net trades are negatively correlated across the two regions. The negative correlation reflects an adding-up constraint: if one group is buying, another group must be selling.

The relations between trading and stock returns follow patterns predicted by the rational expectations model. When a stock's price goes up, local investors are net sellers and distant investors are net buyers. When a stock's price goes down, local investors are net buyers and distant investors are net sellers. There is a strong first principal component of net trades explaining 31.8 percent of total variation. Net trades that originate from branches in Guangdong province load positively on the first principal component. Net trades that originate from branches in Shanghai municipality load negatively on the component.

Feng and Seasholes (2004) study a market setting in which researchers (ex-ante) expect to find herds developing among investors in the same room/branch office. Instead, the authors find strong evidence that trading behavior and stock returns can be explained by a rational expectations equilibrium model. The authors' research design allows them to divide investors by information sets, providing surprising results. Rational expectations models do not predict that herds "move" stock prices. Instead, holdings, changes in holdings, and prices are co-determined in equilibrium.

SUMMARY AND CONCLUSIONS

This chapter is motivated by the question: "How do social interactions affect investment behavior?" There are many areas in the field of financial economics that provide a basis for attempting to answer this question. For example, there is a well-developed and nearly 20 year old literature on herding and information cascades. Over the past decade, researches have tested predictions from these theories in laboratory experiments.

The emphasis of this chapter is recent empirical papers covering correlated trading (herding), the effects of neighbors/colleagues, information diffusion, and links between social capital and financial development. There is also a nearly 20-year old literature on herd behavior by fund managers, security analysts, and company investment managers. Recent studies look at the effects of neighbors and colleagues on an individual's investment decision.

The chapter discusses the difficulty of identifying a causal link between social interactions and investment behavior. Many papers report suggestive correlations between variables linked to social interactions and variables linked to investment behavior. For example, individuals who attend church are also likely to participate in the stock market. There is, however, ample room for future research to make a causal link between many types of social behaviors and investment-related behaviors. The chapter ends with a review of four identification strategies currently being used to identify causality: (1) laboratory experiments, (2) field experiments, (3) instrumental variable approaches, and (4) exploitation of market structures.

DISCUSSION QUESTIONS

1. If a group of investors tends to buy and sell together, are these investors "herding"? Explain why or why not.
2. How can financial economists measure information diffusion among investors?
3. Why do so few papers combine the fields of sociology and finance when studying social interactions and investing?
4. If a group of investors tends to buy and sell together, should financial economists study their behavior if there is no correlation between the net trades and contemporaneous returns? Explain why or why not.

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Figure 36.1 The Hirshleifer and Teoh Taxonomy

This figure shows the Hirshleifer and Teoh (2003) taxonomy of herding, payoff and reputational interactions, social learning, and cascading. Rectangles represent a hierarchy of informational sources of herding or dispersing. The largest rectangle is the most inclusive category.

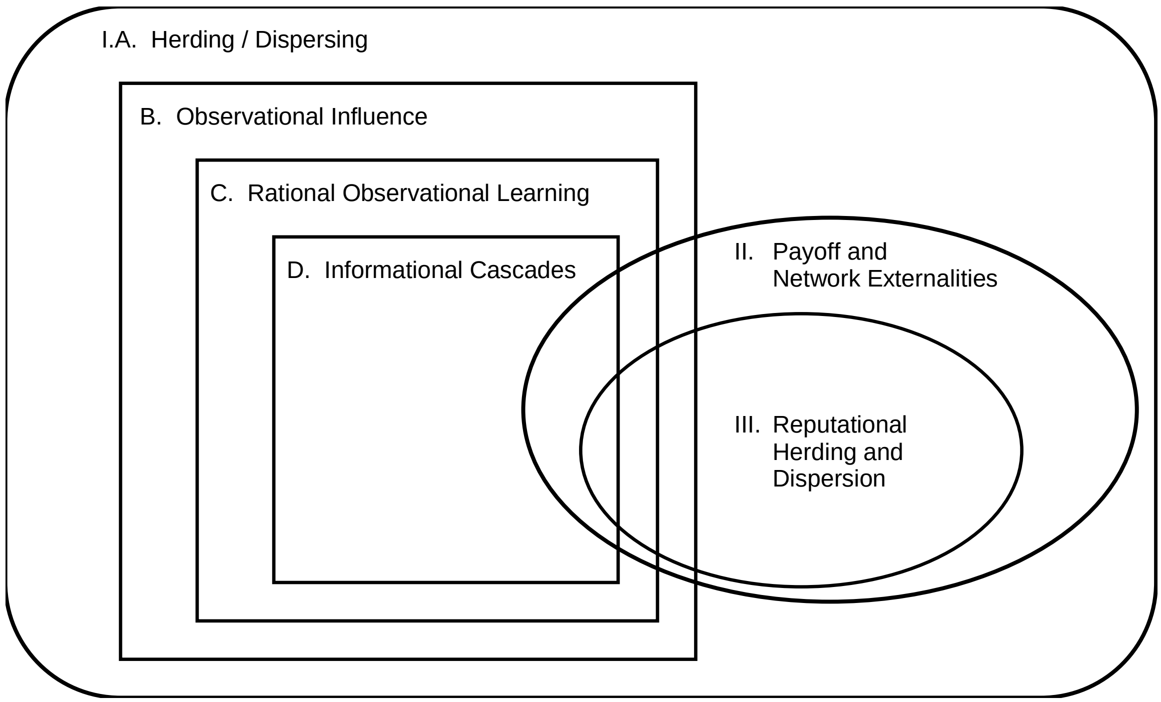

Figure 36.2 Typical Brokerage Office Layout in the PRC

This figure shows the layout of a typical brokerage branch office in the People's Republic of China (PRC). The figure is adapted from Feng and Seasholes (2004).

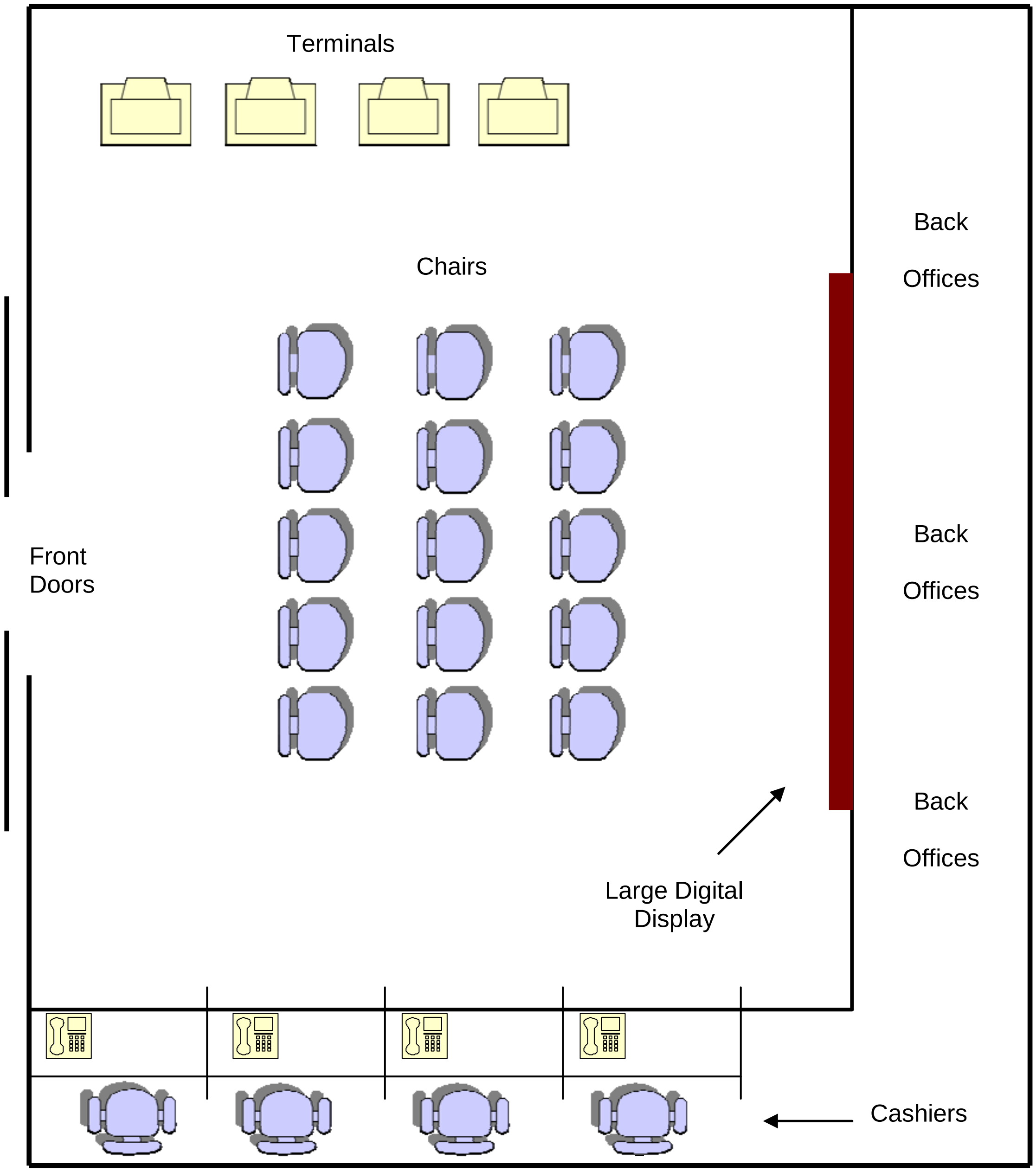

Figure 36.3 Brokerage Office Location in the PRC

This figure depicts brokerage office location in the Feng and Seasholes (2004) study. All brokerage offices are in the People's Republic of China (PRC). There are four offices in the Shanghai municipality (labeled "A", "B", "C", and "D") and three offices in Guandong province (labeled "E", "F", and "G").

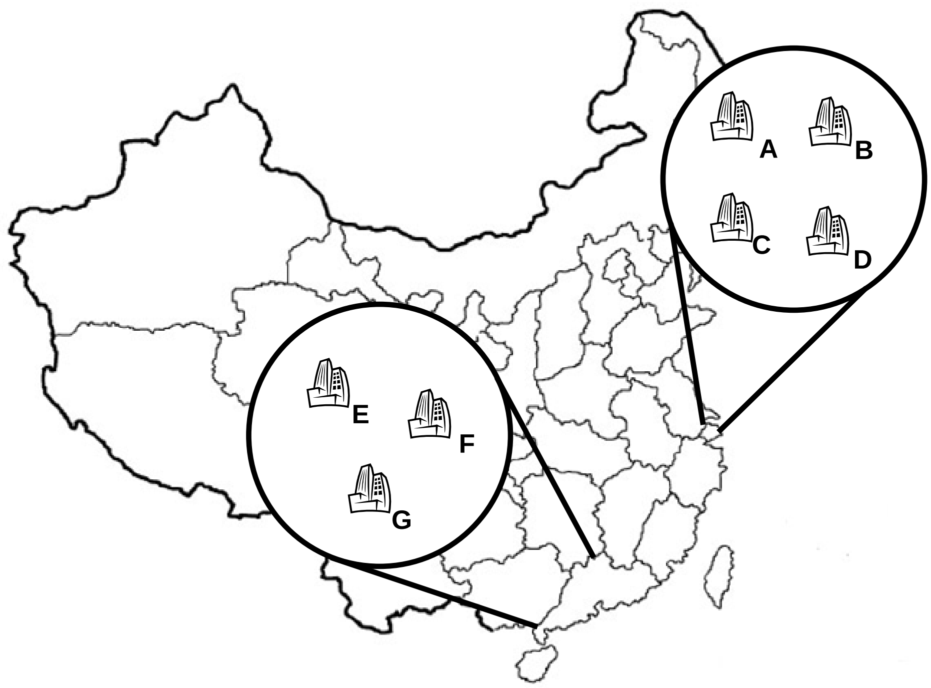

Table 36.1 Comparison of Herding Measures

This table compares Lakonishok, Shleifer, and Vishny (1992) or "LSV" herding measures across different studies. The measure is defined in their paper and in Equations (1) and (2) of this paper.

Note	Study	Country	Investor Group	Freq.	LSV Measure
a.	Grinblatt et al. (1995)	USA	Mutual Funds	Quarterly	0.0250
b.	Feng and Seasholes (2004)	PRC	Individuals	Daily	0.0255
c.	LSV (1992)	USA	Pension Funds	Quarterly	0.0270
b.	Feng and Seasholes (2004)	PRC	Individuals	Weekly	0.0293
d.	Wermers (1999)	USA	Mutual Funds	Quarterly	0.0340
e.	Choe et al. (1999)	Korea	Foreigners	Daily	0.0365
f.	Kim and Wei (2002)	Korea	Foreign Institutions	Monthly	0.0434
g.	Dorn et al. (2008)	Germany	Individuals	Daily	0.0480
g.	Dorn et al. (2008)	Germany	Individuals	Weekly	0.0540
g.	Dorn et al. (2008)	Germany	Individuals	Monthly	0.0640
g.	Dorn et al. (2008)	Germany	Individuals	Quarterly	0.0830
h.	Kim and Wei (2002)	Korea	Foreign Individuals	Monthly	0.1117
i.	Lobão and Serra (2006)	Portugal	Mutual Funds	Quarterly	0.1354
j.	Choe et al. (1999)	Korea	Foreigners	Daily	0.2124

Notes:

a. From Table 4: The mean herding statistic for all 274 funds and all quarters.

b. From Table 2: Table is from a working paper version of Feng and Seasholes (2004) dated Sept-2002. The table with LSV herding measures is not in the final, published version.

c. From Table 2: The mean herding statistic for all cases.

d. From Table II: Data include all funds, from 1975-1994, with five or more trades.

e. From Table 4: Represents a lower bound estimate from this study. The value 0.0365 is the average of all 50 reported measures before crisis and during crisis.

f. From Table 5: Data from non-resident institutions and averaged over the tranquil period, pre-crisis period, and in-crisis period. The value of 0.1117 is the average of the three reported values (0.05781; 0.04690; 0.02553).

g. From Table I: All values are from the mean LSV measure.

h. From Table 5: Data from non-resident individuals and averaged over the tranquil period, pre-crisis period, and in-crisis period. The value of 0.1117 is the average of the three reported values (0.13241; 0.11860; 0.08422).

i. From Table 3: Data from 1998-2000 and include more than five funds trading in the same period.

j. From Table 3: Represents an upper-bound estimate from this study. The value 0.2124 is the average of all 50 reported measures before crisis and during crisis.