The Journal of Behavioral Finance
2004, Vol. 5, No. 4, 222–230

Herding in the Italian Stock Market: A Case of Behavioral Finance

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This article studies the herding effect in the capital markets. Using data from the Italian Stock Exchange, the authors test for the presence of herding as described in Christie and Huang [1995], Chang, Cheng, and Khorana [2000], and Hwang and Salmon [2001]. The tests support Christie and Huang's conclusions that herding is present in extreme market conditions.

One evening we decided to go to Restaurant A, which had been recommended by a very reliable guidebook. When we arrived, we noticed that Restaurant B nearby was very busy, while Restaurant A had only a few customers. So we changed our minds and ate at Restaurant B.

In short, we ignored the available information and chose imitation instead, following the behavior of the majority without knowing what determined their choices. But if we hypothesize that other customers behaved the same way, and that the first person who entered Restaurant B had incorrect information, the consequences are obvious – a disappointing evening for everyone. The fear of making a mistake probably influenced our decision to go with the flow, with the conviction that a shared error (as compared to an individual error) saves face.

Psychological research has shown that differences of opinion create anxiety, so individuals naturally try to reach a consensus. But the search for consensus can lead to reconsidering the validity of our own opinions, and to the sharing of others' opinions. This was exactly the behavior we demonstrated when we ultimately chose Restaurant B.

To further illustrate, let us modify the example. We decide to go to Restaurant A, which is also the most crowded. The information gathered (which we believe to be correct) causes us to decide on a solution that is also shared by the majority. In this case, the choice is individual, not "gregarious," and if the other customers followed the same rational criteria, it is certain that Restaurant A is better than Restaurant B.

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Similar behaviors can be found in finance as well. Consider an example inspired by the tenets of the capital asset pricing model and by efficient market theory. An investment manager decides on the structure of his portfolio by following three axioms:

- The information he has is complete, and the provisions for return and risk are unbiased.
- His objective is to maximize return in a mean-variance context.
- It is not possible to systematically attain a portfolio yield that is greater than market yield.

Another way to proceed is inspired by behavioral finance. The theoretical axioms of this approach are:

- Not all investors are perfectly rational; both *information traders* and *noise traders* are present in the market.
- The efficient portfolio is not the market portfolio. For example, noise traders' preferences for the most speculative stocks (such as Internet stocks) causes those prices to rise. When this happens, the efficient portfolio will include a greater percentage of safe stocks than the market portfolio.
- Investor preferences are not closely related to the mean-variance model, and prices reflect psychological choices.
- The market is not efficient because prices are not rational. Note this does not mean the market can be beaten. In fact, there is a distinct difference between market efficiency in a *beat-the-market* sense and market efficiency in a *rational pricing* sense.

In summary, according to behavioral finance, those who invest behave like the judges of the beauty contest described by Keynes: they do not choose the most beautiful candidate, they choose the one they think will please the majority.

Herding And Informational Cascades

The condition of herding is in disagreement with the efficient market hypothesis (EMH). The EMH states that informed investors estimate expected prices at a future point in time, and then determine the expected return based on an equilibrium model (such as the CAPM). Investors, therefore, can calculate the equilibrium price and compare it with the current quoted price. In other words, if today's price is not consistent with the expected return, the price will change, absorbing the available information in a complete and precise manner.

According to the EMH, we buy if the stock is undervalued (if the current price is inferior to the expected return at equilibrium), and we sell (even short) if the stock is overvalued (if the current price is greater than the expected return at equilibrium).

Investors who *go with the flow* present obvious differences. They reject the process described above and base their own choices on those of the masses – they buy stocks that others are buying and sell stocks that others are selling. Informed and rational investors do not follow the crowd (in which case, of course, the market would be efficient). Therefore, herding indicates an inefficient market situation, one characterized by things like speculative bubbles. In many ways, herding investors behave like prehistoric man, who, with an inadequate knowledge of the environment, grouped together in order to feel more secure. These particular investors seem to feel it is wise to go with the flow, something also noted by Olsen [2000]. The difference in investor mentality is obvious, and its roots originate in "modern finance."

Related Research

One of the methods of verifying herding is suggested by Christie and Huang [1995], who based their studies on the following hypotheses:

- The market alternates between normal and extreme phases (accentuated price increases and decreases). This distinction is relevant because investors modify their behavior depending on the market phase. Herding, in particular, characterizes periods of market extremes. In normal conditions, investors react as described by modern finance theory: they are rational and make decisions based on available information. Extreme conditions, however, tend to generate extreme emotions, and investors seem to find reassurance in following the masses.
- Prices and returns are determined in a context of perfect efficiency from the CAPM, as stated by modern portfolio theory (the existence of a linear relationship between stock returns and their coefficients of systematic risk).
- In cross-sectional analysis, if the number of stocks is large enough, it follows that R_i is explained through beta only from R_m. In this assumption, there exists a relationship between dispersion (the cross-sectional standard deviation, or CSSD) of the various R_i and the absolute value of R_m (AR_m, where R_m is the average of n returns of the cross-sectional portfolio). In particular, in the presence of wide variations of R_m, the CSSD dispersion increases, "because individual assets differ in their sensitivity to the market return" (Christie and Huang [1995]). When investors follow the crowd during extreme market conditions, the value of CSSD increases at decreasing rates; in the case of severe herding, it can also fall.

Christie and Huang's [1995] test was carried out in two phases:

1. The authors estimated the standard cross-sectional deviation of single stock returns with respect to portfolio returns (CSSD). If the dispersion of equity returns is low, it may be a sign of herding. But the value of CSSD can also be low because the fundamentals have changed. In this hypothesis, the concentrated choices of investors would be the consequence of behavior in line with EMH rules, and we would have spurious herding, not intentional herding (the difference is discussed in more detail in the next section).
2. The CSSD of returns was regressed with respect to the extreme and normal market phases. The authors used a dummy technique to identify the extreme market phases, with $D^U = 1$ if the market return on day *t* lies in the extreme upper tail of the distribution of market returns (and zero otherwise), and $D^L = 1$ if the market return on day *t* lies in the extreme lower tail of the distribution of market returns (and zero otherwise). If the estimated coefficients are negative and significant, we have intentional herding.

$$CSSD = \alpha + \beta^L D^L{}_t + \beta^U D^U{}_t + e_t \quad (1)$$

Chang, Cheng, and Khorana [2000] use the same method with the cross-sectional absolute deviation (CSAD).

$$CSAD = \alpha + \beta^L D^L{}_t + \beta^U D^U{}_t + e_t \quad (2)$$

Chang, Cheng, and Khorana [2000] also thoroughly analyzed the hypothesis that the relationship of dispersion to market returns is non-linear. In the absence of herding, the relationship is linear and increasing: the dispersion increases concurrently with the increasing returns of the market. In the presence of herding, the relationship can be increasing, but at a decreasing rate (the dispersion of returns must decrease if R_m increases). The authors hypothesize that the relationship between CSAD and market returns is also asymmetric, so they use two different models:

Bull Market

$$CSAD^{up}_t = \alpha + \gamma^{up}{}_1 |R_{mt}{}^{up}| + \gamma_2{}^{up}(R_{mt}{}^{up})^2 + e_t \qquad (3)$$

Bear Market

$$CSAD^{down}_t = \alpha + \gamma^{down}{}_1 |R_{mt}{}^{down}| + \gamma_2{}^{down} (R_{mt}{}^{down})^2 + e_t \qquad (4)$$

Intentional Herding and Spurious Herding

Hwang and Salmon [2001] propose a different approach. They disagree that herding characterizes periods of extreme market conditions. They believe it can also be observed under normal market conditions. However, to further the discussion, we must make a clearer distinction between intentional herding and spurious herding.

Spurious herding does not conflict with the efficient market hypothesis. If individuals confronted with the same investment decisions and the same available information adopt similar behavior, this constitutes spurious herding. With intentional herding, the decision is purely imitative: The individuals copy each other, neglecting their own information.

The statistics used by Hwang and Salmon [2001] allow for the separation of the two hypotheses of herding and deal with intentional herding only. The statistics do not estimate the variability of returns, but operate on the variability of beta.

We detect intentional herding if we observe significant variations in the cross-sectional variance of beta that are not explained by modifications in the fundamentals. Hwang and Salmon [2001] estimate the beta of single stocks and the market. They standardize the coefficient of systematic risk by dividing the single estimate by its standard error. Finally, they calculate H, the variance of the standardized beta values.

$$\textit{degree of herding} \quad H = \operatorname{var} c \left[\frac{\beta i, t\text{-}1}{\sqrt{s_i^2 S^m}} \right] \qquad (5)$$

If the value of H increases, the various standardized beta values are significantly different than 1, so the returns are dispersed around R_m. This would mean we do not have intentional herding. If the value of H decreases, the beta values are not significantly different from the beta of the market, and the returns are concentrated around R_m. This would signify intentional herding.

Our Empirical Test Of The Italian Stock Market

We used a sample of more than thirteen years of data, from September 1, 1988, to January 8, 2001. The sample is mobile,[1] in that it incorporates newly issued stocks quoted during the research period, and includes large- and small-cap stocks. To study the effects of size, each test on the whole sample was repeated using identical criteria on two subsamples of stocks at elevated capitalizations (over 1,000 billion Euro on the final date), and at low capitalizations (less than the indicated threshold limit). For the global sample, we chose stocks with uninterrupted quotations through January 8, 2001.[2] On the final date of evaluation, this global, mobile sample was made up of 151 stocks (sixty-eight large-cap and eighty-three small-cap). We used the Comit global index as a proxy for market returns.

We followed the method suggested by Christie and Huang [1995], who argued that during periods of market stress, investors use market consensus beliefs as their own beliefs. Our first step involved distinguishing between "normal" periods and periods of excess within the total time frame of the study. Market stress occurs when aggregate returns lie in the upper or lower tail (1% or 5%) of the returns distribution.[3]

The coefficient of dispersion is calculated as follows:

$$CSSD_t = \sqrt{\frac{\sum_{t=1}^{N} \left(R_{i,t} - R_{m,t}\right)^2}{N-1}} \qquad (6)$$

where $R_{i,t}$ is the return of stock i at time t and $R_{m,t}$ is the average return of the sample (the cross-sectional average return of N stocks of the sample at time t).

We test herding on days of stock market stress. We used the following regression model with a dummy variable to identify the days when the index return fell within distribution tails:

$$CSSD_t = \alpha + \beta^L D_t{}^L + \beta^U D_t{}^U \qquad (7)$$

where: $D_t{}^L = 1$ if on day t the Comit index return lies in the lower tail (66%, 95%, and 99%) of the distribution of index returns, and 0 otherwise. $D_t{}^U = 1$ if on day t the Comit index return lies in the upper tail (66%, 95%, and 99%) of the distribution of index returns, and 0 otherwise.

Table 1 shows the criteria and the results of frequency assignment to the dummy variable. The dummy variables permit us to view eventual differences in investor behavior during bear and bull market phases. Herding is proven if the dummy coefficients are negative and statistically significant.

The results of this test are shown in Table 2. The coefficients β^L and β^U are positive and statistically significant,[4] and refute the hypothesis of herding. We next repeated the test using a different formulation of dispersion coefficients. Based on the work of Chang, Cheng, and Khorana [2000], the CSAD coefficient is as follows:

$$CSAD_t = \frac{\sum_{t=1}^{N} \left| R_{i,t} - R_{m,t} \right|}{N} \tag{8}$$

Table 3 shows the results. The dummy coefficients were again positive and statistically different from zero, which indicates a difference between the dispersion of returns in extreme market phases and in normal situations. The positive value of the coefficients indicates the dispersion is greater when the market is in stress. The relationship between the market and stocks changed during periods of stress – the return dispersion increased, so the hypothesis of herding is refuted.

This result is consistent with studies of the American market by Christie and Huang [1995], and studies of the Hong Kong and Japanese markets by Chang, Cheng, and Khorana [2000].

The Non-Linearity Test

Our analysis continues with a different type of test. The presence of herding in extreme market phases signifies that stock returns are in alignment with the market. This implies that the equilibrium relationship between dispersion and returns, which is linear and increasing under normal conditions, may have been

Table 1. *Assignment of Comit Index Yield to Dummy Variables*

	Limits		For a total of 3,111 figures	
Statistical Significance	**Down**	**Up**	**Frequency D_t^L**	**Frequency D_t^U**
66% (Rm ± σ)	–1.267	1.348	2,752 359 (left tail)	2,746 365 (right tail)
95% (Rm ± 2σ)	–2.574	2.656	3,030 81 (left tail)	3,047 64 (right tail)
99% (Rm ± 3σ)	–3.882	3.963	3,086 25 (left tail)	3,094 17 (right tail)

Note: For Frequency D_t^L, outside the left tail = 0, and inside the left tail = 1. For Frequency D_t^U, outside the right tail = 0, and inside the right tail = 1.

Table 2. *Results of the Regression of Daily CSSD During Periods of Market Stress*

		D = 1 if Comit index yield is within the limit of 66%			D = 1 if Comit index yield is within the limit of 95%			D = 1 if Comit index yield is within the limit of 99%		
Sample	**Period of Sample**	α	β^L	β^U	α	β^L	β^U	α	β^L	β^U
Global sample	9/1/88–1/8/01	1.883*	0.343*	0.537*	1.955*	0.500*	0.860*	1.974*	0.777*	0.947*
	(up to 151 stocks)	(103.9)	(6.8)	(10.8)	(119.0)	(5.0)	(7.6)	(121.4)	(4.3)	(4.3)
Large-cap stocks	9/1/88–1/8/01	1.588*	0.244*	0.498*	1.647*	0.418*	0.823*	1.665*	0.673*	0.835*
	(up to 68 stocks)	(124.9)	(6.9)	(14.3)	(142.4)	(5.9)	(10.3)	(144.5)	(5.2)	(5.4)
Small-cap stocks	9/1/88–1/8/01	2.026*	0.361*	0.515*	2.099*	0.513*	0.798*	2.117*	0.804*	0.933*
	(up to 83 stocks)	(87.8)	(5.7)	(8.1)	(100.7)	(4.0)	(5.6)	(103.0)	(3.5)	(3.4)
		D = 1 if average sample yield is within the limit of 66%			**D = 1 if average sample yield is within the limit of 95%**			**D = 1 if average sample yield is within the limit of 99%**		
		α	β^L	β^U	α	β^L	β^U	α	β^L	β^U
Global sample	9/1/88–1/8/01	1.856*	0.468*	0.680*	1.923*	1.207*	1.118*	1.959*	2.168*	1.255*
	(up to 151 stocks)	(104.4)	(9.4)	(13.6)	(120.3)	(12.6)	(11.5)	(123.5)	(13.0)	(5.9)
Large-cap stocks	9/1/88–1/8/01	1.584*	0.269*	0.537*	1.638*	0.584*	0.789*	1.665*	0.662*	0.735*
	(up to 68 stocks)	(125.7)	(7.7)	(15.1)	(142.3)	(8.4)	(11.3)	(144.3)	(5.5)	(4.7)
Small-cap stocks	9/1/88–1/8/01	1.990*	0.522*	0.706*	2.058*	1.424*	1.224*	2.096*	2.684*	1.467
	(up to 83 stocks)	(87.7)	(8.3)	(11.1)	(101.2)	(11.7)	(9.9)	(104.6)	(12.7)	(5.4)

Note: Statistical significance refers to the percent of observations in the higher limits (16.5%, 2.5%, and 0.5%, respectively) of market yield. The coefficients of the t-test are indicated in parentheses. *Denotes the significance of the coefficient at the 5% level.

Table 3. *Results of the Regression of Daily CSSD During Periods of Market Stress*

Sample	Period of Sample	D = 1 if Comit index yield is within the limit of 66%			D = 1 if Comit index yield is within the limit of 95%			D = if Comit index yield is within the limit of 99%		
		α	β^L	β^U	α	β^L	β^U	α	β^L	β^U
Global sample	9/1/88–1/8/01	1.296*	0.525*	0.775*	1.388*	1.084*	1.535*	1.416*	1.949*	2.983*
	(up to 151 stocks)	(119.8)	(17.6)	(26.1)	(142.0)	(18.1)	(22.8)	(148.0)	(18.3)	(23.1)
Large-cap stocks	9/1/88–1/8/01	1.200*	0.369*	0.635*	1.267*	0.881*	1.307*	1.288*	1.742*	2.654*
	(up to 68 stocks)	(104.6)	(11.6)	(20.2)	(123.8)	(14.0)	(18.6)	(130.0)	(15.8)	(19.9)
Small-cap stocks	9/1/88–1/8/01	1.372*	0.649*	0.886*	1.483*	1.244*	1.714*	1.516*	2.109*	3.239*
	(up to 83 stocks)	(118.2)	(2.2)	(27.8)	(139.7)	(19.1)	(23.5)	(144.4)	(18.1)	(22.9)
		D = 1 if average sample yield is within the limit of 66%			**D = 1 if average sample yield is within the limit of 95%**			**D = 1 if average sample yield is within the limit of 99%**		
		α	β^L	β^U	α	β^L	β^U	α	β^L	β^U
Global sample	9/1/88–1/8/01	1.230*	0.357*	0.549*	1.289*	0.751*	0.855*	1.317*	1.090*	0.957*
	(up to 151 stocks)	(153.9)	(16.0)	(24.4)	(175.5)	(17.0)	(19.2)	(173.8)	(13.7)	(9.4)
Large-cap stocks	9/1/88–1/8/01	1.129*	0.226*	0.447*	1.174*	0.502*	0.664*	1.196*	0.596*	0.612*
	(up to 68 stocks)	(141.3)	(10.1)	(19.8)	(159.9)	(11.4)	(14.9)	(160.2)	(7.6)	(6.1)
Small-cap stocks	9/1/88–1/8/01	1.279*	0.403*	0.563*	1.339*	0.906*	0.934*	1.369*	1.432*	1.118*
	(up to 83 stocks)	(130.8)	(14.8)	(20.4)	(151.7)	(17.1)	(17.4)	(152.4)	(15.2)	(9.2)

Note: Statistical significance refers to the percent of observations in the higher and lower limits (16.5%, 2.5%, and 0.5%, respectively) of the market yield. The coefficients of the t-test are indicated in parentheses. *Denotes the significance of the coefficient at the 5% level.

modified. The relationship may no longer be linear, that is, it may be increasing at decreasing rates (inefficiency and herding), or at increasing rates (inefficiency without herding).

Considering that stock behavior may be asymmetric in positive and negative market phases, we conduct the following test:

Bull market

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP}|R_{mt}^{UP}| + \gamma_2^{UP}(R_{mt}^{UP})^2 + e_t \quad (9)$$

Bear market

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}|R_{mt}^{DOWN}| + \gamma_2^{DOWN}(R_{mt}^{DOWN})^2 + e_t \quad (10)$$

Where: CSAD = the average cross-sectional absolute deviation of each stock relative to the return of the market. $|R_{mt}^{UP}|$ $[|R_{mt}^{DOWN}|]$ = the absolute value of the average overall sample return (large- and small-cap) on day t if the market is up (down). $(R_{mt}^{UP})^2$ $[(R_{mt}^{DOWN})^2]$ = the square of the identical return.

We use the absolute values $|R_{mt}^{UP}|$ and $|R_{mt}^{DOWN}|$ because we are concerned with the size of the return, not with its sign. This also makes a comparison between γ_1^{UP} and γ_1^{DOWN} possible. The sign and the statistical significance of the coefficients γ_2^{UP} and γ_2^{DOWN} are revealed.

Table 4 shows the results of this test. The last three columns report the results of a test conducted to verify the statistical equivalence of the coefficients "up" and "down." F_1 investigates the difference between α^{UP} and α^{DOWN}, F_2 is used to determine the difference between γ_1^{UP} and γ_1^{DOWN}, and F_3 the difference between γ_2^{UP} and γ_2^{DOWN} (the figures in bold are significant). The test was carried out using the following regression with a dummy variable:

$$CSAD_t^{ALL} = \alpha + \gamma_1|R_{mt}| + \gamma_2\ (R_{mt})^2 + \alpha D_i + \gamma_1|R_{mt}|D_i + \gamma_2(R_{mt})^2 D_i + e_t \quad (11)$$

From the results, we see that:

1. α is positive and significant.
2. γ_1^{UP} and γ_1^{DOWN} (always positive) confirm the results of the test with the dummy (CSAD increases with $|Rm_t|$); γ_1^{UP} is systematically greater than γ_1^{DOWN}, therefore the dispersion is stronger when the market is "up"; and the difference between the two coefficients is significant with the F-test). The asymmetric reaction to the news is consistent with a CSAD value greater than the average when the market is "up."
3. γ_2^{UP} and γ_2^{DOWN} demonstrate the presence of herding in the global sample. The coefficient γ_2 is negative and statistically different from zero. This phenomenon is not asymmetric, however, because even if γ_2^{UP} is greater than γ_2^{DOWN}, the difference between the two coefficients is not statistically significant (see Test F).

Table 4. *Results of a Regression of Daily Cross-Sectional Absolute Deviation (CSAD) on Simple Yield (in absolute value) and the Square of the Average Yield of the Sample: Up and Down Markets*

	Model A				Model B				Statistics		
Sample Period	α	γ_1^{UP}	γ_2^{UP}	R^2_{corr}	α	γ_1^{DOWN}	γ_2^{DOWN}	R^2_{corr}	F_1	F_2	F_3
Mobile Sample											
Total Sample	1.081*	0.367*	–0.032*	0.238	1.103*	0.233*	–0.012*	0.167	–0.022	0.134	–0.021
(151 stocks)	(66.0)	(18.4)	(–8.5)		(63.0)	(10.6)	(–2.8)		(–0.9)	(4.5)	(–3.6)
Large-Cap	0.992*	0.336*	–0.032*	0.191	1.010*	0.176*	–0.008*	0.118	–0.018	0.160	–0.023
(68 stocks)	(59.2)	(16.5)	(–8.1)		(61.6)	(8.6)	(–2.2)		(–0.8)	(5.5)	(–4.2)
Small-Cap	1.148*	0.337*	–0.028*	0.166	1.175*	0.223*	–0.009	0.107	–0.027	0.114	–0.020
(83 stocks)	(59.8)	(14.4)	(–6.3)		(50.9)	(7.7)	(–1.5)		(–0.9)	(3.1)	(–2.8)

4. Herding is also verified for the large- and small-cap samples, although in different ways. In the large-cap test, the value of γ_2 (and its significance) is confirmed in the up phases, but falls in the down phases (although remaining negative and statistically different from zero). The spread of the coefficients does not justify asymmetric results. The asymmetry is strongly reinforced in the test of small-caps. In fact, the crowding of the coefficients disappears in the up phases, but remains in the down phases. Therefore, the returns of the small-cap stocks tend to become more dense only during the phases of rising prices; in the down market, the influence of specific factors seems to remain strong.

The Beta Coefficient Test

The next step was to test the model proposed by Hwang and Salmon [2001], which is based on the analysis of beta dispersion. As we explain further below, Hwang and Salmon introduced a measure for herding based on the estimate of the coefficients of the linear regression "stock i^{th} return – market return." They hypothesize that in the presence of herding, the beta dispersion diminishes.

The authors proposed a verification of intentional herding. As stated, the variable H is indifferent to spurious herding (where perfectly rational investors all move in unison in reaction to identical news), and captures only intentional herding.

Regarding the different measurements of herding suggested by other studies, Hwang and Salmon's [2001] research evaluates the degree of herding in the selected market. The authors suggest that herding is a relative concept, not an absolute one. It can be present in the market to a more or less elevated degree.

The statistic used, independent of market yield volatility, is the measure of herding H(m,t):

$$H(m,t) = \mathrm{var}_c\left(\frac{\beta_{imt}-1}{\sqrt{s_i^2 S^m}}\right) \tag{12}$$

where β_{imt} is the beta of stock i at time t and s^2_i and S^m are, respectively, the variance of the beta of the stock and that of the market.[5] H(m,t) increases if the value of a certain number of standardized beta becomes significantly different from 1. In this case, herding is absent or very low. On the other hand, whenever s_i^2 and S^m are low (with R_i close to and spread along the line of regression and β near 1), the low value of H(m,t) indicates the presence of herding.

The test was applied to the global sample[6] and to the large- and small-cap subsamples for the time period January 1989 to January 2001. We calculate H for each month starting with December 1993 using the following procedure:

1. We estimated the beta coefficient (sixty monthly returns, market = Comit index[7]) and the standard error of the beta for each stock in the sample. We also calculated the t-Student statistic. The first estimate was made for the period January 1989–December 1993.
2. We repeated the calculation with a rolling procedure, adding the return of the last month and eliminating the figure sixty months before (February 1989–January 1994, etc.). For each of the stocks in the sample we obtained eighty-five consecutive estimates.
3. We eliminated the non-significant data from the sample, and proceeded to measure herding H for each period through the calculation of the variance of the t-Student (see endnote 5). The series of eighty-five estimates gives H(m,t).

Figure 1 shows H(m,t) for the period examined. The series H(m,t) has significant levels of confidence at the 95% level, from which we note that herding varies to a reasonable extent over time. In particular, after a period of relative stability (before December 1997), the progress of H(m,t) appears definitively more volatile (it reaches a peak of a little greater than 10 for December 1998, then drops close to a minimum of about 4 for January 2001).[8]

The increase in the degree of herding after December 1998 indicates that the systematic returns of the

FIGURE 1
Herding Measure H (m,t) (market index: Comit)

stocks tend to level out to the market average (this is particularly true for blue-chip stocks). This phenomenon seems to characterize the concluding phase (which is generally also the most psychological phase) of bull markets. This result partially agrees with the findings of Hwang and Salmon [2001] about the American market (the authors found that herding characterizes bullish phases and reaches elevated levels [low values of H(m,t)] in pre-crash phases).

The large-cap sample results (Figure 2) confirm what we found for the global sample. The small-cap sample test (Figure 3), however, is characterized by the tendency of H(m,t) to decrease for the entire period under examination. The declining trend of the statistics appears greater during the period preceding December 1997 than in later phases. In general, though, it holds that small-cap stocks demonstrate a tendency toward a more stable reduction of H(m,t) over time. The large-cap sample shows a much more obvious and rapid change, from a maximum of approximately twelve rapid drops to about four in three years, as compared to a maximum of 6.5 and minimum of 2.5 for the small-caps.

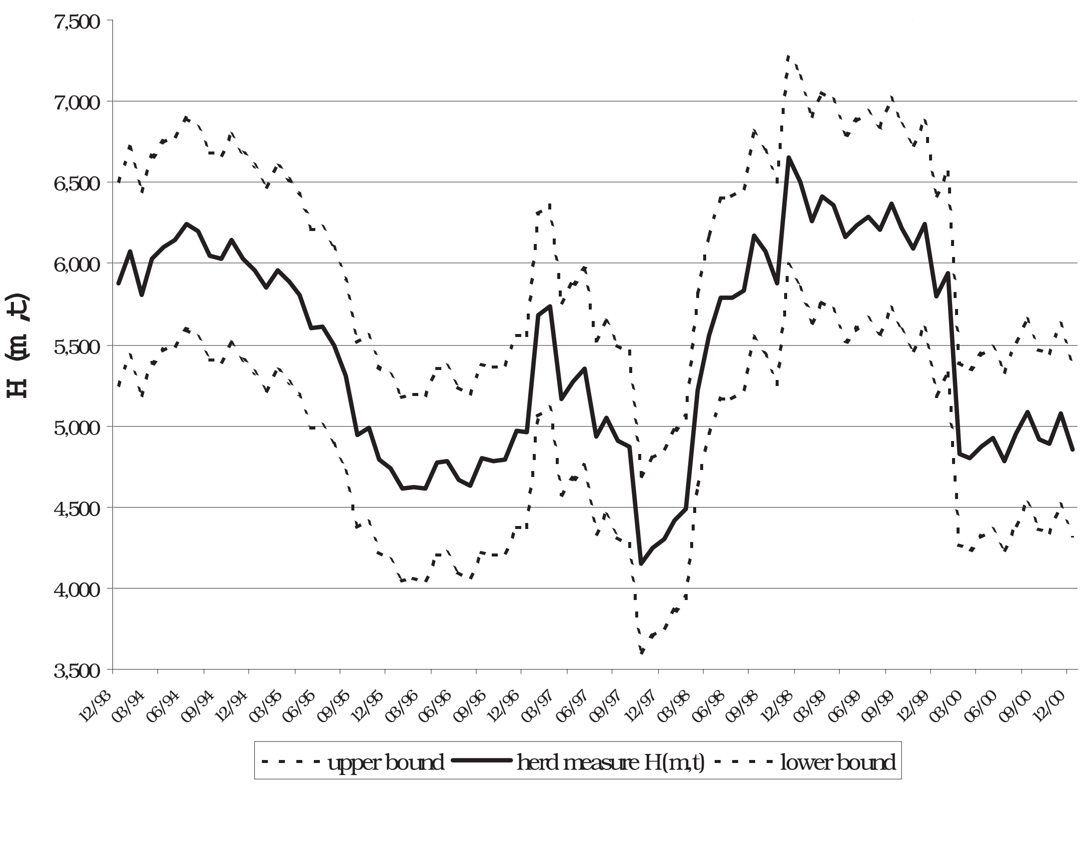
The reduction of beta dispersion for the large-cap sample, implied in the declining dynamics of H(m,t), could be attributed to the behavior of institutional investors, who tend to concentrate the majority of their resources in blue-chips or stocks included in the MIB 30 index. In Italy, the investment management industry is quite young, and small investors still may have difficulty considering long-term investments. Knowing there will be short-term performance evaluation, portfolio managers may be tempted to level out to the average to avoid performing below their competitors. But this inevitably leads to a convergence of performance in general, in which all portfolios become similar and are strongly concentrated in the stock index.

Another relevant factor that emerges immediately from the comparison of Figures 2 and 3 is the diversity of H(m,t) values between large- and small-caps. Note how the maximum level reached in the small-cap group (6.364) is actually a very low figure for the large-cap group. Note also that the measurement of H declines considerably from September 1999 through December 2000. Over the same period, the Comit index grew considerably. But from June to December 1998, the Comit index declined significantly, while H increased to a value of 10. Essentially, we see that when the Comit reaches significant levels, beta condenses and investors adopt defensive behaviors, copying the market. When the Comit declines suddenly, investors change their behavior model, causing the beta dispersion (spurious herding) to increase.

We also note that from March 1997 to March 1998 the market increased markedly, while the value of H declined by about 1 point, which is very different from what occurred from September 1999 (a bull market)

FIGURE 2
Herding Measure H(m,t) (subsample: large-cap stocks, market index: Comit)

FIGURE 3
Herding Measure H(m,t) (subsample: small-cap stocks, market index: Comit)



until March 2000. A possible explanation is that herding is also dependent on the level of the market index. If investors believe the increase of the Comit is a normal, rational occurrence, they maintain rational behavior. But if they consider the market "speculative," the beta dispersion declines.

Conclusion

We propose several tests of herding behavior for the Italian stock market.From the examination of the data and graphics, we conclude that the interpretation of Christie and Huang [1995] is correct for the Italian market during the period examined: Herding is present during extreme market conditions, both in terms of sustained growth rate and high stock levels.

The same conclusions can be made from observing the data in the tables of the values of H for the stocks of major companies. But the conclusion for small-cap stocks is somewhat different. The results show that H is lower for small-cap companies than for large-caps, and is in constant decline. Moreover, in the downward trend, we note phases when the contraction of the measurement of herding is very evident.

For example, from March 1997 to March 1998, the Comit index experienced a market increase (bull), and the decrease of H is particularly evident. The same phenomenon is seen after March 1999, also a period of market increase, when Comit values picked up. During these periods, for both the total sample as well as for the sample of larger companies, there was a confirmation of intentional herding. The explanation for the small-cap sample, where H tends to decrease, remains to be identified. However, we suggest an answer may be found by using the "infrequent trading" approach suggested by Scholes and Williams [1977] and Dimson [1979].

Notes

1. The tests were also repeated on a fixed sample of only the stocks present on the starting date (September 1, 1988). Since those results led to the same conclusions, we present only the summary data of the mobile sample, which includes newly issued assets.
2. Following the indicated criteria, the results from the large-capitalization sample almost coincide with the universal sample, but the lack of continuous price quotes notably diminishes the larger group of small-caps with respect to the total sample.
3. M = 1, 2, or 3, respectively, for the 66%, 95%, and 99% levels of significance.
4. In measuring market dispersion, we considered it more correct to use an element of comparison made up of 1) stocks present only in the sample, and 2) stocks with identical weight. In an alternative test, the coefficient CSSD was calculated with respect to the Comit index as a proxy for the market. The result of this test was identical, with positive statistically significant coefficients.
5. We note that H(m,t) is simply the cross-sectional variance of the value t of the beta coefficients of the sample stocks.
6. The need to prepare at least five years of data for the calculation of beta variables reduced the number of the aggregate; the number of stocks in the global sample varies from 101 initially to 123 on the last date of the survey.
7. The Comit index is a global index of the stock market in which the different components have a weighted function according to their market capitalization. In order to solve the problems due to the greater weight assigned to blue-chip stocks as the independent variable in the linear regression calculations, it was useful to repeat the test on regressions on the vector of the sample average yield (equally weighted).
8. The tests carried out on the equally weighted sample furnished similar results.

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