

## **Institutional industry herding**

Nicole Choi

and

Richard W. Sias\*

August 8, 2008

JEL: G10, G12, G14

Keywords: herding, institutional investors

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\* Both authors are from the Department of Finance, Insurance, and Real Estate, College of Business, Washington State University, Pullman, Washington, 99164-4746. Choi: (509) 335-7822, [choiyj@wsu.edu](mailto:choiyj@wsu.edu); Sias: (509) 335-2347, [sias@wsu.edu](mailto:sias@wsu.edu). The authors thank seminar participants at Washington State University, the AsianFA/NFA conference, Roberto Gutierrez, and Eric Kelley for their helpful comments. Copyright © 2008 by the authors.

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### **Abstract**

We examine whether institutional investors follow each other into and out of the same industries. Our empirical results reveal strong evidence of institutional industry herding. The cross-sectional correlation between the fraction of institutional traders buying an industry this quarter and the fraction buying last quarter, for example, averages 40%. Additional tests suggest institutional industry herding results from managers' decisions (rather than underlying investors' flows), is not fully explained by institutions following each other into and out of similar size and book to market ratio stocks, drives institutional industry momentum trading, is more pronounced in smaller and more volatile industries, and may sometimes drive industry market values from fundamental values.

## Institutional industry herding

*“The gains represent institutional herding, in which money managers chase each other into the hot performing areas regardless of the price they are paying...”* (Financial Times, July 5, 2004)

### 1. Introduction

The popular press often portrays institutional investors as driving prices from fundamental values and generating excess volatility as they herd to and from the latest ‘fad.’ Moreover, a rich theoretical literature suggests five additional reasons institutions may herd including underlying investors’ flows, institutional positive feedback trading, attempting to preserve reputation by acting like other managers (reputational herding), following correlated signals (investigative herding), and inferring information from each others’ trades (informational cascades). Although a growing empirical literature focuses on testing institutional herding in individual securities, the proposed reasons for institutional herding hold at least equally well at the industry level. If, for example, institutions are “piling in” to the technology industry, then an institution attempting to preserve their reputation may follow others into the technology industry. In addition, given institutional investors’ dominant role in the market, they are likely to be the marginal investor whose trades set prices for most securities, and therefore, industries.<sup>1</sup> As a result, if institutional investors herd to and from industries, such herding has the potential to impact industry valuations.

The primary goal of this paper is to address this fundamental question: Do institutional investors herd across industries?<sup>2</sup> By moving beyond examining herding at the individual security level, our study contributes to two related literatures. First, our results have direct implications for understanding why institutional investors herd and the potential price effects associated with such herding. Second, our study is closely related to the rapidly growing “style investing” literature. Barberis and Shleifer’s (2003)

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<sup>1</sup> Institutional investors now dominate the ownership and trading of U.S. securities accounting for 63% of equity holdings in 2002 (NYSE factbook) and an even higher portion of turnover. Schwartz and Shapiro (1992) estimate that institutional investors accounted for 70% of trading volume in 1989. Using proprietary data, Jones and Lipson (2003) estimate that individual investors’ orders accounted for less than 4% of NYSE share volume for a sample of securities in 2002. See Chakravarty (2001), Boyer and Zheng (2004), Froot and Teo (2004), Sias, Starks, and Titman (2006), Kaniel, Saar, and Titman (2008) and Campbell, Ramadorai, and Schwartz (2007) for evidence that institutional investors are the price-setting marginal investors.

<sup>2</sup> To our knowledge this is the first study of institutional industry herding. Several previous studies (Lakonishok, Shleifer, and Vishny, 1992; Sharma, Easterwood, and Kumar, 2006) examine whether institutional investors herd at the individual stock level in some industries more than others, e.g., are institutions more likely to following each other from Microsoft to IBM than they are to follow each other from Pacific Gas and Electric to Duke Energy? Our work, however, focuses on herding across industries, e.g., do institutional investors follow each other out of utilities and into technology stocks?

groundbreaking model of style investing, for example, requires two key elements related to our study: (1) a group of investors that herd to and from styles, and (2) that these investors' herding impacts prices.<sup>3</sup> The growing empirical work on style investing (e.g., Teo and Woo, 2004; Barberis, Shleifer, and Wurgler, 2005; Froot and Teo, 2007) is also based on the proposition that a group of investors herd to a style and this behavior impacts returns.<sup>4</sup>

Our empirical results reveal strong evidence of institutional industry herding—institutional investors follow each other into and out of the same industries. The cross-sectional correlation between the fraction of institutional traders buying an industry this quarter and the fraction buying last quarter, for example, averages 40%. A number of robustness tests reveal that industry herding holds for alternative industry definitions and occurs both on the buy side (institutions following each other into the same industries) and the sell side (institutions following each other out of the same industries). Moreover, institutional investors' demand for a stock is a positive function of both their lag demand for that stock and their lag demand for other stocks in the same industry. Further decompositions reveal that although institutions herding to similar size and book to market style stocks contributes to industry herding, such herding cannot fully explain industry herding. The balance of the paper focuses on understanding what drives institutional industry herding.

We begin by examining whether underlying investors' flows cause institutional industry herding, e.g., retail investors moving funds from managers that focus on utility stocks and to managers that focus on healthcare stocks. We run two sets of tests to examine this explanation. First, following Dasgupta, Prat, and Verardo (2007), we exclude those institutional investors who are most subject to retail flows (mutual funds and independent advisors) from our analysis. Second, we examine changes in institutional investors' industry portfolio weights (that should not be impacted by underlying investors' flows) rather than changes in

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<sup>3</sup> In Barberis and Shleifer's (2003) model, an investment style (which, as the authors note, include industry styles) experiences return momentum and reversals as a result of investors' style herding. Specifically, a positive cash flow shock to a style attracts positive feedback traders (shifting funds from a different style), who drive prices higher and therefore attract more positive feedback traders the following periods, i.e., a group of investors herd to one style and out of another style. While positive feedback style trading may certainly contribute to industry herding, as noted above, a number of other scenarios could also cause industry herding, e.g., attempting to preserve reputation.

<sup>4</sup> In fact, Barberis and Shleifer (2003) suggest that institutions may be style investors. For example, the authors note (page 170), "...if we think of switchers as institutions chasing the best-performing style, then our model is consistent with evidence that demand shifts by institutions in particular influence security prices (Gompers and Metrick, 2001)."

institutional investors' positions (which will be impacted by underlying investors' flows). Both tests suggest that institutional industry herding results from managers' decisions rather than underlying investors' flows.

Second, we investigate whether institutional investors' preference for industries with high lag returns might drive their herding as in the Barberis and Shleifer (2003) style investing model. Specifically, if institutional demand impacts returns and institutional investors industry momentum trade, then institutional investors may follow each other into and out of the same industries as they chase lag industry returns. Although institutional investors tend to purchase industries that have done well in the past and sell those that have done poorly, such momentum trading does not explain their herding. In fact, we find the opposite— institutional industry demand is largely independent of lag industry returns once controlling for institutional industry herding (i.e., the correlation between contemporaneous and lag institutional industry demand). In short, our results suggest institutions momentum trade industries because they herd and their lag demand is positively correlated with lag returns.

Third, we examine herding by investor type (banks, insurance companies, mutual funds, independent advisors, and unclassified investors) to test the reputational herding explanation. Following Sias (2004), we hypothesize that: (1) institutional investors concerned about their reputations are more likely to follow similarly classified institutional investors than differently classified institutions (e.g., mutual funds are more likely to follow other mutual funds than insurance companies), and (2) mutual funds and independent advisors will be more concerned about their reputations than other investors and therefore exhibit a stronger herding propensity. We find mixed evidence for the reputational herding explanation. Four of the five investor groups (independent advisors are the exception) are more likely to follow similarly classified institutions than differently classified institutions. We find little evidence, however, that mutual funds and independent advisors are more likely to herd than other institutional investors.

Fourth, we investigate the relations between industry volatility, industry size, and industry herding to differentiate informational cascades from investigative herding. Following Wermers (1999), we hypothesize that if herding results, at least in part, from institutions ignoring their own private signals and following the perceived consensus information of the herd (informational cascades), investors will tend to herd more as

their signals becomes noisier. In addition, following Sias (2004), we hypothesize that if herding results from correlated signals, then investors will tend to herd more as their signals become less noisy. Thus, if industry herding primarily results from information cascades, herding should be stronger in smaller and more volatile industries. And if industry herding primarily results from correlated signals, herding should be stronger in larger and less volatile industries. Consistent with informational cascades contributing to industry herding, industries with higher levels of herding tend to be smaller and more volatile than other industries.

Fifth, we investigate whether institutional industry herding is stronger once institutions have easy electronic access to other institutions' positions. Specifically, institutions were required to file their position reports through the SEC's *Electronic Data Gathering and Retrieval* (EDGAR) system after 1996. Consistent with the hypothesis that institutional herding results, at least in part, from institutions intentionally following each other into the same industries, we find evidence that institutional herding increases once institutions can easily view other institutions' trades. Specifically, the measure of institutional herding is 17% larger, on average, in the post-EDGAR period than the pre-EDGAR period. The difference is statistically significant at the 5% level based on a non-parametric test, but not statistically significant ( $p$ -value of 0.11) based on differences in means test.

Last, we investigate whether institutional industry herding drives prices from fundamentals as expected if: (1) herding does not fully result from the manner in which information is incorporated into prices (i.e., investigative herding) and (2) herding impacts prices. Specifically, we examine the relation between institutional industry demand and returns over the herding period and the three years following the herding period. Our results reveal that institutional industry demand is strongly positively correlated with industry returns over the herding period, i.e., those industries institutions most heavily purchase over a given period average significantly higher returns over that period than those industries institutions sell. We also find some evidence that industries institutions herd to underperform those they herd out of in the year *following* the herding. The relation between institutional industry demand and contemporaneous and subsequent industry returns is consistent with explanations that suggest institutional industry herding sometimes drives industry prices from fundamental values and the Barberis and Shleifer (2003) style investing model.

The balance of the paper is organized as follows—we provide a brief review of related literature and discuss data in the next section. Section 3 presents our primary empirical tests while Section 4 focuses on the causes of institutional industry herding. The final section presents conclusions.

## 2. Background and data

### 2.1. Herding

Industry (stock) herding is defined as a group of investors following each other into and out of the same industry (stock) over *some period*.<sup>5</sup> As noted in the introduction, previous work proposes six reasons institutional investors may herd—underlying investors’ flows, fads, institutional positive-feedback trading, reputational herding, investigative herding, and informational cascades. First, institutional investors may herd to industries because underlying investors shift toward those industries (see Frazzini and Lamont, 2008). For example, if retail investors’ flows shift to technology funds both this quarter and last quarter (for whatever reason), then, as a group, mutual funds will herd to technology stocks.

The fads argument proposes that institutional investors may herd to industries simply because those industries become more popular. Friedman (1984), for example, notes the close-knit nature of the professional investment community, the importance of relative performance, and the asymmetry of incentives (i.e., the cost of poor relative performance is greater than the reward for superior performance), all suggest that institutional investors will herd to and from the latest fads, and concludes, “There is simply no reason to believe that institutional investors are less subject to such social influences on opinion than other investors and there are substantial grounds for thinking that they may be even more so.”

Institutional herding may also result if institutional investors momentum trade. In the framework of the Barberis and Shleifer (2003) model, for example, style investors follow other style investors into (and out

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<sup>5</sup> As noted by Sias (2004), herding is sometimes loosely defined as investors buying or selling the same industry (or security) at the ‘same’ time. Because trades occur sequentially, however, investors cannot buy or sell the same stock at the same time—hence, stock herding has a temporal component. Although it is possible for a group of investors to buy (or sell) the same industry at the same time (e.g., one institutional investor buys Yahoo while another buys Google at the exact same moment), we focus on industry herding over time. In addition, some authors limit the definition to intentional herding (i.e., intentionally following other investors, such as an informational cascade) and exclude unintentional (or spurious) herding (e.g., correlated signals causing investors to follow other investors). In this study, we follow most previous empirical work (e.g., Lakonishok, Shleifer, and Vishny, 1992) and define herding to include both intentional and unintentional herding.

of) the same industries as they chase returns that are driven by the trades of previous style investors. If, for instance, institutions strongly buy the technology industry this quarter (for whatever reason) and their demand drives up the value of the technology industry this quarter, then other institutions chasing returns next quarter will follow these institutions into the technology industry.

Institutional investors may herd because they face a reputational cost from acting different from the herd, i.e., it is more costly to be alone and wrong than to be with the herd and wrong (see Scharfstein and Stein, 1990; Trueman, 1994; Zwiebel, 1995; Dasgupta, Prat, and Verardo, 2007). Value managers who did not purchase technology stocks in the late 1990s, for example, suffered large investor withdrawals (see Shell, 2001). Dass, Massa, and Patgiri (2008) find empirical evidence of reputational herding by mutual funds around the technology bubble.

Investigative herding results from investors following correlated signals and, therefore, may simply reflect the process by which information is impounded into prices (see Froot, Scharfstein, and Stein, 1992; Hirshleifer, Subrahmanyam, and Titman, 1994). Assume, for example, that security signals have an industry component. If an investor receives a private signal at time  $t$  that Google is undervalued and another investor receives a private signal at time  $t+1$  that Yahoo is undervalued, then investors will follow each other into technology stocks.

Informational cascades occur when investors ignore their own noisy signals and attempt to infer information from previous investors' trades (see Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992). Thus, these models require that investors receive valuation signals and trade sequentially.<sup>6</sup> At the firm level, these signals may occur sequentially and contain private information regarding future firm performance. Given many professional managers make industry/sector recommendations, they must also believe they have information (i.e., signals) regarding industry/sector valuation not yet reflected in prices.<sup>7</sup> Moreover, because

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<sup>6</sup> In the classical informational cascade models (e.g., Bikhchandani, Hirshleifer, and Welch, 1992) agents receive private signals sequentially. Later work demonstrates this assumption can be relaxed as long as agents act on signals in sequence. In the Chamley and Gale (1994) model, for example, agents may wait to act on information because they learn from watching the decisions of previous traders. In the Gul and Lundholm (1995) and Zhang (1997) models, agents act sequentially because their signal quality differs.

<sup>7</sup> A search of marketwatch.com revealed sector/industry recommendations by Prudential, Lehman, Morgan Stanley, Credit Suisse, Wachovia, Goldman, Piper Jaffrey, Deutsche Bank, Bear Sterns, UBS, Bank of America and Citi. Moreover, a Google search of "sector rotation" yielded over 200,000 hits.

sector upgrades and downgrades do not occur simultaneously, managers must either receive or act on industry signals sequentially. Thus, for example, a manager who's industry signal indicates energy stocks are overvalued may nonetheless ignore the signal and increase his/her energy sector exposure if managers trading earlier increased their exposure to the energy sector.<sup>8</sup>

## *2.2. Empirical tests of institutional investor stock herding*

Despite common perceptions, empirical evidence of institutional investors herding into individual securities is mixed. Most early studies of institutional stock herding focus on the Lakonishok, Shleifer, and Vishny (1992) "herding measure" (see Section 3.6 for details). In general, these studies find statistically significant, but relatively weak, evidence of institutional investors herding in the average stock (e.g., Lakonishok, Shleifer, and Vishny, 1992; Grinblatt, Titman, and Wermers, 1995; Wermers, 1999; Wylie, 2005). A number of recent papers (Sias, 2004; Foster, Gallagher, and Looi, 2005; Dasgupta, Prat, and Verardo, 2007; Puckett and Yan, 2007), however, show strong evidence of institutional stock herding by directly examining whether cross-sectional variation in institutional demand for securities this quarter is related to cross-sectional variation in institutional demand for securities in the previous quarter(s).

## *2.3. Data*

The data for this study come from three sources. We use the Center for Research in Security Prices (CRSP) for return, market capitalization, and industry classification (SIC codes) data. We use Compustat data to compute book values. Each institutional investor's holdings of each stock come from their quarterly 13(f) reports.<sup>9</sup> Our institutional ownership data span the first quarter of 1983 through the last quarter of 2005 for a total of 92 quarters. We include all ordinary (CRSP share code of 10 or 11) securities with adequate data.

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<sup>8</sup> Although, for tractability, cascade models typically assume a single signal per agent prior to revelation of the state of the world, in practice managers' industry signals are likely constantly updated, e.g., a telecom analyst likely revises his/her expectations for the telecom sector continuously.

<sup>9</sup> The data were purchased from Thomson Financial. All institutions with at least \$100 million under management are required to report equity positions (greater than 10,000 shares or \$200,000) to the SEC each quarter. Managers with stale reports (i.e., report date unequal to quarter-end date) are excluded for the quarter. The data are also cleaned of obvious reporting errors (e.g., lags in adjustment for stock splits).

We begin by assigning each security (each quarter) to one of the 49 Fama and French (1997) industries.<sup>10</sup> To ensure our results are not influenced by stocks switching industry classifications (due to a change in the SIC code), we do not allow stocks to change industry classifications over the herding or return evaluation period. If ABC, for example, is classified in industry 1 at the beginning of quarter  $t-1$ , but industry 2 at the beginning of quarter  $t$ , then the company is classified as in industry 1 when evaluating herding between quarters  $t-1$  and  $t$ , but industry 2 when evaluating herding between quarters  $t$  and  $t+1$ .

We define institution  $n$  as purchasing industry  $k$  this quarter if the dollar value of the institution's position in the industry increased over the quarter. As pointed out by Grinblatt, Titman, and Wermers (1995), however, the dollar value of a manager's position will increase if the industry had a positive return (and decline if the industry had a negative return) even if the investor does not trade. To eliminate such "passive momentum," we use the product of beginning of quarter prices and end of quarter shares held to compute the "dollar value" of end of quarter holdings for manager  $n$ .<sup>11</sup> Specifically, manager  $n$  is classified as a buyer in industry  $k$  if:

$$\sum_{i=1}^{I_{k,t}} P_{i,t-1} (Shares_{n,i,t} - Shares_{n,i,t-1}) > 0, \quad (1)$$

where  $I_{k,t}$  is the number of securities in industry  $k$  in quarter  $t$ ,  $P_{i,t-1}$  is the price of security  $i$  ( $i \in k$ ) at the beginning of quarter  $t$ , and  $Shares_{n,i,t-1}$  and  $Shares_{n,i,t}$  are the number of (split-adjusted) shares of security  $i$  held by manager  $n$  at the beginning and end of quarter  $t$ , respectively.<sup>12</sup> Analogously, manager  $n$  is classified as a seller of industry  $k$  if Eq. (1) is negative.

We define institutional industry demand as the ratio of the number of institutional investors buying industry  $k$  in quarter  $t$  to the number of institutions buying or selling industry  $k$  in quarter  $t$ :

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<sup>10</sup> We use the updated industry definitions posted on Ken French's website.

<sup>11</sup> To account for passive momentum, previous work (e.g., Badrinath and Wahal, 2002; Wermers, Yao, and Zhao, 2007) uses the product of end of quarter prices and beginning of quarter shares held to compute the "dollar value" of beginning of quarter holdings for manager  $n$ . We find qualitatively equivalent results using this approach. We report results based on beginning of quarter prices because there may be correlation between end of quarter prices and institutional demand resulting in an upward bias in the number of buyers.

<sup>12</sup> Because institutional investors are required to report holdings at quarter-end, we cannot observe intra-quarter trading. Nonetheless, the data do allow us to classify institutions as net buyers or net sellers over the quarter. If, for example, an institution made a small increase in their industry bet in the first month of the quarter, but then heavily sold the industry over the following two months, the institution would be classified as a net seller of the industry over the quarter.

$$\Delta_{k,t} = \frac{\# \text{Institutional buyers of industry } k \text{ in quarter } t}{\# \text{Institutional buyers of industry } k \text{ in quarter } t + \# \text{Institutional sellers of industry } k \text{ in quarter } t}. \quad (2)$$

For ease of exposition, we henceforth refer to institutional *industry* demand as simply “institutional demand.”

Table 1 reports the time-series mean of cross-sectional quarterly descriptive statistics. Panel A reveals that, on average, industries contain 116 stocks, ranging from a minimum of six securities to a maximum of 609 securities. The largest industry, on average, accounts for 11.35% of the market portfolio. We also show that industries have high levels of concentration. On average, the single largest firm in an industry accounts for 32% of the industry’s capitalization. Panel B reports analogous statistics for the number of institutional investors (overall and by type) and institutional demand. The average industry has 692 institutional traders each quarter ranging from a minimum of 150 to a maximum of 1,076. Institutional demand averages near 50% reflecting that, on average, institutional investors are as likely to be buyers as sellers. There is, however, substantial cross-sectional variation in institutional demand—on average, institutional buyers account for over 60% of institutional traders in the highest institutional demand industry and less than 40% of institutional traders in the lowest institutional demand industry.

[Insert Table 1 about here]

### 3. Tests for institutional industry herding

#### 3.1. Correlation between contemporaneous and lag institutional industry demand

Following Sias (2004), we test for institutional herding by computing the cross-sectional correlation between institutional investors’ industry demand this quarter and their demand last quarter. The intuition is straightforward—if institutional investors follow each other into and out of the same industries, then cross-sectional variation in institutional demand this quarter will be positively related to cross-sectional variation in institutional demand last quarter.

A given institutional investor following their own lag industry trading, however, will also induce positive correlation between institutional demand this quarter and last quarter. Positive correlation may arise, for example, if: (1) Fidelity Investments purchased the healthcare industry both this quarter and last, or (2) Fidelity Investments purchased the healthcare industry this quarter and other institutions purchased it last

quarter. Sias (2004) demonstrates that the correlation between institutional demand this quarter and last can be directly partitioned into these two components. Specifically, the correlation can be written as the sum of the products of demeaned dummy variables (denoted  $D_{n,k,t}$ ) that equal one if institution  $n$  buys industry  $k$  in quarter  $t$  and zero if institution  $n$  sells industry  $k$  (see Appendix A for proof):<sup>13</sup>

$$\rho(\Delta_{k,t}, \Delta_{k,t-1}) = \left[ \frac{1}{(K)\sigma(\Delta_{k,t})\sigma(\Delta_{k,t-1})} \sum_{k=1}^K \left[ \sum_{n=1}^{N_{k,t}} \left( \frac{D_{n,k,t} - \overline{\Delta_{k,t}}}{N_{k,t}} \bullet \frac{D_{n,k,t-1} - \overline{\Delta_{k,t-1}}}{N_{k,t-1}} \right) \right] + \right. \\ \left. \left[ \frac{1}{(K)\sigma(\Delta_{k,t})\sigma(\Delta_{k,t-1})} \sum_{k=1}^K \left[ \sum_{n=1}^{N_{k,t}} \sum_{m=1, m \neq n}^{N_{k,t-1}} \left( \frac{D_{n,k,t} - \overline{\Delta_{k,t}}}{N_{k,t}} \bullet \frac{D_{m,k,t-1} - \overline{\Delta_{k,t-1}}}{N_{k,t-1}} \right) \right] \right], \quad (3)$$

where  $K$  is the number of industries (49 in our primary tests),  $N_{k,t}$  is the number of institutions trading industry  $k$  in quarter  $t$ ,  $\sigma(\Delta_{k,t})$  is the standard deviation of institutional demand across industries at time  $t$ , and  $\overline{\Delta_{k,t}}$  is the average institutional demand in quarter  $t$  across the 49 industries. The first term on the right-hand side of Eq. (3) is the portion of the correlation attributed to individual institutional investors following their own lag demand (i.e., investor  $n$  following her own lag demand for industry  $k$ ) and the second term is the portion of the correlation attributed to institutions following the lag demand of other institutional investors (i.e., investor  $n$  following investor  $m$ 's lag demand for industry  $k$ ).

Panel A in Table 2 reports the time-series average of the 90 cross-sectional correlation coefficients between institutional demand this quarter and last quarter (associated  $t$ -statistics are computed from the time-series standard error). Institutional investors' demand for an industry this quarter is strongly related to their demand last quarter—the cross-sectional correlation averages 40% and is statistically significant at the 1% level. The next two columns report the time-series averages of the portion of the correlation (and associated  $t$ -statistics) due to institutional investors following their own lag industry demand [i.e., the first term in Eq. (3)] and the portion due to institutional investors following the lag demand of other institutional investors [i.e., the second term in Eq. (3)]. Both components are statistically significant at the 1% level. The evidence that institutional investors follow their own lag demand is consistent with the hypothesis that institutional

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<sup>13</sup> This equation is identical to Eq. (4) in Sias (2004) except written in terms of industries rather than individual securities.

investors spread their trades out over time to minimize the price impact of their trading (“stealth-trading”) consistent with Barclay and Warner (1993), Chakravarty (2001), and Sias (2004).<sup>14</sup> The results also reveal that institutional investors follow the lag demand of other institutions, i.e., industry herd. Specifically, although both components are statistically significant (at the 1% level), 92% of the average correlation (0.3743/0.4049) arises from institutional investors following other institutional investors into and out of the same industries.

[Insert Table 2 about here]

### 3.2. Buy herds and sell herds

A number of previous studies (e.g., Grinblatt, Titman, and Wermers, 1995; Wermers, 1999; Wylie, 2005) of stock herding examine buy herding (institutions following each other into the same stock) versus sell herdings (institutions following each other out of the same stock). As pointed out by Brown, Wei, and Wermers (2007), for example, it is possible that institutional sell herding may be more limited than buy herding because many institutional investors cannot sell securities short.

To examine whether institutional investors are more likely to buy herd or sell herd industries, we classify industries into those institutions bought in quarter  $t-1$  ( $\Delta_{k,t-1} > 0.5$ ) and those institutions sold in quarter  $t-1$  ( $\Delta_{k,t-1} < 0.5$ ). We then partition Eq. (3) into buy-herding and sell-herding industries to compute the portion of the correlation arising from institutions following each other into the same industries (buy herding, first row in Panel B) and institutions following each other out of the same industries (sell herding, second row in Panel B). The third row in Panel B reports the difference between the buy herding and sell herding contributions and associated  $t$ -statistics (computed from the time-series standard errors). The results reveal no evidence that industry buy herding differs meaningfully from industry sell herding (consistent with Wermers’ (1999) investigation of stock herding).

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<sup>14</sup> This interpretation is potentially more complex in an industry context. Specifically, an investor may buy a stock in an industry this quarter and a different stock in the same industry next quarter in an attempt to conceal trading on industry-specific information.

### *3.3. Value-weighted correlation and alternative industry definitions*

Table 1 reveals substantial variation across industry capitalizations with the smallest industry accounting for, on average, 0.05% of the total market capitalization and the largest industry accounting for 11.35% of the total market capitalization. Each industry, however, contributes equally in the calculation of the correlation between institutional demand this quarter and last. To ensure the correlations are not driven by the very smallest of industries, we compute and decompose the industry-weighted correlation, where each industry's weight is equal to their fraction of market capitalization at the beginning of quarter  $t-1$  (see Appendix A for additional detail). Panel C in Table 2 reports the time-series average of the 90 cross-sectional industry-weighted correlation coefficients between institutional demand this quarter and last quarter (associated  $t$ -statistics are computed from the time-series standard error). The results are nearly identical to the equal-weighted correlations—institutional industry demand is strongly correlated with lag institutional demand and is primarily driven by institutions following other institutions into and out of the same industries.

Although the 49 Fama and French (1997) industries are often used in academic studies, they serve as only one of a number of possible industry definitions. To examine the sensitivity of our results to finer industry definitions, we repeat the analysis in Panel A but define industries based on two digit SIC codes (on average, this results in 73 industries each quarter). Results, reported in the first row of Panel D, reveal strong, albeit slightly weaker correlation (averaging 24.65%) that is primarily driven by institutions following other institutions into the same industry. We next try coarser industry definitions. Specifically, we repeat the analysis in Panel A with the additional industry definitions available on Ken French's website that classify firms into 5, 10, 12, 17, 30, and 38 industries. The results, presented in the bottom six rows of Panel D, are consistent with base case of 49 industries—strong evidence of institutional industry herding primarily driven by institutions following other institutions into the same industry.

### *3.4. Does stock herding drive industry herding?*

Table 1 reveals that many industries are highly concentrated, e.g., the largest single stock in an industry accounts for, on average, 32% of the total industry capitalization. It is possible, therefore, that

industry herding is simply a manifestation of stock herding. If institutional investors are herding to Microsoft and Microsoft accounts for nearly half the technology industry, then institutional investors are likely herding to the technology industry (as long as institutions' Microsoft purchases are not fully offset by sales of other technology stocks).

To examine whether industry herding is a manifestation of stock herding, we define an alternative measure of institutional industry demand as the capitalization-weighted average institutional demand for securities in each industry. We begin by defining the institutional demand for each stock  $i$  (in quarter  $t$ ) as the number of institutions buying (i.e., increasing the split-adjusted number of shares they hold) the stock as a fraction of the number of institutions trading the stock:

$$\Delta_{i,t} = \frac{\# \text{ Institutional buyers of stock } i \text{ in quarter } t}{\# \text{ Institutional buyers of stock } i \text{ in quarter } t + \# \text{ Institutional sellers of stock } i \text{ in quarter } t}. \quad (4)$$

We then define the weighted institutional demand for industry  $k$  (henceforth, “weighted institutional demand” and denoted  $\Delta_{k,t}^*$ ) as the market-capitalization weighted average institutional demand across stocks in industry  $k$  (where  $w_{i,t}$  is security  $i$ 's capitalization weight in industry  $k$  at the beginning of quarter  $t$ ):<sup>15</sup>

$$\Delta_{k,t}^* = \sum_{i=1}^{I_{k,t}} w_{i,t} \Delta_{i,t}. \quad (5)$$

Because the weighted institutional industry demand is a linear function of institutional demand for each security in that industry, we can directly decompose the cross-sectional correlation between weighted institutional demand this quarter and last quarter into four components: the portions that arise from following each other or themselves into the same stock and the portions that arise from following each other or themselves into different stocks in the same industry (see Appendix A for proof):

$$\rho(\Delta_{k,t}^*, \Delta_{k,t-1}^*) = \frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \left( w_{i,t} w_{i,t-1} \left( \sum_{n=1}^{N_{i,t}} \left( \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{n,i,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{i,t-1}} \right) \right) \right) \right) +$$

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<sup>15</sup> We verify that this alternative measure of institutional industry demand is closely related to the number of institutions increasing their position in the industry divided by the number trading the industry [i.e., Eq. (2)]. Specifically, each quarter we compute the cross-sectional correlation across the 49 industries between the measures given in Eq. (2) and Eq. (5). The cross-sectional correlation averages 81% (statistically significant at the 1% level).

$$\begin{aligned}
& \frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \left( w_{i,t} w_{i,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{i,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,i,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{i,t-1}} \right) \right) \right) + \\
& \frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{n,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right) + \\
& \frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right), \quad (6)
\end{aligned}$$

where  $D_{n,i,t}$  is a dummy variable that equals one if institutional investor  $n$  increases her position in security  $i$  in quarter  $t$  and zero if the investor decreases her position in security  $i$ , and  $N_{i,t}$  is the number of institutions trading security  $i$  in quarter  $t$ .

The first term on the right hand side of Eq. (6) is the portion of the correlation that arises from institutional investors following their own trades in the same stock (i.e., institution  $n$  following their own lag trades in security  $i$ ) and the second term is the portion that arises from institutional investors following other institutions into the same stock (i.e., institution  $n$  following institution  $m$ 's lag trades in security  $i$ ). The third term is the portion of the correlation that arises from institutions following themselves into different stocks in the same industry (i.e., institution  $n$ 's trades in security  $i$  following their lag trades in security  $j$  where both  $i$  and  $j$  are in industry  $k$ ), while the last term is the portion that arises from institutions following other institutions into different stocks in the same industry (i.e., institution  $n$ 's trades in security  $i$  following institution  $m$ 's lag trades in security  $j$  where both  $i$  and  $j$  are in industry  $k$ ).

As shown in the bottom right-hand cell in Table 3, the time-series of the 90 cross-sectional correlations between weighted institutional demand this quarter and last quarter averages 57% (statistically significant at the 1% level). The four interior cells of Table 3 report the time-series average of each of the four components given in Eq. (6) and associated  $t$ -statistics. Summing across columns partitions the correlation into following themselves versus following others (reported in the last column), while summing across rows partitions the correlation into following into the same stock versus into different stocks in the

same industry (reported in the last row). As before, all  $t$ -statistics are computed from the time-series standard errors.

[Insert Table 3 about here]

The results in Table 3 reveal that all four components—following themselves into the same stock and different stocks in the same industry and following other institutions into the same stock and different stocks in the same industry—are statistically significant at the 1% level. The results in the top row are consistent with the hypothesis that institutional investors spread their trading out over time in both an individual security and in an industry (see Barclay and Warner, 1993; Chakravarty, 2001; Sias, 2004) to minimize the price impact of their trading.

The results in Table 3 also reveal, however, that most of the correlation between weighted institutional demand this quarter and last is driven by institutional investors following other institutional investors (0.5177/0.5716). Moreover, consistent with the explanation that the combination of stock herding and high industry concentration contributes to industry herding, institutional investors following other institutional investors into the same stock accounts for the largest single component of the quarterly correlation (0.3235/0.5716). This result is consistent with recent evidence that institutional investors herd into and out of individual securities (Sias, 2004; Foster, Gallagher, and Looi, 2005; Dasgupta, Prat, and Verardo, 2007; Puckett and Yan, 2007).

The figure shown in the center cell, accounting for 34% of the overall correlation (0.1942/0.5716) and statistically significant at the 1% level ( $t$ -statistic=14.46), however, is the key result reported in Table 3. Specifically, an institutional investor's demand for a stock this quarter is related not only to other institutions' demand for that stock last quarter, but also to other institutional investors' demand for different stocks in the same industry last quarter. In sum, although institutional investors herding into individual stocks contributes to institutional industry herding, industry herding is unique from stock herding.<sup>16</sup>

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<sup>16</sup> As a robustness test, we also compute an industry-weighted, weighted institutional demand [i.e., Eq. (6)] correlation (analogous to Panel C in Table 2) and correlations based on the alternative industry definitions (analogous to Panel D in Table 2). Although specific results are not reported (to conserve space), with the exception of the extremely broad 5-industry classification, these alternative approaches yield qualitatively identical results.

### 3.5. Does industry herding result from herding into size and book/market styles?

Although Barberis and Shleifer (2003) note that style investing includes industry styles, most empirical work (e.g., Teo and Woo, 2004) focuses on styles defined by market capitalization and book-to-market ratios (henceforth, size-BE/ME styles). Size-BE/ME styles are also often used in defining mutual fund classifications or manager strategies. Moreover, industry membership is correlated with size-BE/ME styles (e.g., the technology industry primarily consists of low BE/ME growth stocks). Thus, it is possible that institutions industry herd because they herd to and from size-BE/ME styles rather than industry styles per se.

We begin by partitioning securities into six styles based on the median NYSE market equity breakpoint (big/small) and the 30<sup>th</sup> and 70<sup>th</sup> book to market NYSE percentile breakpoints (value/neutral/growth) following Fama and French (1993).<sup>17</sup> Because Eq. (6) can be decomposed to the stock level, we can investigate the possibility that industry herding simply reflects size-BE/ME style herding by further partitioning the last term in Eq. (6) (i.e., the industry herding contribution) into managers following other managers into: (1) different, but same size-BE/ME style, stocks in the same industry, and (2) different style stocks in the same industry (see Appendix A for proof):

$$\begin{aligned} & \frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right) = \\ & \frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1, i \in s}^{I_{k,t}} \sum_{j=1, j \neq i, j \in s}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right) + \\ & \frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1, i \in s}^{I_{k,t}} \sum_{j=1, j \neq i, j \notin s}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right), \quad (7) \end{aligned}$$

where  $i \in s$  indicates security  $i$  is in size-BE/ME style  $s$ .

<sup>17</sup> Following Fama and French (2006) book equity is computed as total assets (Compustat item #6) minus liabilities (#181) plus balance sheet deferred taxes and investment tax credits (#35) if available, minus preferred stock liquidating value (#10) if available, or redemption value (#56) if available, or carrying value (#130). Further following Fama and French, the book to market ratio is computed each year  $t$  based on market value at the end of December in year  $t$  and the book value for the fiscal year that ends in calendar year  $t$ . For the quarters ending in June, September, and December of year  $t$ , we use the book to market ratio from the end of year  $t-1$ . For the quarter ending in March, we use the book to market ratio from the end of year  $t-2$ .

The first column in Table 4 (identical to the middle cell in Table 3) reports the time-series average of the portion of the correlation attributed to institutions following other institutions into different stocks in the same industry, i.e., the industry herding contribution. The next two columns in the first row further partition the industry herding contribution into the portion that arises from institutions following other institutions into different, but same size-BE/ME style, stocks in the same industry [the first term on the right hand side of Eq. (7)] and the portion that arises from institution following other institutions into different size-BE/ME style stocks in the same industry [the last term in Eq. (7)].

[Insert Table 4 about here]

The results reveal that institutions following each other into and out of same size-BE/ME style stocks and different size-BE/ME style stocks both contribute to industry herding. Specifically, 65% (0.1260/0.1942) of the industry herding contribution [i.e., the last term in Eq. (6)] is due to following each other into same size-BE/ME style stocks and 35% (0.0683/0.1942) results from institutions following other institutions into different size-BE/ME style stocks in the same industry. Both portions are statistically significant at the 1% level.

Although the decomposition by style reveals that size-BE/ME style herding does not fully explain industry herding, it does not test whether size-BE/ME style herding contributes to industry herding. To examine this question, we compute the expected contribution by same and different style stocks by recognizing that if size-BE/ME herding does not contribute to industry herding, then manager  $n$  should be as likely to purchase (as opposed to sell) security  $i$  following manager  $m$ 's purchase of security  $j$  ( $i, j \in \mathcal{K}$ ) whether securities  $i$  and  $j$  are in the same size-BE/ME styles or in different styles (see Appendix A for details).

The second row in Table 4 reports the time-series average (across the 90 quarters) of expected contributions from following other managers into same and different size-BE/ME stocks in the same industry under the null that managers are as likely to follow each other into and out of same size-BE/ME style stocks as different size-BE/ME style stocks. The last row reports the difference between the realized and expected contributions from following others into same and different style stocks in the same industry. The results reveal that although size-BE/ME style herding does not fully explain industry herding, size-

BE/ME style herding appears to contribute to industry herding. Specifically, the realized contribution from following others into same size-BE/ME style stocks in the same industry accounts 65% of the herding contribution (0.1260/0.1942) versus 39% (0.0765/0.1942) under the null hypothesis that institutional industry herding is independent of size-BE/ME style. The difference (0.0495=0.1260-0.0765) is statistically significant at the 1% level.<sup>18</sup>

### 3.6. The Lakonishok, Shleifer, and Vishny (1992) herding measure

Most early investigations of institutional herding focus on the Lakonishok, Shleifer, and Vishny (1992, henceforth ‘LSV’) herding measure. Specifically, the LSV herding measure,  $H_{k,t}$  is computed for each industry-quarter as:

$$H_{k,t} = \left| \Delta_{k,t} - \overline{\Delta_{k,t}} \right| - AF_{k,t}, \quad (8)$$

where, as in Eq. (2),  $\Delta_{k,t}$  is the ratio of the number of institutions buying industry  $k$  to the number trading industry  $k$  in quarter  $t$  (and  $\overline{\Delta_{k,t}}$  is its cross-sectional average). The adjustment factor ( $AF_{k,t}$ ) accounts for the fact that the expected value of the first term is positive regardless of institutional herding and is computed by assuming the number of institutional traders in industry  $k$  during quarter  $t$  follows a binomial distribution with the probability of buying set equal to  $\overline{\Delta_{k,t}}$ . This metric tests for institutional herding by recognizing that if institutional investors follow each others’ demand (i.e., temporal cross-sectional dependence within a quarter), then institutional investors will primarily be buyers of industries they herd to and primarily be sellers of industries they herd from within that quarter.<sup>19</sup>

For our sample, the LSV herding measure averages 1.39% across the 4,459 industry-quarter observations (91 quarters \* 49 industries) and differs significantly from zero at the 1% level ( $t$ -statistic=34.66). The value is similar to the average reported by Sias (2004) for individual stocks. Given the average institutional demand (i.e.,  $\Delta_{k,t}$ ) is approximately 50% (see Table 1), the average LSV industry herding measure

<sup>18</sup> Because the first two rows of Table 4 are a simple partitioning of the last term in Eq. (6), the differences (reported in the last row) are exactly offsetting.

<sup>19</sup> Both the LSV and Sias (2004) herding tests measure herding over time, i.e., whether institutions follow other institutions. The LSV metric, however, indirectly captures the temporal nature of the herding by testing whether institutional investors *follow* other institutional investors within the same quarter.

of 1.39% can be interpreted as meaning that if there were 100 institutional traders in a random industry-quarter, we would expect 51.39 on one side of the market (buyers or seller) and 48.61 on the other. Thus, consistent with previous work (e.g., Wermers, 1999; Sias, 2004), the LSV measure reveals highly significant, albeit not particularly large, levels of institutional herding in the average industry-quarter.

The key difference in reconciling the ‘strength’ of the results between the LSV and Sias (2004) herding tests is that the correlation focuses on whether those industries that had the greatest institutional demand (or supply) last quarter have the greatest demand (or supply) this quarter. In contrast, the LSV measure evaluates the average herding across *every* industry *every* quarter. Thus, the correlation tests will reveal strong evidence of herding if institutions are strongly herding into three industries and strongly herding out of three other industries, but have net demand near zero for the remaining 43 industries. The LSV measure will also capture such herding, although the *average* across all 49 industries will be relatively small.<sup>20</sup> In short, the results of the LSV tests are fully consistent with our previous tests. See Wermers (1999), Sias (2004), and Wylie (2005) for more detailed discussions of the LSV measure.

#### **4. Why do institutions industry herd?**

We next attempt to differentiate between the six proposed herding motives: underlying investors’ flows, momentum trading, reputational herding, informational cascades, investigative herding, and fads. We draw heavily on the methods used in the stock herding literature to investigate these hypotheses for industry herding.

##### *4.1. Do underlying investors drive institutional industry herding?*

Institutional industry herding could simply reflect underlying investors’ flows. Frazzini and Lamont (2008) note, for example, that in 1999 retail investors added \$37 billion to technology-oriented Janus Funds

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<sup>20</sup> Consider an extreme example: Assume that institutional investors are herding to three industries such that 70% of institutional traders are buyers both this quarter and last, and institutional investors are herding out of three industries such that 70% of institutional traders are sellers this quarter and last. In the remaining 43 industries, institutional traders are exactly 50% buyers and 50% sellers. Further assume the sample sizes are large enough that the adjustment factors in the LSV measure are approximately zero. In such a case, the average LSV metric is 0.024 (measure over either quarter, or both quarters together) while the cross-sectional correlation is one, i.e., the cross-sectional variation in last quarter’s institutional demand perfectly explains the cross-sectional correlation in this quarter’s institutional demand.

while adding only \$16 billion to more conservative, and much larger, Fidelity funds. And by 2001, retail investors moved strongly out of Janus and into Fidelity. We take two approaches to testing whether underlying investors' flows can explain institutional industry herding. First, we repeat our empirical tests excluding those institutional investors most subject to retail flows. Specifically, Thomson Financial classifies institutions into five groups: banks, insurance companies, mutual funds (investment companies), independent investment advisors, and unclassified institutions.<sup>21</sup> Dasgupta, Prat, and Verardo (2007) argue that mutual funds and independent investment advisors are most likely to be subject to the vagaries of retail investors. Thus, if institutional industry herding is primarily driven by underlying investor flows, our results should be substantially weaker when excluding mutual funds and independent investment advisors.

Panel E in Table 2 reports the industry herding analysis [i.e., Eq. (3)] when excluding mutual funds and independent advisors. The results reveal no evidence that institutional industry herding is driven by retail investors' flows. In fact, the point estimates are slightly larger when excluding mutual funds and independent advisors from the analysis (Panel E) than when including them (Panel A).

As a second test of whether flows from underlying investors explain institutional industry herding, we focus on changes in institutions' industry portfolio weights rather than industry positions (following Sias, 2004). The intuition is straightforward—although underlying investors' flows would impact whether a manager buys an industry, it should not impact the managers' industry portfolio weight.<sup>22</sup> That is, the portfolio weight should already reflect the manager's industry preferences. Thus, to investigate whether underlying investors' flows contribute to industry herding, we redefine whether an institution buys or sells an industry each quarter by focusing on changes in institutions' industry portfolio weights. Specifically, manager  $n$  is classified as a buyer of industry  $k$  if their end of quarter portfolio industry weight is greater than their beginning of quarter industry portfolio weight:

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<sup>21</sup> Unclassified investors include foundations, university endowments, ESOPs, internally managed pension funds, and individuals who invest others' money who are not otherwise categorized. The classifications are inexact in that institutions file 13(f) reports in the aggregate and some institutions would qualify as more than one type. For example, mutual funds that also act as independent investment advisors are classified as mutual funds if more than 50% of their assets are in mutual funds and as independent investment advisers otherwise. Thomson Financial began a different classification scheme at the end of 1998. For our study, classifications from December 1998-2005 were based on additional classification data provided by Thomson Financial (details available on request).

<sup>22</sup> It is possible, however, that some large managers have different investment vehicles and therefore the manager may be affected by correlated flows, e.g., money flowing out of Fidelity's utility funds and into Fidelity's healthcare funds.

$$\frac{\sum_{i=1}^{N_{k,t}} P_{i,t-1} Shares_{n,i,t}}{\sum_{k=1}^K \sum_{i=1}^{N_{k,t}} P_{i,t-1} Shares_{n,i,t}} - \frac{\sum_{i=1}^{N_{k,t-1}} P_{i,t-1} Shares_{n,i,t-1}}{\sum_{k=1}^K \sum_{i=1}^{N_{k,t-1}} P_{i,t-1} Shares_{n,i,t-1}} > 0. \quad (9)$$

As before, we use beginning-of-quarter share prices at both the beginning and end of the quarter to ensure we capture changes in portfolio weights driven by trading rather than differences in industry returns. We then compute institutional investors' demand for industry  $k$  as the number of institutions increasing their industry  $k$  portfolio weight divided by the number of institutions changing their industry  $k$  portfolio weight [analogous to Eq. (2)].

Panel F of Table 2 reports the time-series average correlation between institutional demand (based on changes in portfolio weights) this quarter and their demand last quarter as well as the portion that arises from institutions following their own lag changes in industry portfolio weights and the portion that arises from institutions following other institutions' lag changes in industry portfolio weights. The results reveal no evidence that underlying investors' flows drive institutional investors' industry herding. Specifically, the results are nearly identical to the previous analysis (reported in Panel A)—the correlation averages 37% and is primarily driven by following other institutions' changes in portfolio weights (0.3498/0.3687).

#### 4.2. Does industry momentum trading drive industry herding?

Another possible cause of institutional industry herding is that institutions, as a group, are attracted to industries with high lag returns and repelled from industries with low lag returns as in Barberis and Shleifer's (2003) style investing model. That is, as noted above, institutional demand this quarter may be positively related to institutional demand last quarter because institutional demand last quarter is positively correlated with last quarter's industry returns and institutions momentum trade at the industry level. To investigate this possibility, we first test whether institutional investors momentum trade in industries by estimating quarterly cross-sectional regressions of institutional industry demand [i.e., Eq. (2)] on industry returns over the previous quarter, six months, or year [following Fama and French (1997) industry returns are value-weighted]. For comparison, we also estimate quarterly cross-sectional regressions of institutional

demand on lag institutional demand over the previous quarter, six months, or year. To directly compare coefficients in subsequent tests, we standardize (i.e., rescale to zero mean and unit variance, each quarter) both institutional industry demand and industry returns.

The first column of Table 5 reports that the time-series average of the cross-sectional correlation between institutional demand and lag quarterly institutional demand averages 40% (statistically significant at the 1% level) consistent with Table 2.<sup>23</sup> The fourth and seventh columns reveal that institutional demand is also positively correlated with institutional demand measured over the previous six months or year. For the lag six month and lag annual industry demand, we redefine buyers and sellers based on changes in their holdings over the previous six months or year [analogous to Eq. (1)], respectively.<sup>24</sup> The second, fifth, and eighth columns in Table 5 also reveal, however, that institutional demand is positively correlated with industry returns over the previous quarter, six months, and year, respectively (all statistically significant at the 1% level). Thus, the results reveal that institutional investors momentum trade at the industry level consistent with the Barberis and Shleifer (2003) style investing model and evidence at the individual security level [see Sias (2007)].

[Insert Table 5 about here]

To test whether institutional industry momentum trading explains their industry herding, we include both lag institutional demand and lag industry returns in the quarterly regressions (the tildes indicate the variables are standardized):

$$\tilde{\Delta}_{k,t} = \beta_{1,t} \tilde{\Delta}_{k,t-1} + \beta_{2,t} \tilde{R}_{k,t-1} + \varepsilon_{k,t} . \quad (10)$$

The time-series average coefficients for the 90 cross-sectional regressions are reported in the third (lag quarter), sixth (lag six months), and last columns (lag year) of Table 5. Because both lag returns and lag demand are standardized, the coefficients are directly comparable (and the intercept is zero). Institutional momentum trading does not explain institutional industry herding, i.e., institutional demand remains positively related to lag institutional demand even after accounting for lag industry returns. In fact, the

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<sup>23</sup> Because both variables are standardized and there is only one independent variable, the average coefficient is the average correlation.

<sup>24</sup> For example, if an institutional investor made a large increase in their utilities holdings two quarters ago and a small decrease last quarter, the investor would be classified as a seller last quarter but a buyer over the lag six month period.

evidence suggests that institutional investors' industry momentum trading results from their herding—there is no evidence that institutional demand is related to lag industry returns once accounting for lag institutional demand.

#### 4.3. Herding and reputation

Sias (2004) hypothesizes that if professional investors' reputational concerns drive their herding, then institutional investors should be more likely to follow similarly classified institutions than differently classified institutions. Sias also proposes, consistent with Dasgupta, Prat, and Verardo (2007), that mutual funds and independent advisors are most likely to experience investor flows as a result of changes in their reputation. Thus, if reputation concerns drive herding, then mutual funds and independent advisors should exhibit a greater herding propensity than other investor types.

Sias (2004) points out that analysis by investor type is complicated by the fact that the number of each type of institutional investor differs (e.g., the number of banks trading does not equal the number of insurance companies trading). As a result, a given investor type may contribute relatively more to the herding measure [i.e., the second term in Eq. (3)] because there are many of those investors rather than because that investor type exhibits a greater propensity to follow other investors (see Sias for additional discussion). Thus, we follow Sias and measure each investor types' propensity to engage in herding as their average (rather than total) contribution from following similarly classified institutions and their average contribution from following differently classified institutions. Specifically, for a given quarter, the average same-type herding contribution for banks is given by the last portion of the second term in Eq. (3) limited to banks averaged over the 49 industries:

$$\text{Average same-type herding contribution}_{i_t}^{\text{Banks}} = \frac{1}{49} \sum_{k=1}^{49} \left[ \sum_{b=1}^{B_{k,t}} \sum_{m=1, m \neq b, m \in B}^{B_{k,t-1}^*} \frac{(D_{b,k,t} - \overline{\Delta}_{k,t})(D_{m,k,t-1} - \overline{\Delta}_{k,t-1})}{B_{k,t} B_{k,t-1}^*} \right], \quad (11)$$

where  $B_{k,t}$  is the number of banks trading industry  $k$  in quarter  $t$  and  $B_{k,t-1}^*$  is the number of different banks trading industry  $k$  in quarter  $t-1$ . Similarly, the average different-type herding contribution for banks is given

by the last portion of the second term in Eq. (3) limited to banks trading in quarter  $t$  and non-banks trading in quarter  $t-1$  (averaged over the 49 industries):

$$\text{Average differnt-type herding contribution}_t^{\text{Banks}} = \frac{1}{49} \sum_{k=1}^{49} \left[ \sum_{b=1}^{B_{k,t}} \sum_{m=1, m \notin B}^{N_{k,t-1} - B_{k,t-1}} \frac{(D_{b,k,t} - \overline{\Delta_{k,t}})(D_{m,k,t-1} - \overline{\Delta_{k,t-1}})}{B_{k,t}(N_{k,t-1} - B_{k,t-1})} \right], \quad (12)$$

where  $N_{k,t-1} - B_{k,t-1}$  is the number of non-banks trading industry  $k$  in quarter  $t-1$ . We compute analogous statistics for each of the other investor types. For completeness, we also compute the average contribution from following their own previous trades [i.e., the last portion of the first term in Eq. (3) limited to each investor type] and the average contribution from following other investors' trade regardless of trader type.

Table 6 reports the time-series average of the 90 estimates by investor type. The first and second columns in Table 6 report the average contribution from following their own industry trades and the average contribution from following other investors' (regardless of classification) industry trades, respectively. The results reveal strong evidence of following their own trades and following other investors' trades for each investor type (statistically significant at the 1% level in all cases). The third and fourth columns report the average contribution from following similarly classified traders [i.e., Eq. (11)] and from following differently classified traders [i.e., Eq. (12)], respectively. The last column reports the difference between the third and fourth columns as a test of whether each investor type is more likely to follow similarly classified investors or differently classified investors. All  $t$ -statistics are computed from time-series standard errors.

[Insert Table 6 about here]

The results reveal mixed support for the reputational herding model. Specifically, the results in the last three columns reveal that four of the five types are more likely to follow a similarly classified institution than a differently classified institution consistent with the reputational herding explanation. Independent advisors (who, as shown in Table 1, are the largest investor group), however, do not exhibit the pattern.<sup>25</sup> In fact, although the difference is small, independent advisors are more likely to follow other institutional investor types than other independent advisors. In addition, consistent with Sias' (2004) evidence of herding

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<sup>25</sup> One possible reason that independent managers do not follow each other more than other investors is that hedge funds (who are included in the set of independent advisors) recognize that 13(f) reports only reflect the long positions of other funds which may be offset by unreported short positions. Therefore, 13(f) reports may be less informative regarding other independent investors' net positions.

at the individual stock level, banks exhibit the strongest herding propensity, followed by unclassified institutions. Inconsistent with the reputational herding explanation, mutual funds and independent advisors exhibit among the lowest herding propensities.

#### 4.4. Herding and industry characteristics

Informational cascades suggest an investor is more likely to follow the perceived consensus information of the herd and ignore their own signal as signal quality deteriorates. As a result, Wermers (1999) hypothesizes that if informational cascades are the primary cause of stock herding, institutions should herd more in smaller stocks with noisier signals. Analogously, Sias (2004) proposes that the cross-sectional correlation between investors' signals is likely stronger in less volatile large stocks. Adapting these arguments for industry herding suggests that if informational cascades primarily drive industry herding then smaller and more volatile industries will exhibit greater herding. In contrast, if correlated signals (i.e. investigative herding) primarily drive industry herding, then larger and less volatile industries will exhibit greater herding.

We begin by computing, each quarter, each industry's contribution to the cross-sectional correlation between institutional demand this quarter and last quarter, i.e., each industry's contribution to Eq. (3):

$$\text{Industry } k' \text{ s contribution}_t = \left[ \frac{1}{(K)\sigma(\Delta_{k,t})\sigma(\Delta_{k,t-1})} \right] (\Delta_{k,t} - \overline{\Delta_{k,t}})(\Delta_{k,t-1} - \overline{\Delta_{k,t-1}}). \quad (13)$$

Each quarter, we then sort the 49 industries by their contribution and define the top ten industries as “high-herding industries” and the remaining 39 industries as “low-herding industries.”

Next we compute the standard deviation of daily industry returns over the year prior to quarter  $t$  (i.e., over quarters  $t-1$  to  $t-4$ , inclusive) and industry capitalization at the beginning of quarter  $t$ . We then rank, each quarter, all industries based on industry return volatility (or size) and compute the median and mean percentile industry standard deviation rankings (size rankings) for high-herding and low-herding industries (we use percentile rankings to account for non-normality and minimize the impact of outliers). Table 7 reports the time-series average of the mean and median industry return volatility or size percentile ranking for

high- and low-herding industries. The last column reports their difference and associated  $t$ -statistic (computed from the time-series standard error of the 90 quarterly differences).

[Insert Table 7 about here]

The results reveal that high-herding industries tend to be more volatile and smaller (statistically significant at the 1% level in all cases) than low-herding industries. The results: (1) are consistent with the hypothesis that informational cascades contribute to industry herding, and (2) inconsistent with the joint hypothesis that industry herding is primarily driven by institutional investors following correlated signals (investigative herding) and the correlation between signals is stronger in less volatile and larger industries.<sup>26</sup>

#### *4.5. Herding pre- and post-Electronic Data Gathering and Retrieval (EDGAR) service*

If institutional industry herding arises from institutional investors intentionally following each other into and out of the same industries, then institutions must somehow learn what industries other institutions are buying or selling. Although this information may arise from a number of sources (e.g., interaction with broker-dealers, information inferred through order flow or returns), institutions can directly view other institutions' transactions through their 13(f) reports. Beginning in 1999, the SEC required institutions to file their 13(f) reports electronically through the SEC's EDGAR service.<sup>27</sup> Thus, in the last 40 quarters of the sample, institutional investors were able to easily access every other institutional investors' previous quarter's trades.<sup>28</sup> If institutional investors are intentionally following each other into the same industries, then institutional herding may be stronger in the post-EDGAR period.

Panel G of Table 2 reports the average correlation and its partitioned components (institutions following themselves into the same industry and institutions following other institutions into the same

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<sup>26</sup> We run several robustness tests including: (1) repeating the analysis based on each industry's total contribution to the correlation in weighted institutional industry demand [Eq. (6)]; (2) repeating the analysis based on each industry's contribution to the last term in Eq. (3); and (3) repeating the analysis based on each industry's contribution to the last term in Eq. (6). The results remain qualitatively similar in all cases. Recall also that the industry-weighted correlation reported in Table 2 is slightly stronger than the equal-weighted correlation despite the evidence that smaller industries contribute more to the correlation. This occurs because although smaller industries, on average, provide a larger contribution to the equal-weighted covariance, smaller industries also exhibit greater cross-sectional variation in institutional demand. As a result, the denominator in the value-weighted correlation is smaller than the denominator in the equal-weighted correlation, yielding a slightly larger value-weighted correlation than equal-weighted correlation.

<sup>27</sup> Managers were able to voluntarily file electronic 13(f) reports prior to this period.

<sup>28</sup> As noted above, institutions must file 13(f) reports within 45 days of quarter-end.

industry) for the post-EDGAR period (1996-2005,  $n=40$  quarters) and the pre-EDGAR period (1983-1995,  $n=50$  quarters). The results reveal some evidence that the portion of the correlation due to institutions following other institutions' lag industry demand is larger following EDGAR initiation. Specifically, the last column reveals the mean herding component averages 17% larger ( $0.4066/0.3484 - 1$ ) in the post-EDGAR period. The last two rows in Panel G report a  $t$ -statistic from a difference in means test and a  $\chi$ -statistic from a Wilcoxon rank sum test that the herding components are equal in the pre- and post-EDGAR periods. Although we cannot reject the hypothesis with the  $t$ -test for difference in means ( $p$ -value=0.11), the non-parametric Wilcoxon test rejects the hypothesis at the 5% level (two-tail tests in both cases). In sum, the results in Panel G provide some evidence for the supposition that institutional investors intentionally follow each other into and out of the same industries and that their ability to do so increases in the post-electronic filing era.

#### *4.6. Institutional industry demand and industry returns*

Institutional herding need not necessarily drive prices from fundamentals. Specifically, investigative herding models propose that herding may result from institutions receiving, or acting on, correlated information at different times and therefore simply reflects the process by which information is incorporated into prices (see Froot, Scharfstein, and Stein, 1992; Hirshleifer, Subrahmanyam, and Titman, 1994). In contrast, most of the alternative explanations for institutional herding suggest such herding may drive prices from fundamentals. The proposition that institutional herding may drive prices from fundamental values implicitly assumes, consistent with recent empirical work (e.g., Chakravarty, 2001; Froot and Teo, 2004; Sias, Starks, and Titman, 2006; Kaniel, Saar, and Titman, 2008; Campbell, Ramadorai, and Schwartz, 2007), that institutional investors are usually the price-setting marginal investor, i.e., as a group institutions net remove, rather than supply, liquidity.

It is important to keep in mind, however, that any relation between institutional demand and contemporaneous or subsequent security/industry prices does not necessarily imply institutional *herding* (i.e., the decision of institutions to follow other institutions) impacts prices but may simply reflect institutional

demand shocks. Gompers and Metrick (2001), for example, propose that demand shocks associated with the growth in institutional assets under management and institutional investors' historical preference for large capitalization stocks may help explain the disappearance of the small firm premium in recent years.

Assuming institutional herding sometimes impacts returns and does not always reflect the process by which information is incorporated into prices, then institutional demand should be positively related to contemporaneous industry returns and inversely related to subsequent industry returns. In contrast, if institutional industry herding simply reflects the manner that industry information is impounded into prices, then institutional demand should be positively correlated with contemporaneous industry returns and not inversely related to subsequent industry returns. The herding explanations, of course, are not mutually exclusive. Institutional industry herding may sometimes reflect the process by which industry information is impounded into prices and other times result from non-information factors.

We begin by computing, each quarter, each industry's contribution to the cross-sectional correlation between institutional demand this quarter and last quarter [i.e., Eq. (13)]. Securities where the last two terms of Eq. (13) are both positive (i.e., institutions buying more than the average industry in both quarters) are denoted buy-herding industries. We then select the ten buy-herding industries that contribute the most to the industry herding measure [i.e., with the largest Eq. (13)] as our buy-herding sample. Analogously, we denote the top ten industries where the last two terms are both negative as sell-herding industries.<sup>29</sup>

To compute buy- and sell-herd industry returns, each quarter, we calculate the equal-weighted average return across the ten buy-herd industries and the ten sell-herd industries. We then examine industry returns for the formation period (quarters -1 to 0) and up to three years following formation (quarters 1 to 12). As before, industry returns are value-weighted based on beginning of quarter capitalizations.

We use Jegadeesh and Titman's (1993) calendar time aggregation method to calculate returns each quarter from overlapping observations.<sup>30</sup> From the time-series of quarterly buy- or sell-herd returns (as well as

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<sup>29</sup> The last two terms can have different signs in a given industry. In all quarters, however, there are at least ten industries that institutions "sold" both this quarter and last, and ten industries that institutions "bought" both this quarter and last.

<sup>30</sup> Because the portfolios are updated each quarter, evaluation periods longer than one quarter produce overlapping observations. Following Jegadeesh and Titman (1993), we aggregate results for each calendar quarter. Consider, for example, the first quarter of 1999 when evaluating the holding period for the two quarters following formation. The

their difference), we estimate the abnormal return as the intercept from a time-series regression of the quarterly portfolio return on the Fama and French (1993) market, size, and value factors:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p (R_{m,t} - R_{f,t}) + \beta_{SMB} R_{SMB,t} + \beta_{HML} R_{HML,t} + \varepsilon_{p,t}, \quad (14)$$

where  $R_{p,t}$  is the quarterly return on the winner (or loser or difference) portfolio,  $R_{f,t}$  is the risk-free rate and  $R_{m,t}$ ,  $R_{SMB,t}$  and  $R_{HML,t}$  are the Fama-French market, size, and value factor returns, respectively.<sup>31</sup>

Results of the analysis are reported in Panel A of Table 8. The first two columns report the average quarterly raw return from the buy- and sell-herd industry portfolios over the indicated period. The third column reports their difference and associated  $t$ -statistic. The next three columns report the buy-herd portfolio, sell-herd portfolio, and difference portfolio (quarterly) alphas from Eq. (14).<sup>32</sup>

[Insert Table 8 about here]

The results reveal evidence consistent with the hypothesis that institutional industry demand impacts prices. In the two formation quarters, industries most heavily purchased by institutions outperform those most heavily sold by 2.73% per quarter (the difference in alphas is slightly larger).<sup>33</sup> In the four quarters immediately following formation, however, buy-herding industries underperform the sell-herding industries by 1.03% per quarter (statistically significant at the 5% level).<sup>34</sup> Some of this difference, however, is due to

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cross-sectional average return for the second quarter following the April-September of 1998 formation period is the first observation for the first quarter of 1999. The cross-sectional average return for the first quarter following the July-December 1998 formation period is the second observation for the first quarter of 1999. Averaging these two observations yields the average return during the first calendar quarter of 1999 over event quarters 1 and 2.

<sup>31</sup> Quarterly market, size, and value factor returns and the quarterly risk-free rate are calculated as compound monthly values (downloaded from Ken French's website).

<sup>32</sup> The  $t$ -statistics for raw industry returns are based on nonoverlapping quarters following the calendar aggregation method in Jegadeesh and Titman (1993). The  $t$ -statistics for the Fama-French alphas are based on time-series regressions of the Jegadeesh and Titman (1993) calendar aggregation returns.

<sup>33</sup> As noted by Sias, Stark, and Titman (2006) the positive relation between institutional demand and returns measured over the same period is consistent with three explanations: Institutional trading impacts prices, institutions are short-term positive-feedback traders, or institutions are able to forecast short-term prices. Regardless, this result is consistent with previous studies that show a positive relation between institutional demand (or subsets of institutional investors such as mutual funds) and individual security returns the same quarter including Grinblatt and Titman (1989, 1993), Grinblatt, Titman, and Wermers (1995), Jones, Lee, and Weis (1999), Nofsinger and Sias (1999), Wermers (1999, 2000), and Sias (2007).

<sup>34</sup> Although early work suggests that cross-sectional variation in institutional demand for individual securities is positively related to future returns (e.g., Nofsinger and Sias, 1999; Gompers and Metrick, 2001), recent work (e.g., San, 2007; Dasgupta, Prat, and Verardo, 2007) suggests an inverse relation between institutional demand and subsequent security returns in more recent periods. In untabulated results, we split the sample into two periods and find that although sell-herd industries outperform buy-herd industries in both the early (1983:12-1994:12) and late (1995:03-2005:12) periods, the difference is greater (-1.49% versus -0.56% per quarter over quarters 1 to 4) and statistically significant only in the early period. The Fama-French 3-factor intercept is also statistically significant in the early period (at the 5% level).

differences in exposure to the Fama-French factors. Specifically, the difference in 3-factor alphas is -0.67% per quarter (over quarters 1 to 4), but not statistically significant at traditional levels ( $p$ -value  $< 0.16$ ). Although factor loadings are not reported (to reduce clutter), this largely arises from sell-herding industries' greater sensitivity to the value factor. To the extent that the value premium reflects risk, the results are consistent with the explanation that at least part of the return difference is due to institutions herding out of riskier industries and toward safer industries. Alternatively, to the extent that the value premium reflects mispricing, the results are consistent with the explanation that institutional industry herding sometimes drives industry prices from their values.

In an interesting study, Dasgupta, Prat, and Verardo (2007) find that securities persistently purchased by institutions (e.g., over the last four quarters) subsequently underperform those persistently sold by institutions. The authors interpret the apparent price correction as resulting from mispricing induced by long-term institutional herding. To investigate this possibility for industries, each quarter we partition the 49 industries into those that were purchased more than average (i.e.,  $(\Delta_{k,t} - \overline{\Delta_{k,t}}) > 0$ ) by institutions in each of the four previous quarters ( $t=0$  to  $t=-3$ ) and those that were sold more than average in each of the four previous quarters. The number of industries that meet these criteria ranges from 2 to 14 and averages 7.31 industries that institutions bought over each of the last four quarters and 7.94 industries that institutions sold over each of the last four quarters. We then repeat the analysis in the previous section based on these longer-term buy- and sell-herd industries.

The results, reported in Panel B of Table 8, reveal further evidence consistent with the hypothesis that institutional industry herding sometimes drives prices from fundamental values. Specifically, those industries institutions purchased over the last four quarters subsequently underperform, on average, those industries institutions sold over the last four quarters. In the first year following formation, differences are statistically significant at the 5% level for both raw and abnormal returns.

## 5. Conclusions

Institutional investors follow each other into and out of the same industries (i.e., “industry herd”). Our results have implications for two related literatures. First, our evidence suggests that whatever factors drive institutional investors to herd have an industry component.<sup>35</sup> If, for example, institutional investors herd in attempt to preserve reputation, then our results are consistent with the hypothesis that managers attempt to preserve reputation by adjusting industry positions as well as stock positions. Analogously, if fads drive institutional herding, then there must be industry fads. If following correlated signals cause institutional herding, then institutions’ signals must have an industry component. And if informational cascades drive herding, then institutions must, at least sometimes, infer industry signals from each others’ trades.

Second, our evidence is also consistent with the growing style investing literature. Specifically, the Barberis and Shleifer (2003) style model requires a group of investors to style herd and that their herding impacts prices. Related empirical studies also contain these assumptions (sometimes implicitly). Our results demonstrate that institutions herd to industry styles and are consistent with the explanation that such herding impacts prices.

Our evidence suggests that institutional investors’ industry herding results from managers’ decisions rather than underlying investors’ flows, inconsistent with the explanation that institutional industry herding simply reflects the latest retail investor fad. Although size-BE/ME style herding appears to contribute to institutional industry herding, such herding fails to fully explain institutional industry herding. We also find that institutional investors momentum trade at the industry level (consistent with evidence at the stock level). Institutional industry momentum trading, however, does not explain their herding. In fact, the evidence suggests that industry herding explains their industry momentum trading—once accounting for lag industry demand, institutional industry demand is independent of lag industry returns.

Consistent with reputational herding models, four of the five institutional investor types are more likely to follow similarly classified institutions than differently classified institutions into and out of the same industry. Consistent with industry informational cascades, institutional investors exhibit greater herding in

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<sup>35</sup> As noted above, multiple factors may contribute to herding. Thus, the primary factors that drive stock herding may not be the same as the primary factors that drive industry herding.

smaller and more volatile industries. Further consistent with the explanation that institutions at least sometimes intentionally follow others' trades, we find some evidence that industry herding increases following mandatory electronic filing (i.e., post-EDGAR). Consistent with the hypothesis that institutional industry herding at least sometimes results from fads, reputational concerns, or informational cascades, institutional industry demand is, on average, inversely related to future industry returns. The relation between institutional industry herding and industry returns is also consistent with the Barberis and Shleifer (2003) style investing model. In sum, the evidence suggests that institutions engage in industry herding for a number of reasons, institutional industry demand impacts industry values, and institutional industry herding may, at least sometimes, drive industry prices from fundamental values.

## References

- Badrinath, S.G., Wahal, S., 2002. Momentum trading by institutions. *Journal of Finance* 57, 2449-2478.
- Banerjee, A.V., 1992. A simple model of herd behavior. *Quarterly Journal of Economics* 107, 797-817.
- Barberis, N., Shleifer, A., 2003. Style investing. *Journal of Financial Economics* 68, 161-199.
- Barberis, N., Shleifer, A., Wurgler, J., 2005. Comovement. *Journal of Financial Economics* 75, 283-317.
- Barclay, M.J., Warner, J.B., 1993. Stealth trading and volatility: which trades move prices? *Journal of Financial Economics* 34, 281-305.
- 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.
- Boyer, B., Zheng L., 2004. Who moves the market? A study of stock prices and sector cashflows. Unpublished working paper, Brigham Young University and University of Michigan.
- Brown, N., Wei, K., Wermers, R., 2007. Analyst recommendations, mutual fund herding, and overreaction in stock prices. Unpublished working paper, University of Southern California, University of Texas – Dallas, University of Maryland.
- Campbell, J., Ramadorai, T., Schwartz, A., 2007. Caught on tape: institutional trading, stock returns, and earnings announcements. Unpublished working paper, Harvard University and University of Oxford.
- Chakravarty, S., 2001. Stealth trading: which traders' trades move stock prices? *Journal of Financial Economics* 61, 289-307.
- Chamley, C., Gale, D., 1994. Information revelation and strategic delay in a model of investment. *Econometrica* 62, 1065-1085.
- Dasgupta, A., Prat, A., Verardo M., 2007. Institutional trade persistence and long-term equity returns. Unpublished working paper, London School of Economics.
- Dass, N., Massa, M., Patgiri, R., 2008. Mutual funds and bubbles: the surprising role of contractual incentives. *Review of Financial Studies* 21, 51-99.
- Fama, E., MacBeth, J., 1973. Risk, return and equilibrium: empirical tests. *Journal of Political Economy* 81, 607-636.
- Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.
- Fama, E., French, K., 1997. Industry costs of equity. *Journal of Financial Economics* 43, 153-194.
- Fama, E., French, K., 2006. Profitability, investment and average returns. *Journal of Financial Economics* 82, 491-518.
- Frazzini, A., Lamont, O.A., 2008. Dumb money: mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics* 88,299-322.
- Friedman, B.M., 1984. A comment: stock prices and social dynamics. *Brookings Papers on Economic Activity* 2, 504-508.
- Foster, F.D., Gallagher, D.R., Looi, A., 2005. Institutional trading and share returns. Unpublished working paper, The University of New South Wales, Australia.
- Froot, K.A., Scharfstein, D.S., Stein J.C., 1992. Herd on the street: informational inefficiencies in a market with short-term speculation. *Journal of Finance* 47, 1461-1484.
- Froot, K.A., Teo, M., 2004. Equity style returns and institutional investor flows. NBER Working Paper No. 10355.

- Froot, K.A., Teo, M., 2007. Style investing and institutional investors. *Journal of Financial and Quantitative Analysis*, forthcoming.
- Gompers, P., Metrick, A., 2001. Institutional investors and equity prices. *Quarterly Journal of Economics*, 116, 229-260.
- Gul, F., Lundholm, R., 1995. Endogenous timing and the clustering of agents' decisions. *Journal of Political Economy* 103, 1039-1066.
- Grinblatt, M., Titman, S., 1989. Portfolio performance evaluation: old issues and new insights. *Review of Financial Studies* 2, 393-422.
- Grinblatt, M., Titman, S., 1993. Performance measurement without benchmarks: an examination of mutual fund returns. *Journal of Business* 66, 47-68.
- Grinblatt, M., Titman, S., Wermers, R., 1995. Momentum investment strategies, portfolio performance, and herding: a study of mutual fund behavior. *American Economic Review* 85, 1088-1105.
- Hirshleifer, D., Subrahmanyam, A., Titman, S., 1994. Security analysis and trading patterns when some investors receive information before others. *Journal of Finance* 49, 1665-1698.
- Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance* 48, 65-91.
- Jones, C., Lipson, M., 2003. Are retail orders different? Unpublished working paper, Columbia University and University of Georgia.
- Jones, S., Lee, D., Weis, E., 1999. Herding and feedback trading by different types of institutions and the effects on stock prices. Unpublished working Paper, Indiana University–Indianapolis, Kennesaw State University and Merrill Lynch.
- Kaniel, R., Saar, G., Titman, S., 2008. Individual investor trading and stock returns. *Journal of Finance* 63, 273-310.
- Lakonishok, J., Shleifer, A., Vishny, R.W., 1992. The impact of institutional trading on stock prices. *Journal of Financial Economics* 32, 23-43.
- Nofsinger, J., Sias, R., 1999. Herding and feedback trading by institutional and individual investors. *Journal of Finance* 54, 2263-2295.
- Puckett, A., Yan, X.S., 2008. Short-term institutional herding and its impact on stock prices. Unpublished working paper, University of Missouri.
- San, G., 2007. Who gains more by trading—institutions or individuals? Unpublished working paper, Hebrew University of Jerusalem.
- Scharfstein, D., Stein, J., 1990. Herd Behavior and investment. *American Economic Review* 80, 465-479.
- Schwartz, R., Shapiro, J., 1992. The challenge of institutionalization for equity markets. In: Saunders, A. (Ed.), *Recent developments in finance*. Business One Irwin, Homewood, IL, 31-45.
- Sharma, V., Easterwood, J., Kumar R., 2006. Institutional herding and the internet bubble. Unpublished working paper, University of Michigan-Dearborn, and Virginia Tech.
- Shell, A., 2001. Tech teetotalers have the last laugh. *USA Today*, January 10, 2001.
- Sias, R.W., 2004. Institutional herding. *Review of Financial Studies* 17, 165-206.
- Sias, R.W., 2007. Reconcilable differences: momentum trading by institutions. *The Financial Review* 42, 1-22.
- Sias, R.W., Starks, L., Titman, S., 2006. Changes in institutional ownership and stock returns: assessment and methodology. *Journal of Business* 79, 2869-2910.

- Teo, M., Woo, S., 2004. Style effects in the cross-section of stock returns. *Journal of Financial Economics* 74, 367-398.
- Trueman, B., 1994. Analyst forecasts and herding behavior. *Review of Financial Studies* 7, 97-124.
- Wermers, R., 1999. Mutual fund herding and the impact on stock prices. *Journal of Finance* 54, 581-622.
- Wermers, R., 2000. Mutual fund performance: an empirical decomposition into stock-picking talent, style, transactions costs, and expenses. *Journal of Finance* 55, 1655-1695.
- Wermers, R., Yao, T., Zhao, J., 2007. The investment value of mutual fund portfolio disclosure. Unpublished working paper, University of Maryland, University of Iowa and University of Arizona.
- Wylie, S., 2005. Fund manager herding: a test of the accuracy of empirical results using U.K. data. *Journal of Business* 78, 381-403.
- Zwiebel, J., 1995. Corporate conservatism and relative compensation. *Journal of Political Economy* 103, 1-25.
- Zhang, J., 1997. Strategic delay and the onset of investment cascades. *RAND Journal of Economics* 28, 188-205.

**Table 1. Descriptive statistics**

Stocks are classified each quarter (between March 1983 and December 2005) into one of 49 industries. Panel A reports the time-series average of the cross-sectional descriptive statistics for the number of firms in each industry, the fraction of market capitalization accounted for by each industry, and the fraction of industry capitalization accounted for by the largest firm in the industry. Panel B reports the time-series average of the cross-sectional descriptive statistics for the number of institutional investors trading in each industry (overall and by type) and the ratio of the number of institutional buyers to institutional traders in each industry.

	Mean	Median	Minimum	Maximum
<u>Panel A: Industry statistics</u>				
Number of firms in industry	116	77	6	609
Industry capitalization/Market capitalization	2.04%	1.18%	0.05%	11.35%
Largest firm in industry/Industry capitalization	31.79%	26.99%	5.09%	80.19%
<u>Panel B: Institutional investor statistics</u>				
Number of institutions trading in an industry	692	748	150	1,076
Number of banks trading	134	153	32	177
Number of insurance companies trading	36	38	9	55
Number of mutual funds trading	42	45	12	60
Number of independent advisors trading	440	468	82	723
Number of unclassified institutions trading	40	42	7	64
#Buyers/(#Buyers + #Sellers)	50.04%	50.08%	39.76%	60.38%

## Table 2. Tests for herding

The first column in Panel A reports the time-series average of 90 correlation coefficients between institutional industry demand this quarter and institutional industry demand last quarter (from September 1983 to December 2005). Institutional industry demand is defined as the number of institutional investors buying the industry that quarter divided by the number of institutional investors trading the industry that quarter. The next two columns partition the correlation coefficient into the portion that results from institutional investors following their own lag industry demand and the portion that results from institutions following the lag industry demand of other institutional investors [see Eq. (3)]. In Panel B, the correlation is further partitioned into those industries institutions purchased in quarter  $t-1$  (buy herding) and those industries institutions sold in quarter  $t-1$  (sell herding). Panel C reports time-series average industry-weighted correlation (and its components). Panel D uses alternative industry definitions. Panel E excludes mutual funds and independent investment advisors from the analysis. In Panels A-E, an institution is defined as a buyer (seller) if the institution increases (decreases) their position in industry over the quarter. In Panel F an institution is defined as a buyer (seller) if the institution increases (decreases) their industry portfolio weight over the quarter. Panel G partitions the results in Panel A into the post-EDGAR period ( $n=40$  quarters) and the pre-EDGAR period ( $n=50$  quarters). Fama-MacBeth (1973)  $t$ -statistics are reported in parentheses and computed from the time-series standard error. \*\* indicates statistical significance at the 1% level; \* at the 5% level.

**Table 2. Tests for herding (continued)**

	<u>Partitioned correlation coefficient</u>		
	Average correlation coefficient	Institutions following their own lag industry demand	Institutions following other institutions' lag industry demand
<u>Panel A: All institutions</u>			
49 industries	0.4049 (22.90)**	0.0307 (23.24)**	0.3743 (21.12)**
<u>Panel B: Buy herding versus sell herding</u>			
Buy herding	0.2016	0.0157	0.1859
Sell herding	0.2034	0.0150	0.1884
Difference	-0.0018 (-0.12)	0.0007 (0.53)	-0.0025 (-0.17)
<u>Panel C: All institutions – Industry-weighted correlation</u>			
49 industries	0.4177 (16.85)**	0.0238 (21.80)**	0.3939 (15.94)**
<u>Panel D: All institutions – Alternative industry definitions</u>			
2-digit SIC code	0.2465 (6.98)**	0.0218 (1.01)	0.2246 (7.14)**
38 industries	0.3475 (12.68)**	0.0572 (5.56)**	0.2903 (10.32)**
30 industries	0.4135 (18.84)**	0.0293 (20.75)**	0.3842 (17.49)**
17 industries	0.3627 (11.96)**	0.0289 (20.12)**	0.3338 (11.01)**
12 industries	0.3930 (12.24)**	0.0266 (18.89)**	0.3664 (11.29)**
10 industries	0.4073 (12.24)**	0.0259 (18.08)**	0.3814 (11.36)**
5 industries	0.2811 (5.34)**	0.0499 (10.74)**	0.2312 (4.32)**
<u>Panel E: Excludes mutual funds and independent advisors</u>			
49 industries	0.4121 (24.50)**	0.0326 (23.88)**	0.3795 (22.57)**
<u>Panel F: All institutions – Buyer if increased portfolio weight in industry</u>			
49 industries	0.3687 (19.94)**	0.0189 (20.31)**	0.3498 (19.07)**
<u>Panel G: Pre- and post-EDGAR electronic 13(f) filing</u>			
Post-EDGAR (1996-2005)	0.4284	0.0217	0.4066
Pre-EDGAR (1983-1995)	0.3861	0.0378	0.3484
t-test for difference			1.65
Wilcoxon $\xi$ -statistic			2.04*

**Table 3. Regression of weighted institutional industry demand on lag weighted institutional industry demand**

Institutional demand for security  $i$  is computed as the number of institutional investors buying security  $i$  in quarter  $t$  divided by the number of institutions trading security  $i$  in quarter  $t$ . Weighted institutional demand for industry  $k$  is computed as the cross-sectional weighted average (by beginning of quarter capitalization) demand for all securities in industry  $k$ . The bottom right-hand cell reports the time-series average of 90 correlation coefficients between weighted institutional industry demand this quarter and weighted institutional industry demand last quarter (from September 1983 to December 2005). This correlation is partitioned [see Eq. (6)], each quarter, into four components: (1) institutions following themselves into the same stock (top left-hand cell), (2) institutions following other institutions into the same stock (middle row, left-hand cell), (3) institutions following themselves into different stocks in the same industry (top row, middle cell), and (4) institutions following other institutions into different stocks in the same industry (middle row, middle cell). Summing across columns (last column) yields the totals for following themselves versus following other institutions. Summing across rows (last row) yields the totals for following into the same stock versus following into different stocks in the same industry. All  $t$ -statistics are computed from the time-series standard errors. \*\* indicates statistical significance at the 1% level.

	Into the same stock	Into different stocks in the same industry	Total
Following themselves	0.0206 (14.80)**	0.0333 (8.61)**	0.0539 (11.42)**
Following others	0.3235 (22.42)**	0.1942 (14.46)**	0.5177 (29.91)**
Total	0.3441 (24.20)**	0.2275 (15.60)**	0.5716 (33.95)**

**Table 4. Institutional industry herding into same size-BE/ME style stocks and different size-BE/ME style stocks**

Institutional demand for security  $i$  is computed as the number of institutional investors buying security  $i$  in quarter  $t$  divided by the number of institutions trading security  $i$  in quarter  $t$ . Weighted institutional demand for industry  $k$  is computed as the cross-sectional weighted average (by beginning of quarter capitalization) demand for all securities in industry  $k$ . Each quarter we compute the correlation coefficient between weighted institutional industry demand this quarter and weighted institutional industry demand last quarter (from September 1983 to December 2005). The first column reports the portion of this correlation due to institutions following other institutions into different stocks in the same industry (this figure is identical to the middle row of the middle column in the previous table). The next two columns in the first row further partition the contribution into the portion attributed to institutions following others into (and out of) different stocks in the same industry within the same size-BE/ME style and into (and out of) different size-BE/ME style stocks in the same industry. The second row reports the time-series mean expected values computed under the null hypothesis that managers are as likely to follow other managers into and out of same size-BE/ME style stocks as different size-BE/ME style stocks (see Appendix A). The last row reports the mean difference between the realized and expected values. All  $t$ -statistics are computed from the time-series standard errors. \*\* indicates statistical significance at the 1% level.

	Into different stocks in the same industry	Same size-BE/ME style	Different size-BE/ME style
Realized contribution	0.1942	0.1260 (16.91)**	0.0683 (7.12)**
Expected contribution	0.1942	0.0765 (14.56)**	0.1178 (14.25)**
Realized - expected		0.0495 (9.07)**	-0.0495 (-9.07)**

**Table 5. Tests for herding and momentum trading**

Each column in this table reports the time-series average coefficient from 90 cross-sectional regressions of standardized institutional industry demand this quarter on: (1) standardized lag institutional industry demand over the previous quarter, six months, or year (first, fourth, and seventh columns), (2) standardized industry returns the previous quarter, six months, or year (second, fifth, and eighth columns), or (3) standardized industry returns and standardized institutional industry demand over the previous quarter, six months, or year (third, sixth, and last columns). Institutional industry demand is defined as the number of institutional investors increasing their position in the industry divided by the number of institutional investors trading the industry. Fama-MacBeth (1973) *t*-statistics are reported in parentheses and computed from the time-series standard error. \*\* indicates statistical significance at the 1% level.

	Measured over previous quarter		Measured over previous six months			Measured over previous year			
Lag institutional demand	0.4049 (22.90)**	0.4052 (20.17)**	0.3802 (22.44)**	0.3752 (20.98)**	0.3858 (22.89)**	0.3716 (21.48)**			
Lag return		0.0590 (2.66)**	-0.0134 (-0.65)	0.0928 (4.13)**	0.0004 (0.02)		0.1221 (4.97)**	0.0356 (1.58)	
Adjusted R <sup>2</sup>	17.46%	2.70%	19.23%	15.21%	3.28%	16.91%	15.57%	4.69%	17.99%

**Table 6. Analysis by investor type**

Institutional demand for each industry quarter is computed as the ratio of the number of institutional buyers to the number of institutional traders. This table reports the average contribution to the correlation between institutional demand this quarter and last quarter by investor type. The first column reflects each investor's propensity to follow their own lag industry demand and the second column reflects each investor's propensity to follow other institutional investors into and out of the same industry. The third column reports the average contribution to the correlation from each investor type following similarly classified institutions, e.g., banks following other banks [see Eq. (11)]. The fourth column reports the average contribution to the correlation from each investor type following differently classified institutions, e.g., banks following insurance companies [see Eq. (12)]. The last column reports the difference between columns three and four. All *t*-statistics (reported in parentheses) are computed from time-series standard errors. \*\* indicates statistical significance at the 1% level.

	Average contribution from following their own industry trades	Average contribution from following others' industry trades	Average contribution from following same type traders	Average contribution from following different type traders	Average "same contribution" less average "different contribution"
Banks	0.0232 (34.66)**	0.0011 (19.77)**	0.0023 (16.80)**	0.0007 (13.06)**	0.0016 (12.87)**
Insurance companies	0.0226 (17.83)**	0.0003 (4.76)**	0.0019 (6.93)**	0.0002 (3.06)**	0.0017 (6.01)**
Mutual funds	0.0326 (26.84)**	0.0004 (5.59)**	0.0011 (4.31)**	0.0003 (4.50)**	0.0008 (2.94)**
Independent advisors	0.0296 (39.19)**	0.0004 (12.89)**	0.0003 (8.89)**	0.0005 (10.96)**	-0.0001 (-3.59)**
Unclassified investors	0.0283 (16.81)**	0.0007 (9.26)**	0.0022 (7.86)**	0.0006 (7.75)**	0.0015 (5.37)**

**Table 7. Industry volatility, size, and herding**

Each quarter between September 1983 and December 2005 (for a total of 90 quarters), we sort industries by their contribution to the cross-sectional correlation between industry demand this quarter and last [i.e., Eq. (13)]. We define the top ten industries as “high-herding industries” and the remaining 39 industries as “low-herding industries.” The table reports the time-series mean of the quarterly cross-sectional median and mean industry return volatility and size percentile rankings of high- and low-herding industries. The last column reports the percentile ranking difference and associated *t*-statistics (computed from the time-series standard error). \*\* indicates statistical significance at the 1% level.

	High-herding industries	Low-herding industries	Difference ( <i>t</i> -statistic)
Mean industry return standard deviation percentile	54.96	48.73	6.23 (5.24)**
Median industry return standard deviation percentile	58.43	48.09	10.34 (5.77)**
Mean industry weight percentile	45.94	51.04	-5.10 (-4.20)**
Median industry weight percentile	43.90	51.58	-7.68 (-4.54)**

**Table 8. Industry herding and subsequent returns**

This table reports the average quarterly raw and abnormal returns for buy-herding and sell-herding industries over the formation period and the post-formation period. Institutional industry demand is defined as the number of institutional investors increasing their position in the industry that quarter divided by the number of institutional investors trading the industry that quarter. In Panel A, the 49 industries are sorted, each quarter, into the top ten buy-herding industries (those industries that institutions buy in both quarter  $t=0$  and  $t=-1$  that contribute the most to the cross-sectional correlation between demand this quarter and last) and the top ten sell-herding industries (those industries that institutions sell in both quarter  $t=0$  and  $t=-1$  that contribute the most to the cross-sectional correlation between demand this quarter and last). In Panel B, the 49 industries are sorted, each quarter, into those with above average institutional demand (buy herds) in each of the four previous quarters ( $t=0$  to  $t=-3$ ) and those with below average institutional demand (sell herds) in each of the four previous quarters. The  $t$ -statistics (reported in parentheses) for raw industry returns are based on non-overlapping quarters following the calendar-aggregation method in Jegadeesh and Titman (1993). The  $t$ -statistics for the Fama-French alphas are based on time-series regressions of the Jegadeesh and Titman (1993) calendar aggregation returns on market, size, and value factors. \*\* indicates statistical significance at the 1% level; \* at the 5% level.

	<u>Raw industry returns</u>			<u>Fama-French 3-factor model alphas</u>		
	Buy herds	Sell herds	Difference	Buy herds	Sell herds	Difference
Panel A: Portfolios based on herding over quarters $t=0$ to $t=-1$						
Quarter -1 to 0	0.0477	0.0204	0.0273 (4.99)**	0.0152	-0.0172	0.0324 (5.48)**
Quarter 1	0.0315	0.0384	-0.0069 (-1.16)	-0.0002	0.0005	-0.0007 (-0.12)
Quarters 1 to 2	0.0321	0.0382	-0.0061 (-1.09)	-0.0003	0.0002	-0.0005 (-0.09)
Quarters 1 to 4	0.0293	0.0396	-0.0103 (-2.16)*	-0.0042	0.0025	-0.0067 (-1.45)
Quarters 5 to 8	0.0319	0.0378	-0.0059 (-1.42)	-0.0054	0.0010	-0.0064 (-0.64)
Quarters 9 to 12	0.0356	0.0381	-0.0026 (-0.65)	-0.0026	0.0030	-0.0055 (-1.32)
Panel B: Portfolios based on herding over quarters $t=0$ to $t=-3$						
Quarter -3 to 0	0.0498	0.0273	0.0224 (3.59)**	0.0180	-0.0107	0.0286 (4.35)**
Quarter 1	0.0340	0.0430	-0.0090 (-1.40)	-0.0006	0.0063	-0.0069 (-1.04)
Quarters 1 to 2	0.0304	0.0430	-0.0126 (-2.15)*	-0.0051	0.0065	-0.0116 (-2.02)*
Quarters 1 to 4	0.0298	0.0414	-0.0117 (-2.07)*	-0.0060	0.0051	-0.0110 (-2.11)*
Quarters 5 to 8	0.0292	0.0377	-0.0085 (-1.71)	-0.0081	0.0012	-0.0093 (-1.94)
Quarters 9 to 12	0.0336	0.0370	-0.0034 (-0.73)	0.0002	0.0041	-0.0039 (-0.77)

## Appendix A: Proofs

### A. Proof of Eq. (3)

Eq. (2) defines institutional demand ( $\Delta_{k,t}$ ) for industry  $k$  as the ratio of the number of institutions buying industry  $k$  in quarter  $t$  to the number of institutions buying or selling industry  $k$  in quarter  $t$ . Defining  $D_{n,k,t}$  as a dummy variable that equals one if institutional investor  $n$  increases her position in industry  $k$  in quarter  $t$ , and zero if the investor decreases her position in industry  $k$ , institutional demand can be written:

$$\Delta_{k,t} = \frac{\sum_{n=1}^{N_{k,t}} D_{n,k,t}}{N_{k,t}}, \quad (\text{A1})$$

where  $N_{k,t}$  is the number of institutions trading industry  $k$  in quarter  $t$ .

The cross-sectional correlation between institutional demand this quarter and last is given by:

$$\rho(\Delta_{k,t}, \Delta_{k,t-1}) = \frac{1}{\sqrt{\sum_{k=1}^K w_k (\Delta_{k,t} - \overline{\Delta_{k,t}})^2} \sqrt{\sum_{k=1}^K w_k (\Delta_{k,t-1} - \overline{\Delta_{k,t-1}})^2}} \sum_{k=1}^K w_k (\Delta_{k,t} - \overline{\Delta_{k,t}}) (\Delta_{k,t-1} - \overline{\Delta_{k,t-1}}), \quad (\text{A2})$$

where  $w_k$  is one divided by the number of industries ( $1/K$ ) for the equal-weighted correlations and the industry's market weight at the beginning of quarter  $t-1$  for the value-weighted correlations. Analogously,  $\overline{\Delta_{k,t}}$  is equal-weighted average institutional demand across industries for the equal-weighted correlations and the value-weighted average institutional demand across industries for the value-weighted correlations.

For ease of notation, define:

$$C_t = \sqrt{\sum_{k=1}^K w_k (\Delta_{k,t} - \overline{\Delta_{k,t}})^2} \sqrt{\sum_{k=1}^K w_k (\Delta_{k,t-1} - \overline{\Delta_{k,t-1}})^2}. \quad (\text{A3})$$

Substituting (A1) and (A3) into (A2) yields:

$$\rho(\Delta_{k,t}, \Delta_{k,t-1}) = \left[ \frac{1}{C_t} \right] \sum_{k=1}^K w_k \left[ \left( \sum_{n=1}^{N_{k,t}} \frac{D_{n,k,t} - \overline{\Delta_{k,t}}}{N_{k,t}} \right) \left( \sum_{n=1}^{N_{k,t-1}} \frac{D_{n,k,t-1} - \overline{\Delta_{k,t-1}}}{N_{k,t-1}} \right) \right]. \quad (\text{A4})$$

This sum of products can be further partitioned into those that arise from investors following their own lag industry demand (i.e., investor  $n$ 's industry demand at times  $t$  and  $t-1$ ) and those that arise from investors

following the lag industry demand of other institutional investors (i.e., investor  $n$ 's demand at time  $t$  and investor  $m$ 's demand at time  $t-1$ ), yielding:

$$\rho(\Delta_{k,t}, \Delta_{k,t-1}) = \left[ \frac{1}{C_t} \right] \sum_{k=1}^K w_k \left[ \sum_{n=1}^{N_{k,t}} \left( \frac{D_{n,k,t} - \overline{\Delta_{k,t}}}{N_{k,t}} \cdot \frac{D_{n,k,t-1} - \overline{\Delta_{k,t-1}}}{N_{k,t-1}} \right) \right] + \left[ \frac{1}{C_t} \right] \sum_{k=1}^K w_k \left[ \sum_{n=1}^{N_{k,t}} \sum_{m=1, m \neq n}^{N_{k,t-1}} \left( \frac{D_{n,k,t} - \overline{\Delta_{k,t}}}{N_{k,t}} \cdot \frac{D_{m,k,t-1} - \overline{\Delta_{k,t-1}}}{N_{k,t-1}} \right) \right]. \quad (\text{A5})$$

### B. Proof of Eqs. (6) and (7)

Eq. (4) defines institutional demand for security  $i$  ( $\Delta_{i,t}$ ) as the ratio of the number of institutions buying security  $i$  in quarter  $t$  to the number of institutions buying or selling security  $i$  in quarter  $t$ . Defining  $D_{n,i,t}$  as a dummy variable that equals one if institutional investor  $n$  increases her position in security  $i$  in quarter  $t$ , and zero if the investor decreases her position in security  $i$ , institutional demand for security  $i$  can be written:

$$\Delta_{i,t} = \sum_{n=1}^{N_{i,t}} \frac{D_{n,i,t}}{N_{i,t}}, \quad (\text{A6})$$

where  $N_{i,t}$  is the number of institutions trading security  $i$  in quarter  $t$ . We define the weighted institutional demand for industry  $k$  (denoted  $\Delta_{k,t}^*$ ) as the market-capitalization weighted average institutional demand across the securities in industry  $k$  (where  $w_{i,t}$  is security  $i$ 's capitalization weight within industry  $k$  at the beginning of quarter  $t$ ):

$$\Delta_{k,t}^* = \sum_{i=1}^{I_{k,t}} w_{i,t} \Delta_{i,t}, \quad (\text{A7})$$

where  $I_{k,t}$  is the number of securities in industry  $k$  in quarter  $t$ . For ease of notation, define:

$$C_t^* = \sqrt{\sum_{k=1}^K w_k \left( \Delta_{k,t}^* - \overline{\Delta_{k,t}^*} \right)^2} \sqrt{\sum_{k=1}^K w_k \left( \Delta_{k,t-1}^* - \overline{\Delta_{k,t-1}^*} \right)^2}, \quad (\text{A8})$$

where  $w_k$  is as defined above (in subsection A). The correlation between weighted institutional industry demand this quarter and last is given by:

$$\rho(\Delta_{k,t}^*, \Delta_{k,t-1}^*) = \frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \Delta_{k,t}^* - \overline{\Delta_{k,t}^*} \right) \left( \Delta_{k,t-1}^* - \overline{\Delta_{k,t-1}^*} \right). \quad (\text{A9})$$

Substituting Eq. (A7) into (A9) yields:

$$\rho(\Delta_{k,t}^*, \Delta_{k,t-1}^*) = \frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} w_{i,t} \Delta_{i,t} - \overline{\Delta_{k,t}^*} \right) \left( \sum_{i=1}^{I_{k,t-1}} w_{i,t-1} \Delta_{i,t-1} - \overline{\Delta_{k,t-1}^*} \right). \quad (\text{A10})$$

Because the weights sum to one, Eq. (A10) can be written:

$$\rho(\Delta_{k,t}^*, \Delta_{k,t-1}^*) = \frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} w_{i,t} \left( \Delta_{i,t} - \overline{\Delta_{k,t}^*} \right) \right) \left( \sum_{i=1}^{I_{k,t-1}} w_{i,t-1} \left( \Delta_{i,t-1} - \overline{\Delta_{k,t-1}^*} \right) \right). \quad (\text{A11})$$

Substituting Eq. (A6) into Eq. (A11) yields:

$$\rho(\Delta_{k,t}^*, \Delta_{k,t-1}^*) = \frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} w_{i,t} \left( \sum_{n=1}^{N_{i,t}} \frac{D_{n,i,t}}{N_{i,t}} - \overline{\Delta_{k,t}^*} \right) \right) \left( \sum_{i=1}^{I_{k,t-1}} w_{i,t-1} \left( \sum_{n=1}^{N_{i,t-1}} \frac{D_{n,i,t-1}}{N_{i,t-1}} - \overline{\Delta_{k,t-1}^*} \right) \right). \quad (\text{A12})$$

Which can be written:

$$\rho(\Delta_{k,t}^*, \Delta_{k,t-1}^*) = \frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} w_{i,t} \left( \sum_{n=1}^{N_{i,t}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \right) \right) \left( \sum_{i=1}^{I_{k,t-1}} w_{i,t-1} \left( \sum_{n=1}^{N_{i,t-1}} \frac{D_{n,i,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{i,t-1}} \right) \right). \quad (\text{A13})$$

Eq. (A13) can be partitioned into those terms that represent trading in the same security this quarter and last (i.e., institutional trading in security  $i$  in both quarter  $t$  and quarter  $t-1$ ) and trading in different securities in the same industry [i.e., institutional trading in security  $i$  in quarter  $t$  and security  $j$  ( $i, j \in k$ ) in quarter  $t-1$ ]:

$$\begin{aligned} \rho(\Delta_{k,t}^*, \Delta_{k,t-1}^*) = & \frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} \left( w_{i,t} \left( \sum_{n=1}^{N_{i,t}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \right) \bullet w_{i,t-1} \left( \sum_{n=1}^{N_{i,t-1}} \frac{D_{n,i,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{i,t-1}} \right) \right) \right) + \\ & \frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} \left( \sum_{n=1}^{N_{i,t}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \right) \bullet w_{j,t-1} \left( \sum_{n=1}^{N_{j,t-1}} \frac{D_{n,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right). \quad (\text{A14}) \end{aligned}$$

Each term in Eq. (A14) can be further partitioned into investors following their own lag trades (i.e., investor  $n$  at time  $t$  and  $t-1$ ) and following other investors' lag trades (i.e., investor  $n$  at time  $t$  and investor  $m$  at time  $t-1$ ) yielding the general form of Eq. (6):

$$\begin{aligned}
\rho(\Delta_{k,t}^*, \Delta_{k,t-1}^*) &= \frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} \left( w_{i,t} w_{i,t-1} \left( \sum_{n=1}^{N_{i,t}} \left( \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{n,i,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{i,t-1}} \right) \right) \right) \right) + \\
&\frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} \left( w_{i,t} w_{i,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{i,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,i,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{i,t-1}} \right) \right) \right) + \\
&\frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{n,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right) + \\
&\frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right). \quad (\text{A15})
\end{aligned}$$

The last term in (A15) represents institutions following other institutions into different stocks in the same industry. This term can be further partitioned into managers following other managers into same size-BE/ME style stocks ( $i, j \in k, i, j \in s$ ) and into different style stocks in the same industry ( $i, j \in k, i \in s, j \notin s$ ) yielding Eq. (7):

$$\begin{aligned}
\frac{1}{C_t^*} \sum_{k=1}^K w_k \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right) = \\
\frac{1}{C_t^*} w_k \sum_{k=1}^K \left( \sum_{i=1, i \in s}^{I_{k,t}} \sum_{j=1, j \neq i, j \in s}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right) + \\
\frac{1}{C_t^*} w_k \sum_{k=1}^K \left( \sum_{i=1, i \in s}^{I_{k,t}} \sum_{j=1, j \neq i, j \notin s}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right). \quad (\text{A16})
\end{aligned}$$

### C. Expected contributions from same- and different-style stocks

The last term in Eq. (6) [or Eq. (A15)] represents institutional investors following other institutions into and out of different stocks in the same industry (i.e., industry herding):

$$\frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \cdot \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right) \quad (\text{A17})$$

Rearranging terms yields:

$$\frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \left( D_{n,i,t} - \overline{\Delta_{k,t}^*} \right) \left( D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*} \right) \right) \right) \right) \quad (\text{A18})$$

If manager  $n$  follows manager  $m$  into (or out of) a different stock in the same industry then the product of the last two terms  $\left( i.e., \left( D_{n,i,t} - \overline{\Delta_{k,t}^*} \right) \left( D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*} \right) \right)$  is positive. Conversely, if manager  $n$  trades in the opposite direction of manager  $m$  (e.g., manager  $n$  purchases security  $i$  following manager  $m$ 's sale of security  $j$ ), the last term is negative. Under the null hypothesis that managers are as likely to follow each other into and out of same style stocks as different style stocks in the same industry, the expected value of the product is the same regardless of whether stocks  $i$  and  $j$  are in the same size-BE/ME style ( $i, j \in k, i, j \in s$ ) or in different size-BE/ME styles ( $i, j \in k, i \in s, j \notin s$ ). As a result, the expected contribution of same- and different size-BE/ME style herding (under the null) is determined by the remaining terms in Eq. (A18). Specifically, the expected proportion of the herding contribution [i.e., the last term in Eq. (6)] attributed to same style stocks is given by the ratio of the expected contribution from same style terms ( $i, j \in s$ ) to the expected contribution from all (i.e., same style and different style) terms:

$$\frac{\frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1, i \in s}^{I_{k,t}} \sum_{j=1, j \neq i, j \in s}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \right) \right) \right)}{\frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \right) \right) \right)} \quad (\text{A19})$$

Cancelling the first term yields:

$$\text{Expected proportion attributed to same style stocks} = \frac{\sum_{k=1}^K \left( \sum_{i=1, i \in s}^{I_{k,t}} \sum_{j=1, j \neq i, j \in s}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \right) \right) \right)}{\sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \right) \right) \right)} \quad (\text{A20})$$

Analogously, the expected proportion of the herding contribution attributed to following other managers into and out of different style stocks is given by the ratio of the expected contribution from different style terms (i.e.,  $i \in s, j \notin s$ ) to the expected contribution from all (i.e., same style and different style) terms:

$$\text{Expected proportion attributed to different style stocks} = \frac{\sum_{k=1}^K \left( \sum_{i=1, i \in s}^{I_{k,t}} \sum_{j=1, j \neq i, j \notin s}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \right) \right) \right)}{\sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \right) \right) \right)} \quad (\text{A21})$$

The last term in Eq. (6) (i.e., the contribution to the correlation attributed to institutions following other institutions into different stocks in the same industry) times Eq. (A20) yields the expected contribution (under the null hypothesis) to the correlation attributed to institutions following other institutions into and out of same size-BE/ME style stocks in the same industry:

$$\begin{aligned} \text{Expected proportion of correlation attributed to herding in same style stocks}_t = & \\ & \frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right) * \\ & \frac{\sum_{k=1}^K \left( \sum_{i=1, i \in s}^{I_{k,t}} \sum_{j=1, j \neq i, j \notin s}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \right) \right) \right)}{\sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \right) \right) \right)} \quad (\text{A22}) \end{aligned}$$

Similarly, the last term in Eq. (6) times Eq. (A21) yields the expected contribution (under the null hypothesis) to the correlation attributed to institutions following other institutions into and out of different size-BE/ME style stocks in the same industry:

$$\begin{aligned} \text{Expected proportion of correlation attributed to herding in different style stocks}_t = & \\ & \frac{1}{(K)\sigma(\Delta_{k,t}^*)\sigma(\Delta_{k,t-1}^*)} \sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{D_{n,i,t} - \overline{\Delta_{k,t}^*}}{N_{i,t}} \bullet \frac{D_{m,j,t-1} - \overline{\Delta_{k,t-1}^*}}{N_{j,t-1}} \right) \right) \right) * \end{aligned}$$

$$\frac{\sum_{k=1}^K \left( \sum_{i=1, i \in \mathcal{I}}^{I_{k,t}} \sum_{j=1, j \neq i, j \notin \mathcal{S}}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \right) \right) \right)}{\sum_{k=1}^K \left( \sum_{i=1}^{I_{k,t}} \sum_{j=1, j \neq i}^{I_{k,t-1}} \left( w_{i,t} w_{j,t-1} \left( \sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{j,t-1}} \frac{1}{N_{i,t}} \frac{1}{N_{j,t-1}} \right) \right) \right)}.$$

(A23)