

NBER WORKING PAPER SERIES

DO ANALYSTS HERD? AN ANALYSIS OF RECOMMENDATIONS AND MARKET
REACTIONS

Narasimhan Jegadeesh
Woojin Kim

Working Paper 12866
<http://www.nber.org/papers/w12866>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2007

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NBER Working Paper No. 12866
January 2007
JEL No. G14,G24

ABSTRACT

This paper develops and implements a new test to investigate whether sell-side analysts herd around the consensus when they make stock recommendations. Our empirical results support the herding hypothesis. Stock price reactions following recommendation revisions are stronger when the new recommendation is away from the consensus than when it is closer to it, indicating that the market recognizes analysts' tendency to herd. We find that analysts from larger brokerages and analysts following stocks with smaller dispersion across recommendations are more likely to herd.

Narasimhan Jegadeesh
Goizueta Business School
Emory University
1300 Clifton Road
Suite 507
Atlanta, GA 30322
and NBER
narasimhan_jegadeesh@bus.emory.edu

Woojin Kim
KDI School of Public Policy
and Management
P.O. Box 184 Cheong-Nyang
Seoul 130-868
South Korea
wjkim@kdischool.ac.kr

1. Introduction

Media accounts and academic studies often attribute many market ills such as excess market volatility, the internet bubble and the emerging market meltdown in the nineties to the phenomenon of herding. The term “herding” refers broadly to the tendency of many different agents, who make their own individual decisions, to take similar actions at roughly the same time. Portfolio managers, stock analysts, individual investors, and corporate managers are among the many who have been portrayed as having been afflicted by herding instincts.

Why do individuals herd? The theoretical and empirical literature in economics and finance offer many reasons.¹ One reason why individuals may herd is because they act based on similar information. Their information may be similar either because they all independently acquired signals that happen to be correlated, or they may have rationally extracted other agents’ information from their actions. Alternatively, individuals may herd because they derive utility from imitating others, either because of an inherent desire to conform² or because their financial incentive structure rewards conformity.

An anecdotal example which is often cited as evidence of herding is the investment patterns during the latter half of the nineties, often referred to as the internet bubble period. During this period, mutual funds as a group invested an increasing portion of their assets in technology stocks. Even funds that traditionally invested in value stocks moved progressively towards investing in new economy stocks. One possible explanation for this herd behavior is that it is information driven. Funds may have optimally utilized

¹ See Bikhchandani and Sharma (2001), Hirshleifer and Teoh (2003), and Devenow and Welch (1996) for detailed surveys of the herding literature.

² The idea of irrational herding dates back at least to Keynes (1936), where he compares stock market to a beauty contest where judges voted on who they thought other judges would vote for.

the information available at that point in time (which includes others' actions), and rationally anticipated unprecedented growth for internet stocks. Although in hindsight we know that such expectations were overly optimistic, it is hard to rule out the possibility that the internet stock prices were rational based on *ex ante* information available to investors. Alternatively, it is possible that many funds moved into internet stocks merely because of a desire to imitate their cohorts, although they truly believed that internet stocks were overvalued based on all available information.

As this anecdote illustrates, it is generally hard to empirically differentiate between imitation and information-driven herding because we only observe the actions, but not the motives behind those actions or the information available to the actors. Nevertheless, the potential consequences of herding, and how observers should interpret others' actions depends on that underlying driving force. For instance, if herding is information-driven, then herding behavior would not have the destabilizing effect on prices that is often attributed to it. Moreover, investors should rationally update their priors based on others' actions if they do indeed contain new information.

On the other hand, if herding is driven largely by a desire to imitate the actions of others, then herding forces may move prices away from fundamentals. Trueman (1994) presents an example where analysts herd to imitate other analysts. In Trueman's model, analysts' compensation depends on their abilities as perceived by their clients. Trueman shows that analysts with low abilities issue earnings forecasts that are close to those announced by other analysts in order to mimic high ability analysts and get a bigger compensation. Truman notes that in his model, "analysts exhibit herding behavior,

whereby they release forecasts similar to those previously announced by other analysts, even when this is not justified by their information” (p. 97).

Herding for the sake of imitation could potentially introduce noise in prices, which in turn may contribute to excess volatility that many view as undesirable. However, here again herding per se would not lead to excess volatility if the users of the information are aware of the herding incentives, and take those incentives into account in their trading decisions. For instance, in Trueman (1994), although the earnings forecasts are biased, they bring new information to the market. The bias would mislead investors about the value of the stock only if they take the forecast at face value. But, if the investors correctly adjust for the herding bias in earnings forecasts, then this bias would not translate into pricing errors. Therefore, to understand the broader consequences of any herding behavior, it is important that we not only focus on whether or not analysts or others herd, but also investigate whether the market recognizes the herding phenomenon, and acts accordingly.

This paper examines whether sell-side analysts herd when they make stock recommendations. We develop a simple model that allows us to specifically examine whether any herding behavior is driven by a desire to imitate. In addition, our model also allows us to draw inferences about whether the market recognizes analysts’ tendencies to deviate or conform at the time they make recommendation revisions. While the phenomenon of herding has been examined in a variety of contexts in the literature, this paper is the first to investigate whether the market recognizes herding behavior.³

³ For instance, Graham (1999), Jaffe and Mahoney (1999), Desai et al. (2000), Hong et al. (2000), Welch (2000) and Clement and Tse (2005) examine herding among stock analysts and newsletters. Lamont (2002) and Gallo, Granger and Jeon (2002) examine herding among macroeconomic forecasters and Chevalier and Ellison (1999) examine herding among mutual fund managers.

In related work, Welch (2000) examines whether analysts herd when they make investment recommendations. He develops a statistical model to investigate herding, and he finds that analysts are more likely to revise their recommendations towards prior consensus recommendations than away from them. However, as he notes, “Lacking access to the underlying information flow, I [Welch] cannot discern if the influence of recent revisions is either a similar response by multiple analysts to the same underlying information or is caused by direct mutual imitation” [Welch (2000), p. 393].

In contrast, our paper empirically differentiates between imitation and information-based herding. While Welch’s tests are based on the likelihoods of recommendation revisions either moving towards or away from consensus, our tests are based on market price reactions to recommendation revisions. Therefore, we are able to not only test whether analysts herd without any assumptions about recommendation transition probabilities, but we are also able to draw inferences about whether the market recognizes analysts’ herding tendencies.

Empirically differentiating between herding due to imitation and herding due to common information is generally difficult because they are both observationally similar in many respects. This difficulty is amply illustrated by the empirical literature that examines whether analysts herd towards the consensus when they issue forecasts. Early papers by Hong, Kubik and Solomon (2000), Lamont (2002), Gallo, Granger and Jeon (2002) and Clement and Tse (2005) examine the clustering of earnings or macroeconomic forecasts around consensus forecasts, and draw the conclusion that analysts herd towards the consensus, consistent with the model of Trueman (1994), Scharfstein and Stein (1990) and others. De Bondt and Forbes (1999) find similar results

using UK data. However, these papers do not adequately account for the fact that analysts may cluster around the consensus because both the consensus and the individual analyst's forecast reflect similar information, and because analysts may attempt to extract and use information from the forecasts of others when they update their own forecasts.

Subsequent papers by Zitzewitz (2001), Bernhardt, Campello and Kutsoati (2006), and Chen and Jiang (2006) investigate herding behavior using methodologies that specifically account for such information effects. In marked contrast with earlier studies, these papers conclude that analysts "anti-herd," or that they issue forecasts that are away from the consensus relative to a forecast conditional on analysts' information set at the time of the forecast. For instance, Bernhardt et al. report that if an analyst's revised forecast is above the consensus then it is more likely that the forecast would overshoot actual earnings than it would fall short of it, and the opposite is true when an analyst's revised forecast is below the consensus.

We present a simple model that captures analysts' potential incentives to herd or exaggerate their differences with the consensus. In our model, analysts optimally revise their stock recommendations based on their private information, and the market prices efficiently reflect all publicly available information including consensus recommendations and analysts' recommendation revisions. We show that price reactions to analysts' recommendation revisions are unrelated to consensus recommendations if analysts optimally revise their recommendations solely based on new information, without attempting to imitate other analysts' old recommendations. We also show that stock price reactions would be positively related to how far analysts' new

recommendations deviate from the consensus if analysts have an incentive to herd and negatively related if analysts have a disincentive to herd.

We use the results of our model to investigate whether analysts tend to herd or anti-herd when they revise their stock recommendations. We also examine the relation between analysts' tendency to herd and their experience and the reputation of their employer. Theoretical models by Trueman (1994) and Scharfstein and Stein (1990) predict that analysts with lower reputation are more likely to herd because of career concerns or because of their desire to imitate others with better abilities. In contrast, Prendergast and Stole's (1996) model predicts that inexperienced analysts are more likely to exaggerate their differences so that they stand out from the crowd and appear talented.⁴

The empirical results in the literature offer mixed support for the predictions of these models. Chevalier and Ellison (1999), Hong et al. (2000), and Clement and Tse (2005) present results that suggest less experienced analysts are more likely to herd. However, Zitzewitz (2001) presents tests that control for information effects and shows that less experienced analysts actually exaggerate their differences from the consensus. Unlike these papers, our tests are based on market's interpretation of any relation between herding and reputation, and our results offer a different perspective.

The rest of this paper is organized as follows. Section 2 presents the model that lays the foundation for our empirical tests. Section 3 describes the data and Section 4 presents the empirical tests. Section 5 concludes the paper.

⁴ Scharfstein and Stein (1990) also point out that analysts' may earn wages that are higher than outside alternatives for experienced analysts, which could enhance the herding incentives.

2. Model

This section presents the model that provides the basis for our empirical tests. Our model has two periods, 0 and 1. Suppose the price of a stock at time 0 is P_0 . Consider a sell-side analyst who makes investment recommendation about this stock. The unconditional distribution of the stock price at time 1 is given by:

$$P_1 = P_0 + \varepsilon, \text{ where } \varepsilon \sim N(0, \sigma_\varepsilon^2) \quad (1)$$

The sell-side analyst observes a private noisy signal. He updates his priors about the time 1 price for the stock, and his posterior S_0 , conditional on his signal is:

$$S_0 = P_1 + \eta, \quad (2)$$

where, η is noise, and $\eta \sim N(0, \sigma_\eta^2)$. The distribution of ε and η are common knowledge.⁵

After the analyst observes his private signal, he has to decide whether to upgrade, downgrade or make no revision to his investment recommendation of the stock. First, consider a situation where there is no incentive for herding. Suppose the analyst's compensation C is a function of the relation between the direction of future price and the direction of his recommendation revision. Specifically, his compensation is:

$$C = \alpha + \beta \cdot D - \gamma \cdot (1 - D), \quad (3)$$

where $D = 1$ if future price change for the stock is in the same direction as the analyst's recommendation revision, and 0 otherwise. The parameters α , β , and γ are positive constants. Since the compensation function rewards skill, the analyst should not have an incentive to make a revision based on no information. Therefore, the penalty for a wrong

⁵ Our main results obtain also when we assume that only the analyst knows the precision of his signal, and not the market.

call exceeds the reward for a correct call, i.e. $\beta < \gamma$. If he makes no revisions, his compensation would be α , which is known at time 0.

The analyst revises his recommendation only if the expected payoff conditional on a revision exceeds α . The proposition below describes the analyst's optimal rule for recommendation revision.

Proposition 1a: The analyst's optimal recommendation revision rule is:

$$\begin{aligned} &\text{Upgrade if } S_0 \geq P_0 + k\sigma_\eta; \\ &\text{Downgrade if } S_0 \leq P_0 - k\sigma_\eta; \text{ and} \\ &\text{No revision otherwise.} \end{aligned} \tag{4}$$

where k is determined by the equation

$$\Phi(k) = \frac{\gamma}{(\beta + \gamma)}, \tag{5}$$

and Φ is the cumulative standard normal distribution function.

Proof: See Appendix.

If the analyst revises his recommendation, then the market rationally incorporates that information into prices. The proposition below presents the market price conditional on a recommendation revision.

Proposition 1b: The stock price conditional on an upgrade is:

$$\begin{aligned} P_{0,up} | \text{Upgrade} &= P_0 + \sigma_{\varepsilon\eta} \frac{\phi[k \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]}{[1 - \Phi[k \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]]}; \text{ and} \\ P_{0,down} | \text{Downgrade} &= P_0 - \sigma_{\varepsilon\eta} \frac{\phi[k \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]}{[1 - \Phi[k \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]]} \end{aligned} \tag{6}$$

where ϕ is the standard normal density function, , and $\sigma_{\varepsilon\eta} = \sqrt{\sigma_\varepsilon^2 + \sigma_\eta^2}$.

Proof: See Appendix.

In our model, the analyst conveys his information through an upgrade or a downgrade. Because our model assumes market efficiency, the particular label that the analyst attaches to the recommendation per se, i.e. whether it is a buy, a hold or a sell, does not convey any incremental information. Essentially, P_0 incorporates all public information including the analyst's recommendation level prior to any revision. Empirical evidence in Jegadeesh and Kim (2006) and others indicates that recommendation levels do not contain any information about future returns and supports this assumption.⁶

Now, consider the case where the analyst has either an incentive or a disincentive to herd with the consensus. We incorporate any incentives or disincentives to herd in the analyst's compensation function, which we specify as:

$$C = \alpha + \beta \cdot D - \gamma \cdot (1 - D) - \delta(Rec_{new} - Consensus)^2, \quad (7)$$

where Rec_{new} is the analyst's new recommendation level and $Consensus$ is the average recommendation level of all the other analysts. If he makes no revisions, his compensation would be $C = \alpha - \delta(Rec_{old} - Consensus)^2$.

The compensation function (7) is a reduced form characterization of the incentives to herd or to exaggerate differences, and it is similar to the objective function that Zitzewitz (2001) uses in the context of analysts' earnings forecasts. Incentives to herd arise endogenously in Trueman (1994), and Ehrbeck and Waldmann (1996). In these models, analysts herd to mimic their more skilled counterparts. It is also possible that analysts herd because they perceive it to be a safe course of action. After all, if their

⁶ In unreported results, we found that recommendation levels are not related to future returns in our sample as well, and hence any information in recommendation levels is fully reflected in stock prices.

predictions turn out to be wrong when they herd, then their cohorts would be wrong as well. Regardless of the underlying reason, when analysts have an incentive to herd, $\delta > 0$ in the analyst's compensation function (7).

Prendergast and Stole (1996) present a model where the opposite incentives are present. In their model, agents who have not yet established a reputation for themselves, or the “newcomers,” overemphasize their own information and exaggerate their differences with others to appear talented. Similarly, Ottaviani and Sorensen (2006) show that when analysts view their tasks as a winner-take-all contest, then they have an incentive to excessively differentiate their views from those of other analysts. When analysts were faced with incentives to deviate from the crowd, or to “anti-herd”, $\delta < 0$.

The proposition below describes the analyst's optimal rule for recommendation revision when his compensation function is given by (7).

Proposition 2a: The analyst's optimal recommendation revision rule is:

$$\begin{aligned} & \text{Upgrade if } S_0 \geq P_0 + (k + \theta)\sigma_\eta; \\ & \text{Downgrade if } S_0 \leq P_0 - (k + \theta)\sigma_\eta; \text{ and} \\ & \text{No revision otherwise.} \end{aligned} \tag{8}$$

where θ is determined by the equation

$$\Phi(k + \theta) = \frac{\gamma}{(\beta + \gamma)} + \frac{\delta[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]}{(\beta + \gamma)}. \tag{9}$$

Proof: See Appendix.

Now the analyst's decision whether to revise his recommendation depends not only on his signal but also on how far away his recommendation would be from the consensus. Since the market rationally recognizes these incentives, the price reaction subsequent to a

revision would reflect the analyst's decision rule. The proposition below presents the market price conditional on a recommendation revision.

Proposition 2b: The stock price conditional on an upgrade is:

$$P_{0,up} | \text{Upgrade} = P_0 + \sigma_{\varepsilon\eta} \frac{\phi[(k + \theta) \cdot (\sigma_{\eta} / \sigma_{\varepsilon\eta})]}{[1 - \Phi[(k + \theta) \cdot (\sigma_{\eta} / \sigma_{\varepsilon\eta})]]}; \text{ and}$$

$$P_{0,up} | \text{Downgrade} = P_0 - \sigma_{\varepsilon\eta} \frac{\phi[(k + \theta) \cdot (\sigma_{\eta} / \sigma_{\varepsilon\eta})]}{[1 - \Phi[(k + \theta) \cdot (\sigma_{\eta} / \sigma_{\varepsilon\eta})]]} \quad (10)$$

Proof: See Appendix.

When there are incentives or disincentives to herd, the market price reaction is a function of not only whether the analyst upgrades or downgrades his recommendation, but also how far the recommendation is from the consensus. This relation is formally described in the proposition below.

Proposition 3a: The price reaction to recommendation revision is stronger when, relative to the old recommendation, the new recommendation moves away from the consensus than when it moves towards the consensus if the analyst has an incentive to herd (i.e. if $\delta > 0$).

Proof: See Appendix.

Proposition 3b: The expected return following recommendation revision is:

- (a) Positively related to the deviation between the analyst's recommendation and the consensus if the analyst has an incentive to herd (i.e. if $\delta > 0$); and
- (b) Negatively related to the deviation between the analyst's recommendation and the consensus if the analyst has an incentive to deviate from the herd (i.e. if $\delta < 0$).

Proof: See Appendix.

Proposition 3a and 3b form the basis for our empirical tests. Our tests use market price reactions to investigate herding. In contrast, prior research on herding typically attempts to set empirical benchmarks for how agents would behave in the absence of herding. For instance, Chevalier and Ellison (1999) report that less experienced managers deviate less from benchmark index than more experienced managers, and conclude that less experienced managers herd more because of career concerns. Here the experienced managers' deviation from the index is used as a benchmark for the less experienced managers. However, it is quite possible that less experienced analysts stay closer to the benchmark because they are not as talented as the more experienced managers. As this example illustrates, when there are differences across agents in skill or in access to information, it is difficult to specify how one set of agents should behave based on the actions of another set of agents and draw reliable inferences about herding.

Since we base our tests on market price reactions, we rely on market efficiency and we do not need to specify a model that focuses on the transition probabilities for recommendation revisions. Our model predicts that if recommendation revisions are driven solely by new information, then market price reaction would not depend on the distance between the consensus and new recommendations.

3. Data and Sample

We obtain the stock recommendations data from the IBES detailed US recommendations file; earnings announcement dates from the IBES actual earnings file; and stock returns and index returns from daily CRSP. The sample period is from November 1993 to December 2005.

Most commonly, analyst recommendations rate stocks as “strong buy,” “buy,” “hold,” “sell,” and “strong sell.” Analysts also use other labels such as “market underperform” and “market outperform,” or “underweight” and “overweight,” to convey their opinions, but IBES standardizes the recommendations, and converts them to numerical scores where “1” is strong buy, “2” is buy, and so on. To map an upgrade to a positive number and a downgrade to a negative number, we reverse IBES’ numerical scores so that “1” would correspond to a strong sell and “5” would correspond to a strong buy.

Our sample comprises all stocks that satisfy the following criteria:

- (a) There should be at least one analyst who issues a recommendation for the stock and revises the recommendation within 180 calendar days⁷.
- (b) At least two analysts, other than the revising analyst, should have active recommendations for the stock as of the day before the revision.
- (c) The stock return data on the recommendation revision date should be available on CRSP; and
- (d) The stock price should be at least \$1 on the day before the recommendation revision date.
- (e) Recommendation revisions should be only one level up or down. That is, absolute difference between the previous recommendation and the new recommendation level should be one. For instance, we exclude all revisions where analysts upgrade from hold to strong buy because the revision spans

⁷ IBES also provides stopped dates of the coverage for each stock and brokerage pair. We filter out revisions that are made after the closest stopped date since the previous recommendation.

two levels, buy and strong buy. We impose this exclusion criterion to ensure consistency with our model.^{8,9}

Table 1 presents the descriptive statistics for the sample. The number of firms in the sample ranges from a low of 139 in 1993 to a high of 1,783 in 2002. The sample size is relatively small in 1993 largely because IBES coverage is incomplete in its first year. The median number of analysts following a firm over the entire sample period is five. The number of brokerages in database increases from 32 in 1993 to 145 in 2004 before decreasing to 140 in 2005. The brokerages in the sample range from large brokerages like Merrill Lynch and Morgan Stanley to small ones that have only one analyst on IBES. The median number of analysts in a brokerage is four.

4. Empirical Tests

Our first set of tests examines stock price changes following recommendation upgrades and downgrades over various horizons. We use the results from our model to investigate whether stock price reactions to analysts' recommendation revisions indicate herding behavior. We then examine the cross-sectional relation between experience and reputation, and analysts' tendency to herd. Finally, we examine the robustness of our results to alternate test specifications.

4.1 Price Reaction to Recommendation Revisions

This subsection examines how stock prices react to recommendation revisions. We characterize each revision as an upgrade or a downgrade by comparing the revised

⁸ Sorescu and Subrahmanyam(2006) report that the market reactions are stronger for two level revisions than for one level revisions.

⁹ Our empirical results, however, do not change when we include multiple level revisions in the sample.

recommendation with the previous active recommendation for the stock by the revising analyst.

After a recommendation revision for stock i on date t , we compute H -day buy-and-hold abnormal returns $ABR_i(t, t + H)$ as follows:

$$ABR_i(t, t + H) = \prod_{\tau=t}^{t+H} (1 + R_{i,\tau}) - \prod_{\tau=t}^{t+H} (1 + R_{m,\tau}) \quad (11)$$

where, $R_{i,\tau}$ and $R_{m,\tau}$ are the return on stock i and the value-weighted index return, respectively.

Table 2 presents abnormal stock returns over various horizons following recommendation revisions. Day 0 is the revision date and the other days in the column headings are the number of trading days from the revision date. For instance, the entries under the column heading “21” presents cumulative abnormal returns over 21 trading days, or roughly one calendar month, after the revision. We compute serial-correlation consistent Hansen and Hodrick standard error estimates allowing for non-zero serial correlation for up to 6 months to take into account that the return measurement intervals overlap across longer horizons.

The average abnormal return on the revision date is 2.03% for all upgrades and - 3.14% for all downgrades. The abnormal return gradually increases to 4.85% by the end of the sixth months for upgrades and decreases to -3.45% for downgrades. Therefore, a large part of stock price response occurs on the day of the revision although the market prices continue to reflect the information in recommendation revisions up to six months

into the future. These results are consistent with the previous literature that examines the impact of analysts' recommendations on stock prices.¹⁰

Table 2 also presents abnormal returns separately for recommendation revisions that move towards the consensus and those that move away from the consensus. We define consensus recommendation level as the equal-weighted average of all active recommendations that are outstanding for the stock as of the day before the revision, excluding the revising analysts' recommendation. We include a revision in the sample only if at least two analysts beside the revising analyst have active recommendations. We consider a recommendation to be active for up to 180 days after it is issued or until IBES stopped file records that the analyst has stopped issuing recommendations for that stock. We impose the 180-day criterion to screen out stale recommendations. We categorize a revision as moving away from the consensus if the absolute value of deviation from the consensus is larger for the new recommendation than for the old recommendation, and moving towards the consensus otherwise.¹¹

The results in Table 2 indicate that the market reaction is stronger for revisions that move away from the consensus than for those that move towards it. For upgrades, the difference in abnormal returns is significant on the revision date. Because longer horizon returns are noisier, we do not detect any reliable difference in returns over horizon beyond two months. For downgrades, the differences between returns are much larger and have a longer lasting effect. These results are consistent with the predictions of our model under herding hypothesis and suggest that the market rationally takes into

¹⁰ For example, Womack (1996), Jegadeesh, Kim, Krische and Lee (2004) and Jegadeesh and Kim (2006).

¹¹ In 985 revisions (2% of the sample), the absolute deviation is the same before and after the revision. We exclude these revisions when we present stock price reactions in Table 2 for revisions that move away from or towards the consensus.

account the herding incentives of sell side analysts when they make recommendation revisions and prices them accordingly.

However, the analysis in this subsection considers only a binary classification of potential indication of herding; movement towards or away from the consensus. Our model also provides predictions regarding the relationship between the magnitude of the move towards or away from the consensus and expected returns, which we expect to be more powerful in testing the herding hypothesis. We now examine these predictions in more detail.

4.2 Herding Regressions

We use the following regression specification to investigate whether analysts herd:

$$ABR_i(t, t + H) = a_H + b_H \times I + c_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) + \varepsilon_{i,j,t,H} \quad (12)$$

where,

$I = +1$ if the revision is an upgrade

$= -1$ if the revision is a downgrade

The indicator variable I takes the sign of expected abnormal returns conditional on an upgrade or a downgrade. We use this indicator variable so that we can pool upgrades and downgrades in the same regression.

The variable $New_rec_{i,j,t}$ is the recommendation level after the revision for stock i by analyst j on day t . If there are multiple revisions on any day t for stock i , then we treat each revision as a separate observation.¹² The variable $Con_rec_{i,t-1}$ is the

¹² About 7% of the sample are related with multiple revisions on a same day.

consensus recommendation the day before the revision, excluding the revising analyst's recommendation.

This regression specification is based on the results of our model given in Equation (9) and (10). As Equation (9) and (10) indicate, if analysts were either herding or exaggerating their differences, then the stock return on the revision date would not only depend on the information in the revision per se, but also on whether the recommendation is closer to or away from the consensus recommendation. As we discuss in Proposition 3b, stock price reaction would be positively related to the deviation from the consensus if analysts herd, and would be negatively related if they exaggerate.¹³

Therefore, our alternate hypotheses are:

A1. Herding: Analysts have an incentive to herd close to the consensus when they make recommendation revisions. Therefore, $c > 0$.

A2. Exaggeration: Analysts have an incentive to exaggerate their differences with the consensus when they make recommendation revisions. Therefore, $c < 0$.

For convenience, we will be referring to c as the herding coefficient in the subsequent analysis. We fit Regression (12) for holding periods ranging from one day to about six-months. By allowing for holding period longer than just the day of revision, we can examine whether market reaction recognizes any herding incentives on the revision date or with some delay. For instance, if analysts tend to herd, but the immediate market reaction does not take herding into account, then the coefficient c would be zero on the revision date but it would be positive over longer horizons as the information in deviation

¹³ We resort to $(New_rec_{i,j,t} - Con_rec_{i,t-1})$ as the main explanatory variable rather than directly use $[(New_rec_{i,j,t-1} - Con_rec_{i,t})^2 - (Old_rec_{i,j,t-1} - Con_rec_{i,t})^2] * I$, since this quantity is equivalent to $2(New_rec_{i,j,t} - Con_rec_{i,t-1}) - I$ when revisions are only one level up or down.

from consensus gets reflected in market prices. However, if coefficient c is not different from zero over any holding period, then we would not be able to reject the null hypothesis of no herding or exaggeration.

Table 3 presents the estimates of Regression (12) using the Fama-MacBeth approach. Specifically, we estimate a separate regression using all revision data within each calendar quarter. The regression estimates and t-stats are based on the time-series averages and standard errors of the corresponding quarterly regression coefficients.

There are a total of 49,255 revisions in our sample. The slope coefficient on the revision indicator on day 0 is 2.05, indicating that the average stock return is 2.05% in the direction of recommendation revision. This slope coefficient increases gradually with the holding period, reflecting the delay in market price reactions to recommendation revisions.

The slope coefficient on deviation from consensus is .75, which is significantly positive. Therefore, in addition to the direction of recommendation revision, the deviation from consensus also conveys information to the market. The stock return is more positive for upgrades and more negative for downgrades when the new recommendation moves farther away from the consensus than when it moves closer to it. As we discussed earlier, the positive coefficient supports the hypothesis that analysts herd towards the consensus.

The point estimates of the slope coefficients on deviation from consensus are .70 and .88 for two- and six-month holding periods, respectively. Although these point estimates are smaller and larger than the corresponding slope coefficient on the revision date return regression, the differences are not statistically significant. Therefore, the

market price fully incorporates the information in the deviation from consensus on the revision date.

Analysts' tendency to herd may be different for upgrades and downgrades. For instance, analysts may be more reluctant to stand out from the herd for downgrades since they are typically reluctant to be negative on a stock.¹⁴ To investigate whether analysts herd differently for upgrades versus downgrades, we fit the following regression:

$$ABR_i(t, t + H) = a_H + b_H \times I + c_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) + d_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) \times downgrade_dummy_{i,j,t} + \varepsilon_{i,j,t,H} \quad (13)$$

where *downgrade_dummy_{i,j,t}* equals 1 for downgrades and 0 for upgrades.

Table 4 reports the regression estimates. The slope coefficient on the herding coefficients for downgrade dummy is .90, which is significantly greater than zero. Therefore, analysts tend to herd more for downgrades than for upgrades.

4.3 Cross-Sectional Determinants of Herding

This subsection examines the factors that are related to analysts' tendency to herd. In the models of Scharfstein and Stein (1990) inexperienced agents are more likely to herd because of career concerns. In contrast, Prendergast and Stole (1996) present a model where "newcomers" exaggerate their differences more than well established employees in order to stand out from the crowd and appear talented. Empirical evidence offers mixed support for these predictions. For example, Hong et al. (2000), Clement and Tse (2005), and Chevalier and Ellison (1999) find that less experienced analysts and mutual fund managers are more likely to herd. On the other hand, Zitzewitz (2001)

¹⁴ Analysts' reluctance to issue negative opinion is evident in the distribution of their recommendations. For example, Barber, LeHavy, McNichols and Trueman (2001) report that only 5.7% of the analysts' recommendations in their sample were sell or strong sell.

reports that more experienced analysts are more likely to herd when they make earnings forecasts, after accounting for information effects. This subsection uses price reactions to analysts' recommendation revisions to investigate analysts' tendency to herd from the market's perspective.

We use two measures of analysts' professional reputation. The first measure is the length of time that the analyst is on the IBES database. The second measure is the size of the brokerage that employs the analyst since larger brokerages are more established and prestigious. We measure the size of the brokerage by the number of analysts who are on the IBES database from that brokerage each year.

We also examine the relation between analysts' tendency to herd and the dispersion of analysts' outstanding recommendation prior to the revision. We expect that if recommendations are dispersed analysts will have less of an incentive to herd because they do not stand out as much when their opinion deviates from the average.

We use the following regression to test the relation between herding and various characteristics:

$$\begin{aligned}
 ABR_i(t, t+H) = & a_H + b_H \times I + c_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) \\
 & + d_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) \times char_dummy_{i,j,t} \\
 & + e_H \times I \times char_dummy_{i,j,t} + \varepsilon_{i,j,t,H}
 \end{aligned} \tag{14}$$

where $char_dummy_{i,j,t}$ is a dummy variable for each characteristic. The dummy variable for analysts' experience equals 1 if the analyst has more than three years of experience. The dummy variable for brokerage reputation equals 1 if the number of analyst is employed by a top 20 brokerage the previous year, based on the number of analysts employed by the brokerage. The cross-sectional dispersion dummy equals 1 if the

standard deviation of the consensus recommendation prior to the revision is greater than 0.75, which is the average dispersion in the sample.¹⁵ We also include an additional independent variable that interacts each dummy variable with I to examine whether the characteristic directly affects market response to recommendation revisions.

Table 5 reports the estimates of regression (14). Panels A, B, and C report results for analyst experience, brokerage size, and pre-revision dispersion in recommendations, respectively. The results from panel A indicate that the tendency to herd does not differ across analysts depending on their experience.¹⁶ In contrast, Clement and Tse (2005) and Zitzewitz (2001) find evidence of herding and anti-herding when analysts revise their earnings forecasts.

Panel B uses brokerage size as a measure of reputation. The herding coefficient on brokerage size dummy is significantly positive, which indicates that analysts from large brokerages tend to herd more than analysts from small brokerages. This finding suggests that analysts from the less prestigious brokerage may try to stand out from the crowd to attract attention, and it is consistent with the predictions of Prendergast and Stole (1996).

Panel C examines the relation between cross-sectional dispersion in recommendations and analysts' tendency to herd. The herding coefficient of the dispersion dummy is significantly negative, which indicates that analysts are less likely to herd when there is a large dispersion across analysts' opinion. This result is consistent with our prediction.

¹⁵ The sample mean of cross-sectional dispersion in recommendations is 0.75 and the median is 0.753.

¹⁶ The sub-sample used in panel A only includes those revisions that are made at least three years after the beginning of the sample period so that we have at least a three-year history of employment.

4.4 Robustness Check

This subsection examines the robustness of our results to various changes in our sample selection criteria. Analysts use a variety of different information when they arrive at their recommendations. For instance, Ivkovic and Jegadeesh (2004) note that analysts' recommendations immediately following earnings announcements are likely to be based on their interpretation of financial data that the firm announces while their recommendations at other times are likely to be based on information that they privately gather.

To examine whether analysts' tendency to herd differs depending on the timing of their revisions, we estimate regression (12) excluding revisions made within three days before and after the earnings announcement date. Panel A of Table 6 presents the regression estimates.¹⁷ We find that the herding coefficients now are quite similar to the estimates we report in Table 3 for the full sample.

It is possible that revisions made by two analysts close to one another are driven by common information. Therefore, we re-estimate regression (12) for a sample of revisions that are made at least five days after the most recent revision by a different analyst. These results are also quite similar to the full sample results.

Next, we exclude revisions that move across the consensus. For example, if an analyst upgrades from 3 to 4 when the consensus is 3.3 it may not be an unambiguous move away from the consensus. Panel C of Table 6 presents the regression estimates for this restricted subsample. Here again, the results are quite similar to the full sample results both in magnitude and significance of the coefficients.

¹⁷ We lose roughly a quarter of our sample when we exclude the seven-day earnings announcement window since analysts' recommendation revisions tend to cluster within this event window.

Finally, we investigate the possibility that the herding coefficient is significant not because of the deviation from consensus, but because of the information contained in the new recommendation level. To examine this possibility, we fit the following regression:

$$ABR_i(t, t + H) = a_H + b_H \times I + c_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) + d_H \times Sell_StrongSell_{i,j,t} + e_H \times StrongBuy_{i,j,t} + \varepsilon_{i,j,t,H} \quad (15)$$

where $Sell_StrongSell_{i,j,t}$ is a dummy variable equal to 1 if the new recommendation is a sell or a strong sell and 0 otherwise, and $StrongBuy_{i,j,t}$ is a dummy variable equal to 1 if the new recommendation is a strong buy and 0 otherwise.

Table 7 presents the estimates of regression (15). The slope coefficient on the $Sell_StrongSell$ dummy is significantly positive on the revision date, while that on the $StrongBuy$, is significantly negative. These results indicate that downgrades or upgrades to these levels are less informative than others. However, the herding coefficient is significantly positive, and of similar magnitude to the corresponding coefficients in Table 3. Therefore the information contained in the deviation from the consensus is orthogonal to the level of recommendations.

5. Conclusions

This paper examines whether sell-side analysts herd when they make stock recommendations. We develop a model that allows us to specifically examine whether any herding behavior is driven by a desire to imitate. In addition, our model allows us to draw inferences about whether the market recognizes analysts' tendencies to deviate from or conform to the consensus at the time they make recommendation revisions. While the

phenomenon of herding has been examined in a variety of contexts in the literature, this paper is the first to investigate whether the market recognizes herding behavior.

We find that the market reaction to analysts' recommendation revision is stronger when the revised recommendations move away from the consensus than when they move towards the consensus. Our results are robust to a variety of controls. Our results indicate that recommendation revisions are partly driven by analysts' desire to herd with the crowd.

We find stronger herding effects for downgrades than for upgrades, which suggests that analysts are more reluctant to stand out from the crowd when they convey negative information. We also find that analysts from more reputed brokerages are more likely to herd than analysts from less reputed brokerages. This finding supports the prediction of Prendergast and Stole (1996) that "new comers," which in our context represents analysts from less prestigious brokerages, are more likely to stand out from the crowd than well established agents.

Media accounts and some academic papers have suggested that analysts' herding tendencies could introduce noise into prices because the market could potentially overweight the common mistakes of the herd. However, our results indicate that the market anticipates analysts' tendencies to herd, and the market price reaction on the revision date accounts for such herding tendencies. Therefore, we doubt that herding by analysts when they make recommendations would have any destabilizing effect on prices.

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Appendix

Proof of Proposition 1a

Let

$$X = \Pr[P_1 > P_0 | S_0]. \quad (\text{A.1})$$

The condition for issuing an upgrade is given by;

$$(\alpha + \beta)X + (\alpha - \gamma)(1 - X) > \alpha, \quad (\text{A.2})$$

and thus

$$X = \Pr[P_1 > P_0 | S_0] > \frac{\gamma}{(\beta + \gamma)} > \frac{1}{2}. \quad (\text{A.3})$$

Define k such that

$$\Phi(k) = \frac{\gamma}{(\beta + \gamma)} \quad (\text{A.4})$$

where Φ is the cumulative standard normal distribution function.

Since $P_1 | S_0 \sim N(S_0, \sigma_\eta^2)$, Eq. (A.3) implies $\frac{(P_0 - S_0)}{\sigma_\eta} < -k$. Therefore, the analyst optimally upgrades his recommendation when $S_0 > P_0 + k\sigma_\eta$. The optimal rule for issuing downgrades can be similarly determined.

Proof of Proposition 1b

The expected stock price conditional on observing an upgrade is given by;

$$P_{0,up} | \text{Upgrade} = E(S_0 | S_0 > P_0 + k\sigma_\eta) = \int_{P_0 + k\sigma_\eta}^{\infty} S_0 f(S_0 | S_0 > P_0 + k\sigma_\eta) dS_0. \quad (\text{A.5})$$

From the market's perspective, $S_0 = P_0 + \varepsilon + \eta$ so that $S_0 \sim N(P_0, \sigma_\varepsilon^2 + \sigma_\eta^2)$.

Then, based on the properties of the normal distribution, it can be shown that,

$$E(S_0 | S_0 > P_0 + k\sigma_\eta) = P_0 + \sigma_{\varepsilon\eta} \lambda[k \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})] = P_0 + \sigma_{\varepsilon\eta} \frac{\phi[k \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]}{[1 - \Phi[k \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]]} \quad (\text{A.6})$$

where $\sigma_{\varepsilon\eta} = \sqrt{\sigma_\varepsilon^2 + \sigma_\eta^2}$, ϕ is the density function and $\lambda = \frac{\phi}{(1 - \Phi)}$ is the hazard function of standard normal distribution or inverse Mill's ratio.¹⁸

Similarly, the expected stock price conditional on observing a downgrade is given by;

$$E(S_0 | S_0 < P_0 - k\sigma_\eta) = P_0 - \sigma_{\varepsilon\eta} \lambda[k \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})] = P_0 - \sigma_{\varepsilon\eta} \frac{\phi[k \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]}{[1 - \Phi[k \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]]} \quad (\text{A.7})$$

¹⁸ See for example, Greene, W. H., 2000, *Econometric Analysis*, 4th edition, Chap 20, Prentice Hall for detailed discussion.

Proof of Proposition 2a

Let $X = \Pr[P_1 > P_0 | S_0]$. Now, the analyst issues an upgrade if:

$$\alpha + (\beta + \gamma)X - \gamma - \delta(\text{Rec}_{new} - \text{Consensus})^2 > \alpha - \delta(\text{Rec}_{old} - \text{Consensus})^2 \quad (\text{A.8})$$

Therefore,

$$X = \Pr[P_1 > P_0 | S_0] > \frac{\gamma}{(\beta + \gamma)} + \frac{\delta[(\text{Rec}_{new} - \text{Consensus})^2 - (\text{Rec}_{old} - \text{Consensus})^2]}{(\beta + \gamma)} \quad (\text{A.9})$$

Define θ such that:

$$\Phi(k + \theta) = \frac{\gamma}{(\beta + \gamma)} + \frac{\delta[(\text{Rec}_{new} - \text{Consensus})^2 - (\text{Rec}_{old} - \text{Consensus})^2]}{(\beta + \gamma)}. \quad (\text{A.10})$$

Since $P_1 | S_0 \sim N(S_0, \sigma_\eta^2)$, Eq. (A.10) implies that $\frac{(P_0 - S_0)}{\sigma_\eta} < -(k + \theta)$. Therefore, an analysts upgrades his recommendation when $S_0 > P_0 + (k + \theta)\sigma_\eta$. The optimal rule for downgrades can be similarly determined.

Proof of Proposition 2b

The expected stock price conditional on observing an upgrade is now given by;

$$P_{0,up} | \text{Upgrade} = E(S_0 | S_0 > P_0 + (k + \theta)\sigma_\eta) = \int_{P_0 + (k + \theta)\sigma_\eta}^{\infty} S_0 f(S_0 | S_0 > P_0 + (k + \theta)\sigma_\eta) dS_0 \quad (\text{A.11})$$

By Proposition 1b, it follows that,

$$\begin{aligned} E(S_0 | S_0 > P_0 + (k + \theta)\sigma_\eta) &= P_0 + \sigma_{\varepsilon\eta} \lambda[(k + \theta) \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})] \\ &= P_0 + \sigma_{\varepsilon\eta} \frac{\phi[(k + \theta) \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]}{[1 - \Phi[(k + \theta) \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]]} \end{aligned} \quad (\text{A.12})$$

Similarly, the expected stock price conditional on a downgrade is:

$$\begin{aligned} E(S_0 | S_0 < P_0 - (k + \theta)\sigma_\eta) &= P_0 - \sigma_{\varepsilon\eta} \lambda[(k + \theta) \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})] \\ &= P_0 - \sigma_{\varepsilon\eta} \frac{\phi[(k + \theta) \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]}{[1 - \Phi[(k + \theta) \cdot (\sigma_\eta / \sigma_{\varepsilon\eta})]]} \end{aligned} \quad (\text{A.13})$$

Proof of Proposition 3a

A move away from the consensus implies that

$[(\text{Rec}_{new} - \text{Consensus})^2 - (\text{Rec}_{old} - \text{Consensus})^2]$ is positive. Suppose that analysts have incentives to herd so that $\delta > 0$. Then, from Eq. (A.10), $\theta > 0$. Similarly, a movement

towards the consensus implies that $\theta < 0$. Based on the properties of normal distribution, it follows that,

$$\lambda'(\alpha) = \lambda(\alpha)[\lambda(\alpha) - \alpha] \in (0,1). \quad (\text{A.14})$$

Thus, according to Eq. (A.12) and (A.13), positive θ implies a higher expected price for upgrades and a lower expected price for downgrades and negative θ leads to a lower expected price for upgrades and a higher expected price for downgrades

Proof of Proposition 3b

Let

$$\Delta = (Rec_{new} - Rec_{old}), \quad (\text{A.15})$$

and

$$Deviation = (Rec_{new} - Consensus). \quad (\text{A.16})$$

Then, it follows that

$$[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2] = \Delta[2 \cdot Deviation - \Delta] \quad (\text{A.17})$$

For upgrades, *Deviation* would *increase* as the analyst first moves towards the consensus and then away from it for given levels of Δ and *Consensus*. Since $\Delta > 0$, an increase in *Deviation* implies an increase in $[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]$. From Eq. (A.10), this implies an increase θ when $\delta > 0$. It follows from Eq. (A.12) and (A.14) that an increase in θ implies a *higher* expected price.

For downgrades, *Deviation* would *decrease* as the analyst first moves towards the consensus and then away from it. Since $\Delta < 0$, a decrease in *Deviation* implies an increase in $[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]$. Then, based on Eq. (A.10), (A.13) and (A.14), this implies increases in θ and a *lower* expected price when $\delta > 0$.

Thus, *Deviation* and expected returns would be positively related for both upgrades and downgrades. The opposite result obtains when analysts have incentives to anti-herd (i.e. if $\delta < 0$).

Table 1

Sample Descriptive Statistics

This table presents the descriptive statistics for the sample. The sample includes all firms that have at least two active recommendations in the IBES Detailed US Recommendations database with at least one being revised during the sample period. The sample excludes all stocks priced lower than \$1 on the day before the recommendation revision date. Finally, a brokerage house enters into the sample in a given year if it employs at least one analyst who entered the sample. For each calendar year covered by the sample, the table shows the number of firms followed by analysts, number of analysts, and the number of brokerage firms. The remaining columns of the table present the mean and median numbers of analysts per brokerage firm and the number of analysts following each firm, respectively. The sample period is from November 1993 to December 2005.

Year	Number of Firms Followed	Number of Analysts	Number of Brokerages	Number of Analysts per Brokerage		Number of Analysts Following each Firm	
				Mean	Median	Mean	Median
1993	139	126	32	3.94	3	5.87	5
1994	1,331	898	85	10.78	5	7.74	6
1995	1,196	931	91	10.43	4	5.60	5
1996	1,240	993	111	9.15	4	4.96	4
1997	1,284	1,048	123	8.63	3	4.77	4
1998	1,602	1,429	145	10.08	4	5.31	4
1999	1,648	1,617	139	11.96	5	5.85	5
2000	1,472	1,468	135	11.22	5	5.70	5
2001	1,433	1,475	123	12.28	6	6.72	5
2002	1,783	1,761	138	12.96	6	7.69	6
2003	1,658	1,478	133	11.28	4	7.66	6
2004	1,418	1,198	145	8.39	3	6.69	5
2005	1,320	1,122	140	8.10	3	5.76	5
All Years	5,104	5,370	331	10.30	4	6.37	5

Table 2

Cumulative Market-Adjusted Returns following Analysts' Recommendation Revisions

This table presents the cumulative abnormal returns (in %) following recommendation revisions. We characterize each revision as an upgrade or a downgrade by comparing the revised recommendation with the previous active recommendation for the stock by the revising analyst. Within upgrades and downgrades, we further classify them into revisions that move towards the consensus and those that move away from it. Consensus is the average of all outstanding recommendations with at least two analysts following the stock as of the day before the revision, excluding the revising analyst. A revision is categorized as moving towards the consensus if the absolute value of deviation from consensus is larger for the new recommendation than for the old recommendation. The abnormal return is the raw return minus the CRSP value-weighted index return. Day 0 is the revision date and the other days in the column headings are the number of trading days from the revision date. The average returns reported in bold face are statistically significant at least at the five percent level (absolute value of t -statistics greater than 1.96). We use heteroskedasticity and serial correlation consistent standard errors to compute the t -statistics. The sample period is November 1993 to December 2005.

Recommendation Revision		Number of Observations	Number of Trading Days					
			0	1	2	21	42	126
Upgrades	All	23,785	2.03	2.33	2.40	3.34	3.72	4.85
	towards consensus	11,211	1.88	2.19	2.25	3.34	3.87	5.06
	away from consensus	12,108	2.14	2.42	2.50	3.34	3.59	4.78
	towards – away from		-0.26	-0.23	-0.25	0.00	0.28	0.27
Downgrades	All	25,470	-3.14	-3.33	-3.38	-3.78	-3.71	-3.45
	towards consensus	11,096	-2.31	-2.49	-2.61	-2.84	-2.89	-2.61
	away from consensus	13,855	-3.84	-4.03	-4.04	-4.54	-4.32	-3.98
	towards – away from		1.54	1.54	1.43	1.70	1.43	1.36

Table 3

Regressions Testing for Herding

This table reports the estimates of the following regression:

$$ABR_i(t, t + H) = a_H + b_H \times I + c_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) + \varepsilon_{i,j,t,H},$$

where t is the forecast revision date, $ABR_i(t, t + H)$ is the H -period abnormal return following the revision date, I is the indicator variable for upgrades ($I = +1$) and downgrades ($I = -1$), $New_rec_{i,j,t}$ is the revised individual recommendation on date t and $Con_rec_{i,t-1}$ is the consensus recommendation the day before the revision, excluding the revising analyst's recommendation. We estimate the regression coefficients and the standard errors using quarterly Fama-MacBeth regressions. The sample period is November 1993 to December 2005.

Dependent Variable: Cumulative Return	Explanatory Variables							
	N	I (=1 if up, -1 if down)		deviation from consensus		constant		R ²
Days since Revision		coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	
0	49,255	2.05	14.579	0.75	9.151	-0.45	-5.566	0.110
1	49,253	2.30	14.565	0.73	9.261	-0.41	-4.800	0.105
2	49,246	2.39	14.669	0.70	9.504	-0.41	-4.472	0.099
21	48,973	3.07	15.729	0.69	6.028	-0.08	-0.297	0.053
42	48,584	3.31	15.729	0.70	4.213	0.10	0.237	0.036
126	46,418	3.65	8.640	0.88	2.377	0.26	0.282	0.018

Table 4

Regressions Testing for Herding: Upgrades vs. Downgrades

This table reports the estimates of the following regression:

$$ABR_i(t, t + H) = a_H + b_H \times I + c_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) + d_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) \times downgrade_dummy_{i,j,t} + \varepsilon_{i,j,t,H}$$

where t is the forecast revision date, $ABR_i(t, t + H)$ is the H -period abnormal return following the revision date, I is the indicator variable for upgrades ($I = +1$) and downgrades ($I = -1$), $New_rec_{i,j,t}$ is the revised individual recommendation on date t , $Con_rec_{i,t-1}$ is the consensus recommendation the day before the revision excluding the revising analyst's recommendation, and $downgrade_dummy_{i,j,t}$ equals 1 for downgrades and 0 for upgrades. We estimate the regression coefficients and the standard errors using quarterly Fama-MacBeth regressions. The sample period is November 1993 to December 2005.

Dependent Variable: Cumulative Return	Explanatory Variables									
	N	I (=1 if up, -1 if down)		deviation from consensus		deviation*dummy for downgrades		constant		R ²
Days since Revision		coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	
0	49,255	2.05	14.535	0.27	4.551	0.90	5.972	-0.22	-3.738	0.113
1	49,253	2.30	14.535	0.24	3.371	0.91	5.924	-0.17	-2.706	0.107
2	49,246	2.39	14.628	0.27	3.444	0.79	4.933	-0.21	-2.820	0.101
21	48,973	3.08	15.568	0.17	1.064	0.99	3.868	0.17	0.655	0.055
42	48,584	3.31	15.489	0.15	0.768	1.06	3.565	0.37	0.945	0.037
126	46,418	3.64	8.441	0.14	0.316	1.44	2.069	0.62	0.680	0.020

Table 5

Cross Sectional Variation in Herding

This table reports the estimates of the following cross sectional regression:

$$ABR_i(t, t+H) = a_H + b_H \times I + c_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) + d_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) \times char_dummy_{i,j,t} + e_H \times I \times char_dummy_{i,j,t} + \varepsilon_{i,j,t,H}$$

where t is the forecast revision date, $ABR_i(t, t+H)$ is the H -period abnormal return following the revision date, I is the indicator variable for upgrades ($I = +1$) and downgrades ($I = -1$), $New_rec_{i,j,t}$ is the revised individual recommendation on date t and $Con_rec_{i,t-1}$ is the consensus recommendation the day before the revision excluding the revising analyst's recommendation. The $char_dummy_{i,j,t}$ in Panel A equals 1 if the analyst has more than three years of experience, and zero otherwise; in Panel B it equals 1 if the number of analysts employed by the brokerage is one of the top 20 the previous year, and zero otherwise; in Panel C it equals 1 if the standard deviation of the consensus recommendation prior to the revision is greater than 0.75, which is the average dispersion in the sample. We obtain the regression estimates using quarterly Fama-MacBeth regressions. The sample period is November 1993 to December 2005.

Panel A: Analyst Experience

Dependent Variable: Cumulative Return	Explanatory Variables											
	N	I (=1 if up, -1 if down)		deviation from consensus		deviation* experience>3years		I* experience>3years		constant		R ²
Days since Revision		coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	
0	39,383	2.56	18.404	0.90	6.179	0.00	0.005	-0.19	-1.912	-0.56	-5.795	0.133
1	39,381	2.89	18.252	0.89	6.556	-0.03	-0.219	-0.22	-2.252	-0.51	-4.958	0.128
2	39,374	2.99	18.161	0.81	6.590	0.04	0.265	-0.22	-1.980	-0.51	-4.596	0.120
21	39,119	3.77	15.996	0.80	4.118	0.12	0.412	-0.35	-1.572	-0.13	-0.360	0.065
42	38,747	4.04	13.561	0.80	3.029	0.14	0.383	-0.39	-1.285	0.15	0.298	0.044
126	36,758	4.27	6.744	1.01	1.661	0.48	0.590	-0.68	-1.056	0.58	0.486	0.022

Table 5 — Continued

Panel B: Broker Size

Dependent Variable: Cumulative Return	Explanatory Variables											
	N	I (=1 if up, -1 if down)		deviation from consensus		deviation *top 20 broker		I*top 20 broker		constant		R ²
		coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	
Days since Revision												
0	49,255	1.74	13.009	0.56	7.288	0.37	2.893	0.60	6.406	-0.46	-5.767	0.116
1	49,253	2.01	13.068	0.56	6.481	0.31	2.239	0.58	5.369	-0.42	-5.028	0.110
2	49,246	2.10	13.005	0.53	6.373	0.31	2.260	0.57	5.050	-0.42	-4.650	0.104
21	48,973	2.78	11.981	0.60	3.904	0.14	0.581	0.58	2.765	-0.09	-0.330	0.056
42	48,584	3.04	10.535	0.55	2.231	0.19	0.595	0.51	1.629	0.08	0.211	0.039
126	46,418	3.78	7.806	0.48	0.965	0.60	0.901	-0.11	-0.184	0.22	0.242	0.021

Panel C: Pre-Revision Dispersion

Dependent Variable: Cumulative Return	Explanatory Variables											
	N	I (=1 if up, -1 if down)		deviation from consensus		deviation* large pre-revision dispersion		I*large pre- revision dispersion		constant		R ²
		coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	
Days since Revision												
0	49,255	2.13%	14.015	0.88%	9.587	-0.30%	-3.439	-0.19%	-2.114	-0.45%	-5.575	0.113
1	49,253	2.45%	13.622	0.82%	9.157	-0.21%	-2.042	-0.35%	-3.148	-0.41%	-4.804	0.108
2	49,246	2.55%	13.930	0.80%	9.090	-0.21%	-1.815	-0.38%	-3.176	-0.41%	-4.501	0.102
21	48,973	3.28%	14.065	0.75%	5.347	-0.14%	-1.005	-0.46%	-2.327	-0.08%	-0.291	0.055
42	48,584	3.40%	12.009	0.99%	4.534	-0.67%	-2.716	-0.20%	-0.610	0.10%	0.238	0.038
126	46,418	3.54%	6.831	1.53%	3.147	-1.45%	-2.715	0.21%	0.442	0.29%	0.318	0.021

Table 6

Robustness Checks

This table estimates average herding across multiple recommendation revisions for various sub-samples. Panel A excludes all revisions made within a window three days before and three days after the earnings announcement dates, panel B includes only those revisions that are made at least five days after the most recent revision made by a different analyst, and panel C excludes revisions that move across the consensus recommendation level. All specifications are based on quarterly Fama-MacBeth regressions where the coefficient and t-stats are based on time-series averages and standard errors and require at least two analysts with active recommendations before the revision. The sample period is November 1993 to December 2005.

Panel A: Exclude revisions made within a seven-day window around earnings announcement dates									
Dependent Variable:		Explanatory Variables							
Cumulative Return		I (=1 if up, -1 if down)		deviation from consensus		constant		R ²	
Days since Revision	N	coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat		
0	36,172	1.83	14.406	0.73	8.711	-0.46	-5.033	0.101	
1	36,170	2.07	14.153	0.70	8.491	-0.40	-4.243	0.096	
2	36,163	2.17	13.940	0.66	8.886	-0.41	-4.199	0.091	
21	35,920	2.83	14.535	0.67	4.594	-0.20	-0.801	0.047	
42	35,633	2.96	13.240	0.69	3.207	0.18	0.482	0.032	
126	34,086	3.39	7.784	0.84	2.013	0.30	0.329	0.018	

Panel B: Revisions made at least five days after the most recent revision by a different analyst									
0	34,022	2.11	14.746	0.70	7.746	-0.49	-4.963	0.116	
1	34,020	2.36	14.469	0.69	7.335	-0.44	-4.360	0.112	
2	34,017	2.45	14.825	0.68	8.522	-0.45	-4.092	0.106	
21	33,839	3.13	14.907	0.64	4.634	-0.02	-0.071	0.055	
42	33,561	3.29	14.963	0.61	2.876	0.22	0.500	0.037	
126	32,024	3.51	7.544	0.72	1.615	0.34	0.363	0.019	

Panel C: Exclude Revisions moving across the consensus recommendation level									
0	27,797	2.09	13.912	0.72	8.989	-0.55	-5.889	0.113	
1	27,797	2.37	14.210	0.69	8.929	-0.53	-5.300	0.109	
2	27,792	2.45	14.174	0.67	9.028	-0.53	-5.018	0.103	
21	27,621	3.16	16.128	0.66	5.652	-0.30	-1.102	0.057	
42	27,384	3.39	14.774	0.68	3.837	-0.13	-0.309	0.040	
126	26,146	3.74	8.522	0.80	1.986	0.27	0.291	0.021	

Table 7

Herding and Recommendation Levels

This table reports the estimates of the following cross sectional regression:

$$ABR_i(t, t + H) = a_H + b_H \times I + c_H \times (New_rec_{i,j,t} - Con_rec_{i,t-1}) + d_H \times Sell_StrongSell_{i,j,t} + e_H \times StrongBuy_{i,j,t} + \varepsilon_{i,j,t,H}$$

where t is the forecast revision date, $ABR_i(t, t + H)$ is the H -period abnormal return following the revision date, I is the indicator variable for upgrades ($I = +1$) and downgrades ($I = -1$), $New_rec_{i,j,t}$ is the revised individual recommendation on date t and $Con_rec_{i,t-1}$ is the consensus recommendation the day before the revision excluding the revising analyst's recommendation. $Sell_StrongSell_{i,j,t}$ is a dummy variable equal to 1 if the new recommendation is a sell or a strong sell and 0 otherwise, and $StrongBuy_{i,j,t}$ is a dummy variable equal to 1 if the new recommendation is a strong buy and 0 otherwise. We obtain the regression estimates using quarterly Fama-MacBeth regressions. The sample period is November 1993 to December 2005.

Dependent Variable: Cumulative Return	Explanatory Variables											
	N	I (=1 if up, -1 if down)		deviation from consensus		dummy for sell / strong sell		dummy for strong buy		constant		R ²
Days since Revision		coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	coeff. (%)	t-stat	
0	49,255	2.09%	14.451	0.86%	7.864	0.76%	2.107	-0.51%	-3.864	-0.35%	-5.030	0.113
1	49,253	2.34%	14.324	0.80%	7.619	0.42%	1.190	-0.40%	-2.933	-0.31%	-4.010	0.108
2	49,246	2.42%	14.132	0.75%	7.465	0.37%	1.075	-0.30%	-1.998	-0.33%	-4.010	0.102
21	48,973	3.10%	15.315	0.66%	4.299	-0.27%	-0.448	-0.27%	-0.662	-0.04%	-0.165	0.057
42	48,584	3.35%	15.294	0.76%	3.418	-0.20%	-0.248	-0.46%	-0.814	0.13%	0.321	0.040
126	46,418	3.92%	10.412	1.27%	2.118	-1.71%	-1.120	-1.88%	-1.458	0.58%	0.653	0.025