The Effect of Institutional Herding on Stock Prices:

The Differentiating Role of Credit Ratings

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Abstract

This paper investigates the impact of institutional herding on stock price formation conditioning on firm credit rating using 13F data from 1986 to 2019. In line with the current literature, we find the herding intensity is driven by past returns consistent with momentum trading; however, we also find that herding is more sensitive to past returns among low-credit quality stocks than high-credit quality stocks resulting in a market bifurcation. In terms of price impact, we find evidence of return continuations among low-credit quality stocks and price reversals among high-credit quality stocks, indicating that herds in non-investment grade equities enhance price discovery while herds in investment grade equities disrupt price discovery. One potential explanation is that investment grade stocks are widely followed, and herding activity, instead of helping the price discovery, leads to an overreaction. In contrast, non-investment grade stocks with smaller followings are likely to underreact due to information uncertainty, and herding behavior strengthens the information discovery. Finally, we show both momentum-triggered herding and non-momentum-triggered herding contribute to the price discovery among non-investment grade stocks.

Keywords: Institutional Investors, Herding, Credit Rating

JEL classification: G02, G11, G14, G20, G40

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1. Introduction

Herding has attracted tremendous interest from researchers, regulators, and market participants. Early studies such as Lakonishok et al. (1992), Grinblatt et al. (1995), and Wermers (1999) examine the herding behavior among pension funds and mutual funds in the equity markets and find weak evidence of this behavior. In contrast, Cai et al. (2019) find robust evidence of herding among institutional investors within the US corporate bond market. Despite these heterogeneous findings about herding among asset classes, the common belief is that institutional herding affects security prices and causes market fragility. However, the empirical evidence is mixed, with some studies concluding that institutional herding stabilizes prices (Nofsinger and Sias, 1999; Wermers, 1999; Sias, 2004; Yan, Zhao, and Sun, 2012), while other studies conclude that institutional herding destabilizes prices (Jiao and Ye, 2014; Brown et al., 2014; Dasgupta et al., 2011).

Despite the lack of consensus about the price impact, there is broad agreement that institutional investors employ positive feedback trading or momentum strategies by herding into past winners and simultaneously herding out of stocks that are past losers. For example, Grinblatt et al. (1995) find that the majority of mutual funds can be classified as momentum traders. Choi and Sias (2009) studied institutional herding at the industry level and confirmed the predominant role of momentum trading played.[1] In terms of momentum profitability, Jegadeesh and Titman (1993, 2001) document economically significant payoffs from momentum trading strategies and further research has shown momentum profits depend on the state of the market (Chordia and Shivakumar, 2002; Cooper, Gutierrez and Hameed, 2004). Adding to these findings, Zhang (2006) shows that greater information uncertainty results in higher momentum profits and Avramov et al. (2007) find that momentum profits are concentrated among firms with low-credit quality, which is in line with the gradual information diffusion model of Hong and Stein (1999) as credit rating may partly reflect a firm's overall

[1] Bikhchandani and Sharma (2001) and Spyrou (2013) provide a thorough review of institutional investor herding in financial markets.

information environment (Cheng and Subramanyam, 2008).

Since momentum investing plays a vital role in institutional herding and momentum profit varies conditional on a firm's credit rating, we, therefore, investigate institutional herding and its impact on stock price formation by differentiating the role of credit rating in this paper. Credit quality and, in particular, the distinction between investment and non-investment grade reflects information quality. Institutional investors, the majority of whom are momentum traders, benefit from an opaque information environment and profit from more gradual information discovery (Hong and Stein, 1999). We, therefore, hypothesize that institutional investors tend to exploit the momentum strategy to a greater extent when trading low-grade stocks, and the resulting herding in those stocks where information is noisy will, in turn facilitate price discovery. In contrast, for investment grade stocks, we hypothesize herding activity will lead to an overreaction consistent with information cascade models (Banerjee, 1992; Bikhchandani et al., 1992) as traders rush to react to new information and other institutional trades creating a cascade and thereby overshoot the underlying value of the security.

In our empirical analysis, we construct the conventional herding measure (LSV measure, Lakonishok et al., 1992) using the institutional holding database (13F) from Thomson Reuters. We further restrict the stocks to those with rating information from Compustat S&P Ratings database or S&P Credit Ratings from Capital IQ. For the average stock, we find a relatively low level of herding in trades by institutional investors in which the buying intensity is slightly lower than the selling intensity, which is consistent with the studies on equity market herding (Lakonishok et al., 1992; Wermers, 1999). The herding intensity for the entire sample is driven by a momentum trading strategy as there is an overall significant positive relationship between herding intensities and past stock performances. However, when exploring the herding of sub-samples partitioned by firm rating, we find that the impact of past returns is much more prominent in non-investment grade stocks. In other words, institutional investors are more likely to employ momentum-investment strategies among non-investment grade securities. Given our robust evidence of market bifurcation, we next investigate the price impact of institutional herding on security prices that are conditional on the firm rating.

Our most important contribution is analyzing the long-term effect on prices from institutional herding conditional on rating. Thus far, the evidence on the impact of herding on prices is mixed. Earlier studies such as Wermers (1999) and Sias (2004) find no evidence of price reversals after herding, which leads to the conclusion that herding speeds up the process of adjusting prices and improves market efficiency. However, recent papers have found significant price reversals when they extend the sample period (Brown et al., 2014; Dasgupta et al., 2011).[2] Using the 13F database from 1985 to 2019, we find on average that buy herding of stocks outperforms sell herding in the next quarter but is then followed by a significant price reversal, which suggests market inefficiency. However, when we distinguish the effect of herding on prices by credit rating, we find that the price reversal only occurs among investment grade stocks. In contrast, we observe a lasting price continuation for non-investment grade stocks. This result supports our underlying hypothesis that herding strengthens the price discovery among non-investment grade stocks and is consistent with the gradual information diffusion model of Hong and Stein (1999), where herding behavior can facilitate price discovery, mainly when information is noisy or highly uncertain as in the case of low credit-quality securities (Cheng and Subramanyam, 2008).

In a further examination of buy-side herding and sell-side herding, we find the market stabilization effect of herding in non-investment grade stocks comes from the sell side. That is, non-investment grade stocks with the lowest intensity of sell herding outperform those with the highest intensity of sell herding, and this positive spread lasts for four quarters. For the buy side, we find a weak return reversal. This finding is consistent with the fact that the short leg accounts for a substantial proportion of momentum profits in low-grade stocks (Avramov et al., 2013). Our findings show that institutional herding is not a key source of fragility but helps facilitate price discovery, particularly among poorly performing non-investment grade securities.

[2] Brown et al. (2014) find that the sell herding of mutual funds following analysts' downward revisions leads to subsequent reversals.

Empirically it is difficult to distinguish the motivation for institutional investors to herd. The empirical identification of herding behavior obfuscates the source of the price impact as herding is not necessarily driven by past returns but can also be motivated by other factors such as informational cascades (Banerjee, 1992; Bikhchandani et al., 1992), reputation-based motives (Scharfstein and Stein 1990; Trueman 1994; Graham, 1999), fads (Barberis and Shleifer, 2003), or investigative trading (Froot et al., 1992; Hirshleifer et al., 1994). To separate pure momentum-triggered herding from non-momentum-triggered herding, we disentangle momentum trading from institutional herding. We find that both the momentum-triggered herding and non-momentum-triggered herding play a role in speeding the price discovery for non-investment grade securities. Thus, we conclude that herding behaviors among low-grade stocks may also be related to other factors that contribute to price discovery, such as investigative herding. One potential explanation for market bifurcation is that investment grade stocks are widely followed, and herding activity, instead of helping the price discovery, leads to an overreaction. In contrast, non-investment grade stocks with smaller followings are likely to underreact due to information uncertainty, and the resulting herding behavior helps information discovery.

We also explore institutional herding by type. Based on the type code provided by Brian Bushee, we classify the institutions into three types: banks, insurance companies, and investment companies/advisors.[3] The herding intensity is lowest for insurance companies. Most importantly, we find that only the herding of investment companies/advisors in non-investment grade stocks plays a role in speeding up the process of adjusting prices. Specifically, we observe permanent stock price adjustments following the herding behavior of investment companies/advisors in non-investment grade equities, which is not present for banks and insurance companies. This result highlights the critical role of investment companies/advisors in price discovery for these difficult-to-value securities, suggesting their herding behavior is

[3] For more details about the classification methods, please refer to the website of Brian Bushee at https://accounting-faculty.wharton.upenn.edu/bushee/.

primarily motivated by investigative herding.

The rest of the paper is organized as follows. Section 2 expands upon the literature. Section 3 discusses the institutional holding database (13F), S&P firm rating database, and the conventional construction of herding measures. We study the relationship between herding and momentum trading that is conditional on firm ratings in Section 4. In Section 5, we assess the price effects of institutional herding. We conclude the paper in Section 6.

2. Related Literature

Several studies have proposed theories to explain why institutional investors might trade together and how this behavior might affect market efficiency. For example, when herding is triggered by informational cascades (Banerjee, 1992; Bikhchandani et al., 1992), reputation-based motives (Scharfstein and Stein 1990; Trueman 1994; Graham, 1999), or simply fads (Barberis and Shleifer, 2003), then herding weakens information collection and promotes market inefficiency. On the other hand, if institutional herding is investigative, it can speed up the incorporation of information and facilitate price discovery (Froot et al., 1992; Hirshleifer et al., 1994). Therefore, the effect of institutional herding on stock prices is an empirical question as theory predicts both efficient and inefficient price responses. While price continuations indicate an efficient response, price reversals are taken as an inefficient response.

Empirical studies cannot differentiate these theories of herding behavior due to data limitations and instead observe the tendency of institutional trades to cluster regardless of the underlying reason.[4] The consensus is that institutional investors' trades are correlated to past price movements (Lakonishok et al., 1992; Grinblatt et al., 1995; Nofsinger and Sias, 1999; Wermers, 1999; Cai et al., 2019). Grinblatt et al. (1995), for example, find that 77 percent of

[4] While empirical evidence clearly shows herding behavior among institutional investors, whether such behavior is intentional or spurious is hard to disentangle. Holmes, Kallinterakis, and Ferreira (2013) provide evidence that institutional herding is intentional by using a unique dataset on monthly holding of individual funds. Specifically, they find herding behavior is stronger in the second month of each quarter and conclude reputational considerations drive the herding behavior, a result that is also consistent with the window dressing explanations offered by Lakonishok, Shleifer, Thaler, and Vishny (1991).

the mutual funds are "momentum investors" with a predominant strategy of buying past winners over selling past losers. Wermers (1999) further shows that herding levels are higher for portfolios with significant positive or negative returns in the prior quarter. Specifically, for extreme buying portfolios, the size-adjusted return of the preceding quarter is 4.22% and is highly significant. In contrast, the previous quarter's return for extreme selling portfolios is marginally positive but significantly negative during the formation quarter. These studies suggest institutional investors engage in herding behavior consistent with momentum-investment strategies.

Whether momentum-investment strategies enhance market efficiency depends on how information is transmitted among investors. Suppose information is gradually revealed through trading activity. In that case, active traders learn, and prices adjust upwards to buying pressure and downwards to selling pressure, thereby inducing the expected result where winners continue to outperform and losers continue to underperform. The basis for the slow diffusion of information varies in the literature. [5] Still, regardless of the cause, the resulting herding can induce a price response that speeds up the discovery of knowledge and facilitate price discovery. Hong and Stein (1999) explicitly model the gradual diffusion of information. In their model, informed traders receive a noisy signal, which becomes more apparent as they observe other knowledgeable traders' trades. Momentum traders can mimic the crowd's behavior and capture momentum profits. The outcome is slow dissemination of information as the market discovers the asset's fundamental value. A key prediction of this gradual information diffusion model is that the slower the flow of information, the more sustainable the momentum profits. Consistent with this prediction, Hong et al. (2000) test the gradual diffusion model and find momentum profitability is limited to the smallest stocks with low analyst coverage suggesting that when information is difficult to interpret, it may take time for the market to learn the fundamental value. Jiang, Lee, and Zhang (2005) also document higher momentum profits among small,

[5] In the case of Froot et al. (1992) market frictions cause the gradual diffusion of information; while in Hirshleifer et al. (1994) differences in the speed of discovery allow early informed traders to profit at the expense of late informed traders.

young firms. Furthermore, Avramov et al. (2007) find that momentum profits are concentrated among low-grade firms, which are generally associated with poor information quality as they tend to be followed by fewer analysts (Cheng and Subramanyam, 2008).

By differentiating by credit quality, we are probing the role of institutional traders in price discovery by examining two groups of stocks where the information environments are substantially different. We hypothesize that institutional herding in low-grade stocks where information is noisy will facilitate price discovery as traders slowly discover the underlying value of the security by observing other institutional traders' trades. In contrast, for investment grade stocks, we hypothesize herding activity will lead to an overreaction consistent with information cascade models (Banerjee, 1992; Bikhchandani et al., 1992) as traders rush to react to new information and other institutional trades creating a cascade and thereby overshoot the underlying value of the security.

3. Data

3.1 Credit Rating

The S&P issuer ratings used in this paper are an essential component of our analysis and are extracted from two sources: Compustat S&P Ratings database and S&P Credit Ratings from Capital IQ. The first database was discontinued in February 2017, while the latter is still available. The rating variable we use from Compustat S&P Ratings is *splticrm*, which reflects the agent's opinion of the issuer's overall creditworthiness, apart from its ability to repay individual debt obligations. Meanwhile, S&P Credit Ratings database directly provides entity ratings (the variable name is *ratingsymbol*). Most firms covered in both databases share the same rating, and if it is not, we opt for *splticrm*. For the period from March 2017 to December 2019, we use the entity ratings. We extract the rating information from December 1985 to December 2019 and merge the firm ratings with the stock data from the Center for Research in Security Prices (CRSP) monthly tapes for all NYSE, AMEX, and NASDAQ stocks.

3.2 The Institutional Holdings Database (13F)

We use Thomson Reuters' institutional holdings database (13F or s34) to construct our sample. While previous studies use their mutual fund holdings (s12) to study the herding in mutual funds, the Thomson Reuters' institutional holdings database is more complete as it includes banks, insurance companies, parents of mutual funds, pension funds, university endowments, and numerous other types of professional investment advisors. 13F provides quarter-end filings of portfolio holdings for all institutions identified by *mgrno*. From 1980 to 2019, the total number of institutions has increased from about 500 to more than 5000, which is mainly driven by the rapid growth of independent investment advisors.[6]

3.3 Measurement of Institutional Herding

Following Lakonishok et al. (1992), Wermers (1999), and Brown et al. (2014), $HM_{i,q}$ is the measure of herding by institutions into (or out of) stock *i* during quarter *q* that is expressed as:

$$HM_{i,q} = \left|p_{i,q} - \mathrm{E}\left[p_{i,q}\right]\right| - \mathrm{E}\left|p_{i,q} - \mathrm{E}\left[p_{i,q}\right]\right|, \tag{1}$$

where $p_{i,q}$ is the proportion of institutions that trade stock *i* during quarter *q* that are buyers. For a given institution *j* that holds stock *i*, if the holding at the end of quarter *q* is larger than the holding in the previous quarter, it is classified as an institutional buyer.[7] $\mathrm{E}\left[p_{i,q}\right]$ is the proportion of all stock trades by institutions that are purchased during quarter *q*. Thus, this measure stays constant across all stocks during a given quarter and measures the market-wide intensity of buying. $\mathrm{E}\left|p_{i,q} - \mathrm{E}\left[p_{i,q}\right]\right|$ is a factor that adjusts for random fluctuations in the expected proportion of buyers (Wermers, 1999). Under the null hypothesis of no herding, the number of purchases for stock *i* follows a binomial distribution with a probability $\mathrm{E}\left[p_{i,q}\right]$ of

[6] The 13F database uses TYPECODE to classify institutional managers into five types. However, this classification is wrong starting from 1997:Q4 and beyond due to a mapping error by Thomson that improperly classifies institutions in the first four categories (mainly TYPECODE=4, i.e. independent investment advisors) into group 5 (Others). Thus, in the following analysis by investor type, we use the classification data from Professor Brian Bushee. For more details about the mapping error, see Gompers and Metrick (2001).

[7] Thus, $p_{i,q} = \frac{No.\ of\ institutions\ buying_{i,q}}{No.\ of\ institutions\ buying_{i,q} + No.\ of\ institutions\ selling_{i,q}}$。

success. Given $\mathrm{E}[p_{i,q}]$ and the number of managers active in stock *i* (total buys plus sells), this adjustment factor can be easily computed.

To further distinguish between buy and sell herding by institutions, we follow Wermers (1999) and define the following two measures:

$$BHM_{i,q} = HM_{i,q} \mid p_{i,q} > E[p_{i,q}], \tag{2}$$

$$SHM_{i,q} = HM_{i,q} \mid p_{i,q} < E[p_{i,q}], \tag{3}$$

the "buy (sell) herding measure", $BHM_{i,q}$ ($SHM_{i,q}$) is a conditional herding measure that measures stocks with a higher (lower) proportion of buyers than the average stock during the same quarter.[8] These two measures help analyze herding into stocks separately from herding out of stocks by institutions.

Finally, we introduce an "adjusted herding measure" ($ADJHM_{i,q}$). The adjusted herding measure is used to capture the case where the direction of herding changes from one period to another for a specific stock, which allows us to combine the buy herding and sell herding samples for further analysis. Following Brown et al. (2014), we define the adjusted herding measure as:

$$ADJHM_{i,q} = \begin{cases} BHM_{i,q} - Min_{j \in Buy}\{BHM_{j,q}\} & \text{for buy herding} \\ Min_{j \in Sell}\{SHM_{j,q}\} - SHM_{i,q} & \text{for sell herding} \end{cases} \tag{4}$$

Thus, a higher positive (negative) value of $ADJHM_{i,q}$ indicates that stock *i* was heavily bought (sold) by herds of institutions during quarter *q*.

The final rated sample with herding measures includes 126,685 stock-quarter observations from 1985Q4 to 2019Q4, in a total amount of 137 quarters. We separate stocks into IG and NIG to disentangle our research question.

[8] The adjustment factor is recalculated conditioned on $p_{i,q} > \mathrm{E}[p_{i,q}]$ or on $p_{i,q} < \mathrm{E}[p_{i,q}]$ for $BHM_{i,q}$ and $SHM_{i,q}$, respectively, again under the null hypothesis of independent trading decisions by institutions.

4. Institutional Herding

4.1 Levels of Herding

Panel A of Table 1 presents the summary statistics for herding measures at three different hurdle rates: a minimum of five institutional trades, 25 institutional trades, and 50 institutional trades. *BHM* and *SHM* show little variations and are close to 2.45% and 3.05%, respectively, indicating that institutional investors herd more strongly on the sell side. The numbers are slightly lower than those reported by Wermers (1999), which is 2.98% for *BHM* and 3.70% for *SHM*.[9] However, they are not directly comparable as we use a broader institutional holding database than the mutual fund holding database. Nevertheless, we can still conclude that the herding levels are low in the equity market.

Next, we compute the herding measures conditional on firm ratings. Specifically, we divide our sample into investment grade (IG) and non-investment grade (NIG) firms and report the statistics of herding measures. For stocks issued by IG firms, sell herding is more prevalent than buy herding by 1.12% with a minimum of 25 trades. On the contrary, *BHM* and *SHM* are on the same scale among NIG stocks. This initial result suggests substantial differences in the herding behavior in IG and NIG equities.

In Panel B, we study the herding levels for different types of institutions. We find similar differences in herding by credit quality, with sell herding generally dominating buy herding for IG equities and a more equitable distribution among NIG securities. Like Sias (2004), banks and investment companies/advisors show a greater tendency to herd, while the herding among insurance companies is moderate.

[Insert Table 1 Here]

4.2 Institutional Herding and Momentum Trading

In this subsection, we investigate the factors driving institutional herding, focusing on

[9] Wermers (1999) imposes a hurdle rate of five trades per stock-quarter.

isolating the momentum effects identified through lagged returns. Avramov et al. (2007) show that momentum profits are dominated by NIG firms. We, therefore, hypothesize that momentum trading will play a bigger role in herding among NIG stocks. To empirically test this, we include the past performance of stocks. Empirical studies on stock herding suggest that past performance affects investors' trading behavior due to the positive feedback strategy (Wermers, 1999). Specifically, investors tend to buy stocks that perform well and tend to sell stocks that perform poorly (momentum trading).

Following the literature, we also include variables and stock characteristics, which are potentially associated with herding. Specifically, we include the herding level in the prior quarter. The variable is used to examine the persistence of herding (Cai et al., 2019). Cai et al. (2019) also report that past rating changes affect the herding in corporate bonds. Thus, we test if this effect exists in the stock market by incorporating dummies that indicate past upgrades or downgrades. We also add firm size as Lakonishok et al. (1992) document higher herding levels among small stocks. We then estimate the following model using the Fama-MacBeth (1973) approach with the Newey-West (1987) standard errors with three lags.

$$\begin{aligned} ADJHM_{i,q} \ &= \beta_0 + \beta_1 Ret_{i,q-1} + \beta_2 CumRet_{i,q-5,q-2} + \beta_3 ADJHM_{i,q-1} + \beta_4 LnSize_{i,q-1} \\ &\quad + \beta_5 Upgrade_{i,q-1} + \beta_6 Downgrade_{i,q-1} + \epsilon_{i,q}, \end{aligned} \tag{5}$$

where the dependent variable is the adjusted herding measure of stock i in quarter q, $Ret_{i,q\text{-}1}$ is the lagged raw return of stock i. $CumRet_{i,q\text{-}5,q\text{-}2}$ is the cumulative returns during quarters q–5 to q–2. $LnSize_{i,q\text{-}1}$ is the lagged logarithm of stock i's market capitalization, and $Upgrade_{i,q\text{-}1}$ ($Downgrade_{i,q\text{-}1}$) is a dummy variable that equals one if stock i's rating is upgraded (downgraded) in the prior quarter and zero otherwise.

[Insert Table 2 Here]

Table 2 presents the regression results for equation (5). In column 1, the estimated coefficients on *Ret* and *CumRet* are significantly positive, indicating that institutional investors' buying activities are induced by the stocks' past outperformance, and selling activities are associated with past underperformance, which is consistent with the positive feedback strategy. Comparing the coefficients, we find that the performance in the most recent quarter is more important in determining the herding levels. Moreover, we find strong evidence of persistence of herding, as indicated by the significant positive coefficient on lagged *ADJHM*. Changes in rating also appear to be a substantial catalyst for herding activity and are consistent with the information-based theories of herding behavior, suggesting institutional trades tend to cluster around information events. Specifically, the coefficients on rating upgrade and downgrade dummies have opposite signs, and both are significant, indicating that institutional investors herd to buy stocks with a rating just upgraded and herd to sell stocks with a rating downgraded.

In column 2 of Table 2, we further consider whether there is a linear relationship between herding and past performance. Specifically, we split *Ret* into two variables indicating large and small past returns, respectively: *Large Ret* and *Small Ret*. The variable *Large Ret* (*Small Ret*) takes the value of *Ret* when the returns are at least (less than) one standard deviation above or below the cross-sectional mean and 0 otherwise. To facilitate the comparison across the coefficients, we standardize these two variables to have a mean of zero and a standard deviation of one. Results suggest that the sensitivity of institutional herding to past extreme performance is indeed larger, which is consistent with Wermers (1999).

Will the sensitivity of herding to past returns be the same for both positive and negative returns? We answer this question in column 3 of Table 2, where we define *Positive Ret* (*Negative Ret*), which is the raw return in the prior quarter if it is larger (smaller) than zero, and zero otherwise. We also standardize these two variables for ease of comparison. Results show that herding is more evident following negative past returns. This asymmetry suggests that institutional investors may also herd due to reputational concerns: unskilled managers tend to mimic the behaviors of skilled managers when markets fall to obscure their incompetence and attribute the bad performance to adverse market conditions.

Brown et al. (2014) find strong evidence that mutual funds herding in the same direction as prior-quarter analyst recommendation revisions and earnings surprises. To control for this possible herding-information link and the possibility that institutional investors may herd in response to earnings news, we add standardized unexpected earnings (*SUE*) and analyst recommendation revisions (*Revision*) in column 4.[10] Controlling for *SUE* and *Revision*, stocks' past performance continues to be an important determinant of institutional herding.

Next, we split the full sample into IG subsample and NIG subsample and explore whether their herding response to past performance is different. Consistent with the overall estimates of the full sample, the coefficients on past returns are positive and statistically significant for both the IG and NIG stocks. However, the magnitude of the coefficients for IG stocks is much smaller than those for NIG stocks. For example, column 5 shows that a 1% increase in the past quarter's return leads to a 0.051% increase in herding for IG stocks, while column 9 shows that a 1% increase in the past quarter's abnormal return leads to a 0.088% increase in herding for NIG stocks. Thus, herding among NIG stocks is more sensitive to past performance. Consequently, we should expect herding among IG and NIG stocks to have different price impacts as momentum only exists in low-grade stocks (Avramov et al., 2007, 2013).

In summary, the results show that institutional investors do herd, that their herding behavior is influenced by past returns consistent with momentum investment strategies, and that more extreme returns result in higher levels of herding. Distinguishing between investment grade and non-investment grade securities, institutional traders do appear to be more proactive to past returns for non-investment grade securities. In addition to the positive feedback mechanism, herding is also closely related to information events such as earnings announcements and changes in analyst recommendations suggesting trades tend to cluster around these events as traders use the crowd to discover the security's fundamental value potentially. These results are similar when the sample is divided into investment and non-

[10] *SUE* is retrieved from I/B/E/S Summary History, which is the number of standard deviations the actual (reported) earnings that differ from the I/B/E/S surprise mean estimates for a company for the fiscal period indicated. *Revision* is obtained from I/B/E/S Recommendations. We reverse the standard five-point scale of I/B/E/S recommendations so that an increased value indicates an upgrade (i.e., 1=Sell, 2=Underperform, 3=Hold, 4=Buy, 5=Strong Buy). *Revision* is the change in quarter-end consensus recommendations.

investment grades.

5. The Effect of Herding on Stock Prices

5.1 The Effect of Herding by Firm Credit Ratings on Prices

The post-herding price dynamics are fundamental for us to understand the impact of institutional herding on market efficiency. The strong price reversals documented in the recent literature (Brown et al., 2014; Dasgupta et al., 2011) indicate that institutional herding destabilizes stock prices. In contrast, early studies conclude that herding helps discover and stabilize prices (Wermers, 1999; Sias, 2004). In this section, we further investigate the impact of the effect of herding on prices that is conditional on credit rating. To explore this issue, we conduct the standard portfolio approach to analyze the relation between herding and past returns, contemporaneous returns, and future returns. The dynamics of past returns help us determine how herding is related to the positive feedback strategy. Those future returns help us determine whether observed herding stabilizes or destabilizes stock prices. By definition, stabilization means that herding conveys valuable private signals about firms' prospects and permanently affects prices. In contrast, destabilization indicates herding contains no relevant information but temporarily shifts the demand for the stock and hence produces short-term changes in stock prices followed by reversals. Recognizing that momentum profits are concentrated in worst-rated firms (Avramov et al., 2007, 2013), we hypothesize that herding among NIG stocks will stabilize stock prices while herding among IG stocks will not.

The standard portfolio procedure is as follows: At each quarter-end q, we sort sample into decile portfolios by *ADJHM*. Thus, P10 (P1) consists of stocks with the highest buy (sell) herding intensities. Then we construct a zero-investment portfolio P10-P1 and compute the equally weighted characteristic-adjusted abnormal returns of Daniel et al. (1997) from quarter q-2 to quarter q+4.[11]

[11] Institutional trading often has a longer-term impact on stock prices (see, e.g., Chan and Lakonishok 1995; Dasgupta et al. 2011)

[Insert Table 3]

Table 3 reports the results of portfolio sorts. Consistent with the positive feedback strategy, we find that the stock returns are related to the direction of the herding in stocks during the formation quarter and the two quarters before the formation quarter for both IG and NIG stock portfolios.[12] The performance difference between P10 and P1 is more dramatic among NIG stocks. For example, in the NIG subsample, the return spreads in quarters q-2, q-1, and q are 9.36%, 15.15%, and 15.79%, while in the IG subsample, the corresponding return spreads are only 1.80%, 3.27%, and 4.49%. This finding is consistent with Section 4.2 where we empirically show that a positive feedback strategy (momentum trading) plays a more critical role in herding among NIG stocks.

Using mutual fund holding data, Wermers (1999) shows that the intensity of herding is a strong predictor of future stock returns. Specifically, a heavy buy portfolio outperforms a heavy sell portfolio by 2.29% in the subsequent quarter with a t-value greater than 4.70. The significant return spread lasts for two quarters, then becomes insignificant but remains positive. However, using the institutional holding data from 1985 to 2019, we find that the return predictability of the herding intensity only exists for the following quarter. Specifically, stocks heavily bought (P10) by herds outperform stocks heavily sold (P1) by 1.24% in quarter q+1, and in the subsequent three quarters, P10 underperforms P1 by about 48-70 basis points.

We further inspect the return predictability conditional on the credit rating, and an interesting pattern emerges. The short-term return predictability is concentrated in stocks issued by firms with poor credit ratings. Specifically, NIG stocks with the highest intensity of buy herding (P10) significantly outperform NIG stocks with the highest intensity of sell herding (P1) by 2.73% in quarter q+1. Although less significant, P10 continues to outperform P1 for at least three quarters. As we discussed earlier, the observed return dynamics indicate that NIG

[12] We use the rating information of the formation quarter to divide the sample into IG and NIG subsamples. For a given stock, we assume it stays either in IG or NIG from quarter q-2 to quarter q+4. Results are qualitatively similar if we consider the rating transitions (i.e., IG to NIG, and NIG to IG) and update the stocks in the portfolio accordingly.

herding helps stabilizes stock prices. For IG stocks, we find no evidence of price continuation but see significant return reversals in quarters q+2 and q+4 and therefore conclude that IG herding is associated with stock market destabilization.

We also examine whether our findings are robust to the state of the market. Past studies have shown that momentum profits are concentrated in the periods following up markets (Cooper, Gutierrez, and Hameed; 2004) or significant when the investor sentiment is high (Antoniou, Doukas, and Subrahmanyam; 2013). In our analysis, we define an up or bull market if the cumulative CRSP VW index return in the past 24 months is positive (Daniel and Moskowitz, 2016). We find that for NIG stocks, the P10-P1 return spread in quarter q+1 is 2.98% (t-value=4.18) when the formation quarter is in a bull market, compared with 1.08% (t-value=0.55) when the formation quarter is in a bear market.[13] Next, we explore the effect of investor sentiment. The high and low sentiment periods are defined based on the median value of the sentiment index of Baker and Wurgler (2006). For NIG stocks, if the quarter before the formation quarter is associated with the low sentiment, the P10-P1 return spread in quarter q+1 is 2.25% (t-value=2.11), compared with 3.50% (t-value=4.09) if the herding quarter is after high sentiment period. For the IG stocks, the P10-P1 return spreads are -0.28% (t-value=-0.73) and -0.00% (t-value=0.15), for herding quarter that follows low and high sentiment periods, respectively. Therefore, our findings are more pronounced for periods when momentum profits are significant, such as bull markets or periods with high investor sentiment.

Overall, we find significant asymmetry between NIG and IG herding in terms of price dynamics around herding. On the NIG side, herding facilitates price discovery. On the IG side, herding destabilizes stock prices. Our results are consistent with the slow information diffusion model of Hong and Stein (1999), which suggests that momentum investment strategies help facilitate price discovery when information is noisy and, therefore, difficult to interpret.

5.2 Multivariate Test for Investment Herding

[13] Full results are available upon request.

Besides momentum-investment strategies, other factors might influence the relation between herding and stock returns. Thus, in this subsection, we further assess the robustness of the return predictability of herding in a multivariate setting. Specifically, we estimate the following model using the Fama-MacBeth (1973) regression (FM-OLS):

$$DGTW_{i,q+1} = \beta_0 + \beta_{NIG} NIG_{i,q} ADJHM_{i,q} + \beta_{IG}\left(1 - NIG_{i,q}\right) ADJHM_{i,q} + \delta_q' \boldsymbol{X_{i,q}} + \epsilon_{i,q+1}, \quad (6)$$

where $DGTW_{i,q+1}$ is the Daniel et al. (1997) characteristic-adjusted abnormal return for stock *i* during quarter $q+1$, $NIG_{i,q}$ is a dummy variable that equals one if stock *i* falls into the NIG group in quarter q, $ADJHM_{i,q}$ is the adjusted herding measure during quarter q, $\boldsymbol{X_{i,q}}$ is a vector of stock characteristic variables including the logarithm of market capitalization and book to market ratio, stock returns during the current quarter and prior four quarters. We also incorporate two variables (financial analyst following and forecast dispersion) used in Zhang (2006) to control for the information environment.[14] The coefficients of interest are β_{NIG} and β_{IG}, which reflect the effects of NIG and IG herding on prices, respectively. The *t*-statistics are calculated using the Newey-West (1987) method with a lag order of three to account for the effect of overlapping data.

The first column of Table 4 shows that the adjusted herding can successfully predict future returns for the next quarter. Controlling for the information environment, results in the second column suggest that adjusted herding continues to show marginal predictability. Furthermore, both information uncertainty variables, *Dispersion* and *Cov,* are statistically significant showing that increased information uncertainty predicts lower future returns. In the next column, we separate the impact of institutional herding for IG and NIG securities. The insignificant β_{IG} suggests that IG herding fails to predict future returns. In contrast, we find NIG herding significantly and positively predicts future stock returns even after controlling for the information uncertainty variables used in Zhang (2006). We therefore conclude that the

[14] *Dispersion* is the standard deviation in analysts' EPS forecasts standardized by the absolute value of the consensus forecast. *Cov* is the natural logarithm of the number of analysts following. These two measures are from the IBES summary database.

credit rating effect (i.e., the return predictability associated with herding for NIG stocks) is robust to controlling for other information uncertainty variables and credit rating has information beyond information uncertainty, such as default risk, or distress risk as argued by Avramov et al. (2007, 2013).

The predictability of NIG herding may be due to NIG stocks being smaller stocks. To address this concern, we run Fama-MacBeth regression with the weighted least squares method (FM-WLS) that uses firm market capitalization as the weights. Results in the last two columns show that our results are robust to firm size.[15]

[Insert Table 4]

The preceding analysis shows that the predictive power of herding for future returns is concentrated in the NIG herding, which is consistent with the portfolio sort results reported in Table 3 and robust to controlling for conventional cross-sectional effects. In other words, this result helps validate our previous result showing that institutional traders facilitate price discovery for NIG stocks by showing that the herd gets it right by correctly identifying the winners and losers in the noisy information environment of NIG stocks.

5.3 The Effect of Herding by Investor Types on Prices

In this subsection, we investigate the price impact of herding by investor types. Different institutional investors have different investment focuses, objectives, and strategies, so they may exhibit different herd behaviors. We divide institutional investors into banks, insurance companies, and investment companies/advisors and examine the price impact of their herding behaviors. The results are reported in Table 5.

[Insert Table 5]

Panel A shows the price impact of herding from banks. All return spreads are positive during formation and pre-formation quarters, consistent with the positive feedback strategy.

[15] We exclude *LnSize* from the model as it is used as the weight in the model.

However, we observe evidence of return reversals for the full sample and IG stocks. For the NIG sample, the return reversal is insignificant but larger in magnitude compared with the IG sample. Panel B presents the results for insurance herding, which are qualitatively similar.

In the last panel of Table 5, we explore the price impact of herding among investment companies/advisors. Their herding among IG stocks overall has little effect on future prices in quarter q+1, but there is a significant reversal in quarter q+4. In contrast, NIG investment herding leads to a significant positive return in quarter q+1. The significant price continuation lasts for three quarters, indicating that NIG investment herding facilities the stabilization of stock markets.

In summary, this section shows that the herding by banks, insurance companies, and investment companies/advisors is positively associated with past, and contemporaneous returns but has different effects on future returns. Specifically, investment companies' and advisors' herding of low-grade stocks tends to stabilize stock prices, while other herding generally tends to destabilize stock prices.

5.4 Sell-side Herding vs. Buy-side Herding

Avramov et al. (2013) document that the short leg dominates the momentum payoffs on a risk-adjusted basis. Recognizing this finding, we thus hypothesize that the stabilization effect associated with institutional herding comes from the sell side rather than the buy side.

To empirically test this hypothesis and disentangle the return dynamics around sell herding from buy herding, each quarter, we sort stocks into two sets of quintile portfolios: B1-B5 and S1-S5, where the ranking variables are *BHM* and *SHM*, respectively. Portfolios B1 and B5 include stocks with the lowest and highest buy herding levels, respectively, and portfolios S1 and S5 include stocks with the lowest and highest sell herding levels. Next, we construct two hedge portfolios: B5-B1 and S1-S5, and examine the equally weighted quarterly DGTW-adjusted returns before, during, and after the portfolio formation quarter. Table 6 presents the results.

Panel A of Table 6 reports quarterly abnormal returns on portfolio B5-B1 for all stocks, high-grade stocks, and low-grade stocks. For all three groups, we observe that a higher level of buy herding is associated with higher past abnormal returns, which is consistent with the positive feedback trading strategy. In terms of post-herding price dynamics, there is weak evidence that the price continuation for the full sample is driven by the NIG group, but this weak effect reverses in the subsequent three quarters. For the IG group, we observe return reversals starting in quarter q+2. These results suggest that institutional buy herding does not enhance the price process but most likely destabilizes stock prices.

The results for sell-side herding (S1-S5) are presented in Panel B of Table 6. The positive-feedback trading strategy also contributes to sell herding. Take quarter q-1, for example, stocks with the lowest sell herding levels (S1) outperform stocks with the highest sell herding levels (S5) by 2.97% for the full sample, 1.31% for the IG sample, and 5.61% for the NIG sample, respectively. More importantly, the post-herding price dynamics show a different picture. We observe an evident price continuation among NIG stocks, which lasts for four quarters, and the return spread is significant for the first two quarters. In contrast, there is an insignificant return reversal among IG stocks. These distinct return patterns indicate that stabilization after NIG herding is mainly driven by sell herding, which is consistent with our hypothesis.

[Insert Table 6]

5.5 Alternative Herding Measure

We conduct a robustness test in this subsection using an alternative herding measure. Sias (2004) examines the relationship between institutional investors' demand for security with their demand for security from the prior quarter via the first order autocorrelation coefficient. Following Sias (2004), we start with the stock-quarter level herding contribution, defined as:

$$HC_{i,q} = \sum_{n=1}^{N_{i,q}} \sum_{m=1, m\neq n}^{N_{i,q-1}} \frac{\left(B_{n,i,q} - E[p_{i,q}]\right)\left(B_{m,i,q-1} - E[p_{i,q-1}]\right)}{N_{i,q}N_{i,q-1} - N_{i,q}^{*}}, \tag{7}$$

where $N_{i,q}$ is the number of managers trading stock *i* in quarter q and $N_{i,q}^{*}$ is the number of managers trading stock *i* in both quarter q-1 and quarter q. $B_{n,i,q}$ is a dummy variable that equals one (zero) if manager *n* is a buyer (seller) of stock *i* in quarter q.

Since this measure does not allow us to differentiate buy herding and sell herding, we partition it into buy-side herding contribution ($BHC_{i,q}$) if stock *i* has a higher proportion of buyers than the average during quarter q (i.e., $p_{i,q} > E[p_{i,q}]$]). Similarly, sell-side herding contribution ($SHC_{i,q}$) equals $HC_{i,q}$ if stock *i* has a lower proportion of buyers than the average during quarter *q* (i.e., $p_{i,q} < E[p_{i,q}]$]) and is set to missing otherwise.

Finally, the stock-quarter level Sias herding measure $Sias_{i,q}$ is defined as:

$$Sias_{i,q} = \begin{cases} BHC_{i,q} - Min_{j\in Buy}\{BHC_{j,q}\} & \text{for buy herding} \\ Min_{j\in Sell}\{SHC_{j,q}\} - SHC_{i,q} & \text{for sell herding} \end{cases} \tag{8}$$

We then perform portfolio analysis based on the Sias herding measure $Sias_{i,q}$ and report the results in Table 7. P1 consists of stocks with the lowest $Sias_{i,q}$ (highest sell herding intensities) while P10 consists of stocks with the highest $Sias_{i,q}$ (highest buy herding intensities). For the full sample, P10 outperforms P1 by 0.89% in quarter *q*+1. However, when we break down the sample by rating, we only observe a significant positive return spread for the NIG subsample, and the positive return spread lasts up to quarter *q*+4. For the IG stocks, we observe no price continuation but significant reversals. Thus, our results are robust to the alternative herding measure.

[Insert Table 7]

5.6 Momentum Triggered Herding and Non-momentum Triggered Herding

A vast amount of literature has confirmed that herding is associated with the positive feedback strategy (momentum trading). Nevertheless, herding can be attributed to other factors, such as investigative herding, that may also contribute to price discovery. To disentangle momentum trading from institutional herding and recognize a strong contemporaneous relationship between herding and stock performance, we make the following decomposition.

Specifically, each quarter, we estimate the following cross-sectional model:

$$ADJHM_{i,q} = \beta_0 + \beta_1 Ret_{i,q} + \beta_2 Ret_{i,q-1} + \epsilon_{i,q}, \tag{9}$$

The sum of the intercept and residual from the above equation produces the portion of herding that is unrelated to momentum trading, which we refer it as $ADJHM^{O}$ (orthogonal), and the fitted value minus the intercept is the portion of herding that is associated with momentum trading ($ADJHM^{M}$).[16] Next, we investigate the predictive power of these measures for future abnormal returns. This analysis is designed to determine the extent to which the post-herding price dynamics can be explained by the use of positive feedback strategies by institutional investors to capture momentum in stock returns.

In the first column of Table 8, we only allow the momentum-triggered herding to enter into the predictive model. Not surprisingly, the stabilization effect of momentum-triggered herding ($ADJHM^{M}$) is concentrated in low-grade stocks. In the next model, we observe $ADJHM^{O}$ also possesses predictive power for stock future abnormal returns. However, this predictability is again restricted to stocks with non-investment grade ratings. Finally, in the last column, we incorporate both herding measures, each interacted with NIG and IG dummies. Results suggest that the predictive power of each herding measure is not subsumed by the presence of the other and a comparison between the coefficients suggests that momentum-triggered herding plays a more important role in facilitating the price discovery process of low-grade stocks than non-momentum triggered herding.

Overall, the results suggest that the stabilization effect associated with NIG herding is not the sole result of momentum trading by institutional investors. Non-momentum-triggered herding also facilitates price discovery of NIG securities. While it is difficult to differentiate the various theories of non-momentum-triggered herding as they can manifest themselves in past returns, we postulate that this factor captures at least partially investigative herding as other

[16] To facilitate comparisons across the coefficients, we standardize these two measures to have a mean of zero and a standard deviation of one.

factors such as information cascades and reputational-based trading are likely to result in less efficient outcomes. This conclusion is consistent with the gradual information diffusion model of Hong and Stein (1999) where prices adjust slowly as the market discovers the asset's fundamental value.

[Insert Table 8]

6. Conclusions

This study investigates the herding of institutional investors and the subsequent effect of the underlying herding intensity on stock prices. Our study complements the literature by investigating the herding by using comprehensive institutional holding data, and the key contribution is investigating the role of credit rating on such behavior. We find that on average, the institutional herding intensity is relatively low with sell herding slightly stronger than buy herding, which is consistent with the literature that only focuses on mutual funds (Wermers, 1999) or pension funds (Lakonishok et al., 1992). We confirm the finding that institutional investors follow the positive feedback strategy (momentum trading), which is manifested as a form of herding. However, there appears to be a market bifurcation with herding intensity more sensitive to past returns among low-credit quality stocks than high-credit quality stocks a finding that is consistent with Avramov et al. (2007) that momentum profits only exist among low-grade stocks.

In terms of post-herding price dynamics, our findings suggest that the short-term return predictability of the herding intensity only concentrates on non-investment grade stocks. Furthermore, it is the sell herding that acts as a stabilizer of stock prices. These findings are consistent with the slow information diffusion model of Hong and Stein (1999) and the findings of Avramov et al. (2007, 2013) that momentum is nonexistent among high-quality firms, and the short leg dominates the momentum payoff. Finally, although not as strong as the positive feedback strategy (momentum trading), we document that the herding behaviors among low-grade stocks by institutional investors are also related to other factors such as investigative herding that contribute to price discovery.

One limitation of our work is that the quarterly institutional holding data fail to quantify the herding intensities that occur over short intervals, especially for stocks with more active institutional trading. However, this should have no material effects on non-investment grade stocks but could be a concern for investment grade stocks. We leave this for future research.

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Table 1: Summary statistics for herding measures

Panel A presents the mean buy herding measures and mean sell herding measures of institutional investors for IG and NIG stocks over the sample period 1985:Q4-2019:Q4. The buy (sell) herding measure $BHM_{i,q}$ ($SHM_{i,q}$) for a given stock quarter is defined as $HM_{i,q} \mid p_{i,q} > E[p_{i,q}]$ ($HM_{i,q} \mid p_{i,q} < E[p_{i,q}]$), where the conventional herding measure $HM_{i,q}$ is defined as $HM_{i,q} = | p_{i,q} - E[p_{i,q}] | - E| p_{i,q} - E[p_{i,q}] |$ in which $p_{i,q}$ is the proportion of institutions trading stock i during quarter q that are buyers. $E[p_{i,q}]$ represents the proportion of all stock trades by institutions that are purchases during quarter q. The adjustment factor $E| p_{i,q} - E[p_{i,q}] |$ is calculated under the null hypothesis that the number of purchases for stock i follows a binomial distribution. The numbers in the brackets reflect the number of stock quarters that are included in the calculation. Panel B gives the mean herding measures for IG and NIG stocks by institution types.

Panel A. Herding measures by IG/NIG stocks

	Number of Trades ≥ 5			Number of Trades ≥ 25			Number of Trades ≥ 50		
	Full	IG	NIG	Full	IG	NIG	Full	IG	NIG
BHM (%)	2.42	1.97	2.88	2.46	1.95	3.04	2.44	1.95	3.04
	(58,725)	(29,780)	(28,945)	(52,877)	(28,180)	(24,697)	(46,597)	(25,703)	(20,894)
SHM (%)	3.04	3.03	3.06	3.07	3.07	3.08	3.09	3.15	2.96
	(67,960)	(43,038)	(24,922)	(63,039)	(42,069)	(20,970)	(58,150)	(40,245)	(17,905)
ADJHM (%)	-1.71	-3.30	0.43	-1.90	-3.53	0.60	-2.23	-3.88	0.58
	(126,685)	(72,818)	(53,867)	(115,916)	(70,249)	(45,667)	(104,747)	(65,948)	(38,799)

Panel B. Herding measures by IG/NIG stocks and institution types

	Bank ≥ 5			Insurance ≥ 5			Investment Companies ≥ 5		
	Full	IG	NIG	Full	IG	NIG	Full	IG	NIG
BHM (%)	2.13	1.62	2.68	1.50	0.98	2.26	1.85	1.53	2.22
	(56,853)	(29,729)	(27,124)	(49,687)	(29,470)	(20,217)	(57,164)	(30,869)	(26,295)
SHM (%)	2.91	3.40	1.93	2.21	2.23	2.17	2.39	2.32	2.50
	(63,221)	(42,126)	(21,095)	(51,880)	(34,696)	(17,184)	(67,438)	(41,426)	(26,102)
ADJHM (%)	-1.13	-3.15	1.88	-0.74	-1.73	0.96	-1.62	-2.48	-0.44
	(120,074)	(71,855)	(48,219)	(101,567)	(64,166)	(37,401)	(124,602)	(72,295)	(52,307)

Table 2: Institutional herding and momentum trading

This table presents the Fama-MacBeth cross-sectional regressions of adjusted herding measures on stocks' past performance. The dependent variable $ADJHM_q$ is the adjusted herding measure of stock i in quarter q. $Ret_{q\text{-}1}$ is stock return during quarter q. $CumRet_{q\text{-}5,\, q\text{-}2}$ is cumulative returns during quarters q - 5 to q - 2. *Large* $Ret_{q\text{-}1}$ (*Small* $Ret_{q\text{-}1}$) takes the value of $Ret_{q\text{-}1}$ for returns that are at least (less than) one standard deviation from the mean and 0 otherwise. *Positive* $Ret_{q\text{-}1}$ (*Negative* $Ret_{q\text{-}1}$) takes the value of $Ret_{q\text{-}1}$ for returns that are positive (negative) and 0 otherwise. $LnSize_{q\text{-}1}$ is the logarithm of stock i's market capitalization in the prior quarter. $Upgrade_{q\text{-}1}$ ($Downgrade_{q\text{-}1}$) is a dummy that equals one if there is an upgrade (downgrade) of firm ratings in quarter q - 1. $SUE_{q\text{-}1}$ is the standardized unexpected earnings in the prior quarter. $Revision_{q\text{-}1}$ is the analyst recommendation revisions in the prior quarter. The *t*-values are calculated using Newey-West procedures with a lag equal to three and are reported in parentheses. The ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Full Sample				IG				NIG			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Ret_{q\text{-}1}$	0.076***			0.075***	0.051***			0.059***	0.088***			0.084***
	(12.39)			(10.47)	(5.47)			(5.36)	(13.88)			(13.60)
Large $Ret_{q\text{-}1}$		0.013***				0.005***				0.019***		
		(11.77)				(5.18)				(13.31)		
Small $Ret_{q\text{-}1}$		0.007***				0.003***				0.011***		
		(10.60)				(3.96)				(13.97)		
Positive $Ret_{q\text{-}1}$			0.003***				-0.000				0.005***	
			(2.63)				(-0.32)				(4.02)	
Negative $Ret_{q\text{-}1}$			0.016***				0.008***				0.022***	
			(17.44)				(10.10)				(16.93)	
$SUE_{q\text{-}1}$				-0.000				-0.000				0.000
				(-0.47)				(-1.12)				(0.35)
$Revision_{q\text{-}1}$				0.012***				0.013***				0.012***
				(3.96)				(3.69)				(3.26)
$CumRet_{q\text{-}5,\, q\text{-}2}$	0.018***	0.018***	0.017***	0.009***	0.016***	0.016***	0.016***	0.008	0.014***	0.014***	0.013***	0.005
	(5.56)	(5.59)	(5.45)	(2.76)	(2.96)	(2.96)	(2.95)	(1.33)	(4.42)	(4.48)	(4.38)	(1.64)
$ADJHM_{q\text{-}1}$	0.257***	0.256***	0.253***	0.256***	0.283***	0.282***	0.281***	0.291***	0.206***	0.205***	0.198***	0.193***
	(27.85)	(27.89)	(28.42)	(23.07)	(32.99)	(32.78)	(33.21)	(26.58)	(18.76)	(18.78)	(19.44)	(15.18)
$LnSize_{q\text{-}1}$	-0.013***	-0.013***	-0.014***	-0.014***	-0.016***	-0.016***	-0.017***	-0.016***	-0.002	-0.002	-0.003*	-0.003**
	(-12.44)	(-12.62)	(-13.61)	(-13.65)	(-13.88)	(-13.94)	(-13.97)	(-10.75)	(-0.96)	(-1.05)	(-1.86)	(-2.21)
$Upgrade_{q\text{-}1}$	0.008***	0.009***	0.009***	0.007***	0.010***	0.010***	0.010***	0.010**	0.006	0.007	0.008	0.002
	(3.44)	(3.46)	(3.81)	(2.92)	(2.76)	(2.83)	(2.81)	(2.31)	(1.37)	(1.37)	(1.57)	(0.45)
$Downgrade_{q\text{-}1}$	-0.019***	-0.019***	-0.015***	-0.020***	-0.013***	-0.013***	-0.012***	-0.014***	-0.025***	-0.025***	-0.018***	-0.027***
	(-7.34)	(-7.29)	(-5.76)	(-6.21)	(-4.05)	(-3.93)	(-3.54)	(-3.32)	(-6.49)	(-6.38)	(-4.85)	(-5.29)
Intercept	0.165***	0.168***	0.187***	0.184***	0.220***	0.221***	0.224***	0.212***	0.021	0.024	0.042*	0.046**
	(11.82)	(11.97)	(13.03)	(12.80)	(12.66)	(12.65)	(12.74)	(9.55)	(0.94)	(1.07)	(1.87)	(2.32)
Average R^2	0.152	0.154	0.158	0.155	0.173	0.176	0.178	0.181	0.128	0.131	0.137	0.124
No. of observations	118,943	118,943	118,943	84,358	70,097	70,097	70,097	49,549	48,846	48,846	48,846	34,809

Table 3: Price impact of herding: by IG/NIG

This table presents the quarterly DGTW-adjusted returns (in percent) from the zero-investment portfolio constructed based on stocks' adjusted herding measures for two quarters before the portfolio formation quarter *q* and four quarters after. In each quarter, all, IG, and NIG stocks are sorted into decile portfolios by *ADJHM*. P10 (P1) consists of stocks with the highest buy (sell) herding intensities. Portfolio P10 - P1 buys long in the equally weighted portfolio P10 and sells short in the equally weighted portfolio P1. Stocks traded by fewer than five institutions in a given quarter are excluded. The *t*-values are in parentheses. The ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	q - 2	*q* – 1	Portfolio formation quarter *q*	*q* + 1	*q* + 2	*q* + 3	*q* + 4
Panel A: Full sample							
P1	-2.91***	-4.19***	-4.33***	-0.91***	0.04	0.28	0.01
	(-11.70)	(-11.98)	(-10.69)	(-2.88)	(0.12)	(0.94)	(0.02)
P10	2.36***	4.55***	5.00***	0.33	-0.66***	-0.25	-0.47*
	(7.24)	(12.99)	(11.66)	(1.48)	(-2.73)	(-1.11)	(-1.93)
P10 - P1	5.28***	8.74***	9.33***	1.24***	-0.70	-0.53	-0.48
	(12.66)	(14.91)	(13.87)	(3.21)	(-1.48)	(-1.45)	(-1.54)
Panel B: IG							
P1	-1.00***	-1.35***	-2.02***	0.20	0.37	0.22	0.26
	(-4.46)	(-6.01)	(-7.72)	(0.84)	(1.46)	(0.83)	(1.16)
P10	0.80***	1.92***	2.47***	0.11	-0.15	-0.08	-0.60**
	(2.77)	(7.19)	(8.51)	(0.42)	(-0.53)	(-0.29)	(-2.12)
P10 - P1	1.80***	3.27***	4.49***	-0.09	-0.52*	-0.30	-0.86***
	(5.28)	(9.12)	(10.63)	(-0.32)	(-1.67)	(-0.96)	(-3.07)
Panel C: NIG							
P1	-5.67***	-8.21***	-8.22***	-2.10***	-1.81***	-0.95*	-0.59
	(-13.20)	(-13.69)	(-12.09)	(-3.70)	(-3.10)	(-1.78)	(-1.08)
P10	3.69***	6.94***	7.57***	0.63*	-0.37	0.31	-0.02
	(6.79)	(12.48)	(11.08)	(1.79)	(-1.05)	(0.81)	(-0.06)
P10 - P1	9.36***	15.15***	15.79***	2.73***	1.44**	1.26*	0.57
	(14.84)	(16.39)	(15.04)	(4.07)	(2.14)	(1.89)	(0.81)

Table 4: Cross-sectional regressions of future abnormal returns on adjusted herding measures

This table presents the Fama-MacBeth cross-sectional regressions of stock future DGTW-adjusted returns on adjusted herding measures interacted with NIG or IG dummies and other stock-specific variables. The dependent variables are the stock DGTW adjusted returns in quarter $q + 1$. Stock-specific variables include the logarithm of market capitalization ($LnSize_q$), logarithm of book to market ratio (BM_q), share turnover ($Turnover_q$), stock return during current quarter (Ret_q), cumulative returns during quarters $q – 4$ to $q – 1$ ($CumRet_{q-4, q-1}$), forecast dispersion ($Dispersion_q$), and the logarithm of the number of analysts following (Cov_q). The *t*-values are calculated using Newey-West procedures with a lag equal to three and are reported in parentheses. In columns 1 and 2, the regression is estimated by ordinary least squares month by month (FM-OLS). In columns 3 and 4, the regression is estimated by weighted least squares (FM-WLS) where the weights are firm size. The ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	FM-OLS				FM-WLS	
	(1)	(2)	(3)	(4)	(5)	(6)
$ADJHM_q$	0.010**	0.010*			0.008	
	(2.02)	(1.91)			(1.28)	
$ADJHM_q * NIG_q$			0.032***	0.031***		0.030***
			(3.71)	(3.38)		(2.67)
$ADJHM_q * (1-NIG_q)$			-0.003	-0.002		-0.003
			(-0.62)	(-0.37)		(-0.51)
$LnSize_q$	0.002***	0.000	0.002***	0.000		
	(4.07)	(0.33)	(3.91)	(0.24)		
BM_q	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.73)	(-0.72)	(-0.55)	(-0.58)	(-0.69)	(-0.54)
$Turnover_q$	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(-2.04)	(-2.06)	(-2.04)	(-2.05)	(-2.22)	(-2.20)
Ret_q	0.007	0.004	0.006	0.003	0.003	0.001
	(0.80)	(0.40)	(0.69)	(0.27)	(0.29)	(0.16)
$CumRet_{q-4, q-1}$	-0.001	-0.001	-0.001	-0.002	-0.001	-0.002
	(-0.24)	(-0.27)	(-0.30)	(-0.31)	(-0.23)	(-0.28)
Cov_q		0.003*		0.003*	0.003**	0.003**
		(1.79)		(1.79)	(2.37)	(2.35)
$Dispersion_q$		-0.007***		-0.007***	-0.006***	-0.006***
		(-3.06)		(-3.03)	(-2.87)	(-2.84)
Intercept	-0.037***	-0.014	-0.035***	-0.013	-0.010*	-0.010*
	(-3.77)	(-1.20)	(-3.65)	(-1.12)	(-1.74)	(-1.73)
Average R^2	0.039	0.049	0.041	0.051	0.046	0.048
No. of observations	122,975	109,534	122,975	109,534	109,534	109,534

Table 5: Price impact of herding: by IG/NIG and institution types

This table presents the quarterly DGTW-adjusted returns (in percent) from the zero-investment portfolio constructed based on stocks' adjusted herding measures for two quarters before the portfolio formation quarter *q* and four quarters after. In each investor type subgroups (banks, insurance companies, investment companies and advisors), each quarter all, IG, and NIG stocks are sorted into decile portfolios by *ADJHM*. P10 (P1) consists of stocks with the highest buy (sell) herding intensities. Portfolio P10-P1 buys long in the equally weighted portfolio P10 and sells short in the equally weighted portfolio P1. Stocks traded by fewer than five institutions in a given quarter are excluded. The *t*-values are in parentheses. The ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

P10 – P1	*q* - 2	*q* – 1	Portfolio formation quarter *q*	*q* + 1	*q* + 2	*q* + 3	*q* + 4
Panel A: Bank							
Full sample	5.02***	5.22***	5.13***	-0.53	-0.48	-0.44	-0.67**
	(12.56)	(12.54)	(12.22)	(-1.27)	(-1.27)	(-1.43)	(-2.45)
IG	3.06***	2.94***	3.42***	-0.16	-0.35	-0.37	-0.65**
	(10.97)	(9.49)	(10.78)	(-0.50)	(-1.05)	(-1.30)	(-2.30)
NIG	7.65***	8.93***	7.84***	-0.63	-0.08	-0.27	-0.93
	(11.81)	(12.10)	(11.03)	(-0.78)	(-0.12)	(-0.55)	(-1.47)
Panel B: Insurance							
Full sample	2.26***	4.11***	3.67***	-0.35	-0.26	-0.52	-0.83***
	(7.07)	(10.39)	(9.60)	(-1.13)	(-0.74)	(-1.57)	(-2.79)
IG	0.53**	1.88***	2.15***	-0.39	0.01	-0.37	-0.42
	(2.09)	(5.62)	(6.83)	(-1.41)	(0.03)	(-1.18)	(-1.50)
NIG	4.24***	8.12***	5.49***	0.97	-0.64	-0.08	-1.51**
	(5.87)	(10.12)	(6.22)	(1.16)	(-0.75)	(-0.11)	(-2.21)
Panel C: Investment Companies/Advisors							
Full sample	3.31***	7.09***	9.73***	1.33***	0.35	0.35	0.07
	(8.57)	(12.63)	(12.81)	(3.91)	(1.15)	(1.07)	(0.23)
IG	0.63**	2.08***	4.02***	0.29	-0.26	-0.07	-0.55**
	(2.17)	(6.04)	(9.07)	(1.12)	(-0.84)	(-0.25)	(-2.02)
NIG	6.16***	13.31***	16.23***	3.06***	1.56***	1.11*	1.00*
	(9.33)	(14.67)	(14.31)	(4.79)	(2.71)	(1.88)	(1.66)

Table 6: Price impact of herding: buy side vs. sell side

This table presents the quarterly DGTW-adjusted returns (in percent) from the portfolios constructed based on stocks' herding measures for two quarters before the portfolio formation quarter *q* and four quarters after. In each quarter, all, IG, and NIG stocks bought with higher intensity than the market average are sorted into quintiles "B1" to "B5," with "B5" representing the group of stocks with the highest buy herding intensities. Similarly, all, IG, and NIG stocks sold with higher intensity than the market average are sorted into quintiles "S1" to "S5," with "S5" representing the group of stocks with the highest sell herding intensities. Portfolio B5 - B1 buys long in the equally weighted portfolio B5 and sells short in the equally weighted portfolio B1. Portfolio S1 - S5 is similarly defined. Stocks traded by fewer than five institutions in a given quarter are excluded. The *t*-values are in parentheses. The ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	q - 2	*q* – 1	Portfolio formation quarter *q*	*q* + 1	*q* + 2	*q* + 3	*q* + 4
Panel A: Buy side (B5 – B1)							
Full sample	2.70***	4.96***	5.57***	0.59*	-0.36	0.32	-0.20
	(8.15)	(13.28)	(12.80)	(1.82)	(-1.53)	(0.98)	(-0.62)
IG	0.64**	2.16***	2.30***	0.02	-0.41	-0.00	-0.74**
	(2.16)	(6.80)	(8.26)	(0.06)	(-1.58)	(-0.01)	(-2.54)
NIG	4.66***	7.30***	8.59***	1.05**	-0.16	0.30	-0.40
	(8.79)	(12.44)	(12.57)	(2.12)	(-0.39)	(0.66)	(-0.82)
Panel B: Sell side (S1 – S5)							
Full sample	2.12***	2.97***	2.87***	0.62**	0.27	-0.21	0.04
	(6.96)	(7.91)	(7.49)	(2.10)	(0.98)	(-0.62)	(0.15)
IG	1.11***	1.31***	1.69***	-0.24	-0.19	-0.35	-0.30
	(4.75)	(5.00)	(5.90)	(-0.99)	(-0.82)	(-1.37)	(-1.28)
NIG	3.25***	5.61***	6.16***	1.33**	1.18*	0.45	0.28
	(5.78)	(8.18)	(8.23)	(2.21)	(1.76)	(0.71)	(0.40)

Table 7: Price impact of herding: by IG/NIG and Sias (2004) herding measure

This table presents the quarterly DGTW-adjusted returns (in percent) from the portfolios constructed based on Sias (2004) herding measures for two quarters before the portfolio formation quarter q and four quarters after. In each quarter, all, IG, and NIG stocks are sorted into decile portfolios by ranking the Sias (2004) herding measure. P1 consists of stocks with the highest sell herding intensities (lowest $Sias_{i,q}$) while P10 consists of stocks with the highest buy herding intensities (highest $Sias_{i,q}$). Portfolio P10-P1 longs P10 and shorts P1. Stocks traded by fewer than five institutions in a given quarter are excluded. The t-values are in parentheses. The ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

P10 – P1	q - 2	q – 1	Portfolio formation quarter q	q + 1	q + 2	q + 3	q + 4
Panel A: Full sample							
P1	-4.50***	-5.31***	-2.97***	-0.66***	-0.27	-0.18	-0.07
	(-14.51)	(-12.94)	(-8.06)	(-2.08)	(-0.85)	(-0.58)	(-0.28)
P10	4.00***	5.62***	3.09***	0.23	-0.33	-0.30	-0.35
	(11.45)	(12.22)	(11.66)	(1.08)	(-1.44)	(-1.41)	(-1.31)
P10 - P1	8.50***	10.93***	6.06***	0.89**	-0.06	-0.13	-0.28
	(16.14)	(14.54)	(12.45)	(2.32)	(-0.15)	(-0.36)	(-0.80)
Panel B: IG							
P1	-1.68***	-2.18***	-1.07***	0.51*	0.45*	0.37	0.33
	(-7.29)	(-8.21)	(-4.85)	(1.93)	(1.75)	(1.43)	(1.26)
P10	1.31***	2.12***	1.43***	-0.03	-0.38	-0.41	-0.46
	(4.62)	(6.76)	(4.70)	(-0.10)	(-1.33)	(-1.34)	(-1.47)
P10 - P1	2.99***	4.30***	2.50***	-0.53	-0.83**	-0.77**	-0.78**
	(8.87)	(9.89)	(7.19)	(-1.60)	(-2.39)	(-2.41)	(-2.52)
Panel C: NIG							
P1	-8.76***	-9.61***	-6.02***	-2.30***	-1.01*	-0.76	-0.63
	(-16.68)	(-14.52)	(-8.69)	(-4.01)	(-1.67)	(-1.44)	(-1.07)
P10	6.25***	8.36***	4.44***	0.01	-0.23	-0.17	-0.57
	(10.23)	(12.24)	(9.82)	(0.04)	(-0.59)	(-0.43)	(-1.17)
P10 - P1	15.01***	17.97***	10.46***	2.31***	0.78	0.60	0.06
	(17.77)	(16.21)	(12.07)	(3.41)	(1.15)	(1.02)	(0.09)

Table 8: Cross-sectional regressions of future abnormal returns on momentum triggered herding and non-momentum triggered herding

This table presents the Fama-MacBeth cross-sectional regressions of stock future DGTW-adjusted returns on herding that are triggered by momentum ($ADJHM_q^M$) and unrelated to momentum ($ADJHM_q^O$), each first standardized and then interacted with NIG or IG dummies and other stock-specific variables. The dependent variable is the stock DGTW adjusted returns in quarter q+1. Stock-specific variables include the logarithm of market capitalization ($LnSize_q$), logarithm of book to market ratio (BM_q). The t-values are calculated using Newey-West procedures with a lag equal to three and are reported in parentheses. The ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	FM-OLS		
	(1)	(2)	(3)
$ADJHM_q^M * NIG_q$	0.006**		0.006**
	(2.67)		(2.51)
$ADJHM_q^M * (1 - NIG_q)$	-0.004*		-0.004**
	(-1.98)		(-2.02)
$ADJHM_q^O * NIG_q$		0.003**	0.003**
		(2.21)	(2.05)
$ADJHM_q^O * (1 - NIG_q)$		0.001	0.001
		(0.68)	(0.79)
$LnSize_q$	0.002***	0.002***	0.002***
	(2.89)	(2.93)	(2.98)
BM_q	-0.001	-0.001	-0.004*
	(-0.46)	(-0.41)	(-1.87)
$Turnover_q$	-0.001**	-0.001	-0.001**
	(-2.16)	(-1.61)	(-2.28)
Intercept	-0.025**	-0.030***	-0.021**
	(-2.38)	(-2.66)	(-2.03)
Average R^2	0.035	0.024	0.040
No. of observations	122,975	122,975	122,975