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# FIRM SPECIFIC AND MACRO HERDING BY PROFESSIONAL AND AMATEUR INVESTORS AND THEIR EFFECTS ON MARKET

By

ITZHAK VENEZIA, AMRUT NASHIKKAR,
and ZUR SHAPIRA

Discussion Paper # 586 Aug 2011

מרכז לחקר הרציונליות

CENTER FOR THE STUDY
OF RATIONALITY

Feldman Building, Givat-Ram, 91904 Jerusalem, Israel
PHONE: [972]-2-6584135 FAX: [972]-2-6513681
E-MAIL: ratio@math.huji.ac.il
URL: http://www.ratio.huji.ac.il/

Journal of Banking & Finance 35 (2011) 1599–1609

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

# Firm specific and macro herding by professional and amateur investors and their effects on market volatility

Itzhak Venezia [a,*], Amrut Nashikkar [b], Zur Shapira [b]

[a] The Hebrew University, Jerusalem, Israel
[b] Stern School of Business, New York University, United States

ARTICLE INFO

*Article history:*
Received 16 June 2009
Accepted 13 November 2010
Available online 20 November 2010

*JEL classification:*
G0
G11
G14

*Keywords:*
Herding
Professional investors
Amateur investors
Behavioral finance

ABSTRACT

We find a herding tendency among both amateur and professional investors and conclude that the propensity to herd is lower in the professionals. These results are obtained both when we consider herding into individual stocks and herding into stocks in general. Herding depends on the firm's systematic risk and size, and the professionals are less sensitive to these variables. The differences between the amateurs and the professionals may be attributable to the latter's superior financial training. Most of the results are consistent with the theory that herding is information-based. We also find that the herding behavior of the two groups is a persistent phenomenon, and that it is positively and significantly correlated with stock market returns' volatility. Finally, herding, mainly by amateurs, causes market volatility in the Granger causality sense.

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## 1. Introduction

Herding behavior by investors is important because of its potential effects on fluctuations in returns.[1] Researchers argue that in many cases herding is a by-product of information availability or the lack thereof. Different groups of investors receive information of varying types and quality. Differences between group characteristics and available information may cause investor groups to behave differently from one another while also exhibiting herding within each group. Understanding the bases of the herding behavior of the various groups may lead to a better understanding of price variations, since diverse groups' trading may correlate differently with the market.

While there are various ways of classifying investors into groups for the purpose of analyzing their behavior, such classification and analysis can be useful only if the groups are sufficiently large, so that their actions can potentially affect key market features.[2] Therefore, classifying investors into two general types, amateurs and professionals, can help in distinguishing between two large groups whose herding has significant effects on markets; it can also serve as a tool for examining the effect of increasing market savvy on behavior. Whereas there exists considerable empirical research analyzing institutional herding behavior, with varying degrees of agreement as we show below, research on herding differences between professionals and amateurs is scant.[3] This is partially due to the frequent use of actual market data in research on herding behavior by institutions, while research on herding by individuals uses mainly experimental methods and data.[4]

* Corresponding author. Tel.: +972 (0)54 6272836; fax: +972 (0)3 5660730.
*E-mail addresses:* msvenez@mscc.huji.ac.il (I. Venezia), anashikk@stern.nyu.edu (A. Nashikkar), zshapira@stern.nyu.edu (Z. Shapira).

[1] For examples showing how herding and other demand fluctuations affect prices see, e.g., Choe et al. (1997), Sias and Starks (1997), and Nofsinger and Sias (1999). For a comprehensive review of the herding literature see Bikhchandani and Sharma (2000) and Hirshleifer and Teoh (2001).

[2] Groups that are too large are counterproductive for the study of herds. If the groups cover the whole market, then the sell of one group would be the buy of the other, hence the behavior of the groups would mirror each other. Groups should be somewhat homogeneous and the members of the groups should have some possibility of guessing or observing the actions of other members. Whereas we consider the behavior of amateurs versus professionals, many researchers study the herding behavior of other groups. For example: Graham (1999) and Jegadeesh and Kim (2007) study analysts, Gleason et al. (2004) examine herding among the sector ETFs, and Kodres and Pritsker (1995) investigate herding among futures traders.

[3] Two examples are Nofsinger and Sias (1999) and a recent paper on herding in the Chinese stock market by Li et al. (2009).

[4] See Hirshleifer and Teoh (2001).

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doi:10.1016/j.jbankfin.2010.11.015

Lakonishok et al. (1992) study the trading behavior of tax-exempt mutual funds, and find little evidence of herding. Grinblatt et al. (1995) find weak evidence of herding in the mutual funds they analyzed. However, they find that when herding exists, its impact is important: stocks purchased by funds that herd outperform by four percent stocks sold over the subsequent six months. This return difference is especially pronounced for small stocks. At the same time, they do not provide any evidence about herding behavior by individual investors. Wermers (1999), using quarterly holding data, finds that mutual funds herd when trading small stocks, mainly with growth-oriented funds, but he observes little herding on average by mutual funds. Brown et al. (2007) find that mutual funds herd into stocks with consensus analyst upgrades and herd out of stocks with consensus downgrades.

Nofsinger and Sias (1999) examine herding by both institutional and individual investors. They report evidence on herding behavior by institutions using quarterly holdings data. Using a smaller data-set than the one they use for their analysis of institutions, they also find herding by individuals, and show that herding by institutions impacts prices more than herding by individual investors. In addition, they note that institutional herding into specific stocks results in better performance relative to the market than does herding by individuals. Moreover, they demonstrate that institutional herding shows a strong contemporaneous relationship with daily stock returns. In a later study, Sias (2004), finds positive auto-correlation between institutional investors' demand for a security from one quarter to the next and argues that most of this apparent momentum trading by institutional investors can be explained by herding rather than by the claim that institutions follow a momentum strategy based on past winners and losers.[5]

Further insights on herding are obtained from studies in non-US markets. Walter and Weber (2006) investigate herding behavior in German mutual funds, and find some evidence that managers of those funds tend to herd and exhibit positive feedback trading patterns. They also find that a large proportion of apparent herding behavior can be attributed to changes in the benchmark index composition. Wylie (2005) examines the portfolio holdings of equity mutual funds in the UK using quarterly data to test for herding. He finds a modest amount of herding in both the largest and the smallest individual UK stocks, but little herding in average size stocks. Wylie also finds that mutual fund managers tend to herd out of large stocks after high excess returns. Kim and Nofsinger (2005) study institutional herding in Japan and find evidence of a lower incidence of herding than in the US, but a higher impact of herding on Japanese stock prices.[6]

In the present study we examine herding behavior by individuals and professionally-managed investors by using a unique data-set detailing all the transactions of a sizeable group of investors in a large brokerage house in Israel over a four-year period. The investors are classified into two subgroups. One subgroup consists of individuals who make their investment decisions on their own, and the other comprises investors whose accounts are managed by professional investment managers. This data-set allows us to directly test the effects of characteristics usually associated with professional managers, such as superior information and financial savvy, on the herding behavior of investors. It facilitates the analysis of factors that potentially contribute to herding behavior – factors specific to the herded stocks as well as factors that are market-wide. It also allows us to examine the differential effects of these factors on independent and professionally-managed investors.

Our study adds to the literature in various ways. First, we provide new evidence on herding and its relation to firm characteristics such as firm size, systematic risk, and idiosyncratic risk. Second, we study herding in a market that has not been studied previously. This is important, since this market differs from other markets studied in terms of market setting, size, investment culture, and the different characteristics of the independent and professional investors. To the extent that the results of this study conform to those obtained in analyses of other markets, they add to their validity. If on the other hand the results differ, then the sources of such differences will shed more light on herding behavior. In addition, the type of professional investors we use in our study differs from those used in earlier studies; whereas research on professionals' herding in the US concentrates on the behavior of mutual funds and institutions, we study professional money managers. In addition, our sample contains an important feature that distinguishes it from the institutions studied in the US, making its analysis valuable. The professional investors in our study, unlike many mutual funds in the US, do not exhibit any particular style and are not benchmarked to any specific index.[7] The incentive of our investors to "beat" any specific index is weaker, and their motivation to herd is therefore lower than that of mutual funds in the US. If herding behavior is nevertheless found among the professional investors in our sample, it reinforces other behavioral and informational explanations for their conduct. Finally, our study is based on more detailed data than previous studies. Nofsinger and Sias (1999), for example, base their conclusions on quarterly reports, and therefore their herding measures are dependent only on holdings on the last days of the quarter; our study, however, employs daily data from which monthly herding measures are formed.[8]

The paper is structured as follows. In Section 2, we describe the data. Section 3 presents the methodology used for constructing the herding measures and for designing the empirical tests. In Section 4 we explore the herding tendencies of both amateurs and professionals, and study stock-specific characteristics (e.g., size, idiosyncratic and systematic risk) that affect herding. In Section 5 we examine market-wide factors that lead to herding. Section 6 concludes.

## 2. Data

The data consist of records of all investment transactions of 2428 managed and 7429 independent clients of one of the largest banks in Israel (banks in Israel also act as brokerage houses) during the period January 1, 1994 through December 31, 1997. We count as clients in any given year only those who transacted at least once during that year.[9] Independent clients manage their own portfolios, but process their transactions through the bank. Managed clients solicit the assistance of professional portfolio and money managers (PMMs) who also act as brokers. Most of these PMMs are not members of the Tel Aviv Stock Exchange (TASE), so they execute their transactions through a member of the Exchange (usually a large bank or other financial institution). When a client chooses to have her portfolio managed by a PMM, she opens an account at a bank

[5] Griffin et al. (2003) document strong evidence of feedback trading (a behavior closely related to herding) by institutional investors at the daily level. They find that, on average, the top-performing securities based on the previous day's return are more likely to be bought by institutions (and sold by individuals) than are poorly-performing securities. However, the authors do not explore herding behavior.

[6] While herding by institutional investors has been extensively studied, this behavior among individuals and its effect on prices has received less attention (see, however, Feng and Seasholes, 2002).

[7] See Choi and Sias (2008) on the effects of style investing on institutional herding.

[8] When only institutional ownerships at the quarter-end are observed, a manager who buys and sells the same number of shares within a quarter will not be counted as a trader.

[9] The number of amateurs is higher than that of professionals. However, since the professionals traded almost five times more frequently than the amateurs, there were no significant differences between the groups in terms of total volume and total number of transactions.

and authorizes the PMM to manage it. According to the law, all persons who engage professionally in investment advice, investment marketing, or investment portfolio management in Israel, and hence also the PMMs in our sample, must be licensed by the Israel Securities Authority (ISA), the Israeli equivalent of the SEC in the US, and their license must be renewed annually. To become licensed they must pass examinations in finance, economics, statistics, and ethics. Their compensation is not tied to any specific individual or group benchmark, and they enjoy bonuses in boom years. The amateurs in our sample represent a mix of investors from across all walks of life, hence it is safe to assume that the professionals' training and knowledge of financial markets is superior to theirs. Our database consists of all the transactions of clients, both independent and managed, who maintained accounts on January 1, 1994.

In 1997, 62.8% of the stocks traded on the TASE were held by the Israeli public, 25.1% were held by local institutional investors, and 12.1% by foreign investors.[10] The average daily volume of the stock market in Israel ranged between $103.7 million in 1994 and $58.6 million in 1997, and the daily volume of transactions made by the investors in our sample was about 4% of the total daily stock market volume. To the extent that this is a representative sample from the groups of public investors, it is indicative of their behavior and influence.

## 3. Methodology

Herding occurs when investors imitate the behavior of other investors and in doing so partially disregard their own information and beliefs. However, not all herding can be described as non-rational. We find in the literature three types of herding that are classified as rational: First, *information-based herding*: Investors observing other investors who invested earlier in a stock may assume that the latter did so in a Bayesian updating manner. Therefore, the former may conclude that there is no point in obtaining further signals about the stock, because it is unlikely that they would sufficiently affect the investors' prior opinions and cause them to change their mind. This argument is in line with work carried out by researchers who study cascades (see Banerjee (1992) and Bikhchandani et al. (1992)). Second, *reputation-based herding*: The model developed by Froot et al. (1992) includes two investment managers and an employer, where no one is certain of the two managers' ability. In this model the managers imitate one another, unwilling to risk reputation loss.[11] Third, *compensation-based herding*: Since compensation of investment managers is often linked to some market benchmark, the managers find it worthwhile to imitate actions taken by other investors (Maug and Naik, 1996).

It is usually impossible to directly test which of these types of herding is present and whether herd-like behavior of investors is "true" herding, or just seems to be so, since all investors receive similar signals and therefore behave alike.[12] For practical purposes however, one needs to construct some proxies for herding behavior. In what follows, we employ techniques and herding measures similar to those used by Lakonishok et al. in a study from 1992 (LSV) and by Grinblatt et al. in a study from 1995 (GTW). The main variable used in the current analysis is the proportion of buy transactions out of all trades (buy and sell) of some stock during a given period of time relative to the long-run proportion of buy transactions. Since the long-run proportion of buy transactions of any stock is 50%, the above definition only applies when it is restricted to a particular class of investors, and for a limited period of time. Herding is considered to be the case when the proportion of buys significantly differs from its long-run average.[13]

We examine two types of herding: The first is herding into specific stocks, which we call "micro herding." The micro herding measures we construct assess to what extent there is a concentration of buy trades or sell trades on a specific stock. We use this herding measure to analyze the characteristics of the stocks that lead to herding. The second measure, which we call "macro herding," evaluates the extent to which investors' trades are concentrated on either the buy side or the sell side of the market.[14] This measure is used to scrutinize how market-wide factors, such as total market volume, volatility, and market returns, correlate with herding.

For every stock we calculate we measure its monthly herding, as follows: For each type of investor – individuals or professionals, we calculate for every stock $i$, and each time period $t$, the proportion, $P_{it}$, of buy transactions out of all trades of stock $i$ during month $t$.[15] We also calculate the average proportion of buy trades across all stocks at time $t$, $P_t$. If $P_{it}$ significantly deviates from $P_t$, it may indicate that investors are herding on security $i$ in that time period. Following LSV and GTW, we consider large absolute deviations of $P_{it}$ from $P_t$, $\text{abs}(P_{it} - P_t)$ as signs of herding. We test whether these deviations are due to chance or are systematic. To this end we assume that the number of buys of security $i$ at time $t$, under the null hypothesis of no herding, is binomially distributed with the number of "trials," $N_{it}$ (number of both buy and sell trades of security $i$ at time $t$) and probability of "success," $P_t$, where a buy transaction is considered a "success." We then calculate, for all stocks $i$ traded at time $t$, the following herding measure:

$$H_{i,t} = \text{abs}(P_{i,t} - P_t) - E[\text{abs}(P_{i,t} - P_t)] \tag{1}$$

The computation of the first term on the right-hand side of (1) is straightforward. The absolute value of $(P_{i,t} - P_t)$, however, does not follow any known distribution for which exact formulas can be obtained. Hence, we developed a method for calculating a normal distribution approximation to the expectation, $E[\text{abs}(P_{i,t} - P_t)]$, for the binomial distribution with $N_{it}$ tosses (see Appendix A). As shown in Venezia et al. (2010), this approximation is quite accurate even for small numbers of $N_{it}$'s, and as $N_{it}$ gets larger this approximation becomes more accurate, according to the law of large numbers.

The method for calculating the macro herding measures is analogous. In the analysis of macro herding, however, we use daily data, where all the transactions of amateurs and professionals across securities are aggregated to a total number of transactions of their respective groups.[16] The macro herding measures are similar to those of the micro herding except that in the former we omit the index for the specific security. Accordingly, we define $P_t$ as the proportion of buy transactions of investors of each specific type during time $t$, and we denote by $P^*$ the long-run proportion of buy transactions of this investors' class during the period of time of the study. In this case the macro herding measure is given by:

$$H_t = \text{abs}(P_t - P^*) - E[\text{abs}(P_t - P^*)] \tag{2}$$

[10] These data are taken from Bank of Israel publications (http://www.bankisrael.gov.il/data/p62.htm). In 2009 the distribution changed to 63.4% Israeli public, 18.9% institutions, and 17.7% foreign investors. The relative weight of the public sector from which our sample is taken hence did not change significantly over time.

[11] Villatoro (2009) explores which conditions lead to equilibrium where intermediaries with a good reputation invest in private information and those with a poor reputation herd.

[12] See, however, Graham (1999), who uses several proxies to test for the existence of reputational-based herding among investment newsletters.

[13] This measure does not take into account the volume of trades. For example, buyers and sellers could be of the same number but each of the buyers demands a large amount and each of the sellers a small amount. In such a case herding actually occurs, but the measure will not pick it up. Wermers (1999) developed the Portfolio Change Measure (PCM) to correct for this. This measure, however, provides larger investors greater weight, and the measure itself has other statistical deficiencies.

[14] Choi and Sias (2008) examine herding across industries.

[15] We consider the number of transactions rather than volume, since the number of transactions is more indicative of the decision of whether or not to transact.

[16] Given data extending only four years, we found the analysis of daily returns to be both efficient in terms of the number of the observations and in providing information on the effect of herding on short-term return fluctuations.

Based on the above definitions of herding, we proceed in the next section to determine the correlation between the herding measures and several features of the securities.

## 4. Micro herding behavior: types of investors, firm size, and risk

There are several possible reasons for the differences in herding between amateurs and professionals. Herding by professionals has a higher chance of stemming from considerations of compensation and reputation, while informational motives are stronger for amateurs' herding. Amateurs are usually less informed than professionals, not overconfident, and more inclined to mimic the behavior of others.[17] In a Bayesian framework this implies that professionals place higher weight on their prior beliefs than do amateurs, and are less likely to revise their beliefs upon observing signals emanating from the behavior of other investors.

Information-based herding can also lead to different effects of stock characteristics on herding by all types of investors and to differential effects on professionals versus amateurs. Since more information usually exists about larger firms, one can anticipate lower herding in such firms. Also, if professionals are savvier and more eclectic in their choices due to their superior information, we would expect their behavior to be less sensitive than that of amateurs to common information such as size and systematic risk.[18]

The herding measures for all months and all firms were calculated according to Eq. (1). The average herding measures for all securities for the amateurs and the professionals in our sample are 0.065 and 0.058, respectively. Intuitively, a measure of herding of 0.065 means that about 6.5% of the time, the deviation of the proportion of buyers from its long term average is larger than this deviation's expected value under the null hypothesis of no herding. The herding measure of the amateurs is significantly higher than that of the professionals ($p$-value < 0.01), with 6381 observations for amateurs and 6549 observations for the professionals. The monthly measures of herding were based on 28,259 and 51,554 transactions by amateurs and professionals, respectively.

Herding measures found in other countries using similar methodology refer only to institutional investors, and vary between studies. In the US, we find reported average herding measures of 0.02 in Lakonishok et al. (1992), 0.036 in Wermers (1999), and 0.04 in Brown et al. (2007). In his study of the UK market, Wylie (2005) reports a herding level of 0.026 for his entire UK data-set, but this figure rises to 0.09 when 25 managers or more trade. These figures are lower than those found in the present study; however, Choe et al. (1997) find much higher herding measures in their study of herding in Korea than those found in the US and the UK. They report many measures depending on several criteria, but none falls below 0.16. Similar high herding measures are also reported by Lobao and Serra (2002) in Portugal, and by Voronkova and Bohl (2005) in Poland. An inference can be drawn that herding is lower in the more developed stock markets (US and UK), but additional countries need to be studied to establish a statistically significant conclusion.[19]

The differences in herding tendencies between amateurs and professionals are further explored in the analysis below, in which we control for different features of stocks and investigate how differences in the various characteristics of the securities affect herding behavior. We analyze separately the effect of each factor on herding, and then examine their simultaneous effects. In Subsection 4.1 we present the analysis when stocks are sorted by size, in Subsection 4.2 we examine the herding measures when the securities are sorted by risk (unique and systematic), and in Subsection 4.3 we evaluate the simultaneous effects of all explanatory variables.

**Table 1**
Average market capitalization and the number of firms in each size decile.

| Size decile | Average market capitalization | Number of firms |
|---|---|---|
| 1 | 4207 | 37 |
| 2 | 9007 | 37 |
| 3 | 12,573 | 37 |
| 4 | 16,514 | 37 |
| 5 | 22,360 | 37 |
| 6 | 31,647 | 37 |
| 7 | 43,907 | 37 |
| 8 | 69,250 | 37 |
| 9 | 143,287 | 37 |
| 10 | 4,593,870 | 37 |
| Overall | 494,662 | 370 |

*Note*: The values are in 1000's US dollars. The average size denotes the average capitalization over the four years 1994–1997, where the size for each year is the book value of the firm at the end of the year. During the sample period the exchange rate of the Israeli currency (Shekel, IS) followed a rising trend from an average of 2.99 IS/$ in 1994 to 3.54 IS/$ in 1998.

### 4.1. Herding and the size of the firm

To examine the correlation between herding and firm size, we classify firms into increasing deciles of size and then compare the average monthly herding measures across all stocks and over all their trades performed during the examined period. For size, we employ the book value of total assets of the firm at the end of the year. Summary statistics of the average values of total market capitalization of the firms according to stock-size deciles and the number of firms in each decile are presented in Table 1.

To obtain a rudimentary idea of how herding varies across different size deciles, we make the following calculations. For each year all the firms are ranked according to size decile and the average herding measure for the firms in each decile is calculated.[20] The yearly herding measures of each decile are then averaged over the years. These averages are presented in panel A of Table 2, and are also depicted in Fig. 1. It appears that for almost all size deciles, professionals tend to herd less than amateurs (the difference between average amateurs' and professionals' herding is positive in 9 deciles, and this difference is significant at least at the 10% level in six of them). Fig. 1 does not demonstrate a negative correlation between size and herding as suggested by the information-based herding theory, nor does a regression of the average herding measures on the decile size demonstrate such a correlation.[21]

### 4.2. Herding and securities' risks

In this subsection we examine whether the herding behavior of investors changes with the stock's risk; we explore separately the

[17] In our case however, since the professionals' compensation is not based in the short run on their performance, this motive is weaker than in other countries, such as the US.

[18] In a study of similar investors, but in a different period of time and analyzing different issues, Shapira and Venezia (2001) show that professionals are indeed more eclectic and less correlated with the market than are amateurs.

[19] Chiang and Zheng (2010) examine herding in 18 countries, but they use a considerably different herding metric from the one used in the current study. Their measure captures the cross-section correlation between returns of different firms, whereas the measure we use demonstrates the correlation between transactions of traders.

[20] The year 1994 is an exception, since we did not have the size at the beginning of that year and so we had to use the size as of the end of the year. We calculate the frequency of changes in the size rankings of firms in all years and find that the changes in rankings are quite small, so we do not believe that using the end of 1994 size made any significant difference.

[21] Due to the small number of observations this should be interpreted cautiously; in what follows further tests are provided.

**Table 2**
Average herding measures by increasing deciles of size, $\beta$, and idiosyncratic risk.

| | | | Professionals | | | Amateurs | | |
|---|---|---|---|---|---|---|---|---|
| | | | Mean herding measure | Std. Dev. | Number of observations | Mean herding measure | Std. Dev. | Number of observations |
| Panel A | Size decile | 1 | 0.052** | 0.147 | 303 | 0.077 | 0.156 | 471 |
| | | 2 | 0.064 | 0.161 | 454 | 0.076 | 0.149 | 463 |
| | | 3 | 0.070 | 0.164 | 436 | 0.081 | 0.151 | 519 |
| | | 4 | 0.047*** | 0.163 | 474 | 0.081 | 0.153 | 477 |
| | | 5 | 0.053* | 0.166 | 489 | 0.069 | 0.138 | 441 |
| | | 6 | 0.061* | 0.160 | 765 | 0.074 | 0.153 | 720 |
| | | 7 | 0.060** | 0.159 | 597 | 0.081 | 0.156 | 536 |
| | | 8 | 0.057*** | 0.160 | 747 | 0.086 | 0.147 | 717 |
| | | 9 | 0.053 | 0.147 | 985 | 0.059 | 0.151 | 884 |
| | | 10 | 0.057 | 0.142 | 1299 | 0.038 | 0.141 | 1153 |
| | | Average | 0.057* | 0.157 | 655 | 0.072 | 0.150 | 638 |
| | | Std. Dev. | 0.006 | 0.008 | 302 | 0.014 | 0.006 | 233 |
| Panel B | $\beta$ decile | 1 | 0.028*** | 0.168 | 349 | 0.077 | 0.145 | 412 |
| | | 2 | 0.081 | 0.134 | 392 | 0.090 | 0.149 | 453 |
| | | 3 | 0.051 | 0.157 | 603 | 0.062 | 0.151 | 578 |
| | | 4 | 0.063 | 0.148 | 616 | 0.061 | 0.145 | 587 |
| | | 5 | 0.052 | 0.165 | 635 | 0.062 | 0.144 | 611 |
| | | 6 | 0.062 | 0.152 | 654 | 0.072 | 0.150 | 569 |
| | | 7 | 0.048** | 0.154 | 807 | 0.065 | 0.143 | 752 |
| | | 8 | 0.067 | 0.158 | 732 | 0.069 | 0.158 | 722 |
| | | 9 | 0.050*** | 0.159 | 868 | 0.068 | 0.155 | 853 |
| | | 10 | 0.063 | 0.150 | 893 | 0.064 | 0.153 | 844 |
| | | Average | 0.056* | 0.154 | 655 | 0.069 | 0.149 | 638 |
| | | Std. Dev. | 0.014 | 0.010 | 182 | 0.009 | 0.005 | 151 |
| Panel C | Idiosyncratic risk decile | 1 | 0.057 | 0.140 | 1311 | 0.036 | 0.144 | 1131 |
| | | 2 | 0.057 | 0.160 | 815 | 0.060 | 0.143 | 559 |
| | | 3 | 0.063 | 0.152 | 721 | 0.063 | 0.150 | 633 |
| | | 4 | 0.063* | 0.162 | 649 | 0.077 | 0.156 | 589 |
| | | 5 | 0.064** | 0.163 | 665 | 0.081 | 0.142 | 596 |
| | | 6 | 0.064** | 0.160 | 543 | 0.080 | 0.149 | 540 |
| | | 7 | 0.066 | 0.152 | 555 | 0.064 | 0.150 | 493 |
| | | 8 | 0.044*** | 0.152 | 463 | 0.081 | 0.149 | 563 |
| | | 9 | 0.043*** | 0.165 | 458 | 0.080 | 0.150 | 606 |
| | | 10 | 0.042*** | 0.156 | 369 | 0.077 | 0.160 | 671 |
| | | Average | 0.056* | 0.156 | 655 | 0.070 | 0.149 | 638 |
| | | Std. Dev. | 0.010 | 0.007 | 267 | 0.014 | 0.006 | 180 |

*Note*: The average $\beta$ ranges from 0.55 in the lowest decile to 1.57 in the highest decile; the average idiosyncratic risk ranges from 0.037 in the lowest decile to 0.137 in the highest decile.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

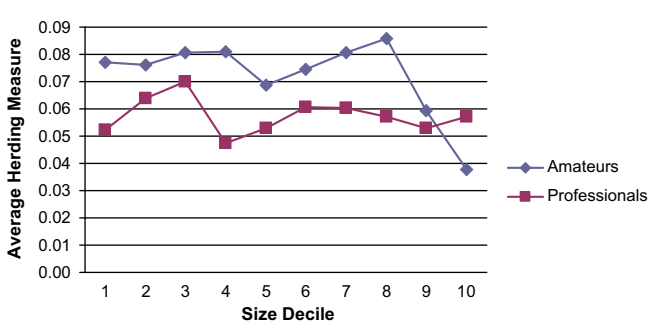


**Fig. 1.** Average herding measures from the period 1994–1997 across deciles of size. Decile size is based on book values as of June 1998. (Decile 1 is lowest.)

effects of the systematic risk, $\beta$, and the idiosyncratic risk.[22] Since the risk measures may evolve with time, we calculate for each stock time-dependent $\beta$'s and idiosyncratic risk measures. Concomitant with the questions of whether and how the risk measures affect herding, the following questions remain: Which period's risk measures affect herding, and based on which period's data should the time-dependent risk measures be constructed? One could use the period just preceding the trading decisions of the investors, the contemporaneous periods, or some average across years, as a case could be made for each of these alternatives. On the one hand, use of the most recent data seems appropriate, since such an approach assumes that investors use the most recent data. However, perhaps investors, especially amateurs, do not frequently follow such data, and they may base their decisions on longer-term views of the firms.[23] To be on the safe side, several formulations are examined; if all formulations yield similar qualitative results, then they could be relied upon, otherwise one should be cautious in their interpretation. As will be shown below, the qualitative results indicate robustness in the choice of formulation.

[22] Falkenstein (1996) shows that mutual funds are averse to stocks with low idiosyncratic volatility; he does not, however, study the effect of total volatility on herding.

[23] The professionals in our sample trade five times more frequently than the amateurs.

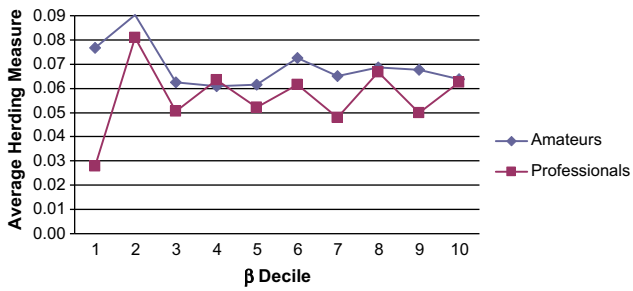


**Fig. 2.** Average herding measures from the period 1994–1997 across deciles of $\beta$. (Decile 1 is lowest.)

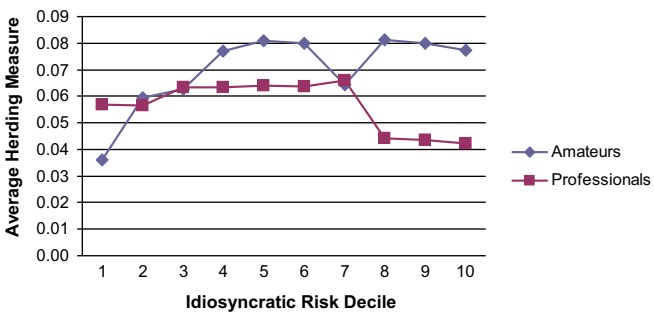


**Fig. 3.** Herding by deciles of idiosyncratic risk. (Decile 1 is lowest.)

We compute the value of the $\beta$'s for the securities in our sample using the TASE-100 index as the measure of market return, using weekly returns over each of the years for which we have data.[24] We then sort our stocks into deciles on the basis of their $\beta$ values (from least risky to most risky) and compute monthly average herding measures for each of these deciles for each year, and then average them over the years.[25] These averages are presented in Table 2, panel B, and are depicted in Fig. 2.[26] The difference between average amateurs' and professionals' herding is positive in 9 deciles, and this difference is significant at least at the 10% level in three of them. No discernible correlation can be seen in Fig. 2 between herding and $\beta$ deciles.

The relationship between herding and idiosyncratic risk is investigated next, using the same techniques used for the analysis of the $\beta$'s, since both risk measures are simultaneously estimated. The stocks are sorted into deciles based on their unique risk, and monthly average herding measures are calculated for each of these deciles. These averages are presented in Table 2, panel C, and plotted in Fig. 3. We observe smaller herding measures for professionals in almost all deciles (the difference between average amateurs' and professionals' herding is positive in 7 deciles and this difference is significant at least at the 10% level in 6 of them). One can observe a positive correlation between herding and idiosyncratic risk deciles for the amateurs. A regression of herding on idiosyncratic risk deciles for this class of investors supports this observation (the coefficient of the regression is 0.0034, $p < 0.05$), but due to the small number of observations this result should be cautiously interpreted.

The above results exhibit some features consistent with the information-based herding theory. The amateurs, who presumably have less information (and may be less confident in their knowledge), have a higher tendency to herd. If, despite the compensation/reputation motivation for professionals (but not for amateurs) to herd, the professionals herd less, then this suggests that informational-based herding is stronger for the amateurs, a feature that could be attributable to the professionals' superior education in finance.

The compensation/reputation motivation to herd of the professionals in the current study is weaker compared to that of US institutional investors, since the former's compensation in the short-run is not benchmarked. Hence, our finding of a herding tendency among the professionals is more indicative of information-based herding than the findings in studies performed in the US. Studies in the US demonstrating herding among institutional investors attribute this behavior to either the information or the compensation/reputation motivation. As in the US, in our study herding behavior can also be attributed to either of these two alternatives, but in the present study it is more likely that herding stems from information-based factors.

In the next subsection we refine the above tests by simultaneously considering the effects of the above factors on herding.

### 4.3. Simultaneous effects of size, $\beta$, and idiosyncratic risk on herding

The partial correlations of the herding measures with stocks' characteristics are informative, yet more definitive conclusions regarding the effects of firm characteristics on herding may be obtained by performing multiple regressions, where all explanatory variables (size, $\beta$, idiosyncratic risk, type of investor) are included. To improve the quality of our estimates, we use in the following analysis all the stock-month herding measures we calculated rather than their herding measures by decile groups.

We performed various regressions under different assumptions about the appropriate period upon which the risk measures and sizes should be evaluated (i.e., the period just preceding the herding measure, its contemporaneous period, or the average across-the-sample period). For each formulation we ran two versions of fixed periodical effects: one with a different effect for each month-year (yielding 47 monthly effects: $4 \times 12-1$), and one with monthly effects, assuming the same monthly effect for each month of the year (yielding 11 monthly effects: 12–1).[27] For each formulation we also ran two models: one with and one without interactions between the explanatory variables and the type of investor (professionals). We chose these diverse formulations in order to allow us to examine the effects of a greater versus a lesser aggregation of data and a larger versus a smaller time proximity between the time periods upon which the exogenous variables are estimated, and the time periods for which the herding measures are taken. All formulations provide very similar qualitative results, thus enhancing the robustness of our results. For the sake of brevity, however, we present the results of just one representative formulation.[28]

[24] TASE-100 index is the index of the largest 100 stocks at the Tel Aviv stock exchange. It is the Israeli equivalent of the S&P 500. The reason for choosing a weekly frequency is to give us a sufficient number of return observations to pin down the $\beta$, while at the same time enabling us to avoid asynchronous timing issues between the prices of the stocks and the observed market return that may arise when higher frequency daily data are used. In some formulations, where shorter periods were available to estimate the risk measures, we used daily data to calculate them.

[25] Since the qualitative differences between the years are small, we present only the averages of the herding measures of the $\beta$'s across the sample period.

[26] Small differences appear between the average herding measures when compiled according to different factors (size, $\beta$, all observations), because in each case there are small variations in the samples. For some securities we have size data but not $\beta$ data, and vice versa. Also, when the sample is divided into deciles and then the averages within each decile are averaged, the weights of the measures shift, compared to the case where an overall average is computed.

[27] One month is subtracted to avoid perfect multicollinearity.

[28] The results of two other formulations are presented in Venezia et al. (2010), and the results of others can be obtained from the authors upon request. For example, under one of the alternative formulations, we use for each month, $t$, the firm's size at the end of the year preceding $t$ as its size measure (for example: the size corresponding to March, 1996, is the size of the firm at the end of 1995). Likewise, for each month t during the period we employ the $\beta$'s and the idiosyncratic risks estimated from the data during the previous year. The risk measures in that formulation are estimated using weekly returns.

**Table 3**
Effects of type of investor, size, and risk on herding. Panel 1 shows the results of a regression of the monthly herding measures, $H_{it}$, on the size, $\beta$, number of trades, and the idiosyncratic volatility of the stock, and a professionals' dummy variable (1 for professionals' transactions, 0 for amateurs' transactions). Panel 2 shows the results of a similar regression including interactions effects of the professionals' dummy with each of the other explanatory variables.

| Explanatory variable | Independent variable | Independent variable | Interaction effect of the explanatory variable with the professionals' dummy |
|---|---|---|---|
| | Panel 1 | | Panel 2 |
| Ln(size) | −0.0048*** | −0.0070*** | 0.0044* |
| | (0.0012) | (0.0018) | (0.0024) |
| Professionals' dummy | −0.0076** | | |
| | (0.0037) | | |
| $\beta$ | −0.0127*** | −0.0199*** | 0.0161* |
| | (0.0047) | (0.0064) | (0.0090) |
| Idiosyncratic risk | 0.1936 | 0.1964 | −0.0511 |
| | (0.1859) | (0.2616) | (0.3461) |
| Number of trades | 0.0002** | 0.0001 | 0.0004* |
| | (0.0001) | (0.0002) | (0.0002) |
| Intercept | 0.1721*** | 0.2068*** | −0.0782** |
| | (0.0203) | (0.0275) | (0.0351) |
| Number of observations | 10,135 | 10,135 | |
| $R^2$ | 0.0131 | 0.0140 | |

*Note*: The dependent variable, $H_{it}$, is the herding measure of a security *i*, during month *t*. The number of observations is approximately the number of months during the sample period times the number of securities. The number of trades denotes the number of trades made of security *i* during time period *t*. Since some stocks did not trade at time *t* the number of observations is lower than the multiplication of the number of securities by the number of months. Several months' effects turned out significant (out of 47), but since these months were sporadic we chose not to present them here to save space.
Robust *T*-statistics computed using standard errors clustered by month are given below the coefficients.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

In the representative formulation, the average size of the firm during the entire sample period is used as the measure of the size of the firm for all periods. The risk measures, however, are calculated for each period t from the returns observed in the preceding 6 months. In this formulation we calculate the risk measures from daily data, so as to have enough observations for estimating the $\beta$'s and the idiosyncratic risk. This required starting the analysis from mid-1994.[29]

The regressions performed for this formulation, therefore, are of the form:

$$\begin{aligned} H_{it} = {} & \gamma_0 + \gamma_1(\text{Size})_i + \gamma_2(\text{Professionals' Dummy})_{i,t} + \gamma_3(\beta)_{i,T(t)} \\ & + \gamma_4(\text{Idiosyncratic Risk})_{i,T(t)} + \gamma_5(\text{Number of Trades})_{i,t} \\ & + \gamma_6(\text{Professionals'Dummy})_{i,t} \times (\beta)_{i,T(t)} \\ & + \gamma_7(\text{Professionals'Dummy})_{i,t} \times (\text{Idiosyncratic Risk})_{i,T(t)} \\ & + FE_t + \varepsilon_{it} \end{aligned} \tag{3}$$

In the above regression the index *i* denotes the firm and *t* denotes the month for which the herding measure, $H_{it}$, is obtained. The professionals' dummy receives the value one if the herding measure is calculated for trades by professionals, and zero otherwise. $T(t)$ denotes the six-month period preceding period *t*, the $FE_t$'s denote fixed monthly effects, and the $\varepsilon_{it}$'s denote white noise.

The results of the regression are presented in Table 3. In panel 1 we present the results of the regressions for the model without interactions, and in panel 2 those for the model with interactions. One observes form Table 3, panel 1, that the coefficient of the professionals' dummy is significantly negative, −0.0076, $p < 0.05$, indicating that the professionals tend to herd less than the amateurs into specific stocks. The same conclusion is also reached from the observation in panel 2 that the coefficient of the interaction of the intercept with the professionals' dummy is significantly negative, −0.0782, $p < 0.05$.

The coefficients for size are significantly negative (−0.0048 in panel 1, and −0.0070 in panel 2, both with $p < 0.01$). This result supports the negative effect of size on herding, and also is consistent with the information-driven herding hypothesis, as with GTW's evidence that mutual funds tend to herd into small, but not large, stocks.

The coefficients of $\beta$ turn out significantly negative (−0.0127, $p < 0.01$ in panel 1, and −0.0199, $p < 0.01$ in panel 2), indicating that the lower the systematic risk of the firm, the more likely investors herd into it, but the coefficients of idiosyncratic risk turn out to be insignificant. While this cannot be explained with conventional herding theories, it is in agreement with Falkenstein's (1996) theory that trend-following or herding behavior among investors can appear for stocks with specific characteristics (in our case, low $\beta$'s), not only because of information or motivation/reputation reasons, but because as stocks acquire specific characteristics, investors are more likely to hold them.[30] This may have nothing to do with under-weighing private information or responding disproportionately to short run incentives. If, however, such trend-following represents a fad, one would expect that amateurs would be more prone to it, and that professionals' herding would be less sensitive to these characteristics. In the analysis to follow, the question of the relative sensitivity of professionals versus amateurs to firms' characteristics will be explored.

The positive and significant coefficient of the number of trades variable may suggest that the factors leading to greater intensity of trading also lead to greater alignment of the traders' positions. This is consistent with information-induced herding if, as shown by Froot et al. (1992), investors who can develop private information, thereby increasing trading, have an incentive to research the same stocks as other informed traders. This theory is also in line with the observed positive coefficient of the interaction term of the number of trades variable (see panel 2 of Table 3), which indicates a higher effect of the frequency of trading on professionals' herding, since the professionals are better equipped to research the same stocks that amateur traders study.

The coefficients of the interaction terms in panel 2 of Table 3 indicate that size and $\beta$ have weaker effects on the professionals than on the amateurs. Note that the coefficients of size and $\beta$ are negative, whereas those of their interaction terms are positive but smaller in absolute values. The coefficient of $\beta$ is negative, −0.0199, and that of its interaction term is positive, 0.0161, which in crude terms means that the net effect of $\beta$ on professionals is −0.0038 (the difference between the coefficients) versus −0.0199 on amateurs. The coefficient of size, and that of the interaction of size, with the professionals' dummy are −0.0070, and 0.0044, respectively, again demonstrating a weaker size effect for the professionals (−0.0026 vs. −0.0070). The weaker effects of these variables are consistent with information-based herding, as well as with the hypothesis that lesser informed and inferiorly-trained investors are more prone to be influenced by variables that in an efficient market would have no effect on behavior.

Having analyzed features that may cause herding into specific stocks, we next investigate macro herding.

[29] In the versions without interactions, these terms are removed from the equation. The equations are also run once with 47 fixed time effects and once with 11 fixed time effects.

[30] Investors may regard dividend payments as such a characteristic and indeed, Rubin and Smith (2009), show that institutions herd on dividend signals.

## 5. Macro herding: herding behavior and the stock market

In this section we explore the macro aspects of investors' herding tendencies. We examine the factors affecting the total tendency of investors to herd across all stocks rather than into one stock, and whether this propensity differs between amateurs and professionals. We also explore if the behaviors of these groups interact differently with market returns, market volume, and market volatility. In particular, we examine which of these groups' herding has a greater effect on market fluctuations.

Using daily data we first explore the correlation between the current (macro) herding measures and the market. To this end we regress the daily herding measures on market volume, lagged market volume, market returns, lagged market returns, and lags of the dependent variable separately for amateurs and professionals.[31] We chose the minimal number of lags that would yield no serial correlation of the errors, and seven lags turned out sufficient to achieve this property.[32] The regressions are therefore of the form:

$$(\text{Herding})_t = \alpha + \sum_{\tau=0}^{\tau=7} \gamma_\tau (\text{Ln}(\text{Market volume}))_{t-\tau} + \sum_{\tau=0}^{\tau=7} \eta_\tau (\text{Market returns})_{t-\tau} + \sum_{\tau=1}^{\tau=7} \varsigma_\tau (\text{Herding})_{t-\tau} + \varepsilon_t \quad (4)$$

The results of this regression are presented in Table 4 (only variables whose coefficients were significant are presented in the table). Herding behavior of both individuals and professionals appears to be persistent as lags of herding measures of the two groups affect current herding significantly and positively.[33] For professionals the coefficients of herding with lags of two, six, and seven days are significant (with coefficients 0.076, $p < 0.05$, 0.065, $p < 0.05$, and 0.079, $p < 0.05$, respectively), and for amateurs the coefficient of herding with a day's lag turns out significantly different from zero (0.070, $p < 0.05$).

Amateurs' herding is negatively correlated with lagged market returns of one and three days (with coefficients −0.432, $p < 0.05$ and −0.458, $p < 0.05$, respectively), while professionals' herding is negatively correlated with market returns with a two-day lag (with a coefficient of −0.401, $p < 0.05$). Lagged market returns thus negatively affect herding of both groups. This table shows a significant positive relationship between the herding measures of professionals and contemporaneous market volume (with coefficient 0.016, $p < 0.01$). For amateurs, however, we find a positive correlation between herding and three-day lagged volume (with coefficient 0.025), but a negative correlation between herding and a four-day lagged volume.

Herding seems to be correlated (albeit weakly) with returns, hence one may ask whether the correlation also runs the other way; that is, does the trading behavior of investors affect returns or does it have a predictive ability, and if so, which of the groups – amateurs or professionals – would be more influential.[34] To answer these questions we ran regressions of market returns on contemporaneous and lagged herding measures, on lagged market returns, and on contemporaneous and lagged market volume.

**Table 4**
The effects of market variables on herding.

| | $\text{Herding}_t$ | |
|---|---|---|
| | Professionals | Amateurs |
| Intercept | −0.228** | −0.007 |
| | (−2.264) | (−0.068) |
| $(\text{Herding})_{t-1}$ | | 0.070** |
| | | (2.176) |
| $(\text{Herding})_{t-2}$ | 0.076** | |
| | (2.376) | |
| $(\text{Herding})_{t-6}$ | 0.065** | |
| | (2.017) | |
| $(\text{Herding})_{t-7}$ | 0.079** | |
| | (2.472) | |
| $\text{Ln}(\text{market volume})_t$ | 0.016*** | |
| | (2.785) | |
| $\text{Ln}(\text{market volume})_{t-3}$ | | 0.025*** |
| | | (2.696) |
| $\text{Ln}(\text{market volume})_{t-4}$ | | −0.022** |
| | | (−2.376) |
| $(\text{Market return})_{t-1}$ | | −0.432** |
| | | (−2.212) |
| $(\text{Market return})_{t-2}$ | −0.401** | |
| | (−2.119) | |
| $(\text{Market return})_{t-3}$ | | −0.458** |
| | | (−2.35) |
| Number of observations | 966 | 969 |
| $R^2$ | 0.035 | 0.023 |
| Durbin Watson | 1.914 | 2.001 |

*Note*: This table shows the results of the regression $(\text{Herding})_t = \alpha + \sum_{\tau=0}^{\tau=7}\gamma_\tau(\text{Ln}(\text{Market Volume}))_{t-\tau} + \sum_{\tau=0}^{\tau=7}\eta_\tau(\text{Market Returns})_{t-\tau} + \sum_{\tau=1}^{\tau=7}\varsigma_\tau(\text{Herding})_{t-\tau} + \varepsilon_t$. Only variables whose coefficients turned out significant are presented in the table. The left- (right-) hand column presents the results of the regression with professionals' (amateurs') herding data.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

**Table 5**
The effects of herding on market returns.

| | $\text{Market returns}_t$ | | |
|---|---|---|---|
| | Professionals | Amateurs | Professionals and amateurs |
| Intercept | 0.022 | 0.035** | 0.001** |
| | (1.238) | (2.087) | (2.168) |
| $(\text{Market return})_{t-3}$ | −0.100*** | −0.103*** | −0.099*** |
| | (−3.122) | (−3.223) | (−3.099) |
| $(\text{Market return})_{t-7}$ | −0.084*** | −0.083*** | −0.085*** |
| | (−2.631) | (−2.603) | (−2.668) |
| $(\text{Professionals herding})_t$ | −0.009* | | −0.009* |
| | (−1.627) | | (−1.714) |
| $(\text{Amateurs herding})_t$ | | −0.009* | |
| | | (−1.707) | |
| $(\text{Amateurs herding})_{t-4}$ | | −0.011** | −0.012** |
| | | (−2.082) | (−2.229) |
| $\text{Ln}(\text{market volume})_t$ | 0.003* | | |
| | (1.798) | | |
| $\text{Ln}(\text{market volume})_{t-3}$ | −0.004*** | −0.002** | |
| | (−2.672) | (−2.011) | |
| Number of observations | 965 | 965 | 965 |
| $R^2$ | 0.026 | 0.029 | 0.024 |
| Durbin Watson | 1.909 | 1.900 | 1.895 |

*Note*: This table shows the results of regressions of market returns on Ln(market volume), herding measures, and lags of one period of these variables and of market returns. The left-hand, middle, and right-hand columns present the results of the regression with professionals only, amateurs only, and professionals' and amateurs' herding data, respectively.
*T*-statistics are given below the coefficients.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

[31] We also run regressions of the Seemingly Unrelated Regressions (SUR) type and obtained comparable results. We prefer to present the results in the current form to highlight the differences between the groups if any.

[32] The Breusch–Godfrey serial correlation LM test was used to determine the absence of correlation.

[33] This result has also been obtained when using an autoregressive AR(1) model for the errors. To the extent that herding affects returns, persistence of herding can cause persistence of returns; see Bollen and Busse (2005).

[34] Kaniel et al. (2007a,b) claim that subsequent to higher trading by individuals in the US, stock returns tend to increase.

**Table 6**
The effect of buy imbalances on market returns.

| | Market returns$_t$ | | |
|---|---|---|---|
| | Professionals | Amateurs | Professionals and amateurs |
| Intercept | 0.018 | 0.040** | 0.037** |
| | (1.056) | (2.510) | (2.499) |
| (Market returns)$_{t-1}$ | | | −0.061** |
| | | | (−2.106) |
| (Market returns)$_{t-3}$ | −0.128*** | −0.144*** | −0.142*** |
| | (−4.352) | (−4.764) | (−4.907) |
| (Market returns)$_{t-6}$ | −0.069** | −0.064** | −0.070** |
| | (−2.356) | (−2.126) | (−2.438) |
| (Market returns)$_{t-7}$ | −0.079*** | | |
| | (−2.705) | | |
| (Professionals buy imbalance)$_t$ | 0.026*** | | 0.023*** |
| | (13.454) | | (11.440) |
| (Professionals buy imbalance)$_{t-7}$ | | | −0.004** |
| | | | (−2.237) |
| (Amateurs buy imbalance)$_t$ | | 0.022*** | 0.017*** |
| | | (11.333) | (8.539) |
| (Amateurs buy imbalance)$_{t-2}$ | | | −0.004** |
| | | | (−1.981) |
| (Amateurs buy imbalance)$_{t-7}$ | | −0.007*** | |
| | | (−3.537) | |
| Ln(market volume)$_t$ | 0.002* | | |
| | (1.752) | | |
| Ln(market volume)$_{t-3}$ | | −0.002** | |
| | | (−2.385) | |
| Ln(market volume)$_{t-5}$ | −0.003** | | −0.002** |
| | (−2.478) | | (−2.296) |
| Number of observations | 965 | 966 | 966 |
| $R^2$ | 0.182 | 0.136 | 0.235 |
| Durbin Watson | 2.054 | 2.006 | 1.996 |

*Note*: This table shows the results of regressions of market returns on Ln(market volume), buy imbalances, and lags of one period of these variables and of market returns. The left-hand, middle, and right-hand columns present the results of the regression with professionals only, amateurs only, and professionals' and amateurs' herding data, respectively.
*T*-statistics are given below the coefficient.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

**Table 7**
The effects of herding and volume on absolute market returns.

| | Absolute market returns$_t$ | | |
|---|---|---|---|
| | Professionals | Amateurs | Professionals and amateurs |
| Intercept | −0.041*** | −0.038*** | −0.035*** |
| | (−4.305) | (−4.658) | (−4.341) |
| (Absolute market return)$_{t-1}$ | 0.317*** | 0.579*** | 0.554*** |
| | (2.787) | (13.848) | (13.058) |
| (Absolute market return)$_{t-2}$ | 0.194** | | |
| | (2.026) | | |
| (Absolute market return)$_{t-7}$ | 0.057** | 0.076*** | 0.063** |
| | (1.991) | (2.956) | (2.442) |
| (Professionals herding)$_t$ | 0.015*** | | 0.013*** |
| | (4.546) | | (4.207) |
| (Professionals herding)$_{t-7}$ | 0.009*** | | 0.008*** |
| | (2.696) | | (2.678) |
| (Amateurs herding)$_t$ | | 0.009*** | 0.008*** |
| | | (2.991) | (2.769) |
| Ln(market volume)$_t$ | 0.003*** | 0.002*** | 0.002*** |
| | (4.522) | (4.96) | (4.533) |
| AR(1) | −0.218* | −0.465*** | −0.453*** |
| | (−1.901) | (−9.57) | (−9.157) |
| AR(2) | −0.180*** | −0.183*** | −0.172*** |
| | (−3.342) | (−4.235) | (−3.96) |
| Number of observations | 963 | 963 | 963 |
| $R^2$ | 0.166 | 0.145 | 0.17 |
| Durbin Watson | 2.003 | 2.007 | 2.003 |

*Note*: This table shows the results of regressions of absolute market returns on Ln(market volume), on herding measure, on and lags of one period of these variables and of absolute market returns. The left-hand, middle, and right-hand columns present the results of the regression with professionals only, amateurs only, and professionals' and amateurs' herding data, respectively. Since some auto-correlation was detected even with seven lags we added auto-correlation terms, AR(1), . . . , AR(7).
*T*-statistics are given below the coefficients.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

We present in Table 5 the results of these regressions. In the left-hand side, middle, and right-hand side columns of this table we present the results of regressions of herding by professionals only, amateurs only, and by both professionals and amateurs serving as explanatory variables, respectively. These results show a negative correlation between contemporaneous herding and market returns. For amateurs the relevant coefficient in the middle column is −0.009, $p < 0.1$), and for professionals the coefficients are −0.009 ($p < 0.1$) in both the left-hand side and the right-hand side columns. We also find little auto-correlation in returns and some effect of volume (in the left-hand and middle columns of Table 5) on returns.[35]

While tests of Granger causality are rarely conclusive, they often provide some insights about predictability. We therefore ran pair-wise Granger's causality tests between returns and amateurs' herding. These tests reject the hypothesis that market returns do not Granger-cause amateurs' herding (F statistic 3.91, $p < 0.05$), indicating that market returns can actually lead to (or predict) amateurs' herding.

Part of the reason for the low correlation between returns and herding may be due to high intensity of either buying or of selling. If high buying intensity is as frequent as high selling intensity, then their effects on returns can cancel out each other when aggregated into a measure of herding. This suggests that studying the effects of herding (in the general sense of concentrated trading) on market returns could be refined by partitioning the herding measures into their buy and sell components. We thus proceed to examine the correlations between market returns and buy imbalances.[36] For this purpose we estimate regressions similar to those used to explain returns, except that we replace the herding measures with buy imbalances. The results of these regressions are presented in Table 6, in the same format as that of Table 5. In these regressions the dependent variable is market returns and the explanatory variables are investors' buy imbalances, market volume, and lagged dependent and independent variables. We note from this table that market returns depend on contemporaneous amateurs' and professionals' buy imbalances (with coefficients 0.026, $p < 0.01$ and 0.023, $p < 0.01$ in the left-hand side and right-hand side columns, respectively, for professionals and 0.022, $p < 0.01$, and 0.017, $p < 0.01$, for amateurs in the middle and left-hand side columns, respectively).[37] Buy imbalances effects on market returns appear to be significant and similar for amateurs and professionals. Granger causality tests suggest that buy imbalances may predict market returns, and vice versa.[38]

[35] Since there is no discernible pattern to the auto-correlations we found in the returns, they do not seem to pose a serious threat to market efficiency.

[36] Buy imbalances are defined as: (Number of buys–Number of sells)/(Number of buys + Number of sells). These measures are not exactly equivalent to herding, but we chose them as they were used in other research on the effect of groups of investors on market returns (see, e.g., Kaniel et al., 2007).

[37] Some lagged variables turned out statistically significant, but none were economically meaningful.

[38] Granger causality tests show that one cannot reject neither the hypothesis that investors' buy imbalances do not predict market returns (*F*-statistic = 4.07, $p < 0.05$, for professionals, *F*-statistic = 2.92, $p < 0.1$ for the amateurs) nor the hypothesis that market returns cannot predict amateurs' buy imbalances.

**Table 8**
The effects of herding on market returns and the volatility of market returns using GARCH.

| | Market returns$_t$ | | |
|---|---|---|---|
| | Professionals | Amateurs | Professionals and amateurs |
| Intercept | 0.014 | 0.013 | 0.040*** |
| | (1.04) | (0.924) | (3.487) |
| (Market return)$_{t-1}$ | 0.093*** | 0.083** | 0.101*** |
| | (2.645) | (2.438) | (2.699) |
| (Market return)$_{t-7}$ | −0.094*** | −0.089*** | −0.084** |
| | (−2.893) | (−2.853) | (−2.593) |
| (Amateurs herding)$_t$ | | −0.007* | −0.008** |
| | | (−1.828) | (−2.022) |
| Ln(market volume)$_t$ | 0.003*** | 0.003*** | |
| | (2.916) | (3.360) | |
| Ln(market volume)$_{t-7}$ | −0.004*** | −0.004*** | −0.002*** |
| | (−4.085) | (−4.318) | (−3.424) |
| *Variance equation* | | | |
| Constant | 0.000*** | 0.000** | 0.000* |
| | (2.818) | (−2.466) | (1.919) |
| Residuals$^2_{t-1}$ ($\alpha_1$) | 0.081** | 0.062** | 0.136*** |
| | (2.233) | (2.119) | (6.846) |
| GARCH$_{t-1}$ ($\beta_1$) | 0.770*** | 0.752*** | 0.809*** |
| | (30.351) | (24.521) | (40.562) |
| (Market returns)$_{t-1}$ | −0.003*** | −0.002*** | −0.003*** |
| | (−4.778) | (−5.875) | (−5.843) |
| (Market returns)$_{t-2}$ | 0.002*** | | 0.002*** |
| | (2.959) | | (4.531) |
| (Professionals herding)$_t$ | | | 0.000*** |
| | | | (3.709) |
| (Professionals herding)$_{t-7}$ | 0.000*** | | |
| | (3.008) | | |
| (Amateurs herding)$_{t-6}$ | | | 0.000* |
| | | | (1.764) |
| Ln(market volume)$_t$ | | 0.000*** | |
| | | (5.010) | |
| Ln(market volume)$_{t-7}$ | | 0.000*** | |
| | | (−3.620) | |
| $R^2$ | 0.008 | 0.011 | 0.009 |
| Durbin Watson | 2.114 | 2.101 | 2.130 |
| *F*-Statistic | 0.740 | 0.895 | 0.822 |

*Note*: This table shows the results of regressions of market returns on Ln(market volume), herding measures, and lags of one period of these variables and of market returns using GARCH. The left (right) hand column presents the results of the regression with professionals (amateurs) only. It is assumed that the errors are correlated as follows: $\varepsilon_t = v_t\sqrt{h_t}$.
where $\sigma_v^2 = 1$ and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \sum_i \lambda_i$ Explanatory variable$_i$.
*Z*-statistics are given below the coefficients.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Since high herding can emanate either from high buy intensity or high sell intensity, it is possible that herding will affect volatility. Two parallel types of analysis were used to explore this issue. First, we regressed absolute market returns on herding measures and on other market explanatory variables. Second, we ran a GARCH (1, 1) model to examine the relationship between the variability of returns and herding in yet a different methodology, to add robustness to our analysis. The outcomes of the regression of absolute returns on herding and other explanatory variables are presented in Table 7. In the right-hand side columns of this table, we see coefficients of 0.013 and 0.008 for professionals' and amateurs' contemporaneous herding, respectively, both with $p < 0.01$. These indicate that herding by both amateurs and professionals is positively correlated with contemporaneous absolute returns, implying that both groups' behavior is positively related to volatility. The many statistically significant lagged absolute market returns that appear in Table 7 point to a substantial auto-correlation in absolute market returns, as in the case of market returns.

The results of the GARCH analysis are presented in Table 8. The effects of herding on returns discerned from this table are similar to those found in the OLS analysis. Amateurs' herding appears to negatively affect returns (a coefficient of −0.007, $p < 0.1$). The coefficients $\alpha_1$ and $\beta_1$ of the *Variance Equation* part of this table are significantly positive, as are the coefficients of contemporaneous amateurs' and professionals' herding, showing that the variability of returns increases with increased contemporaneous herding. The results of Granger causality tests show that contemporaneous herding, as well as some lagged herding, "cause" volatility but not vice versa. We find Granger causality for amateurs' lagged herding with lags of one day ($p < 0.05$) and four, five, six, and seven days ($p < 0.01$). Granger causality was found for professionals' lagged herding with lags of one day ($p < 0.05$). These findings lend further support for the claim that herding may affect market stability.

## 6. Conclusions

We investigate the factors affecting herding behavior by professionals and amateurs. Both amateurs and professionals tend to herd but the former tend to herd to a greater extent than the latter. Since it is unlikely that amateurs' herding is either reputation- or compensation-driven, the results suggest that their higher herding tendencies are either driven by information search or by a higher tendency to behave irrationally. This latter proclivity may, in turn, result from the amateurs' lesser training in economics and finance. The professionals in our sample do herd, although their compensation is not directly benchmarked to any specific market index. This phenomenon lends greater support to the information-search-motive theory for their herding behavior, than does the relative support given to this theory in studies in other countries, where compensation is benchmarked. In those studies it was more difficult to separate the effect of the information motive from that of the compensation motive, since both of these two effects may have influenced the professionals.

In studying the factors affecting herding behavior of investors in our sample, we find that the greater the size of the firm the lower the herding into the firm's stock. This phenomenon can also be explained by information-based herding, since more information is usually available about larger firms. The effects of firms' risk on herding behavior are also consistent with information-based herding, since professionals are less sensitive to the firms' risk characteristics.

We show that herding is a persistent phenomenon. The data reveal a correlation, albeit weak, between amateurs' herding and (stock market) returns, as well as a significant correlation between returns and buy imbalances of both amateurs and professionals. We also find that herding is positively and significantly correlated with stock market volatility, and that herding, especially amateurs', causes market volatility in the Granger causality sense. The higher herding tendency of amateurs, along with the higher correlation between their herding and market volatility, suggest that this group poses a greater threat to market stability than the professional group. To the extent that herding is lack-of-information driven, this implies that improving transparency, education, and information about firms will help to mitigate market instability.

## Acknowledgements

We acknowledge the financial support of The Sanger Family Chair for Banking and Risk Management, The Galanter Fund, The Berkley Center at the Stern School, The Mordecai Zagagi Fund, The Whitcomb Center for Research in Financial Services, and The School of Accounting, The Hebrew University. The helpful comments of Russ Wermers, John M. Griffin, a referee, participants at the European Financial Management (EFM), Symposium on Behavioral Finance, 2006, and faculty seminar participants at

Rutgers University, Bocconi University, and The University of Toronto are gratefully acknowledged.

## Appendix A. Normal approximation of $E[\text{abs}(p_t - p)]$

Let $x$ denote the number of successes in $n$ trials with a probability $p$ of success in each trial, and let $p_t = x/n$. Denote the expectation of the absolute deviations of $x$ from its mean, $\mu$, by $M$. By definition, this expected value is given by:

$$M = E[\text{abs}(x-\mu)] = \int_{-\infty}^{\mu} (\mu - x) f(x) dx + \int_{\mu}^{\infty} (x-\mu) f(x) dx$$
$$\equiv M_1 + M_2$$

where $M_1$ and $M_2$ are the above two integrals, and $f(\cdot)$ is the density function of the normal distribution. From the symmetry of the normal distribution it follows that $M_1 = M_2$, and from the definition of $f(\cdot)$ we obtain that:

$$M_1 = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\mu} (\mu - x) \times e^{-0.5(x-\mu)^2} dx = \frac{\sigma}{\sqrt{2\pi}} \tag{A1}$$

The second equality in (A1) follows from the previous one by some rearranging of terms and from the fact that $\sigma$ is the standard deviation of $x$. Since $M = 2M_1$ it follows from (A1) that

$$M = \sigma\sqrt{2/\pi} \tag{A2}$$

In our model we have a binomial random variable denoting the number of buys (a buy is a "success") with $n$ tries (transactions), and a probability $p$ of success in each try. For such a binomial model the standard deviation of $x$ is given by:

$$\sigma = \sqrt{np(1-p)} \tag{A3}$$

Substituting (A3) into (A2), we obtain that $M = \sqrt{np(1-p)} \times \sqrt{2/\pi} = \sqrt{2np(1-p)/\pi}$.

It hence follows that: $E[\text{abs}(p_t - p)] = M/n = \sqrt{2p(1-p)/(\pi n)}$.

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