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The impact of institutional trading on stock prices*

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This paper uses new data on the holdings of 769 tax-exempt (predominantly pension) funds, to evaluate the potential effect of their trading on stock prices. We address two aspects of trading by these money managers: herding, which refers to buying (selling) simultaneously the same stocks as other managers buy (sell), and positive-feedback trading, which refers to buying past winners and selling past losers. These two aspects of trading are commonly a part of the argument that institutions destabilize stock prices. The evidence suggests that pension managers do not strongly pursue these potentially destabilizing practices.

1. Introduction

Instead of merely buying and holding the market portfolio, most investors follow strategies of actively picking and trading stocks. When investors trade actively, their buying and selling decisions may move stock prices. Understanding the behavior of stock prices thus requires an understanding of the investment strategies of active investors.

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Institutional investors hold about 50% of the equities in the United States. In 1989, their trading and that of member firms accounted for 70% of the trading volume on the New York Stock Exchange [Schwartz and Shapiro (1992)]. To see if institutional investors' trades influence stock prices, we empirically examine the trading patterns of institutional investors, focusing in particular on the prevalence of herding and positive-feedback trading, which are associated with the popular belief that institutional investors destabilize stock prices. We evaluate a sample of 769 all-equity tax-exempt funds, the vast majority of which are pension funds, managed by 341 different institutional money managers. The data were provided by SEI, a large consulting firm in financial services for institutional investors. The sample is particularly appropriate for addressing the questions of herding and positive-feedback trading in that the money managers directly compete with each other: they pursue the same customers and they are evaluated by the same service. [For an analysis of the investment performance of the money managers in this sample, see Lakonishok, Shleifer, and Vishny (1992).] There is thus more scope for finding herding and positive-feedback trading in this sample of institutions than in a random sample of institutions.

Our data consist of end-of-quarter portfolio holdings for each of the 341 money managers from the first quarter of 1985 through the last quarter of 1989. These data enable us to estimate how much each manager bought and sold of each stock in each quarter. We can then test for herding by assessing the degree of correlation across money managers in buying and selling a given stock (or industry grouping). We can also test for positive-feedback trading by examining the relationship between money managers' demand for a stock and the past performance of that stock. Finally, we can test the relationship between the excess demand by institutions and contemporaneous stock price changes directly. The results of these tests will shed light on the potentially destabilizing effect of institutional investors.

In brief, our results suggest that neither the stabilizing nor the destabilizing image of institutional investors is accurate. The evidence suggests that pension fund managers herd relatively little in their trades in large stocks (those in the top two quintiles by market capitalization), which is where over 95% of their trading is concentrated. There is some evidence of more herding in smaller stocks, but even there the magnitude of herding is far from dramatic. As far as trading strategies go, institutions appear to follow neither positive- nor negative-feedback strategies, on average. There is some evidence of positive-feedback trading in smaller stocks, but not in the large stocks which make up the institutions' preferred holdings. Finally, the correlation between the excess demand by institutions for a stock in a given quarter and the price change of the stock in that quarter is extremely weak, which provides some evidence against the view that large swings in institutional excess demand drive price movements of individual stocks. The overall picture that emerges from this paper is one of institutional investors pursuing a broad diversity of trading styles that, to a large extent, offset each other. Of course, without an accurate measure of the relevant elasticities of demand for stocks, we cannot rule out the possibility of large price impacts from what appear to be small amounts of herding or positive-feedback trading.

Our results are most closely related to research done some twenty years ago by Kraus and Stoll (1972), who address the question of 'parallel trading' (which is the same as herding) by institutions using data from the SEC study of institutional investors on monthly changes in holdings. They find little evidence of herding and weak evidence of a contemporaneous relationship between price changes and excess demand by institutions. Also of great interest and relevance is the study of mutual funds by Friend, Blume, and Crockett (1970), who find that mutual funds tend to buy stocks which in the previous quarter were bought by successful funds, whom they are probably imitating. Such behavior would lead to herding as well as to positive-feedback trading.

In the next section of this paper, we discuss some differing views of the impact of institutional investors on stock prices and review relevant research. Section 3 describes our data in more detail. In section 4 we examine the issue of herding, and section 5 deals with feedback trading strategies. Section 6 presents direct evidence on the correlation between institutional demand and stock prices; section 7 concludes the paper.

2. Theories of the impact of institutional trading on prices

According to one view, institutions destabilize stock prices, which usually means that prices move away from fundamental values, thereby increasing long-run price volatility. This view rests to a large extent on two premises. The first premise is that swings in institutional demand have a larger effect on stock prices than swings in individual demand, in part because institutions have much larger holdings than most individuals and therefore have larger trades. More importantly, however, price destabilization may be aggravated by herding, or correlated trading across institutional investors. When several large investors attempt to buy or sell a given stock at the same time, the effect on price can be large indeed. A pension fund manager has described this problem succinctly: 'Institutions are herding animals. We watch the same indicators and listen to the same prognostications. Like lemmings, we tend to move in the same direction at the same time. And that, naturally, exacerbates price movements' [*Wall Street Journal* (October 17, 1989)].

There are several reasons why herding might be more prevalent among institutions than among individuals. First, institutions might try to infer information about the quality of investments from each others' trades and herd as a result [Shiller and Pound (1989), Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992)]. Since institutions know more about each others' trades than do individuals, they will herd to a greater extent. Second, the objective difficulties in evaluating money managers' performance and separating 'luck' from 'skill' create agency problems between institutional money managers and fund sponsors. Typically, money managers are evaluated against each other. To avoid falling behind a peer group by following a unique investment strategy, they have an incentive to hold the same stocks as other money managers [Scharfstein and Stein (1990)]. Third, institutions might all react to the same exogenous signals, such as changes in dividends or analysts' recommendations, and herd as a result. Again, because the signals reaching institutions are typically more correlated than the signals that reach individuals, institutions might herd more. When large institutional money managers end up on the same side of the market, we expect the stock price to move provided the excess demand curve for this stock slopes downward.

Herding does not necessarily destabilize stock prices, however. As we mentioned above, institutions might herd if they all react to the same fundamental information in a timely manner. If so, they are making the market more efficient by speeding up the adjustment of prices to new fundamentals. Or they might herd if they all counter the same irrational moves in individual investor sentiment, which would also have a stabilizing effect. In such cases, observing herding is not sufficient to conclude that institutional investors destabilize prices.

This leads to the second premise of the argument that institutions destabilize stock prices: their strategies tend not to be based on fundamentals, possibly because of agency problems in money management. Fundamental strategies, such as contrarian investment strategies of buying 'cheap' high-dividend-yield or high-book-to-market stocks, often take a long time to pay off, and may actually do very badly in the short run relative to a popular benchmark such as the S&P 500. Since money managers can be dismissed after only a few quarters of bad performance, contrarian strategies put managers at significant risk. As a consequence, money managers might follow short-term strategies based not on fundamentals but on technical analysis and other types of feedback trading.

One particularly common example of a potentially destabilizing short-term strategy is trend chasing, or positive-feedback trading [De Long et al. (1990), Cutler, Poterba, and Summers (1990)], which is simply the strategy of buying winners and selling losers. Such trading might be driven by a belief that trends are likely to continue, a popular concept in the behavioral literature [Andreassen and Kraus (1988)]. From the money manager's perspective, the strategy of adding winners to the portfolio and eliminating losers has the added advantage of removing 'embarrassments' from the portfolio for the sake of the sponsors, i.e., 'window dressing' [Lakonishok et al. (1991)]. Positive-feedback trading is destabilizing if it leads institutions to jump on the bandwagon and buy overpriced stocks and sell underpriced stocks, thereby contributing to a further divergence of prices away from fundamentals. Positive-feedback trading is not *necessarily* a destabilizing strategy, however; such trading will bring prices closer to fundamentals if stocks underreact to news.

A completely opposing view of institutional investors is that they are rational and cool-headed investors who counter changes in the sentiment of individual investors. Unlike individual investors, institutions are exposed to a variety of news reports and analyses, as well as to the guidance of professional money managers, which puts them in a better position to evaluate the fundamentals. According to this view, institutions will herd if they all receive the same information and interpret it similarly, or if they counter the same swings in individual investor sentiment. But they will not herd if they receive uncorrelated information or interpret the same information in different ways. This view also predicts that rational institutions are likely to pursue negative-feedback strategies, i.e., buying stocks that have fallen too far and selling stocks that have risen too far.

There is also a third, and more neutral, view of institutional investors, which is that institutions are neither smart negative-feedback investors nor destabilizers who herd and chase trends. Instead, institutions are heterogeneous: they use a broad variety of different portfolio strategies which by and large offset each other. Their trading does not destabilize asset prices because there are enough negative-feedback traders to offset the positive-feedback traders. Moreover, the diversity of the trading strategies is great enough that the aggregate excess demand by institutions is close to zero, so that no herding emerges in equilibrium. Institutional pursuit of the various trading strategies is therefore fairly benign, for despite generating a substantial trading volume, institutions are not destabilizing stock prices.

3. Data

Our analysis is based on a sample provided by SEI of 769 tax-exempt equity funds. According to the SEI definition, equity funds hold at least 90% of their assets in equities. For each fund, at the end of each quarter from 1985 through 1989, the dataset contains the number of shares held of each stock. Most of the fund sponsors are corporate pension plans, but there are also a few endowments as well as state and municipal pension funds.

The total amount under management in these 769 funds at the end of 1989 is $124 billion, or about 18% of the total actively-managed holdings of pension funds. The average equity holdings of a fund are $161 million. Equity purchases and sales are estimated based on changes in end-of-quarter holdings of all NYSE, AMEX, and OTC stocks. The prices used to estimate dollar values are averages of beginning- and end-of-quarter stock prices. All holdings and prices are adjusted for stock splits and stock dividends. The data do not allow us to measure intraquarter round-trip transactions, although such transactions are infrequent and should have a minor impact on the results, particularly since we are more interested in price destabilization over horizons of a quarter or more.

Typically, a money manager has more than one fund under management. In our case, the 769 funds are managed by 341 different money managers, with the number of funds per manager ranging from one to 17. In general, different funds managed by the same manager have similar, if not identical, holdings. Therefore, the appropriate unit of analysis is a money manager rather than a fund, and so all the holdings of different funds with the same money manager are aggregated. Of course, money managers in our sample might manage additional funds that are not in our sample if these funds are not evaluated by SEI. The average portfolio of a money manager in our sample at the end of 1989 is $363 million. Twenty-three money managers had more than one billion dollars under management and the largest money manager in the sample had 12 billion dollars.

An important part of this paper will be the distinction between the trading strategies of money managers in large and small stocks, although the vast majority of holdings and trading of these investors are in large stocks. Table 1 presents information on buying and selling activity by size (market capitalization) quintiles. The cut-off points for size quintiles were determined from the universe of NYSE and AMEX stocks and updated quarterly. The table presents the number of portfolio changes and the dollar value traded in each size quintile.

Taking each quarterly change in a stock as a separate observation, we have a total of 26,292 cases where holdings were changed by at least one money

Table 1

Sample characteristics for quarterly holdings changes by 341 tax-exempt money managers in the period 1985–1989.

Number of quarterly changes in holdings and dollar value of changes (in millions) by size (market capitalization) quintiles determined from the universe of NYSE and AMEX stocks. The numbers in parentheses are the percentage of the number of all changes in holdings and the percentage of the dollar value of all changes in holdings that occur in the respective size quintiles.

Quintile	Number of changes in holdings (percent in quintile)	Dollar value of changes in holdings in millions (percent in quintile)
1 (smallest)	338 (1.3%)	270 (0.1%)
2	2,087 (7.9%)	1,648 (0.4%)
3	5,515 (21.0%)	11,030 (2.8%)
4	8,963 (34.0%)	50,373 (12.7%)
5 (largest)	9,389 (35.7%)	333,310 (84.0%)

manager in our universe. Only 338 of these changes, or 1.3%, are in the smallest quintile stocks. In contrast, 35.7% of the changes are in the largest quintile stocks, and an additional 34% are in the second-largest quintile. In terms of dollar values, the results are even more dramatic. While only 0.1% of holding changes by value are in the smallest quintile of stocks, fully 84% are in the largest quintile of stocks and another 12.7% in the second-largest. Roughly speaking, 97% of the dollar value traded by money managers is in the largest 40% of the stocks by market capitalization. Clearly, institutional investors trade large stocks. This observation is important to keep in mind in interpreting our findings on herding and positive-feedback trading.

4. Herding

4.1. Measurement of herding

In this section we explore whether money managers tend to end up on the same side of the market in a given stock in a given quarter, i.e., whether a disproportionate number of money managers are buying (selling) this stock. To illustrate our measure of herding, assume that, in a given quarter, when aggregated across stocks and money managers, half of the changes in holdings are increases and half are decreases. Consider first the case in which half the money managers increased their holdings of most individual stocks and half cut their holdings. In this case, we would conclude that there is no herding at the level of individual stocks. Suppose alternatively that, for many stocks, 70% of the money managers increased their holdings, while only 30% decreased holdings. For other stocks, in contrast, 70% of the money managers decreased their holdings and 30% increased them. In this case, for most stocks, money managers ended up on the same side of the market, and we would conclude that there is herding at the level of individual stocks.

Our measure of herding for a given stock in a given quarter, $H(i)$, is defined as

$$H(i) = |B(i)/(B(i) + S(i)) - p(t)| - AF(i)\,, \tag{1}$$

where $B(i)$ is the number of money managers who increase their holdings in the stock in the quarter (net buyers), $S(i)$ is the number of money managers who decrease their holdings (net sellers), $p(t)$ is the expected proportion of money managers buying in that quarter relative to the number active, and $AF(i)$ is an adjustment factor explained below. The herding measures are computed for each stock–quarter and then averaged across different subgroups.

In a given quarter, we should not necessarily expect the same number of purchasers and sellers of a stock. In fact, in our sample, 51.5% of the quarterly changes in holdings are purchases, consistent with money managers being net buyers during this period. This ratio varies from quarter to quarter. In computing our herding measure H, we therefore have a different p for every quarter. Each quarterly p is the number of money managers buying relative to the number active, aggregated across all stocks that the money managers traded in that quarter.

The adjustment factor AF in eq. (1) accounts for the fact that under the null hypothesis of no herding, i.e., when the probability of any money manager being a net buyer of any stock is p, the absolute value of $B/(B+S) - p$ is greater than zero. AF is, therefore, the expected value of $|B/(B+S) - p|$ under the null hypothesis of no herding. Since B follows a binomial distribution with probability p of success, AF is easily calculated given p and the number of money managers active in that stock in that quarter. For any stock, AF declines as the number of money managers active in that stock rises.

4.2. *Empirical results on herding*

Table 2 presents our main results on herding. Because our samples are so large, all results are statistically significant. The first column reports the mean and median herding measures for the whole sample. The mean herding measure, 0.027, is one of the key numbers in this paper; it implies that if p, the average fraction of changes that are increases, was 0.5, then 52.7% of the money managers were changing their holdings of an average stock in one direction and 47.3% in the opposite direction. The median herding measure is even smaller, only 0.001, which suggests that there is virtually no herding in a typical stock–quarter.

Table 2

Herding statistics for all stock–quarters and for stock–quarters with active trading based on quarterly holdings changes of 341 money managers in the period 1985–1989.

The mean and median herding statistics are presented for all cases ('stock–quarter') and for cases where more than 10 and more than 20 money managers were active. The herding statistic for a given stock–quarter is defined as $H(i) = |B(i)/(B(i) + S(i)) - p(t)| - AF(i)$, where $B(i)$ is the number of money managers who increase their holdings in the stock in the quarter (net buyers), $S(i)$ is the number of money managers who decrease their holdings (net sellers), $p(t)$ is the expected proportion of money managers buying in that quarter relative to the number active, and $AF(i)$ is the adjustment factor explained in the text. The herding measures are computed for each stock–quarter and then averaged across different subgroups. Standard errors (based on the assumption of independence across stock–quarters) are in parentheses.

	All cases	More than 10 money managers active	More than 20 money managers active
Mean	0.027 (0.001)	0.020 (0.001)	0.021 (0.001)
Median	0.001	0.001	0.002

Perhaps we should not be surprised by how low this number is. In the market as a whole, aggregating across all traders, there can be no herding, since for every share bought there is a share sold. If our sample of money managers is a random sample of traders, we would not expect to find any herding. Herding can only be detected within subsets of investors. Since we are analyzing one such subset (pension fund managers), herding within this subset can certainly exist, although we do not find any evidence thereof.

Some might argue that we should look within a finer subset of money managers who share a similar investment style in order to detect herding, but we are not persuaded by this argument. For one thing, virtually all of the money in our sample is managed by stock-picking pension fund managers evaluated by the same service. We do not have individuals or even most types of institutional investors. It is hard to believe that we have a random sample of U.S. equity investors, given how homogeneous our sample is by construction. In fact, we have argued earlier that restricting our sample to all-equity pension fund managers evaluated by the same service significantly increases the chances of detecting herd behavior.

Moreover, suppose that there are some large subgroups of institutions, with each subgroup practicing a distinct investment philosophy, and suppose that there is a great deal of herding among members of each subgroup. This would raise two possibilities. First, the strategies of different subgroups are uncorrelated and, hence, they do not counter each others' demand shifts. For example, growth money managers destabilize growth stocks and value money managers destabilize low-P/E stocks. Our measure of herding calculated even on a random sample of institutions would detect the herding that was going on, since the subgroup of institutions trading in parallel would cause the whole set of institutions to be on one side of the market, with individuals taking the other side. Our results reject this possibility, since we do not find much herding looking over all stocks.

The second possibility is that although money managers herd within subgroups, the subgroups trade with each other so as to systematically counter each other's effects on prices. For example, if growth money managers buy a stock, value money managers sell it to them. But in this case, there is no destabilization since money managers just trade with each other. This possibility is consistent with our evidence of very little herding by institutional investors.

For many stocks in our sample, the number of managers who changed their holdings in that stock is quite small. In table 2 we also provide herding results for stocks in which a substantial number of money managers were active. This restriction eliminates many of the smaller stocks. The results are similar to our earlier findings of little herding.

Another intuitive way to look at herding is to examine the fraction of purchasing behavior of an individual money manager that can be explained by the actions of other money managers. We run a regression across stock–quarters, in which the dependent variable gets the value of one if a randomly-chosen money manager who traded in that stock–quarter is a net buyer, and zero if he is a net seller. The independent variable is the fraction of money managers active in that stock in that quarter who were buyers (excluding the randomly-chosen money manager whose behavior we are trying to explain). The slope coefficient in this regression is 0.05 ($t = 13.8$), but more interestingly, the R-squared is only 0.7%, indicating that, in a cross-section, less than 1% of an individual money manager's behavior in a stock can be explained by the aggregate behavior of other money managers in that stock. In sum, the money managers in our sample do not seem to herd very much; most likely, they use a variety of trading styles that result, on average, in uncorrelated trading decisions.

4.3. *Further results*

We have established so far that, on average, there does not seem to be much herding in individual stocks in our sample. This does not preclude the possibility of more extensive herding in certain types of stocks, such as stocks of a particular size or performance record. Institutions might also be more apt to herd in industry groups as opposed to individual stocks. Finally, herding may be more prevalent among subgroups of pension fund managers than in the aggregate. These possibilities are explored below.

Panel A of table 3 shows herding by stock size. The stocks in which the money managers were active in a given quarter were assigned into size quintiles. The cut-off points for the size quintiles were determined from the universe of NYSE and AMEX stocks and updated quarterly. Herding was then examined within each of the size groups. The results reveal more herding by institutional investors in small stocks than in large stocks; the observed relationship is monotonic in size. For the smallest quintile stocks, our herding measure is 6.1%, while for the largest stocks it is only 1.6%.

There is some reason to believe that the herding statistic for smaller firms is upward-biased. If the firm is either issuing or repurchasing shares from the public, we should observe herding in *any* random sample of investors, simply because the issuing (repurchasing) firm is the unobserved other party to the transaction. But this does not really amount to meaningful correlation among the strategies of investors.

In small firms for which we observe fewer normal trades to start with, repurchase and issue activity may be a larger fraction of the trading activity we observe. The data support this view. When we look at the subsample consisting of only those stock–quarters in which the number of outstanding shares of the firm did not change either way by more than 2%, we find noticeably less herding for the smaller firms and no appreciable difference for the larger firms relative to the results for the full sample. The herding statistics for this subsample of stock–quarters for quintiles 1 through 5 respectively are: 0.028, 0.031, 0.023,

Table 3

Herding statistics by firm size, past-quarter performance, and by money under management based on sample of quarterly holdings changes of 341 money managers in the period 1985–1989.

Panel A reports the mean herding statistic by firm size (market capitalization) quintiles. Panel B reports the mean herding statistic by past-quarter return quintiles. Panel C reports the mean herding statistic by money under management quintiles determined from the universe being evaluated by SEI. The herding statistic for a given stock-quarter is defined as $H(i) = |B(i)/(B(i) + S(i)) - p(t)| - AF(i)$, where $B(i)$ is the number of money managers who increase their holdings in the stock in the quarter (net buyers), $S(i)$ is the number of money managers who decrease their holdings (net sellers), $p(t)$ is the expected proportion of money managers buying in that quarter relative to the number active, and $AF(i)$ is the adjustment factor explained in the text. The herding measures are computed for each stock-quarter and then averaged across different subgroups. Standard errors (based on the assumption of independence across stock-quarters) are in parentheses.

			Panel A: By firm size		
	Quintile 1 (small)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (large)
Mean	0.061 (0.0230)	0.039 (0.0058)	0.028 (0.0034)	0.020 (0.0024)	0.016 (0.0010)
			Panel B: By past-quarter performance		
	Quintile 1 (worst)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (best)
Mean	0.020 (0.0022)	0.018 (0.0027)	0.020 (0.0026)	0.024 (0.0024)	0.027 (0.0019)
			Panel C: By assets under management		
	Quintile 1 (smallest)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (largest)
Mean	0.006 (0.0023)	0.016 (0.0024)	0.016 (0.0019)	0.012 (0.0015)	0.018 (0.0012)

0.017, and 0.016. These results suggest that the true herding statistic for smaller firms may be closer to 0.03 than to 0.06, but still higher than for larger firms. (These results should be interpreted with some caution since, based on a sample of 107 stock-quarters in quintile 1, the standard error on our estimate of the herding statistic is 0.022.)

The finding of greater herding in small stocks has several possible explanations. It might simply reflect unintentional herding, whereby all institutions just respond similarly to particular news. For example, they may all want to sell small obscure stocks that have lost value in order to window dress their portfolios. Dumping losers may be less of an issue with larger stocks, which are held by many institutions. Lakonishok et al. (1991) find more window dressing in small stocks. Conversely, money managers might all want to buy a well-performing small stock because higher market capitalization increases the stock's liquidity and coverage by analysts.

Intentional herding should also be more prevalent in small stocks. There is less public information about these stocks, and, therefore, managers are much more likely to pay attention to each others' behavior and make decisions based on the trades of others in these stocks. This view of herding is consistent with Banerjee's (1992) idea that herding might result from rational inference under very limited information. The result of greater herding in small stocks is also consistent with Scharfstein and Stein's (1990) agency interpretation of intentional herding: fund managers may sell a small stock that other managers sell in order to avoid embarrassment, but holding onto IBM when others sell it is probably acceptable.

We also examine herding conditional on past performance of the stocks. At the beginning of every quarter, we divide the universe of NYSE and AMEX stocks into past-quarter performance quintiles. Stocks in which the money managers traded were then assigned into these quintiles, and herding measures computed for each group. The results are in panel B of table 3. Herding does not seem to depend on past stock performance. At most, there is some weak indication of slightly more herding in better-performing stocks.

One might argue that herding should be more pronounced within certain industry groups of stocks, such as technology stocks, whose cash flows are more uncertain. For example, one might expect to observe more herding in Genentech than in a less-glamorous stock like General Motors. To test this hypothesis, we divide the stocks in our sample into eleven broad industry groupings, provided to us by SEI, and compute our herding measure for each group. Again, we do not find much herding in any group. The measure of herding within various industry groups ranged between 0.029 and 0.015. There is no industry with an unusually large degree of herding.

Another hypothesis is that money managers herd in their portfolio allocations across industries rather than across individual stocks. For example, when money managers are 'excited' about computer stocks, one of them might buy IBM, another might buy Apple Computer, and a third might buy COMPAQ, leading to significant herding at an industry but not a firm level. To test this hypothesis, we look at the 54 two-digit SIC industries with at least ten stocks traded in our sample in each quarter. For each money manager, and for each 'industry–quarter', we compute the dollar purchases and dollar sales. A value of one was assigned to a money manager if he was a net buyer and zero if he was a net seller. For each industry–quarter, then, we had the number of buyers and the number of sellers, and could compute our herding measure while treating the whole industry as if it were a single stock. This calculation produced a herding measure of 0.013, suggesting even less herding at the industry level than at the individual stock level.

A final issue is the possibility of herding among subsets of money managers. One alternative is that money managers with a similar amount of money under management herd with each other, on the theory that similarly-sized money managers are in more direct competition for fund sponsors. Accordingly, we divide our money managers into quintiles each year by asset size under management, and compute our measure of herding within manager-size quintiles. Panel C of table 3 presents the results. There is less herding among the smallest managers than among the largest managers, but neither group herds a lot. Like the evidence on the subgroups of stocks and industries, this evidence on subgroups of money managers reveals little herding.

We conclude with an important caveat. It is possible that while there is very little herding in individual stocks and industries, there are times when money managers simultaneously move into stocks as a whole or move out of stocks as a whole. Since our data set contains only all-equity funds, we cannot examine this type of herding.

5. Feedback strategies

At any level of herding, institutional investors have more potential to destabilize asset prices if they follow strong positive-feedback strategies. So far, our analysis has been based on a count of money managers, which is the right measure of herding, and not on the amount of excess demand. From the point of view of destabilization of prices, however, the relevant variable is excess demand. We therefore compute the current quarter's net buying (aggregated across all money managers in a given stock) conditional on the past quarter's and on the past year's stock performance.

We use two measures of excess demand in a quarter, *Dratio* (dollar ratio) and *Nratio* (numbers ratio). For a given stock–quarter, *i*, *Dratio* is defined as

$$Dratio(i) = [\$buys(i) - \$sells(i)]/[\$buys(i) + \$sells(i)]\ , \tag{2}$$

where *\$buys(i)* is the total dollar increases by all money managers in the given stock–quarter (evaluated at the average price during the quarter) and *\$sells(i)* is similarly defined as the total dollar decreases in holdings. Similarly, *Nratio* is defined as

$$Nratio(i) = \#buys(i)/\#active(i)\,, \tag{3}$$

where *#buys(i)* is the number of money managers increasing the holding of the stock in quarter *i* and *#active(i)* is the number of money managers changing their holdings. In the results presented below, *Dratios* and *Nratios* are simple averages taken over all stock–quarters in a given group. We use two measures because they might, in principle, yield different results. For example, most managers might be engaged in positive-feedback trading, but the negative-feedback managers might be making the larger trades, in which case trend chasing would show up in the *Nratio* but not in the *Dratio*.

Table 4 presents the results for *Dratio* and *Nratio* by past-quarter performance quintiles and size quintiles. The results for *Dratio* show fairly substantial trend chasing for smaller stocks: the excess of sales over purchases in the

Table 4

Past-quarter performance and trading activity of 341 money managers by size quintiles in the period 1985–1989.

In panel A, the mean excess demand by past-quarter performance and size (market capitalization) is presented. The excess demand for a given stock–quarter, *Dratio*, is defined as the difference between dollar buys and dollar sells scaled by total activity (*\$buys* + *\$sells*). In panel B, the proportion of money managers that are net buyers, *Nratio*, by past-quarter performance and size is presented. Standard errors (based on the assumption of independence across stock–quarters) are in parentheses.

	Size				
Past-quarter performance	1 (small)	2	3	4	5 (large)
Panel A: Excess demand (Dratio)					
1 (worst)	−0.180	−0.030	0.105	0.047	0.016
	(0.029)	(0.047)	(0.056)	(0.055)	(0.033)
2	−0.159	−0.080	−0.047	−0.107	0.058
	(0.022)	(0.032)	(0.036)	(0.033)	(0.021)
3	−0.057	−0.015	0.017	0.025	0.110
	(0.018)	(0.024)	(0.025)	(0.025)	(0.016)
4	−0.005	0.038	0.077	0.063	0.025
	(0.016)	(0.019)	(0.020)	(0.018)	(0.013)
5 (best)	0.036	0.056	0.052	0.055	0.011
	(0.013)	(0.015)	(0.014)	(0.014)	(0.011)
Panel B: Proportion of money managers buying (Nratio)					
1 (worst)	0.418	0.485	0.554	0.528	0.488
	(0.014)	(0.026)	(0.028)	(0.027)	(0.016)
2	0.421	0.465	0.469	0.444	0.526
	(0.011)	(0.016)	(0.017)	(0.016)	(0.010)
3	0.477	0.502	0.511	0.508	0.541
	(0.008)	(0.011)	(0.012)	(0.011)	(0.007)
4	0.494	0.523	0.539	0.525	0.510
	(0.007)	(0.008)	(0.008)	(0.008)	(0.006)
5 (best)	0.510	0.520	0.519	0.520	0.493
	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)

worst-performing smallest stocks is 18% of total value traded, whereas the excess of purchases over sales among best-performing smallest stocks is 3.6%. A similar pattern is also observed in the second-smallest size category. Moreover, in both of these size quintiles, excess demand is monotonically increasing in performance. As we move to larger stocks, the relationship between excess demand and past performance disappears. Among the largest quintile stocks, where increases in holdings always exceed decreases, there is no evidence whatsoever of positive-feedback trading. The results thus reveal positive-feedback trading for smaller but not for larger stocks. Aggregating across all size groups, we do not see any evidence of positive-feedback trading on average, because of the concentration of trades in larger stocks.

The results for *Nratio* also point to positive-feedback trading in small but not in large stocks. In small stocks, only 42% of money managers changing their holdings of the worst performers are buyers, whereas 51% of the money managers changing their holdings of the best performers are buyers. Within this size quintile, *Nratio* increases monotonically with past performance. Positive-feedback trading is still evident in the second size quintile, but disappears in larger quintiles. Finally, table 5 reports the results on trading as a function of past-*year* performance and size. Consistent with the results in table 4, there is evidence of positive-feedback trading in small but not in large stocks.

The finding of positive-feedback trading in smaller stocks is intriguing. Perhaps the most obvious explanation is window dressing: money managers dump losers among small stocks to dress up their portfolios. The strategy of dumping small stock losers makes sense if sponsors are less sensitive to holdings of poorly-performing blue chips than to holdings of poorly-performing unknown stocks.

The observed positive-feedback strategies in smaller stocks might also be a consequence of institutional practices and constraints. For example, past losers dumped by money managers might be firms who stopped dividend payments. Some institutions might be prohibited from holding such stocks. Alternatively, money managers might restrict their holdings of small-capitalization or illiquid stocks. These factors create a positive correlation between past returns and institutional excess demand. In any case, whether we are finding evidence of behavioral strategies, agency problems, or of simple institutional restrictions, positive-feedback trading might have an impact on share prices of small stocks.

Interestingly, our result for small stocks is supportive of the evidence that overreaction identified by De Bondt and Thaler (1985) is concentrated in small stocks [Chopra, Lakonishok, and Ritter (1992)]. If institutional investors change their demand for these stocks in response to extreme performance, and if their demand affects prices in the short run, we would expect to observe overreaction.

The preferred holdings of institutional investors are large stocks, however, which is where their trading strategies are probably most important. For these stocks, we see no evidence of positive-feedback trading. Under the most

Table 5

Past-year performance and trading activity of 341 money managers by size quintiles in the period 1985–1989.

In panel A, the mean excess demand by past-year performance and size (market capitalization) is presented. The excess demand for a given stock–quarter, *Dratio*, is defined as the difference between dollar buys and dollar sells scaled by total activity (*\$buys + \$sells*). In panel B, the proportion of money managers that are net buyers, *Nratio*, by past-year performance and size is presented. Standard errors (based on the assumption of independence across stock–quarters) are in parentheses.

	Size				
Past-year performance	1 (small)	2	3	4	5 (large)
	Panel A: Excess demand (Dratio)				
1 (worst)	− 0.158	− 0.222	− 0.101	0.005	0.025
	(0.029)	(0.023)	(0.021)	(0.019)	(0.018)
2	− 0.035	− 0.077	0.012	0.045	0.042
	(0.046)	(0.030)	(0.022)	(0.018)	(0.013)
3	− 0.056	0.029	0.041	0.042	0.067
	(0.061)	(0.038)	(0.026)	(0.019)	(0.014)
4	0.068	0.073	0.029	0.032	0.051
	(0.061)	(0.036)	(0.025)	(0.019)	(0.013)
5 (best)	0.059	− 0.001	0.090	0.036	0.012
	(0.040)	(0.023)	(0.017)	(0.013)	(0.010)
	Panel B: Proportion of money managers buying (Nratio)				
1 (worst)	0.422	0.393	0.458	0.500	0.519
	(0.015)	(0.011)	(0.010)	(0.008)	(0.005)
2	0.483	0.464	0.508	0.519	0.514
	(0.023)	(0.014)	(0.010)	(0.007)	(0.004)
3	0.473	0.510	0.511	0.516	0.511
	(0.030)	(0.018)	(0.012)	(0.008)	(0.005)
4	0.536	0.531	0.510	0.516	0.513
	(0.030)	(0.017)	(0.011)	(0.008)	(0.004)
5 (best)	0.528	0.493	0.538	0.517	0.498
	(0.020)	(0.011)	(0.008)	(0.005)	(0.003)

common notion of destabilizing speculation, this implies that institutions are not destabilizing. The evidence on trend chasing in the largest stocks, like the evidence on herding, does not support the accusation that institutional investors destabilize the prices of the individual stocks they trade. Of course, our results on changes in quarterly holdings for individual stocks leave open the possibility that institutional investors destabilize either aggregate stock prices or the prices of individual stocks day-to-day or week-to-week without much affecting the quarterly time series of stock prices.

6. Institutional excess demand and contemporaneous price movements

Thus far, we have found little evidence that institutions destabilize stock prices through either herding or positive-feedback trading. In this section, we analyze the direct relationship between demand for stocks by our money managers and contemporaneous stock returns.

Of course, even if institutions affect prices, they might move them toward, rather than away from, fundamentals. More importantly, our data set is not ideal for analyzing the impact of institutional demand on prices. Our quarterly data does not enable us to distinguish between the impact of trades on prices and within-quarter trading strategies that respond to within-quarter price moves. For example, if we found that a particular group of stocks that institutions bought in a quarter rose in price in that quarter, it could be evidence either of positive-feedback trading in response to short-term price moves, or of the effect of institutional trading on prices, or even of both effects operating at the same time. In interpreting the results presented below, it is crucial to recognize this limitation of quarterly data.

Table 6 presents some basic statistics on the relationship between institutional demand for stocks in a quarter and size-adjusted excess returns in that quarter, computed by deducting from the quarterly buy-and-hold stock return the return on an equally-weighted quarterly buy-and-hold portfolio of the same size decile. The cut-off points for size deciles were updated quarterly. In each quarter, we divided stocks traded by our money managers into two broad categories: stocks of which in aggregate they were net buyers and those of which in aggregate they were net sellers. Each category is, in turn, divided into three groups depending on the size of the imbalance between dollar purchases and dollar sales (scaled by market capitalization). Small excess refers to the bottom quartile of stocks in terms of dollar excess demand, medium excess to the middle half, and large excess to the quartile of firms with largest excess demand in dollar terms. The same groups are defined for firms for which sales exceed purchases.

The results in table 6 show a statistically-significant size-adjusted excess return of 1.8% per quarter for firms that were bought, on net, by our money managers. This result may reflect a price impact of institutional trades, which might, but does not have to be destabilizing. The positive excess return could also result from positive-feedback trading in response to recent price increases, without causing these increases. When we look at the subcategories of net buying by the magnitude of our institutions' excess demand, we find that the abnormal return is actually somewhat smaller for large excess demand cases than for cases with small excess demand.

Table 6

Contemporary excess demand and quarterly returns for all stock-quarters and by size quintiles based on quarterly holdings changes of 341 money managers in the period 1985–1989.

Average abnormal quarterly returns (size-adjusted) are presented for various levels of excess demand. The results are presented for all stock-quarters as well as by firm size. Excess demand is defined as dollar buys minus dollar sales scaled by market capitalization. Small excess refers to the bottom quartile of stocks in terms of dollar excess demand (supply), medium excess to the middle half, and large excess to the quartile of stocks with the largest excess demand. Standard errors (based on the assumption of independence across stock-quarters) are in parentheses.

Category	All firms	1 (small)	2	3	4	5 (large)
\$buys exceeds *\$sells*	0.0181	− 0.0073	0.0280	0.0269	0.0172	0.0100
	(0.0013)	(0.0075)	(0.0043)	(0.0027)	(0.0021)	(0.0017)
Small excess	0.0162	− 0.0142	0.0171	0.0267	0.0147	0.0158
	(0.0025)	(0.0138)	(0.0072)	(0.0053)	(0.0042)	(0.0036)
Medium excess	0.0206	0.0056	0.0423	0.0285	0.0165	0.0128
	(0.0017)	(0.0107)	(0.0068)	(0.0038)	(0.0028)	(0.0020)
Large excess	0.0133	− 0.0292	0.0163	0.0247	0.0209	− 0.0047
	(0.0029)	(0.0164)	(0.0087)	(0.0053)	(0.0047)	(0.0042)
\$sells exceeds *\$buys*	− 0.0031	− 0.0831	− 0.0188	0.0030	0.0125	0.0163
	(0.0015)	(0.0065)	(0.0038)	(0.0029)	(0.0025)	(0.0021)
Small excess	0.0038	− 0.0721	− 0.0018	0.0140	0.0128	0.0125
	(0.0024)	(0.0136)	(0.0066)	(0.0052)	(0.0043)	(0.0038)
Medium excess	0.0006	− 0.0688	− 0.0074	0.0097	0.0088	0.0128
	(0.0019)	(0.0092)	(0.0060)	(0.0041)	(0.0033)	(0.0025)
Large excess	− 0.0172	− 0.1150	− 0.0572	− 0.0193	0.0200	0.0305
	(0.0034)	(0.0124)	(0.0073)	(0.0063)	(0.0062)	(0.0061)

For stocks which are sold, on net, by institutions, the abnormal return is substantially lower than for stocks which are bought, on net, although in magnitude the former return is a fairly small − 0.3% in the quarter. The average excess return, however, is a more substantial − 1.7% for firms for which the excess of sales over purchases is the largest. This might be evidence of destabilization or of responsiveness of demand to very recent price movements.

To clarify the above picture, the analysis was extended to five size quintiles, with size-adjusted abnormal returns calculated for each of the size groups. The results are also presented in table 6. As before, results differ substantially by size group. For the smallest stocks, the average abnormal return when purchases exceed sales is close to zero. Within that category, more buying is not associated with higher returns; in fact, the mean abnormal return on the smallest stocks with the largest excess demand is − 2.9%. On the other hand, the returns on the smallest stocks for which sales exceed purchases are sharply negative. Moreover, they are the most negative when the excess supply by institutions is the largest.

This evidence suggests that, within the smallest stocks, either institutions sell recent losers, or they depress the prices of stocks they sell.

The results for the second size quintile are consistent with either intraquarter positive-feedback trading or the direct impact of institutional trades on share prices. The mean abnormal return for stocks for which purchases exceed sales is 2.8%, and the mean return for stocks for which sales exceed purchases is − 1.8%. These returns are roughly monotonic in the magnitude of excess demand. In the third size quintile, we again see positive returns for stocks for which purchases exceed sales, but negative returns only for stocks for which the excess of sales over purchases is the largest. Again, however, there is a rough monotonic relationship between excess demand and abnormal returns, indicating either price pressure by institutions or intraquarter positive-feedback trading.

Even these rough relationships, however, disappear in the two largest size quintiles, in which institutional trading is concentrated. In the fourth quintile, both the stocks which are bought, on net, and sold, on net, earn a positive excess return. Moreover, stocks for which the excess supply by institutions is the largest have an abnormal return of 2.0%. In the largest quintile, stocks which institutions buy, on net, have lower abnormal returns than stocks which institutions sell, on net, which seems more consistent with stabilizing negative-feedback trading. Indeed, stocks with the largest excess demand have a return of − 0.5%, and stocks with the largest excess supply have a return of 3.1%. What little support we saw for positive-feedback trading or price pressure from institutions in smaller quintiles disappears in the largest two quintiles.

In sum, the results of this section are the least conclusive. Stocks that institutions buy, on net, have higher contemporaneous abnormal returns than stocks that institutions sell, on net.[1] However, a closer inspection reveals that

[1]In tables 4 and 5, we explored the relation between past returns and current excess demand by money managers. In table 6, we looked at current returns and current excess demand. Another question is: What is the relation between future returns and current excess demand? This question has more to do with the short-run profitability of the strategies pursued by pension managers than with the destabilization question. Friedman (1953) has argued that if prices move in one's favor after trading, then one has contributed to price stabilization. The problem is how to rule out strategies that are short-run-profitable but may actually be destabilizing in the long run. This problem is especially serious when future returns cannot be estimated very precisely over a long period of time.

We have examined the relationship between current excess demand and one-quarter-ahead returns without drawing conclusions about the role of institutions in promoting price stability from these results. The evidence, while quite mixed, suggests that pension fund trading in the smallest three quintiles of stocks is profitable in the short run, while trading in the two largest quintiles is neither particularly profitable or unprofitable in the short run. In other words, when pension funds are net sellers of smaller stocks, future prices tend to fall over the next quarter and prices tend to rise when the funds are net buyers. However, the magnitude of the future return differences as a function of past excess demands is relatively small and there are also some anomalous aspects of the results. For example, across all five quintiles, some of the most negative returns occur after large net buying by fund managers in the previous quarter.

this result is driven by the smaller stocks, particularly those in the second and third quintiles. In the largest two quintiles, the pattern of abnormal returns for the net buy and net sell cases is essentially identical. For the smallest quintile stocks, when institutions are net sellers, a monotonic relationship between gradations of excess supply and abnormal returns is observed. However, no such relationship exists for stocks which institutions buy, on net. In light of this evidence, the destabilizing effect of institutions in individual stocks, even if it exists, is unlikely to be large.

7. Conclusion

This paper has presented evidence on the herding and trend-chasing behavior of institutional money managers. For smaller stocks, we find weak evidence of herding and somewhat stronger evidence of positive-feedback trading. However, the evidence shows relatively little of either herding or positive-feedback trading in the largest stocks, which constitute the bulk of most institutional holdings and trading. There is also no consistent evidence of a significant positive correlation between changes in institutional holdings and contemporaneous excess returns, except again in small stocks where we may just be observing intraquarter positive-feedback trading. We conclude that there is no solid evidence in our data that institutional investors destabilize prices of individual stocks. Instead, the emerging image is that institutions follow a broad range of styles and strategies and that their trades offset each other without having a large impact on prices. We must conclude, however, with two important caveats. First, our results do not preclude either market-wide herding, such as would occur if money managers followed each other in market-timing strategies, or herding in individual stocks that only shows up when measured at shorter time intervals such as daily or weekly. Second, our results do not rule out the possibility of highly inelastic demands for stocks which cause relatively small amounts of institutional herding or positive-feedback trading to have relatively large effects on stock prices.

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