Does Institutional Herding Tendency and Direction Destabilize Stock Prices?

Muhammad Sabeeh Iqbal, Hailey College of Commerce, University of the Punjab, sabeeh.iqbal@hcc.edu.pk
Aslihan Salih, California State University Long Beach, College of Business, asli.salih@csulb.edu

ABSTRACT

We introduce a new methodology to categorize institutional herding tendency and direction that enhances the precision with which herders are identified at the institutional level. The herders are the ones that follow the crowd both on the buy and sell trades, whereas anti-herders are the institutions that tend to move in the opposite direction of the crowd on both sides of the trades. We then focus on the link between institutional herding and stock returns within the context of banks, insurance companies, investment companies, investment advisors, and education endowment funds by using the proposed herding categorization. The results show that herders' trading negatively affects future stock returns, whereas anti-herders' trading is insignificant. Consequently, herders' trading brings a temporary shift in stock prices that is eventually reversed. Thus, herders destabilize stock prices and negatively affect the stock price discovery process.

Keywords: Financial Institutions, Stock Returns, Herding Behavior, Financial Markets

INTRODUCTION

Institutional herding behavior and its impact on the price discovery process in financial markets continue to be an active research area, with numerous questions awaiting to be addressed by the literature. It is usually believed that institutional herding is widespread (Spyrou, 2013), blamed for driving prices away from fundamentals (Chang, 2010; Dasgupta et al., 2011; Gutierrez & Kelley, 2009; Sias, 2004) , and associated with bubbles and market inefficiencies (Brunnermeier & Nagel, 2004; Deng et al., 2018). But is institutional herding behavior prevalent? Do we have the necessary measurement tools and data precision for determining institutional herding tendency and direction? How can we accurately measure the impact of institutional herding on prices? Do all institutional herding trading practices detrimentally drive prices away from fundamentals? Can we specify the types and motives of institutional herding behavior with adverse pricing effects in the short-run and long-run price dynamics?

The debate on how to define, measure and test for institutional herding (Dasgupta et al., 2011; Jiang & Verardo, 2018; Lakonishok et al., 1992; Patterson & Sharma, 2010) is inconclusive. Many widely used herding tendency measures are calculated at the stock level, so one of the main challenges is measuring herding tendency and trading direction at the institutional level. This paper proposes a new dynamic methodology to categorize institutional investors' herding tendencies for buy and sell side trades separately. A multinomial logistic regression framework estimates the marginal effects on the probability of buying, selling, or doing nothing for an individual institution compared to a group of institutions at the cross-section. Marginal effects are then used to estimate time-weighted herding (TWH) probabilities of buy/sell/do nothing trades when the crowd buys or sells. Each institutional investor is classified as a herder, passive, or anti-herder on the buy or sell side. It is a dynamic categorization measure that includes sequential decisions through time using a weighting scheme that gives more weights to the recent data and lower weights to the past average probabilities.

We then focus on the link between institutional herding and stock returns within the context of banks, insurance companies, investment companies, investment advisors, education endowment funds, and others by using the proposed herding categorization. These financial institutions provide a perfect setting since the empirical evidence on the impact of herding tendency on stock returns is inconclusive to date. Whereas some studies found that institutional herding tendency improves the price discovery process (Lakonishok et al., 1992; Sias, 2004; Wermers, 1999), other studies argue that institutional herding destabilizes prices (Dasgupta et al., 2011; Gutierrez & Kelley, 2009). Recent studies suggest that the impact of institutional herding tendency on prices, whether stabilizing or destabilizing, is closely related to the investment horizon and direction of the herding of the institutional investors (Iqbal et al., 2023, 2021; Yuksel, 2015).

We contribute to the empirical literature on herding behavior by first introducing a new methodology to categorize herding tendency and direction at the institutional level. The study by Jiang & Verardo (2018) is closest in spirit to our study as they are proposing a fund-level herding measure rather than a stock-level measure to analyze herding behavior of mutual funds. Unlike Jiang & Verardo (2018), this study proposes a classification of institutions into herders, anti-herders, and other categories not only for mutual funds but all institutions covered by the Thomson Reuters Institutional Holdings (13F) database. Each quarter, we classify all institutions into nine categories based on their time-weighted herding tendency conditional on the crowd's buying and selling. This allows us to identify institutions that may be misclassified as either herders or anti-herders by other herding tendency measures. Hence, it adds to the precision with which herders are identified at the institutional level. In our setting, we define herders as the ones that follow the crowd both on the buy and sell trades, whereas anti-herders are the institutions that tend to move in the opposite direction of the crowd, i.e., they sell when the crowd buys and buy when the crowd sells. Thus, herding or anti-herding on only buy side or sell side do not make an institution a herder or an anti-herder, respectively. With respect to the remaining categories, this study is the first to identify these unique herding behavior tendencies, which are never explored to the best of our knowledge. We are also interested in whether the institutions with different herding tendencies on buy and sell sides impact the stock prices differently.

As of December 2018, the market value of the aggregate institutional portfolio as a percentage of the market value of all shares in the CRSP is 65%. According to our classification, institutional herders hold 45.48%, anti-herders 6.51%, and others 12.59% of the market share. Thus, herders and anti-herders represent a significant proportion of institutions, suggesting that herding and anti-herding are widespread phenomena among institutions. Comparison of our dynamic categorization measure with that of Jiang & Verardo (2018) reveal that our methodology classifies a smaller number of institutions into herders and anti-herders.

Second, we analyze the impact of institutional herders' and anti-herders' trading behavior on stock prices. The literature argues that the price impact of trading by herders and anti-herders depends on whether their trading is motivated by information or behavior (Lakonishok et al., 1992). They may exhibit herding while sequentially learning from their informed counterparts, as in Bikhchandani et al. (1992), or while portraying themselves as talented investors like others, as in Scharfstein & Stein (1990). These models predict that the informativeness of the institutions may be correlated with their herding tendencies. Consequently, less informed institutions tend to herd, while more informed institutions prefer to move away from the crowd exhibiting anti-herding behavior. Given these predictions, we expect herders to drive the prices away from their fundamental values or destabilize and anti-herders to stabilize stock prices.

We test the relationship between trading by institutions with different herding tendencies and future stock returns using a sample of stocks in the CRSP that have stock holdings information in the Thomson Reuters Institutional Holdings (13F) database in our sample period from 1980 to 2019. The stock-level trading measure is from Lakonishok et al. (1992); the LSV measure. The estimation methodology of Fama & Macbeth (1973) is used for the predictive regression of eight quarters ahead stock returns on herders' trading, anti-herders' trading, and variables controlling for common investment styles. A positive/negative change in aggregate institutional ownership represents the crowd's buying/selling.

The results show that herders' trading negatively affects future stock returns, whereas anti-herders' trading is insignificant. The negative relationship suggests that herders' trading brings a temporary shift in stock prices that is eventually reversed. In other words, herders destabilize stock prices and negatively affect the stock price discovery process. Tradings by all other categories are also insignificant in predicting future stock returns. The results are further supported by an analysis of the portfolios based on these trading measures and are robust to the use of control variables. When we segregate institutional trading into buys and sells, the results show that herders' buying rather than selling contributes to the overreaction in prices. This evidence contradicts the findings in the previous studies regarding the informativeness of buy-side trades. The portfolio of stocks with herders' selling outperforms the portfolio of stocks with herders' buying by 1% in one quarter and 2.3% in one year. Additionally, the zero investment strategy based on anti-herders does not produce significant abnormal returns. On the other hand, when we use the categorization of Jiang & Verardo (2018), the zero-investment portfolios do not produce significant returns for both herders and anti-herders. The herding tendency categorization methodology is a vital part of the price impact analysis, and our classification of herders on both the buying and selling sides strongly indicates the destabilizing effect of institutional herders.

In the rest of the article, section 2 describes the data, sample, and methodology to identify the institutional categories. Section 3 tests the price impact of herders' and anti-herders' trading behavior on future stock returns. Section 4 investigates all nine categorizations of institutional herding tendency. Section 5 analyses buy- and sell-side trades of herders and anti-herders and their impact on future stock returns. Section 6 checks for the robustness of our results and section 7 concludes.

DATA AND METHODOLOGY

The sample consists of quarterly observations for firms in the CRSP stock universe from 1980 to 2019, with accounting information in COMPUSTAT and quarterly institutional holdings in CDA/Spectrum database maintained by Thomson Financial. Thomson Financial 13f file contains stock holdings of institutions at the quarterly frequency. All institutions managing more than $100 million must disclose to the SEC all equity holdings greater than 10,000 shares or $200,000 in market value. Stock market data, including stock prices, number of shares outstanding, and exchange codes, are from CRSP. Accounting data that include net income, book value of equity, earnings per share, etc., are combined with the CRSP stock market file. The methodology to obtain institutional categories is described as follows.

Institutional Classification

We are proposing an institutional herding behavior classification using a multinomial logistic regression methodology. Multinomial logistic regression methodology is a good candidate for herding behavior categorization of institutions as the dependent variable can differentiate among more than two choices. Other categorization measures in the literature classify passive investors into herders or anti-herders as they cannot accommodate a third category. Specifically, in our methodology, institutions are classified on the bases of their average marginal effects obtained from the multinomial logistic regression which gives us the predicted probabilities of a trading choice with respect to the average trading behavior of other institutional investors. When a group of institutions buy or sell a stock together, individual institution has three choices: (0) Do not trade (1) Buy (2) Sell. Specifically, our dependent variable y takes 0, 1, or 2 based on whether institutional trade in stock "i" is zero, positive, or negative, respectively. For each institution "k" in quarter "t", we run a multinomial logistic regression where we model the conditional probability of institution "k" in stock "i" to choose outcome j ($j = 0, 1, 2$) as

$$p_{kij} = Pr[y_{ki} = j] = \frac{e^{\alpha_{j,t} + \beta_{k,j,t}\Delta IO_{i,t-1} + \delta_{k,j,t}CAP_{i,t-1} + \gamma_{k,j,t}BM_{i,t-1} + \eta_{k,l,t}MOM_{i,t-1}}}{\sum_{l=0}^{2} e^{\alpha_{l,t} + \beta_{k,l,t}\Delta IO_{i,t-1} + \delta_{k,l,t}CAP_{i,t-1} + \gamma_{k,l,t}BM_{i,t-1} + \eta_{k,l,t}MOM_{i,t-1}}}. \tag{1}$$

In equation 1, ΔIO is the change in aggregated institutional ownership, CAP is the log of market capitalization, and BM is the ratio of book value to market value of equity. These variables are used to control for the common investment styles of the institutions. Moreover, we standardize ΔIO to make its coefficients comparable over time. These variables are defined in the appendix. To guarantee identification, the base case β_0 is set to zero. Hence the $Pr[y_{ki} = 0]$ becomes

$$p_{ki0} = Pr[y_{ki} = 0] = \frac{1}{1 + \sum_{l=1}^{2} e^{\alpha_{l,t} + \beta_{k,l,t}\Delta IO_{i,t-1} + \delta_{k,l,t}CAP_{i,t-1} + \gamma_{k,l,t}BM_{i,t-1} + \eta_{k,l,t}MOM_{i,t-1}}}. \tag{2}$$

Whereas for j= 1, 2, the probabilities are

$$p_{kij} = Pr[y_{ki} = j] = \frac{e^{\alpha_{j,t} + \beta_{k,j,t}\Delta IO_{i,t-1} + \delta_{k,j,t}CAP_{i,t-1} + \gamma_{k,j,t}BM_{i,t-1} + \eta_{k,l,t}MOM_{i,t-1}}}{1 + \sum_{l=1}^{2} e^{\alpha_{l,t} + \beta_{k,l,t}\Delta IO_{i,t-1} + \delta_{k,l,t}CAP_{i,t-1} + \gamma_{k,l,t}BM_{i,t-1} + \eta_{k,l,t}MOM_{i,t-1}}}. \tag{3}$$

This model is estimated by maximizing the following log-likelihood function for each institution.

$$lnL = \sum_{i=1}^{N} \sum_{j=1}^{m} y_{kij} \, ln \, p_{kij} \tag{4}$$

Then, we obtain the marginal effect on the choice probabilities of a change in aggregate institutional ownership as follows.

$$M.E_{kij,t} = \frac{\partial p_{kij}}{\partial \Delta IO_{i,t-1}} = p_{kij}(\beta_{k,j} - \bar{\beta}_{k,i}) \tag{5}$$

In equation 5, p_{kij} are the predicted probabilities, $\beta_{k,j}$ are the coefficient estimates, and $\bar{\beta}_i$ is the probability weighted average of $\beta's$ across different alternatives. We compute predicted probabilities by changing the aggregate institutional ownership and keeping all other control variables at their means. Then, we obtain the average marginal effects that reflect the average tendencies of the institutions to buy, sell, or not to trade against the crowd's move. For each choice j, we compute the average marginal effects conditional on the sign of ΔIO_i as below.

$$Avg.M.E^{cb}_{kj,t} = \frac{\sum_{i=1,\Delta IO_i > 0}^{N} M.E_{k,i,j}}{\sum_{i=1}^{N} I_i^{cb}} \tag{6}$$

$$Avg.M.E^{cs}_{kj,t} = \frac{\sum_{i=1,\Delta IO_i < 0}^{N} M.E_{k,i,j}}{\sum_{i=1}^{N} I_i^{cs}} \tag{7}$$

For j=1, $Avg.M.E^{cb}_1$ shows the average marginal effect on the probability to buy when the crowd is buying. I^{cb} (I^{cs}) is an indicator variable that takes value "1" if the crowd buys (sells). When $Avg.M.E^{cb}_1$ is higher compared to $Avg.M.E_0^{cb}$ and $Avg.M.E_2^{cb}$, the institution is classified as a buy-side herder. Similarly, when $Avg.M.E_2^{cs}$ is higher compared to $Avg.M.E_0^{cs}$ and $Avg.M.E_1^{cs}$, the institution is classified as a sell-side herder. We classify an institution as a herder if it is a herder on both sides. Following a similar methodology, we classified institution into categories in Table 1. In the table, BH-SH (BAH-SAH) are the types of institutions that are more likely to buy (sell) when the crowd buys and sell (buy) when the crowd sells. Finally, we construct a time weighted herding measure (TWH) given as

$$TWH_{kj,t}^{cb(cs)} = \frac{\sum_{h=1}^{t} \frac{1}{h} Avg.M.E_{k,j,t-h+1}^{cb(cs)}}{\sum_{h=1}^{t} \frac{1}{h}}.$$

The weighing scheme gives more weight to recent estimates of average marginal effects. The behavior of these institutional types is further illustrated by plotting their predicted probabilities against changes in aggregated institutional ownership. The predicted probabilities of sample institutions are based on the estimates in quarter t.

3.1.1. Herders (BH-SH)

The institutions in this category are on average more likely to buy stocks when the crowd buys and sell stocks when the crowd sells. Moreover, the likelihood of not trading and selling decreases when the crowd buys, and the likelihood of not trading and buying decreases when the crowd sells. This can be observed in Figure 1, 1st plot, for one institutional herder where y-axis is the predicted trading choice probabilities and x-axis is the change in aggregated institutional ownership. The slope of the predicted probabilities are the marginal effects on the respective probabilities. As can be seen from the graph, the average marginal effect on the probabilities to buy, at the time when the crowd is buying, is greater than the average marginal effect on the probabilities to do nothing and the average marginal effect on the probabilities to sell. In other words, $Avg.M.E_1^{cb}$ is greater than $Avg.M.E_0^{cb}$ and $Avg.M.E_2^{cb}$. Similarly, the average marginal effect on the probabilities to sell, at the time when the crowd is selling, is greater than the average marginal effect on the probabilities to do nothing and the average marginal effect on the probabilities to buy. Therefore, this example clearly shows that our methodology correctly classifies herders according to their trading choice.

3.1.2. Anti-herders (BAH-SAH)

Similarly, Plot 2 in Figure 1 shows a sample institutional anti-herder's trading choice behavior. As can be seen the probability of selling increases on average when the crowd buys and the probability of buying increases when the crowd sells for this type of institution. Again confirming the correct classification by our methodology of this particular institutional trader as an anti-herder. Since, our main focus is on herders and anti-herders, we have also confirmed the classification accuracy of our methodology for the remaining categories. The details are in the appendix A3.

Table 1 reports the number of each type of institutions at the end of even years. The total number of institutions increased from 461 in 1982 to 2,407 in 2018. BAH-SH, BH-SAH, and BP-SP are smaller in number compared to other types of institutions. This indicates that institutions rarely exhibit both herding and anti-herding tendencies. Similarly, there is a small number of passive institutions. Herders and anti-herders represent a more significant proportion than other institutions, which suggests that herding and anti-herding are widespread phenomena among institutions. The last two columns report the number of herders and anti-herders, respectively, using the methodology of Jiang & Verardo (2018).[1] It can be

[1]For details, see appendix.

Figure 1: Predicted Trading Choice Probabilities of Institutional Types

The plot shows the predicted probabilities to be passive, buy, and sell on the y-axis and the change in aggregate institutional ownership on the x-axis.

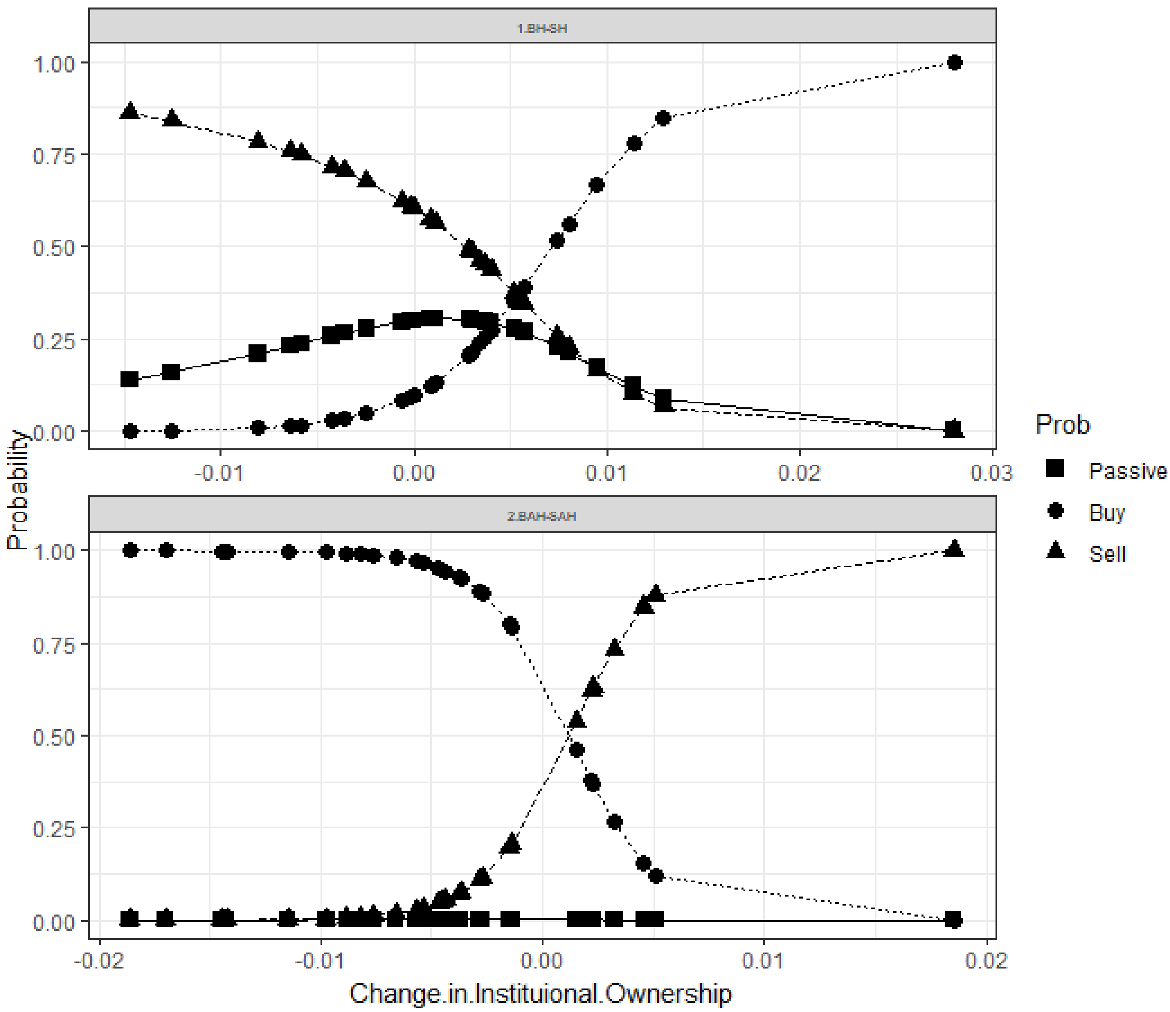


Table 1: No. of Institutions

Institutions are classified into nine classes using a multinomial logistic regression that models the institutional trading choices. These include buy-side anti-herders & sell-side anti-herders (BAH-SAH, anti-herders), buy-side anti-herders & sell-side herders (BAH-SH), buy-side anti-herders & sell-side passives (BAH-SP), buy-side herders & sell-side anti-herders (BH-SAH), buy-side herders & sell-side herders (BH-SH, herders), buy-side herders & sell-side passives (BH-SP), buy-side passive & sell-side anti-herders (BP-SAH), buy-side passives & sell-side herders (BP-SH), and buy-side passives & sell-side passives (BP-SP, passives). These are the column names from left to right, respectively. In the last two columns, we replicate the herding classification methodology of Jiang & Verardo (2018) in an attempt to compare with our methodology. JV-H represents herders whereas JV-AH represents anti-herders according to their methodology.

Year	BAH-SAH	BAH-SH	BAH-SP	BH-SAH	BH-SH	BH-SP	BP-SAH	BP-SH	BP-SP	All	JV-H	JV-AH
1982	62	2	64	0	147	81	50	48	7	461	230	231
1984	74	2	80	4	134	110	59	59	9	531	265	266
1986	77	8	78	12	157	130	56	76	7	601	300	301
1988	94	3	91	6	193	150	83	88	11	719	359	360
1990	110	6	111	6	189	157	88	73	10	750	375	375
1992	143	6	117	8	203	165	107	91	11	851	425	426
1994	125	7	135	10	192	179	94	99	12	853	426	427
1996	156	6	109	11	218	157	102	103	19	881	440	441
1998	176	9	149	12	286	206	144	112	25	1119	559	560
2000	348	7	293	3	115	218	162	84	38	1268	634	634
2002	267	12	234	16	211	250	105	82	24	1201	600	601
2004	305	11	231	9	285	225	130	120	43	1359	679	680
2006	279	7	209	15	363	308	160	157	41	1539	769	770
2008	281	6	181	15	353	254	162	118	46	1416	708	708
2010	300	13	242	23	302	274	179	133	67	1533	766	767
2012	311	10	243	19	402	289	174	161	47	1656	828	828
2014	410	12	268	23	495	375	208	210	52	2053	1026	1027
2016	391	19	305	33	473	364	289	224	58	2156	1078	1078
2018	502	19	346	21	573	390	277	216	63	2407	1203	1204

seen that our methodology gives a shorter list of herders and anti-herders. The numbers show that our methodology is more conservative while categorizing an institution as a herder or an anti-herder. It also allows us to analyze the heterogeneity across institutional classes that has not been studied before.

Stock Level Trading Measures and Descriptive Statistics

Next, to understand the impact of institutional herding on the stock price discovery process we will obtain the stock level trading measure using a methodology of Lakonishok et al. (1992), which we will hereafter refer to as LSV measure. LSV measure captures proportionally large level of trading in individual stocks when many institutional investors move into (or out of) the stocks at the same time. In a given quarter, we compute the trading measure for each stock as follows.

$$Trade_{it} = |Pb_{it} - \overline{Pb}_{it}| - Adj.F_{it}. \tag{8}$$

Pb refers to the proportion of institutions that increase their position in stock *i* in the total number of institutions that either increase or decrease their position in that stock. $\overline{Pb}_{it}$ refers to the expected proportion as measured by the average Pb across the cross-section of stocks during quarter *t*. $Adj.F_{it}$ is subtracted to make adjustment for the random variation around expected proportion of buyers when there is no herding. The measure just defined captures only disproportionate trading irrespective of whether it is a buy trade or a sell trade. To get buy and sell trades, we follow Wermers (1999) and condition $Trade_{it}$ on the proportion of buyers as follows.

$$BT_{it} = Trade_{it}|Pb_{it} > \overline{Pb}_{it} \quad and \quad ST_{it} = Trade_{it}|Pb_{it} < \overline{Pb}_{it}. \tag{9}$$

$Adj.F_{it}$ is re-estimated conditioned on $Pb_{it} > \overline{Pb}_{it}$ or on $Pb_{it} < \overline{Pb}_{it}$ for BT_{it} and ST_{it}, respectively. Finally, we obtain an adjusted trading measure, referred to as LSV, that is equal to $BT_{it} - min(BT_{it})$ for stocks exhibiting buy trades (BT) and $-1 \times (ST_{it} - min(ST_{it}))$ for stocks exhibiting sell trades (ST).

For a given subgroup of institutions, the ic_{it}^{Trade} is calculated for that subgroup as below.

$$ic_{it}^{Trade} = |ic_{it}^{Pb} - \overline{ic}_{it}^{Pb}| - ic_{it}^{Adj.F}. \tag{10}$$

In the above equation, ic refers to an institutional category. ic_{it}^{Pb} is the proportion of buyers of stock *i* in a particular institutional category relative to the total number of traders of that category. $\overline{ic}_{it}^{Pb}$ and $ic_{it}^{Adj.F}$ are recalculated for each institutional category. Similarly, buy trading (ic_{it}^{BT}), sell trading (ic_{it}^{ST}), and adjusted trading measures (ic_{it}^{lsv}) are obtained for all nine categories of institutions. In other words, this results in $BH - SH_{it}^{lsv}$, $BAH - SAH_{it}^{lsv}$, and so on.[2] Additionally, the institutional ownership (ic^{IO}), captures the institutional demand shock, is estimated as the number of shares in aggregate portfolio of institutions belonging to a particular category (ic) divided by total outstanding shares. For example, institutional ownership of herders is given as $BH - SH_{i,t}^{IO} = \frac{\text{Shares of stock } i \text{ held by herders in quarter } t}{\text{Share Outstanding of stock } i \text{ in quarter } t}$.
Table 2 provides various statistics of LSV trading and institutional ownership. Number of observations show that only a few firm-quarter observations exist for categories other than herders and anti-herders. Average $BAH - SAH^{lsv}$ is -0.017, and average $BH - SH^{lsv}$ is -0.028. LSV measures for other types of institutions except passive institutional investors are negative. Institutional ownership of the herders is highest compared to others with 21.1% followed by buy-side herders and sell-side passive and anti-herders with 9.5% and 4.6%, respectively. The passive managers and those herding on one side while anti-herding on the other side own a very small proportion of the shares outstanding.

HERDING TENDENCIES, INSTITUTIONAL TRADING, AND FUTURE STOCK RETURNS

Lakonishok et al. (1992) argue that the informativeness of institutions may explain the role of institutions in stock price formation. Jiang & Verardo (2018) contend that institutions varying in skills exhibit different tendencies towards herding. For example, institutions that lack skills tend to follow the decisions of their counterparts, whereas those with superior skills are more likely to deviate from the crowd. Similarly, the sequential models of herding suggest that the informativeness of institutions can drive herding tendencies. In the informational cascade model, proposed by Bikhchandani et al. (1992), institutions coming later in a sequence may give up their private information and initiate a cascade that stops the information adjustment into prices. However, those with more precise information are more inclined to rely on their own data and shatter the cascade by trading on their private information. In summary, if information quality drives herding tendencies, then herding and anti-herding institutions should have different implications for stock price formation. This section investigates the price impact of herders' and anti-herders' trading on future stock returns.

Portfolios based on Herders' and Anti-herders' trading

We first use portfolio-based approach that is in line with Yan & Zhang (2009). At the end of each quarter, we rank stocks into five portfolios based on the previous-quarter herders' or anti-herders' adjusted LSV trading. The holding period for these portfolios vary from one quarter to four quarters. To be included in a portfolio a stock must have the herders/anti-herders' adjusted LSV trading in the last quarter and returns in the following twelve months. Moreover, we exclude stocks in the lowest size decile, where the break points are based on the market capitalization of NYSE stocks only. We report the cumulative value-weighted returns on the portfolio with lowest herders/anti-herders' adjusted LSV trading (Q1) and returns on the portfolios with highest herders/anti-herders' adjusted LSV trading (Q5). We also create a

[2] For more details, please refer to Tiniç et al. (2020) and Iqbal et al. (2023).

Table 2: Descriptive statistics of stock level trading measures and other stock characteristics

Note: Institutions are classified into nine classes using a multinomial logistic regression that models the institutional choices. These include buy-side anti-herders & sell-side anti-herders (BAH-SAH, anti-herders), buy-side anti-herders & sell-side herders (BAH-SH), buy-side anti-herders & sell-side passives (BAH-SP), buy-side herders & sell-side anti-herders (BH-SAH), buy-side herders & sell-side herders (BH-SH, herders), buy-side herders & sell-side passives (BH-SP), buy-side passive & sell-side anti-herders (BP-SAH), buy-side passives & sell-side herders (BP-SH), and buy-side passives & sell-side passives (BP-SP, passives). The superscript lsv (IO) represents the LSV trading (institutional ownership) of the institutional types.

Statistic	No. of Obs.	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
			LSV measures				
$BAH - SAH^{lsv}$	275,945	−0.011	0.182	−0.751	−0.141	0.125	0.744
$BH - SH^{lsv}$	368,402	−0.018	0.187	−0.736	−0.151	0.125	0.688
$BP - SP^{lsv}$	31,052	0.0003	0.179	−0.576	−0.118	0.112	0.706
$BP - SH^{lsv}$	187,101	−0.004	0.179	−0.700	−0.126	0.117	0.776
$BP - SAH^{lsv}$	155,646	−0.004	0.181	−0.728	−0.128	0.119	0.726
$BH - SP^{lsv}$	321,005	−0.017	0.182	−0.720	−0.143	0.117	0.716
$BAH - SP^{lsv}$	255,242	−0.015	0.181	−0.685	−0.141	0.112	0.734
$BH - SAH^{lsv}$	4,971	0.002	0.178	−0.441	−0.130	0.119	0.734
$BAH - SH^{lsv}$	2,578	0.001	0.183	−0.771	−0.116	0.130	0.689
			Institutional Ownership				
$BAH - SAH^{IO}$	416,244	0.046	0.048	0	0.013	0.064	1.502
$BH - SH^{IO}$	461,416	0.210	0.180	0	0.059	0.328	3.141
$BP - SP^{IO}$	188,252	0.009	0.020	0	0.001	0.009	0.664
$BP - SH^{IO}$	393,423	0.026	0.034	0	0.006	0.034	2.216
$BP - SAH^{IO}$	368,692	0.018	0.029	0	0.003	0.023	2.531
$BH - SP^{IO}$	450,205	0.095	0.082	0	0.033	0.136	7.150
$BAH - SP^{IO}$	426,183	0.046	0.049	0	0.013	0.063	0.974
$BH - SAH^{IO}$	94,655	0.005	0.014	0	0.0002	0.004	0.810
$BAH - SH^{IO}$	96,438	0.005	0.017	0	0.0002	0.003	1.337

zero-investment strategy that buys stocks in portfolio Q1 and sell those in portfolio Q5. The raw returns, the alphas from Fama & French (1992) three-factor model (FF3-adj), and the t-statistics (in parenthesis) are reported in Table 3.

The results in Panel A of Table 3 suggest that the portfolio of stocks that are extensively sold by herders (Q1) outperforms the portfolio of stocks that are extensively bought by them (Q5) in the following quarters. The average cumulative raw return on portfolio Q1 is greater than portfolio Q5 for all holding periods. In other words, the Q1 outperforms Q5 by 1% in the following quarter and by 2.3% in one year following the formation quarter. Both raw and benchmark-adjusted returns support our findings. The zero-investment strategy based on anti-herders' trading does not generate significant returns. In other words, we document that the stocks that are sold by the herders have a higher return in the subsequent 12 months. Also, herders buy stocks that have lower returns compared to the stocks that are sold. This suggest that herders might not have the information in choosing the winning stocks or they may simply follow each other.

In an attempt to compare our classification measure to that of Jiang & Verardo (2018), we analyze the returns on zero-investment portfolios of institutions classified by their methodology.[3] The zero-investment portfolios do not produce significant returns in the quarters ahead. These results suggest the stringent of our measure over that of Jiang's since our measure produces a shorter list of herders and anti-herders compared to them as can be seen in Table 1.

[3]Appendix A provides the details of Jiang's methodology to classify institutions.

Table 3: Herding and Anti-herding Tendencies, and Future Stock Returns:

This table shows the returns, up to four quarters, on the quantile portfolios formed by ranking stocks on the past lsv trading of herders and anti-herders. The returns include simple mean returns and the alphas from the three-factor model of Fama & French (1992). Q1 (Q5) is the portfolio of stocks in the bottom (top) quantile. The Panel A reports the results for herders and anti-herders, where the categorization is done using our dynamic herding measure. Specifically, institutions are classified into herders (BH-SH) and anti-herders (BAH-SAH) using a multinomial logistic regression that models the institutional trading choices. Specifically, we model the institutional trading choices, such as buy, sell, or do nothing, as a function of one quarter lagged change in aggregate institutional ownership that represents the crowd's trading and other control variables. Then, we obtain the average of the marginal effects for stocks in which the change in aggregate institutional ownership is positive, representing the crowd's buying. Similarly, average marginal effects are also estimated for stocks in which the change in aggregated institutional ownership is negative, representing the crowd's selling. We estimate a time-weighted average that gives more weight to the recent marginal effects and less weight to the past quarters. The comparison of these marginal effects specifies the category of the institution. For example, if the average marginal effects on the buying probability is higher compared to the average marginal effects on the selling and passive probabilities, at the time when the crowd is buying, then the institution is ascertained as a buy-side herder. A herder is the one who exhibits herding behavior on both the buy and sell sides. Then, we obtain the stock-level lsv trading using the measure proposed by Lakonishok et al. (1992). In Panel B, again we report the returns, but this time, we categorize the institutions using the methodology of Jiang & Verardo (2018).

	Returns in the following Quarters			
	R_{t+1}	$R_{t+1:t+2}$	$R_{t+1:t+3}$	$R_{t+1:t+4}$
Panel A: Portfolios based on dynamic herding measure				
Herders				
Q1	0.04	0.07	0.11	0.15
Q5	0.03	0.06	0.09	0.12
Q1-Q5	0.01	0.012*	0.019**	0.023**
	(1.43)	(1.92)	(2.18)	(2.12)
Q1-Q5 (FF3-adj)	0.009**	0.016**	0.021**	0.023*
	(2.53)	(2.62)	(2.32)	(1.91)
Anti-herders				
Q1	0.04	0.07	0.10	0.14
Q5	0.03	0.06	0.09	0.13
Q1-Q5	0.00	0.01	0.01	0.01
	(0.40)	(0.66)	(0.90)	(1.03)
Q1-Q5 (FF3-adj)	0.00	0.01	0.00	0.01
	(0.56)	(0.75)	(0.49)	(0.56)
Panel B: Portfolios based on Jiang & Verardo (2018)				
Herders				
Q1	0.037	0.068	0.099	0.138
Q5	0.034	0.062	0.088	0.124
Q1-Q5	0.003	0.006	0.011	0.014
	-0.739	-0.773	-1.24	-1.47
Q1-Q5 (FF3-adj)	0.006	0.008	0.007	0.012
	-1.356	-1.258	-0.86	-1.247
Anti-herders				
Q1	0.038	0.07	0.102	0.142
Q5	0.035	0.061	0.086	0.125
Q1-Q5	0.003	0.009	0.015	0.017
	-0.676	-1.176	-1.558	-1.396
Q1-Q5 (FF3-adj)	0.006	0.011	0.014	0.021
	-1.354	-1.568	-1.468	-1.604

These results suggest a negative relationship between trading by herders and future stock returns which indicates behaviorally motivated trading. On the other hand, anti-herders do not seem to trade on information either. To be more precise, their trading does not destabilize stock prices. These results are in line with the previous findings in Jiang & Verardo (2018) with the mutual funds data that the anti-herders are better informed compared to herders.

Regression Analysis

In this section, we test the impact of the LSV trading of herders and anti-herders on future stock returns using Fama & Macbeth (1973) regression methodology (FM). We also include ownership of herders and anti-herders, as defined in section 2.2 above, to control their respective demand shocks. The ratios, including book-to-market ratio, earnings-to-price ratio, sales-to-price ratio, and cash flows-to-price ratio, control for the value effect. Also, earning growth (EG) controls the growth effect, share turnover (TURN) controls liquidity, market capitalization (CAP) controls the size effect. The composite equity issuance captures the impact of intangible news, that is the information which is not associated with fundamentals. The remaining control variables comprise the long-term return reversal effects ($Ret_{t-15:t-4}$), the momentum effect ($Ret_{t-2:t}$), the firm's age in months (Age), and the return on equity (ROE). The appendix discusses these variables in more details. The regression model is given below.

$$\begin{aligned} R_{i,t+1:t+h} = \alpha + \beta_1 BAH - SAH^{lsv}_{i,t} + \beta_2 BH - SH^{lsv}_{i,t} + \beta_3 BAH - SAH^{IO}_{i,t} + \beta_4 BH - SH^{IO}_{i,t} \\ + \beta_5 B/M_{i,t} + \beta_6 E/P_{i,t} + \beta_7 Sale/P_{i,t} + \beta_8 CF/P_{i,t} + \beta_9 EG_{i,t} + \beta_{10} TURN_{i,t} + \beta_{11} CAP_{i,t} \\ + \beta_{12} CEI_{i,t} + \beta_{13} Ret_{i,t-15:t-4} + \beta_{14} Ret_{i,t:t-2} + \beta_{15} Age_{i,t} + \beta_{16} ROE_{i,t} + \epsilon_{i,t} \end{aligned} \tag{11}$$

$R_{i,t+1:t+h}$ is the h-quarter cumulative return in excess of the market return. Coefficients and the corresponding p values (in parenthesis) are reported in Table 4. The betas are the means of the coefficients from quarterly cross-sectional regressions. Serial correlation in standard errors is corrected using the methodology in Newey & West (1987). The integer value of $T^{1/4}$ provides the lags while correcting for serial correlation, as suggested in Greene (2003). We exclude stocks with prices less than \$5 and those with negative book values.[4]

The results in Table 4 show that the proportionally large trading of anti-herders is insignificant in predicting future eight-quarter returns. Whereas, the herders' trading is negatively related to the futures stock returns over the same period in model 2. The results do not change if we control for other variables as in model 3, however, the negative effect decreases to -0.075. Specifically, a 1% increase in herders' trading will decrease the future returns by 0.075%. That means the prices of the stocks that are sold by herders increase, whereas the prices of stocks bought by the herders decrease. So their trading are destabilizing prices. To sum up, our FM regressions show that stocks sold by herders outperform those bought by them. The dependent variable is one-quarter return in model 4 and two-quarter return in model 5. The coefficients of $BAH - SAH^{lsv}_{i,t}$ and $BH - SH^{lsv}_{i,t}$ are insignificant. One quarter could be a very short period for the prices to revert to their equilibrium values. To be more precise, the herding could continue for some period of time as suggested by Brown et al. (2014); therefore, the destabilization effect of herders might persist in the short run. Similar to the results in portfolio analysis, the evidence here suggest that returns continue in the short run and revert to their equilibrium levels later. In model 6 with one-year return as dependent variable, a 1% increase in herders' trading will decrease the future one-year return by 0.045%. Trading by anti-herders is again insignificant in explaining future stock returns. These results suggest that anti-herders' trading pushes stock prices towards their fundamental values and improve the price discovery process.

In summary, anti-herders are better informed investors than herders. These results are in line with the argument in Jiang & Verardo (2018) that the skilled investors possibly diverge from the past investment decisions of the crowd to a point that they display anti-herding behavior. On the other hand, the herders exert a temporary price impact on stock prices leading to the reversal of long term returns. This shows their tendency to follow the crowd due to behavioral reasons, i.e., reputational concerns.

[4] Our results do not change if we keep penny stocks.

Table 4: Herding and Anti-herding Tendencies, and Future Stock Returns: Regression Analysis

This table reports the coefficients and their standard errors, in parentheses, from the regression of market adjusted returns, over different horizons, on the lsv trading of anti-herders, herders, and other control variables. First, institutions are classified into herders (BH-SH) and anti-herders (BAH-SAH) using an institutional level dynamic herding measure that uses a multinomial logistic regression framework. Specifically, we model the institutional trading choices, such as buy, sell, or do nothing, as a function of one quarter lagged change in aggregate institutional ownership that represents crowd's trading and other control variables. Then, we obtain the average of the marginal effects for stocks in which the change in aggregate institutional ownership is positive, representing the crowd's buying. Similarly, average marginal effects are also estimated for stocks in which the change in aggregated institutional ownership is negative, representing the crowd's selling. We estimate a time-weighted average that gives more weight to the recent marginal effects and less weight to the past quarters. The comparison of these marginal effects specifies the category of the institution. For example, if the average marginal effects on the buying probability is higher compared to the average marginal effects on the selling and passive probabilities, at the time when the crowd is buying, then the institution is ascertained as a buy-side herder. A herder is the one who exhibits herding behavior on both the buy and sell sides. Then, we obtain the stock-level lsv trading using the measure proposed by Lakonishok et al. (1992) for each institutional category. One, two, and three asterisks show the level of significance at 10%, 5%, and 1%, respectively.

	Dependent variable: Market Adjusted Returns					
	$Ret_{t+1:t+8}$			Ret_{t+1}	$Ret_{t+1:t+2}$	$Ret_{t+1:t+4}$
	(1)	(2)	(3)	(4)	(5)	(6)
$BAH-SAH^{lsv}$	−0.014		0.022	0.002	0.010	0.005
	(0.571)		(0.184)	(0.606)	(0.158)	(0.651)
$BH-SH^{lsv}$		−0.167***	−0.075**	−0.002	−0.013	−0.045**
		(0.001)	(0.011)	(0.759)	(0.223)	(0.016)
$BAH-SAH^{IO}$			−0.124	−0.022	−0.021	−0.067
			(0.316)	(0.253)	(0.482)	(0.280)
$BH-SH^{IO}$			0.036	0.0003	0.005	−0.004
			(0.390)	(0.973)	(0.713)	(0.875)
B/M			−0.016	−0.004	−0.004	−0.001
			(0.332)	(0.189)	(0.498)	(0.931)
E/P			−0.179	0.006	−0.016	−0.091
			(0.268)	(0.738)	(0.715)	(0.282)
S/P			0.013***	0.001*	0.002	0.004
			(0.005)	(0.100)	(0.187)	(0.137)
CF/P			0.106	0.004	0.019	0.048
			(0.151)	(0.631)	(0.363)	(0.256)
EG			0.082*	0.006	0.026*	0.071***
			(0.091)	(0.539)	(0.094)	(0.006)
TURN			0.075	−0.010	−0.009	0.011
			(0.242)	(0.241)	(0.561)	(0.713)
CAP			0.003	−0.001	−0.0003	0.0001
			(0.641)	(0.598)	(0.897)	(0.970)
CEI			−0.119***	−0.014***	−0.031***	−0.063***
			(0.00)	(0.00)	(0.00)	(0.00)
$Ret_{t-15:t-4}$			−0.006	−0.001	−0.002	−0.004*
			(0.176)	(0.252)	(0.115)	(0.059)
$Ret_{t-2:t}$			−0.001	0.001	0.002	0.001
			(0.986)	(0.939)	(0.912)	(0.972)
Age			−0.0001**	−0.00000	−0.00001	−0.00002
			(0.036)	(0.723)	(0.439)	(0.178)
ROE			0.027	0.018**	0.023**	0.023
			(0.671)	(0.042)	(0.030)	(0.204)
Constant	0.030	0.027	−0.011	0.008	0.003	0.008
	(0.174)	(0.261)	(0.885)	(0.494)	(0.882)	(0.837)
nobs	224350	299598	124671	144276	142243	136805
R^2	0.0022	0.0031	0.0905	0.1032	0.1054	0.1005

Subperiod Analysis

Dasgupta et al. (2011) argue that financial institutions had smaller presence in the first few years of the development of the portfolio management industry. Our descriptive statistics show the similar pattern suggesting the increase in number over the years. To make our results comparable to those in Dasgupta et

Table 5: Herding and Anti-herding Tendencies, and Future Stock Returns: Subperiod Analysis

This table reports the coefficients and their Newey-West corrected standard errors, in parentheses, from the regression of market adjusted returns, over different horizons, on the lsv trading of anti-herders, herders, and other control variables. The estimates are reported for two subperiods, 1982Q1-1993Q4 and 1994Q1-2019Q4. First, institutions are classified into herders (BH-SH) and anti-herders (BAH-SAH) using an institutional level dynamic herding measure that uses a multinomial logistic regression framework. Specifically, we model the institutional trading choices, such as buy, sell, or do nothing, as a function of one quarter lagged change in aggregate institutional ownership that represents crowd's trading and other control variables. Then, we obtain the average of the marginal effects for stocks in which the change in aggregate institutional ownership is positive, representing the crowd's buying. Similarly, average marginal effects are also estimated for stocks in which the change in aggregated institutional ownership is negative, representing the crowd's selling. We estimate a time-weighted average that gives more weight to the recent marginal effects and less weight to the past quarters. The comparison of these marginal effects specifies the category of the institution. For example, if the average marginal effects on the buying probability is higher compared to the average marginal effects on the selling and passive probabilities, at the time when the crowd is buying, then the institution is ascertained as a buy-side herder. A herder is the one who exhibits herding behavior on both the buy and sell sides. Then, we obtain the stock-level lsv trading using the measure proposed by Lakonishok et al. (1992) for each institutional category. One, two, and three asterisks show the level of significance at 10%, 5%, and 1%, respectively.

	Market Adjusted Returns			
	1982-1993		1994-2019	
	$Ret_{t+1:t+8}$ (1)	Ret_{t+1} (2)	$Ret_{t+1:t+8}$ (3)	Ret_{t+1} (4)
$BAH-SAH^{lsv}$	-0.006	-0.004	0.033	0.005
	(0.829)	(0.603)	(0.123)	(0.435)
$BH-SH^{lsv}$	-0.024	0.018^{*}	-0.094^{***}	-0.008
	(0.588)	(0.051)	(0.010)	(0.183)
$BAH-SAH^{IO}$	0.077	-0.011	-0.196	-0.025
	(0.588)	(0.780)	(0.218)	(0.244)
$BH-SH^{IO}$	0.146^{**}	0.033^{*}	-0.003	-0.011
	(0.015)	(0.065)	(0.945)	(0.204)
B/M	0.007	-0.001	-0.025	-0.005
	(0.752)	(0.866)	(0.237)	(0.164)
E/P	0.119	0.042	-0.287	-0.005
	(0.638)	(0.385)	(0.139)	(0.775)
S/P	0.012	0.001	0.013^{**}	0.002
	(0.183)	(0.516)	(0.011)	(0.135)
CF/P	0.040	-0.005	0.130	0.007
	(0.694)	(0.767)	(0.157)	(0.464)
EG	0.155	0.028^{*}	0.055	-0.002
	(0.126)	(0.090)	(0.305)	(0.891)
TURN	0.015	-0.027^{**}	0.097	-0.005
	(0.758)	(0.016)	(0.257)	(0.671)
CAP	0.006	0.002	0.003	-0.002
	(0.485)	(0.165)	(0.790)	(0.222)
CEI	-0.191^{***}	-0.022^{***}	-0.094^{***}	-0.012^{***}
	(0.00001)	(0.0001)	(0.00000)	(0.0001)
$Ret_{t-15:t-4}$	-0.009	-0.0005	-0.005	-0.001
	(0.334)	(0.796)	(0.311)	(0.243)
$Ret_{t-2:t}$	0.148^{***}	0.029^{***}	-0.054	-0.009
	(0.008)	(0.007)	(0.286)	(0.381)
Age	0.00000	0.00001	-0.0001^{**}	-0.00000
	(0.903)	(0.433)	(0.024)	(0.431)
ROE	0.289^{**}	0.049	-0.067	0.007
	(0.035)	(0.152)	(0.304)	(0.250)
Constant	-0.151^{***}	-0.033^{***}	0.040	0.021
	(0.007)	(0.009)	(0.674)	(0.108)

al., we rerun FM regressions separately for two sub-periods, namely 1982 Q3-1992 Q4 and 1993 Q1-2019 Q4. The results are reported in Table 5.

As expected, due to the small presence in the first sub-period, the impact of herders on future stock returns is not significant. On the other hand, in the second sub-period, our findings are similar to Table 4. In fact, the future return reversals are larger. These results could be explained by the large presence of institutions necessary to see the price impact of their trading.

ALL TYPES OF INSTITUTIONAL HERDING TENDENCIES

Initially, our categorization measure yield nine institutional herding categories as explained in the methodology section. However, we focus on herding and anti-herding institutions on both sides of the trades. In this section, we will include all institutional categories. However, only anti-herders, herders, buy-side anti-herders and sell-side passive, buy-side passive and sell-side anti-herders, buy-side herders and sell-side passive, buy-side passive and sell-side herders are kept in the analysis due to data restrictions in sample size. We regress futures returns on past trades of these institutions. The results are reported in Table 6.

The table shows that the number of observations have decreased greatly. None of the institutional categories except herders impact the future stock returns by their proportionally large trading. Herders' trading, as before, is inversely associated with the future stock returns.

These results support our main findings related to the destabilization impact of herders' trading. Moreover, they also imply caution in using earlier methodologies of classifying institutions into herding and anti-herding categories. The methodology presented in this paper is more precise, and the results suggest that it can offer superior returns if incorporated in portfolio formation.

INSTITUTIONAL BUY- AND SELL-SIDE TRADING AND STOCK PRICES

The literature argues that buy and sell herding of institutions can impact future stock returns differently. Gutierrez & Kelley (2009) states that the asymmetry could be due to the high informativeness of buy trades compared to sell trades since liquidity motivations rather than information of the investors can drive the later.

This section deals with the price impact of buy and sell trades of institutions classified by their tendencies to herd. We obtain the buy- and sell-side lsv trading by conditioning on the sign of our adjusted lsv measures. The stocks exhibiting buy/sell lsv trades are those with positive/negative adjusted lsvs. The resulting variables include the buy lsv trades of herders ($BH - SH^{lsv}_{BT}$), the sell lsv trades of herders ($BH - SH^{lsv}_{ST}$), the buy lsv trades of anti-herders ($BAH - SAH^{lsv}_{BT}$), and sell lsv trades of anti-herders ($BAH - SAH^{lsv}_{ST}$) replacing their adjusted versions used previously. We regress market adjusted returns on trading and other control variables and report the results in Table 7. The buy and sell-side trading of anti-herders are insignificant whereas only buy-side trading of herders is negatively impacting future eight-quarter returns as suggested by negative and significant coefficients on $BH - SH^{lsv}_{BT}$. These results show that herders' buy-side trading affects the price discovery process more than sell-side trading. These results are in line with Gutierrez & Kelley (2009) suggesting that the herd of buys have a large impact on stock prices. The asymmetry in the impacts of buy- and sell-side trading has been noted in many studies (see, e.g., Kraus & Stoll, 1972; Chan & Lakonishok, 1995).

ROBUSTNESS CHECKS

In this section, we check for robustness of our results to alternative trading measures, i.e., institutional trade persistence by Dasgupta et al. (2011), and other estimation technique that controls for time fixed effects and cluster standard errors by firms.

Table 6: All Institutional Categories

This table reports the coefficients and their Newey-West corrected standard errors, in parentheses, from the regression of market adjusted returns on the lsv trading of institutions with different herding tendencies and other control variables. The returns vary from one to eight quarters. First, institutions are classified into herders (BH-SH), anti-herders (BAH-SAH), buy-side herders & sell-side passives (BH-SP), buy-side passives & sell-side herders (BP-SH), buy-side anti-herders & sell-side passives (BH-SP), buy-side passives & sell-side anti-herders (BP-SH) using an institutional level dynamic herding measure that uses a multinomial logistic regression framework. Specifically, we model the institutional trading choices, such as buy, sell, or do nothing, as a function of one quarter lagged change in aggregate institutional ownership that represents crowd's trading and other control variables. Then, we obtain the average of the marginal effects for stocks in which the change in aggregate institutional ownership is positive, representing the crowd's buying. Similarly, average marginal effects are also estimated for stocks in which the change in aggregated institutional ownership is negative, representing the crowd's selling. We estimate a time-weighted average that gives more weight to the recent marginal effects and less weight to the past quarters. The comparison of these marginal effects specifies the category of the institution. For example, if the average marginal effects on the buying probability is higher compared to the average marginal effects on the selling and passive probabilities, at the time when the crowd is buying, then the institution is ascertained as a buy-side herder. A herder is the one who exhibits herding behavior on both the buy and sell sides. Then, we obtain the stock-level lsv trading using the measure proposed by Lakonishok et al. (1992) for each institutional category. One, two, and three asterisks show the level of significance at 10%, 5%, and 1%, respectively.

	Market Adjusted Returns			
	$Ret_{t+1:t+8}$ (1)	Ret_{t+1} (2)	$Ret_{t+1:t+2}$ (3)	$Ret_{t+1:t+4}$ (4)
$BAH-SAH^{lsv}$	0.039*	0.004	0.010	0.013
	(0.063)	(0.453)	(0.241)	(0.229)
$BH-SH^{lsv}$	−0.048**	−0.007	−0.022**	−0.046***
	(0.040)	(0.253)	(0.022)	(0.001)
$BH-SP^{lsv}$	−0.022	0.005	0.003	−0.002
	(0.301)	(0.235)	(0.709)	(0.867)
$BP-SH^{lsv}$	−0.002	−0.007	−0.003	−0.005
	(0.917)	(0.134)	(0.712)	(0.543)
$BAH-SP^{lsv}$	−0.033*	0.002	0.003	−0.006
	(0.066)	(0.602)	(0.609)	(0.613)
$BP-SAH^{lsv}$	−0.019	−0.003	−0.008	−0.001
	(0.233)	(0.479)	(0.157)	(0.939)
$BAH-SAH^{IO}$	−0.034	0.001	0.020	−0.024
	(0.799)	(0.975)	(0.550)	(0.732)
$BH-SH^{IO}$	−0.042	−0.011	−0.016	−0.032
	(0.336)	(0.323)	(0.307)	(0.198)
$BH-SP^{IO}$	−0.013	0.009	0.005	0.024
	(0.884)	(0.516)	(0.843)	(0.563)
$BP-SH^{IO}$	0.014	−0.031	−0.022	−0.006
	(0.930)	(0.318)	(0.723)	(0.941)
$BAH-SP^{IO}$	−0.031	0.025	0.026	−0.019
	(0.784)	(0.331)	(0.483)	(0.763)
$BP-SAH^{IO}$	−0.189	−0.011	−0.079	−0.107
	(0.318)	(0.832)	(0.260)	(0.340)
B/M	−0.031	−0.007	−0.008	−0.006
	(0.227)	(0.155)	(0.329)	(0.681)
E/P	−0.186	0.004	−0.026	−0.133
	(0.370)	(0.892)	(0.649)	(0.221)
S/P	0.009	0.001	0.001	0.002
	(0.143)	(0.459)	(0.810)	(0.505)

Continued on the next page

Table 6: All Institutional Categories (continued)

	Market Adjusted Returns			
	$Ret_{t+1:t+8}$	Ret_{t+1}	$Ret_{t+1:t+2}$	$Ret_{t+1:t+4}$
	(1)	(2)	(3)	(4)
CF/P	0.109	0.015	0.032	0.063
	(0.125)	(0.198)	(0.174)	(0.141)
EG	0.123	0.003	0.037	0.114^{**}
	(0.218)	(0.876)	(0.251)	(0.028)
TURN	0.121^{*}	-0.004	0.002	0.033
	(0.084)	(0.717)	(0.924)	(0.287)
CAP	0.003	-0.001	-0.002	-0.002
	(0.789)	(0.283)	(0.428)	(0.730)
CEI	-0.115^{***}	-0.014^{***}	-0.031^{***}	-0.062^{***}
	(0.00000)	(0.0001)	(0.00000)	(0.00000)
$Ret_{t-15:t-4}$	-0.001	-0.001	-0.002^{*}	-0.003
	(0.900)	(0.275)	(0.093)	(0.191)
$Ret_{t-2:t}$	0.025	0.001	0.006	0.012
	(0.480)	(0.927)	(0.758)	(0.675)
Age	-0.0001^{*}	-0.00000	-0.00001	-0.00002
	(0.088)	(0.348)	(0.197)	(0.168)
ROE	-0.051	0.030^{*}	0.051^{*}	0.069
	(0.767)	(0.080)	(0.054)	(0.121)
Constant	0.009	0.015	0.022	0.027
	(0.922)	(0.262)	(0.379)	(0.568)
nobs	66125	76831	75785	72804
R^2	0.1651	0.1697	0.1711	0.1656

Institutional Trade Persistence

Whereas lsv captures herding in one quarter, the stock-level trade persistence by Dasgupta et al. (2011) captures herding over multiple quarters. The authors claim that their trade persistence (TP) measure is better at capturing herding since the dynamic herding models predict that the herding phenomenon causes persistence in investors' trading decisions. In this section, we incorporate trade persistence measure as an alternative to lsv. Specifically, in this measure, if institutions persistently buy or sell a stock in multiple quarters then they exhibit herding. For example, if a particular institutional category buys or sells (on net) a stock for 3 quarters, its trade persistence is 3 or -3, respectively. To ascertain whether institutions belonging to a given category buys or sells, we look at the change in the number of stocks held in their aggregate portfolio. A positive value represents net buy, whereas a negative value represents net sell. The maximum trade persistence is 5 or -5.

We repeat the methodology adopted in the Table 4 except that this time the trading measure is the persistent trading measure. The results are reported in Table 8, which show that the persistent trading of herders is destabilizing, and the anti-herders do not contribute to the destabilization as before. A one quarter increase in persistence decreases one quarter ahead return by 0.1%, two quarters ahead return by 0.1%, and four quarters ahead return by 0.3%.

Controlling for Fixed Effects and Clustering Standard Errors

Here, we use an alternative estimation technique. We control for time fixed effects and cluster standard errors by firms. Even though Fama & Macbeth (1973) regressions with Newey-West corrections for serial correlations provide more conservative standard errors, this specification also support our previous findings. The results are reported in Table 9 .

Table 7: Institutional Buy and Sell Trading

This table reports the coefficients and their Newey-West corrected standard errors, in parentheses, from the regression of market adjusted returns on the lsv trading of institutions with different herding tendencies and other control variables. The returns range from one quarter to eight quarters. First, institutions are classified into herders (BH-SH), anti-herders (BAH-SAH), buy-side herders & sell-side passives (BH-SP), buy-side passives & sell-side herders (BP-SH), buy-side anti-herders & sell-side passives (BH-SP), buy-side passives & sell-side anti-herders (BP-SH) using an institutional level dynamic herding measure that uses a multinomial logistic regression framework. Then, we obtain the stock-level lsv trading using the measure proposed by Lakonishok et al. (1992) for each institutional category. We obtain the buy- and sell-side lsv trading by conditioning on the sign of our adjusted lsv measures. The stocks exhibiting buy/sell lsv trades are those with positive/negative adjusted lsvs. The resulting variables include the buy lsv trades of herders ($BH - SH^{lsv}_{BT}$), the sell lsv trades of herders ($BH - SH^{lsv}_{ST}$), the buy lsv trades of anti-herders ($BAH - SAH^{lsv}_{BT}$), and sell lsv trades of anti-herders ($BAH - SAH^{lsv}_{ST}$) replacing their adjusted versions used previously. One, two, and three asterisks show the level of significance at 10%, 5%, and 1%, respectively.

	Market Adjusted Returns			
	$Ret_{t+1:t+8}$ (1)	Ret_{t+1} (2)	$Ret_{t+1:t+2}$ (3)	$Ret_{t+1:t+4}$ (4)
$BAH - SAH^{lsv}_{BT}$	0.047	0.011	0.026*	0.028
	(0.029)	(0.009)	(0.014)	(0.020)
$BAH - SAH^{lsv}_{ST}$	0.012	−0.002	−0.011	0.008
	(0.051)	(0.013)	(0.015)	(0.028)
$BH - SH^{lsv}_{BT}$	−0.143***	0.012	0.009	−0.049
	(0.054)	(0.014)	(0.019)	(0.033)
$BH - SH^{lsv}_{ST}$	0.235	0.024	0.065	0.155
	(0.172)	(0.023)	(0.051)	(0.110)
$BAH - SAH^{IO}$	−0.116	−0.025	−0.022	−0.063
	(0.123)	(0.019)	(0.030)	(0.061)
$BH - SH^{IO}$	0.044	0.002	0.008	0.001
	(0.040)	(0.008)	(0.014)	(0.025)
B/M	−0.018	−0.004	−0.003	−0.002
	(0.017)	(0.003)	(0.005)	(0.010)
E/P	−0.184	0.006	−0.018	−0.093
	(0.160)	(0.019)	(0.044)	(0.084)
S/P	0.013***	0.001	0.002	0.004
	(0.004)	(0.001)	(0.002)	(0.003)
CF/P	0.105	0.003	0.018	0.047
	(0.072)	(0.008)	(0.021)	(0.041)
EG	0.086*	0.007	0.029*	0.075***
	(0.047)	(0.010)	(0.016)	(0.026)
TURN	0.070	−0.011	−0.010	0.009
	(0.064)	(0.009)	(0.016)	(0.031)
CAP	0.003	−0.001	−0.0002	0.0003
	(0.007)	(0.001)	(0.002)	(0.004)
CEI	−0.117***	−0.014***	−0.031***	−0.062***
	(0.019)	(0.003)	(0.005)	(0.010)
$Ret_{t-15:t-4}$	−0.006	−0.001	−0.002	−0.004*
	(0.005)	(0.001)	(0.001)	(0.002)
$Ret_{t-2:t}$	−0.002	0.001	0.002	0.0001
	(0.044)	(0.009)	(0.018)	(0.030)
Age	−0.0001**	−0.00000	−0.00001	−0.00002
	(0.00003)	(0.00000)	(0.00001)	(0.00002)
ROE	0.037	0.019**	0.024**	0.028
	(0.066)	(0.009)	(0.011)	(0.019)
Constant	−0.011	0.007	0.001	0.004
	(0.071)	(0.011)	(0.019)	(0.037)
Observations	124,671	144,276	142,243	136,805
R^2	0.163	0.149	0.179	0.170

CONCLUSION

This study investigates the link between institutional herding and managerial informativeness in banks, investment companies, investment advisors, insurance companies, and others. A new institutional-level herding measure is designed that captures the tendency to herd on both the buying and selling sides of

Table 8: Persistent trading by Herders and Anti-herders and Future Stock Returns: A Robustness Check

This table reports the coefficients and their standard errors, in parentheses, from the regression of market adjusted returns, over different horizons, on the lsv trading of anti-herders, herders, and other control variables. First, institutions are classified into herders (BH-SH) and anti-herders (BAH-SAH) using an institutional level dynamic herding measure that uses a multinomial logistic regression framework. Then, we obtain the stock-level trading persistence measure proposed by Dasgupta et al. (2011) for each institutional category. One, two, and three asterisks show the level of significance at 10%, 5%, and 1%, respectively.

	Market Adjusted Returns			
	$Ret_{t+1:t+8}$ (1)	Ret_{t+1} (2)	$Ret_{t+1:t+2}$ (3)	$Ret_{t+1:t+4}$ (4)
$BAH-SAH^{TP}$	−0.003	−0.001	−0.001*	−0.001
	(0.187)	(0.125)	(0.062)	(0.282)
$BH-SH^{TP}$	−0.003*	−0.001**	−0.001**	−0.003***
	(0.064)	(0.024)	(0.036)	(0.003)
$BAH-SAH^{IO}$	−0.023	0.012	0.036	0.027
	(0.845)	(0.437)	(0.229)	(0.652)
$BH-SH^{IO}$	0.026	0.007	0.011	0.0005
	(0.516)	(0.372)	(0.447)	(0.982)
B/M	−0.007	−0.003	−0.003	−0.007
	(0.575)	(0.148)	(0.320)	(0.256)
E/P	−0.068	0.016	0.005	−0.043
	(0.565)	(0.288)	(0.886)	(0.558)
S/P	0.006*	0.001*	0.002	0.002
	(0.051)	(0.064)	(0.125)	(0.258)
CF/P	0.047	0.005	0.011	0.032
	(0.292)	(0.448)	(0.407)	(0.225)
EG	0.028	0.004	0.018*	0.032*
	(0.395)	(0.513)	(0.088)	(0.092)
TURN	−0.006	−0.014	−0.025	−0.022
	(0.893)	(0.109)	(0.107)	(0.446)
CAP	0.003	0.0002	0.001	0.001
	(0.647)	(0.817)	(0.657)	(0.761)
CEI	−0.106***	−0.015***	−0.032***	−0.059***
	(0.000)	(0.000)	(0.000)	(0.000)
$Ret_{t-15:t-4}$	−0.007	−0.001*	−0.003**	−0.005**
	(0.162)	(0.085)	(0.048)	(0.042)
$Ret_{t-2:t}$	−0.029	0.0005	0.001	−0.007
	(0.510)	(0.956)	(0.973)	(0.821)
Age	−0.0001***	−0.00001	−0.00001	−0.00003*
	(0.004)	(0.304)	(0.165)	(0.077)
ROE	−0.005	0.012***	0.021***	0.013
	(0.871)	(0.009)	(0.008)	(0.318)
Constant	0.014	−0.002	−0.006	0.007
	(0.802)	(0.761)	(0.713)	(0.831)
nobs	175826	202022	199491	192296
R^2	0.0604	0.0732	0.0752	0.0703

the crowd. For example, a buy-side herder buys when the crowd buys, and a sell-side herder sells when the crowd sells. In our setting, a herder is a buy- and sell-side herder. From the combination of herding, anti-herding, or passive behavior on buying and selling sides, nine categories of institutions are formed. We then test the link between the trading of herders, anti-herders and others and future stock returns to investigate their role in market efficiency.

First, we find that our measure categorizes a smaller number of institutions into herders and anti-herders. That shows that our dynamic measure is relatively more precise compared to the previous institutional level herding measure of Jiang & Verardo (2018). We find a negative relationship between herders' trading and future stock returns, suggesting a destabilizing role of these institutions. Besides, trading by other categories does not destabilize stock prices supported by an insignificant relationship with future stock returns. These findings are robust to the use of a variety of control variables known to affect returns, dissecting the sample into sub-periods, trading measures, and controlling for fixed effects.

Table 9: Time Fixed Effects with Clustered Standard Errors: A Robustness Check

This table reports the coefficients and their standard errors, in parentheses, from the regression of market adjusted returns, over different horizons, on the lsv trading of anti-herders, herders, and other control variables. We control for time fixed effects and cluster standard errors by firm. First, institutions are classified into herders (BH-SH) and anti-herders (BAH-SAH) using an institutional level dynamic herding measure that uses a multinomial logistic regression framework. Then, we obtain the stock-level trading persistence measure proposed by Dasgupta et al. (2011) for each institutional category. One, two, and three asterisks show the level of significance at 10%, 5%, and 1%, respectively.

	Market Adjusted Returns			
	$Ret_{t+1:t+8}$ (1)	Ret_{t+1} (2)	$Ret_{t+1:t+2}$ (3)	$Ret_{t+1:t+4}$ (4)
$BAH-SAH^{lsv}$	0.030	0.009	0.017***	0.010
	(0.019)	(0.007)	(0.0004)	(0.208)
$BH-SH^{lsv}$	−0.122***	−0.011***	−0.035***	−0.085***
	(0.000)	(0.004)	(0.00000)	(0.000)
$BAH-SAH^{IO}$	−0.082	−0.026	−0.035	−0.080
	(0.355)	(0.056)	(0.141)	(0.075)
$BH-SH^{IO}$	−0.058	−0.008	−0.013	−0.045***
	(0.132)	(0.086)	(0.148)	(0.015)
B/M	−0.024	−0.003	−0.005	−0.010
	(0.212)	(0.259)	(0.393)	(0.261)
E/P	−0.100	−0.001	−0.007	−0.066
	(0.191)	(0.896)	(0.738)	(0.124)
S/P	0.010	0.002	0.003	0.006
	(0.076)	(0.071)	(0.068)	(0.060)
CF/P	0.173***	0.006	0.033	0.085***
	(0.005)	(0.356)	(0.037)	(0.004)
EG	−0.143***	−0.012	−0.043	−0.043
	(0.044)	(0.130)	(0.058)	(0.194)
TURN	0.044	−0.006	−0.009	0.008
	(0.135)	(0.197)	(0.279)	(0.549)
CAP	−0.011***	−0.002***	−0.003***	−0.004
	(0.003)	(0.0002)	(0.001)	(0.009)
CEI	−0.096***	−0.014***	−0.032***	−0.056***
	(0.000)	(0.000)	(0.000)	(0.000)
$Ret_{t-15:t-4}$	−0.006	−0.0005	−0.002	−0.005***
	(0.059)	(0.285)	(0.008)	(0.001)
$Ret_{t-2:t}$	−0.060***	−0.001	−0.009	−0.032***
	(0.000)	(0.395)	(0.010)	(0.00000)
Age	−0.0001	−0.00000	−0.00001	−0.00003
	(0.006)	(0.077)	(0.023)	(0.003)
ROE	−0.00004	−0.0001	−0.00004	−0.0004
	(0.956)	(0.640)	(0.925)	(0.479)
Observations	124,671	144,276	142,243	136,805
Adjusted R^2	0.011	0.001	0.007	0.007

We are inspired by the huge literature on herding that provides conflicting findings in the context of their role in price formation. This study puts forward a precise measure of institutional-level herding tendencies in an attempt to resolve this puzzle. The evidence presented in this paper reports the damaging role of herders, that is, they destabilize stock prices.

APPENDIX

A1: Definitions of Control Variables

1. Size (CAP): Size is the natural logarithm of the total market capitalization of stock *i* in quarter *t*.
2. Share Turnover (TURN): At the end of each quarter and for each stock, share turnover is measured as the number of shares traded divided by total outstanding shares.
3. Return on Equity (ROE): ROE is measured as stock i's income after tax (compustat item niq) divided by book value of equity.

Table A1: Descriptive statistics of stock characteristics

Statistic	No. of Obs.	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
$Ret_{t-15:t-4}$	390,440	0.766	1.839	−0.999	−0.030	1.022	155.794
$Ret_{t-2:t}$	496,384	0.049	0.326	−0.995	−0.118	0.186	19.506
B/M	501,724	0.718	0.984	0.00003	0.320	0.895	55.473
E/P	501,297	0.038	0.216	−24.534	0.019	0.082	20.210
S/P	499,603	1.652	3.433	−1.721	0.401	1.791	236.856
CF/P	431,469	0.118	0.339	−23.780	0.042	0.165	50.887
EG	468,792	−0.018	1.328	−618.644	−0.016	0.023	59.320
TURN	477,703	0.132	0.224	0	0.032	0.161	52.795
CAP	501,724	5.866	1.921	−0.424	4.434	7.119	13.666
CEI	381,930	0.051	0.369	−3.559	−0.129	0.154	5.904
Age	501,724	207.919	192.548	7	66	281	1,129
ROE	314,592	−0.039	15.728	−8,652.750	0.001	0.041	474.176

Book Value: Book value is measured as equity held by stock holders plus deferred taxes and investment tax credits minus preferred stock. Stock holders' equity is from compustat (item header seqq). If seqq is missing, common stock equity plus preferred stock is used. The remaining missing values are obtained by total assets minus total liabilities. Preferred stock is the redeemable preferred stock and then the missing values are replaced by total preferred stock at the end of the quarter. Net income after tax in quarter *t* is from the quarter for which the report date (compustat item rdq) precedes this quarter. We obtain the balance sheet items from the previous quarter.

4. B/M: For book to market ratio, book equity is measured as in Fama & French (1992). For B/M from June of year T to May of year T+1, book value at the end of the fiscal year (ending in year T-1) is divided by the market value in December of year T-1.
5. Age: Age is equal to the number of months since the stock first appears in CRSP monthly stock returns file.
6. Earnings to Price (E/P): Earnings to price ratio is equal to the fiscal-year end earnings in the year T-1 divided by the calendar-year end market equity in the year T-1, employed in June of year T.
7. Cash Flows to Price (CF/P): CF/P is constructed as the fiscal-year end cash flows divided by the calendar-year end market value of equity (in year T-1) and employed starting from June of year T. CF is measured as earnings before extraordinary items plus deferred taxes plus equity's share of depreciation. Where equity's share is defined as market equity divided by total assets minus book equity plus market equity.
8. Sales to Price (S/P): S/P is the fiscal-year end revenues in year T-1 (compustat item sale) relative to the calendar-year end market equity. Moreover, it is employed starting from the June of year T.
9. Earnings Growth (EG): EG is equal to the change in annual earning before extraordinary items (EBI) from the year T-1 scaled by market equity in December of year T-1. It is employed in year T.
10. Past Return ($R_{i,t-15:t-4}$): $R_{i,t-15:t-4}$ is the cumulative return over quarters t-15 to t-4 to capture return reversal effect as documented in Bondt & Thaler (1985).
11. Composite Equity Issuance (CEI): It is estimated following Daniel & Titman (2006) as below.

$$CEI_{i,t} = log(\frac{MarketEquity_{i,t}}{MarketEquity_{i,t-15}}) - log(Ret_{i,t-15:t-4})$$

12. MOM ($R_{i,t}$): $R_{i,t}$ is the return in quarter t.

The summary statistics of the control variables are given in Table A1.

A2: Institutional Classification based on Jiang & Verardo (2018)

We use the following linear regression model to estimate the coefficient that shows the sensitivity of an institution's trade against the crowd's move.

$$\Delta SAS_{i,l,t} = \theta_l + \Gamma_l \Delta IO_{i,t-1} + \theta_{CAP,l} CAP_{i,t-1} + \theta_{BM,l} BM_{i,t-1} + \epsilon_{i,l,t} \tag{12}$$

On left hand side, we have the percentage change in the number of split-adjusted shares of stock "i" in an institutional portfolio "l" during quarter t. The variables on the right hand side are defined earlier. All the variables in the regression are standardized. Here, the coefficient of interest is Γ_l. As before, we compute a weighted average of the coefficients given below.

$$JV_{l,t} = \frac{\sum_{h=1}^{t} \frac{1}{h} \Gamma_{l,t-h+1}}{\sum_{h=1}^{t} \frac{1}{h}}. \tag{13}$$

For more details, see Jiang & Verardo (2018). To make this methodology comparable with ours, we divide the institutions into two classes based on the median $JV_{l,t}$. Those in the top group are classified as herders whereas those in the bottom group are classified as anti-herders.

A3: Institutional Classes

The details of the remaining classes of institutions that are not explained in section 2 are given below.

8.0.1. Buy-side anti-herders and sell-side passives (BAH-SP)

The predicted probabilities of these institutions are exhibited in plot 3. Their probability to sell increases on average against the crowd's buying whereas the probability to not trade increases against crowd's selling. $Avg.M.E_2^{cb}$ and $Avg.M.E_0^{cs}$ are higher for these institutions.

8.0.2. Buy-side anti-herders and sell-side passives (BAH-SP)

The predicted probabilities of these institutions are exhibited in plot 3. Their probability to sell increases on average against the crowd's buying whereas the probability to not trade increases against crowd's selling. $Avg.M.E_2^{cb}$ and $Avg.M.E_0^{cs}$ are higher for these institutions.

8.0.3. Buy-side herders and sell-side passives (BH-SP)

They have high probability to buy when the crowd buys and high probability to stay passive when crowd sells as reflected by their average marginal effects. Their choice probabilities are plotted in plot 4. For these managers, $Avg.M.E_1^{cb}$ and $Avg.M.E_0^{cs}$ are high.

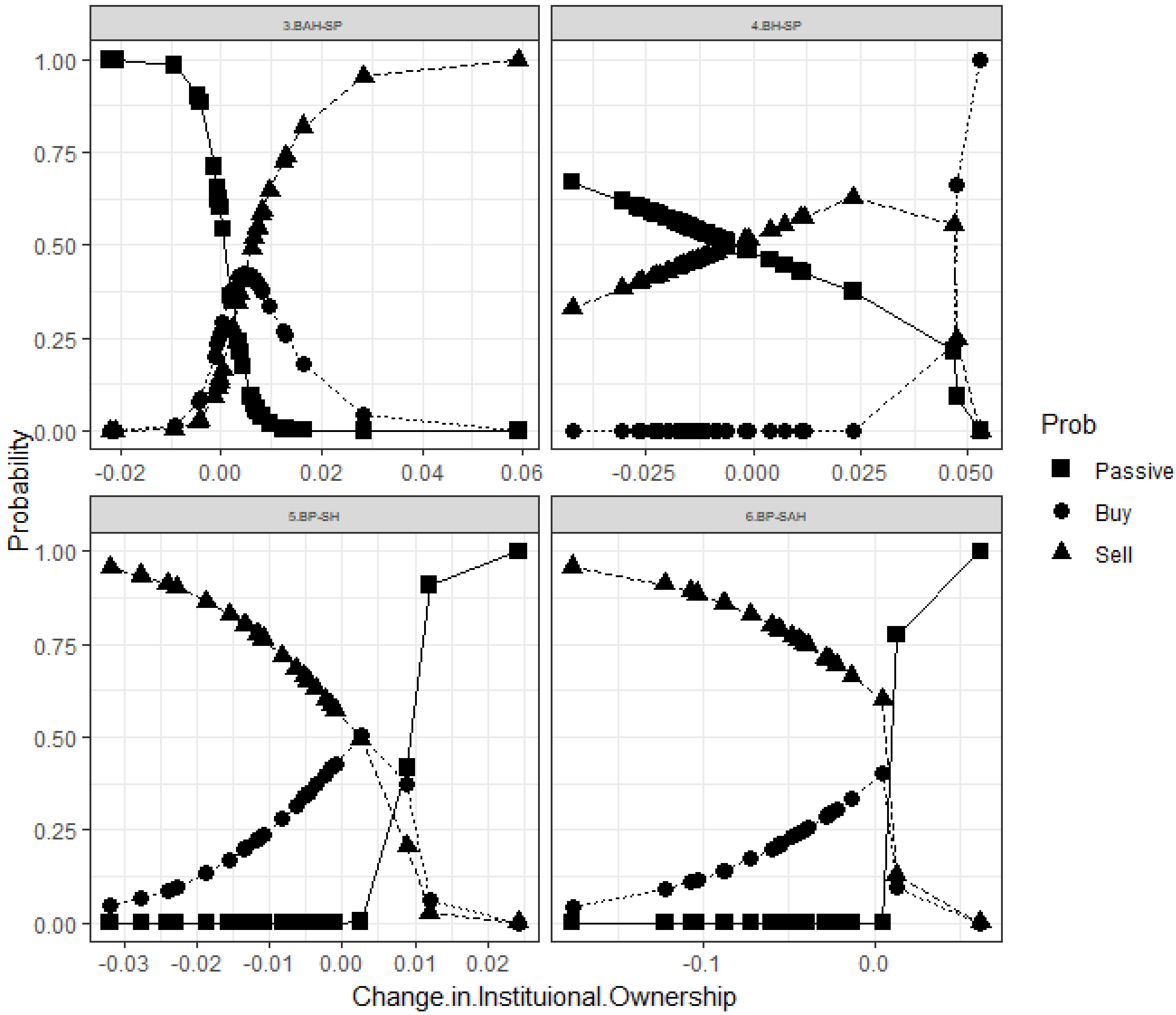
8.0.4. Buy-side passives and sell-side herders (BP-SH)

Buy-side passives and sell-side herders are more likely to remain passive when the crowd buys and more likely to sell when the crowd sells. Plot 5 exhibits their behavior. $Avg.M.E_0^{cb}$ and $Avg.M.E_2^{cs}$ both are high for these institutions.

8.0.5. Buy-side passives and sell-side anti-herders (BP-SAH)

The average marginal effects of buy-side passives and sell-side anti-herders reflect that they do not respond when the crowd buys, but they tend to buy when the crowd sells. These managers have large $Avg.M.E_0^{cb}$ and $Avg.M.E_2^{cs}$. We find very few institutions in the classes buy-side anti-herders and sell-side herders (BAH-SH), buy-side herder and sell-side anti-herders (BH-SAH), and passives (BP-SP). Therefore, we do not list them here.

Figure A1: Predicted Probabilities of the Remaining Institutional Types



References

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, *100*, 992–1026.

Bondt, W. F. M. D., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, *40*, 793–805.

Brown, N. C., Wei, K. D., & Wermers, R. (2014). Analyst recommendations, mutual fund herding, and overreaction in stock prices. *Management Science*, *60*, 1–20.

Brunnermeier, M., & Nagel, S. (2004). Hedge funds and the technology bubble. *The journal of Finance*, *59*, 2013–2040.

Chan, L. K. C., & Lakonishok, J. (1995). The behavior of stock prices around institutional trades. *The Journal of Finance*, *50*, 1147–1174.

Chang, C. (2010). Herding and the role of foreign institutions in emerging equity markets. *Pacific-Basin Finance Journal*, *18*, 175–185.

Daniel, K., & Titman, S. (2006). Market reactions to tangible and intangible information. *The Journal of Finance*, *61*, 1605–1643. doi:10.1111/j.1540-6261.2006.00884.x.

Dasgupta, A., Prat, A., & Verardo, M. (2011). Institutional trade persistence and long-term equity returns. *The Journal of finance*, *66*, 635–653. doi:doi:10.1111/j.1540-6261.2010.01644.x.

Deng, X., Hung, S., & Qiao, Z. (2018). Mutual fund herding and stock price crashes. *Journal of Banking and Finance*, *94*, 166–184.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47*, 427–465. doi:10.1111/j.1540-6261.1992.tb04398.x.

Fama, E. F., & Macbeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*, 607–636.

Greene, W. (2003). *Econometric Analysis*. Pearson Education.

Gutierrez, R., & Kelley, E. (2009). Institutional herding and future stock returns, .

Iqbal, M. S., Salih, A., & Akdeniz, L. (2021). The price impact of same- and opposing-direction herding by institutions with different investment horizons. *Finance Research Letters*, *40*, 101692. doi:https://doi.org/10.1016/j.frl.2020.101692.

Iqbal, M. S., Salih, A., & Akdeniz, L. (2023). Institutions and the book-to-market effect: The role of investment horizon. *International Review of Economics and Finance*, *84*, 140–153. doi:https://doi.org/10.1016/j.iref.2022.10.017.

Jiang, H., & Verardo, M. (2018). Does herding behavior reveal skill? an analysis of mutual fund performance. *The Journal of Finance*, *73*, 2229–2269. doi:https://doi.org/10.1111/jofi.12699.

Kraus, A., & Stoll, H. R. (1972). Price impacts of block trading on the new york stock exchange. *The Journal of Finance*, *27*, 569–588.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, *32*, 23 – 43. doi:https://doi.org/10.1016/0304-405X(92)90023-Q.

Newey, W. K., & West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, (pp. 777–787).

Patterson, D. M., & Sharma, V. (2010). The incidence of informational cascades and the behavior of trade interarrival times during the stock market bubble. *Macroeconomic Dynamics*, *14*, 111–136.

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, (pp. 465–479).

Sias, R. W. (2004). Institutional herding. *The Review of Financial Studies*, *17*, 165–206. doi:10.1093/rfs/hhg035.

Spyrou, S. (2013). Herding in financial markets: a review of the literature. *Review of Behavioral Finance*, *5*, 175–194.

Tiniç, M., Iqbal, M. S., & Mahmud, S. F. (2020). Information cascades, short-selling constraints, and herding in equity markets. *Borsa Istanbul Review*, *20*, 347–357. doi:https://doi.org/10.1016/j.bir.2020.05.007.

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *The Journal of Finance*, *54*, 581–622. doi:10.1111/0022-1082.00118.

Yan, X. S., & Zhang, Z. (2009). Institutional investors and equity returns: Are short-term institutions better informed? *The Review of Financial Studies*, *22*, 893. doi:10.1093/revfin/hhl046.

Yuksel, H. Z. (2015). Does investment horizon matter? disentangling the effect of institutional herding on stock prices. *Financial Review*, *50*, 637–669. doi:10.1111/fire.12080.