Herding in Stock and Option Picking
Evidence and Analysis

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Introduction

Imitative behavior seems to be one of the characteristics bridging humans and animals. As much as there is evidence of copying pattern transmission among animals, especially in territory choice, mating and foraging, there are comparable findings on human reciprocal mimicking. Back in the fourth century B.C. Aristotle already noted in his philosophical essays *Poetica* that humans are far more imitative than animals.

In the financial realm imitative behaviors have come to be defined as herding. They occur when a group of investors trade similarly over the same period of time, even if there is no fundamental information supporting their choices.

Herding arises when investors imitate the observed choices of others, instead of operating choices based on their own beliefs and information and in some instances such behavior can actually be judged as rational. If the leading participants are believed to be better informed or if a deviation from the consensus may result into costs, then imitating the others can have utility-maximizing rationales.

One of the difficulties in investigating correlated behaviors on financial markets is the possibility to discriminate between the so called spurious or unintentional herding and the pure herding or herding *tout court*. The previous phenomenon is simply the result of similar actions generated by fundamental changes; i.e. investors might face similar choices, such as they might react to similar public information or similar interest rate movements. The latter is, on the other hand, an intentional imitation of someone else's choices not motivated on any fundamental consideration.

An array of studies have been put forward to capture herding mechanisms and even though it seems to be generally agreed that such patterns do surface, empirical evidence has given mixed results. Several research challenges have rendered the topic particularly interesting and this paper tries to tackle some of these research points and give them an answer. The central question taken up in the present paper is to which extent it is possible to observe herding behavior in the choices made by private investors. As a matter of fact most of the studies conducted on the topic in the past use database

from institutional investors, which, for several reasons later outlined, suffer from a number of shortcomings and therefore capture herding patterns with difficulty.

This paper adds to the growing literature by examining herding on the intraday level using a set of trading data from 3 financial branches located in an emerging country, namely India. The paper attempts to discriminate between spurious and intentional herding among private investors, by examining the trading conducted by people physically present in the branch and those operating from a remote location and therefore not able to observe and influence directly each other.

The paper is structured as follows. Section 1 provides an overview of theoretical and empirical research on herding in financial markets. It tries to define the concept of herding, the causes of herding behavior and the success of existing studies in identifying the phenomenon. Section 2 present the database and the research methodology utilized to investigate whether herding pattern can be identified in private financial trading. Section 3 presents the results of the tests run on the database and attempts to interpret them in order to answer to the above outlined central question. Finally Section 4 provides a conclusion to the research.

Section 1
Literature Review

One of the first exhaustive papers on the theory of herding is authored by Bikhchandani, Hirshleifer and Welch (1992) and puts forward a concept to explain how imitative behaviors originate and spread. The term used is informational cascades and it refers to the phenomenon occurring when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information. The above mentioned paper tries to offer an explanation not only of why people conform but also of why convergence of behaviors can be fragile and idiosyncratic. Bikhchandani et al (1992) draw a model of imitative decisions that originate readily on the basis of even a small amount of information and following the observation of previous players. The authors argue that once a cascade has

started, it can out of principle last forever, even if it is wrong. However, this fallibility also causes the cascade to be fragile in the event when public information is revealed.

Another theoretical paper drafted by Devenow and Welch (1996) attempt to give a systematic description of rational herding in financial economics in the light of the efficient market hypothesis (EMH). The paper considers herding behavior as the product of rational choices which in this sense can help explain empirical puzzles tarnishing the strong formulation of the EMH. The authors briefly outline three main causes of insurgence of herding in the financial context: direct payoff externalities, principal agent problem and information cascades. According to the payoff externalities the more agents adopt a behavior; the higher is the payoff for all the agents. Examples can be the bank runs, whereby the last to withdraw are likely to suffer the most, or information acquisition costs, whereby agents might deem worthwhile to acquire information only if other agents do. In other words traders tend to herd on information acquisition or lack thereof. The second origin of rational herding can be traced in the principal agents concerns; Devenow and Welch (1996, p. 607) observe that managerial performance evaluation is based on a relative measure and for this reasons managers often prefer to imitate other managers to avoid being revealed as low performing. Finally, the last explanation is modeled around the concept of information cascades introduced by Bikhchandani et al (1992) and it forwards the idea that agents gain information from observing previous actions of other agents to the point where they rationally completely ignore their own private information.

One of the first empirical measures introduced to test for herding on financial markets has been put forward by Lakonish, Shleifer and Vishny (1992) who define and quantify herding as the average trend of a group of money managers to buy (sell) a particular stock at the same time, relative to what could be expected if money managers traded independently. In fact the measure defines the correlation in trading patterns for a given group and the tendency to buy and sell the same set of stocks during a time stretch from 1985 up to 1989. The underling principle is that herding should lead to correlated trading.

The herding gauging measure formulated by Lakonishok, Shleifer, and Vishny (1992) is often referred to as LSH measure and it has become a standard in the financial

literature. It rests on the hypothesis that in the absence of herding, the number of fund managers who buy a stock, as a proportion of those who trade that stock, has the same expected value across all stocks in any particular period. Therefore if notable cross-sectional variation in this proportion is found, then the null hypothesis of no herding is rejected. As a matter of fact, the conclusion is that the money managers of the sample do not exhibit significant herding. Marginal herding evidence is observed in small stocks and the authors suggest that there is less public information on small stocks and therefore money managers pay relatively more attention to the actions of the other players.

Similarly to Lakonishok et al. also a subsequent study authored by Grinblatt, Titman and Wermers (1995) fails to insulate any concluding evidence of herding by mutual funds. The paper examines data on portfolio changes of 274 mutual funds between 1974 and 1984. The measure that Grinblatt et al. utilize is actually the same test statistics formulated by Lakonishok et al. but implemented over a larger dataset. The results showed that over 100 funds, only 2.5 funds tended trade more on the same side of the market. Interestingly enough, the authors also pointed out that the funds in the sample exhibited more pronounced herding in buying past winners that selling past losers. In other words herding on the sell side, though present, was less evident.

Further researchers have tried to interpret these surprising results and namely the failure to highlight herding in the financial context. Bikhchandani and Sharma (2001) investigate the two above mentioned researches and argue that the understatement of herding is probably due to the typology of the dataset. First, the types of mutual funds considered were too heterogeneous and second for many stock quarter pairs the trading volume might be too low for observing any significant herding. A center criticism is that herding levels should be tested within funds with the same characteristics, i.e. either aggressive, international, growth funds and so on. Following this line of reasoning it does not surprise that Wermers (1999) in a further research attempts to run the herding measure on trading differentiated by marker capitalization. Wermers (199) finds that in fact there are more marked mimicking patterns in small growth stocks. The paper shows that for all funds taken together, herds tend to form much more often on the sell side of the market rather than the buy side and this is more pronounced for small international stocks. This is might originate from the fact that traders tend to copy each other when

they have no fundamentals to base their trading choices. In other words in presence of information asymmetries and agency problems, market participants can only resort to observing each other actions.

Hwang and Salmon (2001) also start from the building blocks laid by Lakonishok et al. (1992) and Wermers (1995) and attempt to correct the shortcomings of the statistical measures proposed. In particular the research pinpoints the importance to discriminate between spurious or unintentional herding where traders simply happen to take similar actions by reaction to fundamental changes and intentional herding. This difficult discrimination is drawn in the paper by using a linear factor models in which movements of fundamentals are also taken into consideration. Without entering into the specifics of the statistical measure, it is worth mentioning that Hwang and Salmon (2001) try to calculate the cross sectional standard deviation of the individual assets into a linear factor model and the measure of herding is then calculated from the individual betas of the model. The hypothesis lying behind is that if there is herding towards the market portfolio, the cross sectional variance of the estimated betas will decrease.

Another recent paper titled *Do traders follow each other at the NYSE?* authored by Patterson and Sharma (2006) also elaborates on the challenges posed by herding measures. Once again the methodology owes legacy to the main precursors, and namely Lakonishok et al (1992) and Grinblatt et al. (1995) but also highlights the shortcomings of the previous investigations. Patterson and Sharma (2006) particularly insist on the importance of gathering intraday data rather than the quarterly institutional investor results. In accordance with Henker, Henker and Mitsios (2003) they maintain that herding is more of an intraday phenomenon since agents observe each other to take action, rather than relying on own individual prediction models. Also the paper reiterates that individual investors are more likely to herd than institutional ones but unfortunately the main researches seem to have been based on institutional dataset. On the basis of the above mentioned considerations Patterson and Sharma (2006) proceed to examine herding at intraday level and focusing on individual stocks rather than large funds. The authors run statistical testing on a database of 50 NYSE trading days experiencing extreme price change and also takes into the calculations the arrival times of traders. The specifics of the formulated statistical measure are hardly relevant in the economy of the

present paper, what matters is indeed that also Patterson and Sharma (2006) try to cater for the limitations of the previous works conducted on herding. It is also interesting to note that their research fails to highlight evidence of widespread herding and it confines herding to smaller stocks. Ultimately the conclusion is that markets seem to be functioning in a manner reasonably consistent with the Efficient Market Hypothesis.

Section 2
Database and Research Methodology

2.1 Characteristics of the sample

The sample used to draft the present research includes trading data over the span of 30 days in three different financial branches located in India. The span runs from 1st October 2006 to 31st October 2006 and it lists both stocks and derivatives traded by private investors. Indeed a branch office may have a number of ways for investors to place trades: terminals in the branch; cashier windows, telephone service, and computer links. To sum it up, the trader can either walk into the branch and trade in-house or decide to place the order without personally going to the actual trading desk. What makes the present sample particularly interesting is the possibility to discriminate between the traders physically present in the branch and therefore trading "in house" and those trading from a remote location. So the investigation intentionally examines groups of investors who are physically standing near each other and it compares them with the trades that are called-in. From now onwards, investors will be referred as present, if they were trading by being actually on the floor of the branch, or not-present, if their stock/option picking was communicated from a remote location.

The dataset extrapolated only lists the quantities of the assets traded and not the price or the price changes. This is because the research is oriented towards showing the occurrence of herding in stock picking rather than accounting for the consequences on the market place. The assets considered are secondary trading of shares and derivatives.

The sample is therefore interesting under a few aspects. Firstly it does not gather institutional investors but small private traders, that are more prone to display imitating patterns, given that they are more likely to lack of knowledge in fundamentals (Patterson and Sharma, 2006; Hwang and Salmon, 2001). Secondly, the intraday level of granularity overcomes the limitations observed by Patterson and Sharma (2006, p. 3) and enables to follow any herding momentum that might originate by the circumstance whereby traders sit together and observe each other while trading. Thirdly, the small sample does not run the risk to including balancing transactions that might have the effect to erase trends. As Bikhchandani and Sharma (2001, p. 282) point out a financial asset bought by one market player must be sold by another and to insulate a herding trend it is important to find a group of participants that trade actively and similarly. It can be argued that this is the case for the private investors' data considered by the present paper where the homogeneous group selected is not too large, relative to the size of the market and balancing transaction might are not likely to cancel each other out. To this respect is it worth mentioning what is also indicated by Wermers (1999, p. 593) and that is that the average level of herding decreases to just over three percent among stock-quarters traded by 50 or more funds. In other words popular assets - traded by large numbers of traders - exhibit lower levels of herding because where there is a seller, there is also a buyer and if the sample is large enough, it has a good chance to include both. Finally the sample utilized originates from an emerging marker and namely India. Bikhchandani and Sharma (2001, p. 307) suggest that evidence suggest that in emerging markets there is likely to be a more marked tendency to herd, since information acquisition is more costly and information cascades, as well as reputational herding, are more likely to arise. However, previous statistical attempts and namely the work of Borensztein and Gelos, G. (2000, p. 61) fail to conclusively demonstrate this last circumstance. The above paper finds statistically significant evidence for herding behavior, but the magnitude is smaller than what the authors had expected and no dominant patterns across funds and over time is detected, although herding is deemed to be more prevalent in larger emerging markets. Additionally the behavior is more pronounced when selling than when buying.

2.2 Data manipulation and research methodology

As indicated above, the database consisted of detailed data regarding the trading of private investors. Given the vast information, the first step has been to construct a structured sample by selecting only the trades that conveyed the signals relevant to our investigation. To enhance the power of the test, we therefore restricted the sample to contain only the first trades, either buy or sell, conducted on a stock. This means that if a trader was opening a position to close it at the end of the day, the sample would have counted only the opening position. By recording only the first transaction for each trader on each stock, the sample then includes merely *unique trades*. This is to avoid considering orders that have been placed to be withdrawn.

Data are sorted to include only unique buy and sell orders. That is, if an individual investor makes multiple purchases of a stock on a given day, only one purchase is counted. When the sorting is carried out on the derivatives, the trades are grouped not as sell and buy but as bearish and bullish. The buying of a put and the selling of a call are categorized as a bearish; while the selling of a put and the buying of a call are categorized as bullish. Consistently also in the stock trading data, selling is labeled as bearish and buying as bullish.

However, when it comes to derivative trading, it should be specified that the sampling described above, has the downside of eliminating some information. Indeed traders can buy and sell different quantities of calls and/or put in order to engineer trading strategies. An investor can create spreads by purchasing two or more options of the same type or again he/she can concoct straddles, strangles, butterflies; all these strategies reduce the amount of downside risk while maintaining upside profitability of investments. If a trader has been constructing these strategies by multiple purchases, the sample does not account for this.

2.2.1 Correlations

The data have been organized as follows: everyday the unique trades of present and not-present traders have been matched so to visualize for each stock the activity recorded. Correlations have been run on the trades conducted everyday by the present group and the not-present group.

Correlation analysis is widely used to measure the degree of financial contagion and even a simple pair-wise correlation enables to determine whether a relationship exists between two variables. In this case the two variables considered are: the trading pattern of the people present in the branch and the trading pattern of those acting from a remote location. If the two groups of traders were acting similarly, and hence their trades were to be correlated, it clearly meant that the stock picking was not influenced by direct interaction but rather by fundamental movements common to both groups. The results have been organized into Table 1.a, 2.a., 3.a for stocks and 1.b, 2.b and 3.b for options. The tables visualize the correlation coefficients for the present and not-present traders for both bearish and bullish sentiments as well as for the sum of the total trades, i.e. without discriminating whether traders were selling or buying. This is to check whether the herding tendencies are more marked in the selling or buying activities or whether no relevant difference is to be noticed.

2.2.2 Measure of clustering

Another simple measure has been calculated to check for clustering of stock picking. It enables an immediate visualization of any herding pattern and it has the merit to avoid unnecessary parameterizations in calculation. The measure of clustering is obtained by dividing the highest number of unique trades recorded for a stock by the total number of unique trades recorded on a given day. This day-to-day value is calculated for both bearish and bullish trades as well as for the total number of trades.

The ratio resulting should increase the more clustered the trades and should decrease the more dispersed the trades. This is because if investors herd, they are more

likely to pick the same stocks, whereas if they rationally operate, they should diversify and hence the quantities should be dispersed.

2.2.3 Analysis of variance

The last statistical verification consists of the analysis of variance. The analysis of Variance (AV or ANOVA), originally developed by R. A. Fisher in the 1920's, is widely used in the social sciences. It can be used for parameters in the linear model. Given for instance two samples (in our case present and not-present traders), each normally distributed with the same unknown variance, the analysis of variance enables to test whether the means of all samples are the same. If the means of both samples are identical, it means that the two groups are distributed identically and in the specifics of the present research they behave in the same way. The null hypothesis is that if there are no differences in the population means of the traders present in the branch and those acting from a remote location

If the null hypothesis is true, the population means of the two trading groups should be equal:

$$Ho: \mu 1 = \mu 2$$

However if a difference exists, then the null hypothesis should be rejected, in favor of the conclusion that the two groups behave differently. The expectation is that the variance of the present traders should be lower in compliance with the expectation that traders sitting together are more likely to choose the same stocks and hence herd. On the other hand not-present traders should have a more spread out distribution and hence a higher variance.

In addition to the above predictions, by breaking down the analysis into bearish and bullish transaction, it is also possible to verify the argumentations of previous research on the topic according to which up-markets may aggregate less information, and therefore that up-markets could be more `fragile' than down markets (Welch, 2000, p. 371; Bikhchandani et al., 1992, p. 1001). In other words, if we consider two further sub-

samples and namely the bearish present traders and the bullish present traders, we should see whether the latter are more prone to exhibit similar stock picking decisions than the former. Given a null hypothesis forecasting identical sample means, we could confirm the conclusions of previous researches only if the variance of the two sub-samples is actually different. This is also consistent with the findings of Grinblatt, Titman and Wermers (1995) that indicate that herding on the sell side, though present, is less evident on the financial marketplaces.

Section 3
Results and Interpretation

3.1 Correlation of trades: results

The results are presented in Annex I at the end of the present paper. The first results to be evaluated are the correlations between the trades realized by the present traders and the not-present traders.

There are a total of six tables for the three branches taken into consideration: branch Ashish (codenamed ASH), branch Sanjay (codenamed SANJ) and branch Bhavesh (codenamed BS). Table 1.b, Table 2.a and Table 3.a refer to the correlations between traders of stocks while Table 1.b, Table 2.b and Table 3.b. The data are broken down into bearish transactions and bullish transactions. The former term refers to the selling of stocks or the selling of calls and/or the selling of future contracts and/or the buying of call contracts. The latter term refers to the buying of stocks, the buying of calls and/or future contracts and/or the selling of puts. The column 'Total' shows the totals for both types of transactions. This set up is repeated also in the tabling of the other statistical results and namely the coding of the branches, the order of the branches and the listing of the stock results before the option results.

If the people actually present in the branch herd, the expectation is zero or low correlation with the trades of people that are not present in the branch. The results collected indeed show a low level of correlation between the trades realized by present

traders and remote traders. The average correlation coefficients for the stocks are 0.40 for ASH, 0.36 for SANJ, 0.25 for BS; while the options record 0.68 for ASH, 0.82 for SANJ, 0.45 for BS. This seems to indicate more similar trades when it comes to derivatives between the groups of present and not-present and therefore it suggests less herding and more fundamental-driven movements. When looking closer at the difference between the bearish and the bullish groups the correlation values for bearish transactions are consistently lower. However the statistical significance of this gap should actually be tested in order to formulate conclusions or significant observations. The tables also indicate the median, next to the average. The median is the central point which minimizes the average of the absolute deviations. Unfortunately the series of Tables from 1.b to 3.b does not yield significant median values given the low number of transactions.

3.1 Measure of clustering: results

Another measure that has been run in order to detect herding is aimed at highlighting the clustering of trades. As described in the previous section the ratio has been calculated by dividing the highest number of unique trades recorded for a stock by the total number of unique trades recorded on a given day.

The data collected are presented in Annex II. Tables 1.c, 2.c and 3.c refer to stock trading while Tables 1.d, 2.d and 3.d refer to option trading. The tables show the intra-day results and again they breakdown the measure into bearish and bullish trends. They also list the aggregated results for both directions of trading. The last row visualizes the sum of all the ratios to offer a single reference measure. The expectation is that present traders, who can influence each other and hence herd, would have a higher clustering measure. This is because the unique trades should tend to concentrate more around some stocks (or derivatives), instead of diversifying the portfolio.

One could also maintain that the clustering around a specific title could indeed be due to some fundamental movements or from the disclosure of some public information that might push investors to readjust their portfolios. However, if this is the case, the same ratios should be observable for both present and not-present traders. If this is not the case, then this is evidence of herding. Since the data collected enable to differentiate

between present and not-present trades, it also possible to discriminate between spurious and intentional herding. The data actually show a clear difference between the clustering created among the present traders and the not-present traders and this seems to point towards herding in the present group that can observe and reproduce each other's choices. When considering stocks, the total trade check-sums for branch ASH are 1.44 for present traders versus 1.06 for not-present traders; for branch SANJ the sums are 1.52 for present and 1.04 for not-present; for branch BS the sums are 2.02 for present and 1.85 for not-present. If the clustering around some specific stocks was intentional, then all investors should be facing similar decision problems and they should be using the same information sets, in order to resort to similar decisions. Also, the broken down data for bearish and bullish transactions show the same trend of higher clustering in the present traders.

Interestingly enough, the data obtained for the derivative contracts show a more robust difference between the choices operated by the present traders and the not-present traders. Once again the total trade check-sums offer a quick and effective indication. Branch ASH totals 7.54 for the present traders and 2.68 for the not-present, branch SANJ has 7.63 for the present and 2.42 for the not-present and branch BS has 6.83 for the present and 4.52 for the not-present. The numbers suggest a more marked difference between the behavior of the traders that can influence each other and those who are not trading physically in the branch venue. In other words the herding pattern is more robust in the trading of derivatives carried out by present traders.

3.1 Analysis of variance: results

The intra-day variance of the unique trades has been collected into Annex III. Tables 1.e, 2.e and 3.e show the daily variance recorded in the three branches in the trading of stock; while Tables 1.f, 2.f and 3.f record the daily variance for the options. The data have been aggregated as follows: the first two columns indicate the values of the variance for the bearish trades (respectively present and not-present), the third and forth column list the values of variance for the bullish trades (respectively present and not-present), the fifth and the sixth column show the aggregate trades and once again

discriminate respectively between present and not-present. All six tables follow this structure.

As indicated before, the null hypothesis is that $\mu 1 = \mu 2$, whereby $\mu 1$ is the sample mean of the present traders and $\mu 2$ is the sample mean of not-present traders. By looking at the results gathered, we can see that the total averages of the two group variances are actually different from each other in all three branches. The average variance for the present traders in ASH is 0.122 and the not present is 0.359, in SANJ the values are 0.08 as against 0.215, in BS the gap is between 0.08 and 0.15. The difference between the two samples is so marked to be undoubtedly significant and to be a clear indication of the existence of two defined behavioral patterns. In branch ASH the variance of the stock selection of the not-present traders is almost 3 times larger than the "herding group", in SANJ the variance of the not-present group is 2.5 times larger and in BS the value is 1.7 times larger.

As far as variance of total trades options is concerned, we can see that the values are as follows (averages for present traders precedes the not-present ones): 0.021 against 1.097 in branch ASH; 0.089 against 0.659 in branch SANJ and 0.013 against 0.155 in branch BS. These values show a even larger gap between trades, whereby the variance average is 50 times larger for not-present traders in ASH, 7 times larger in SANJ and 11 times larger in BS.

Further statistical testing aimed at assessing the robustness of the results could also be performed but the sheer comparison of the variance of the two samples points at two distinct behavioral patterns. As defined in the literature review, herding can be spurious or pure but if the present analysis was picking up a consensus following the same fundamental information, then the two samples should pick the same stocks/derivatives when faced with the same choice menu. Therefore the results of this analysis confirm the existence of mimicry among those traders who could actually sit together and observe each others choices.

Another interesting trend that seems to be verifiable in the analysis of variance is the observation that bullish markets should be more prone to herd than bearish markets. Bikhchandani et al. (1992, p. 1001) indicate that up-markets tend to aggregate less information but more trivially one could also expect agents to be more prone to boast

their bullish choices, and hence to start an information cascade, rather than boast a bearish choice. If we look at the difference between the values of variance for present bearish choice and bullish present stock choices, this is present but is not marked enough to draw conclusive results and further statistical testing would actually be needed.

Section 4
Conclusions

Herding in financial markets is often presumed to be present even though the existing empirical evidence is surprisingly sparse. A few challenges in tackling the quantitative analysis of herding make it an interesting topic to tackle. The present research has tried to address some of these challenges in order to bridge existing research gaps and to highlight the existence of herding patterns in stock picking by private investors.

First of all, data are gathered and analyzed on a daily basis. As pointed out by previous studies (Henker et al., 2003 and Patterson & Sharma, 2006) herding is more of an intraday phenomenon and as such should be isolated. The data have therefore been aggregated on a daily basis. It is worth mentioning that the present paper disregards the effect of herding on stock price and the only concentrate on observing and describing the selection pattern of the traders.

The sample also possesses some characteristics that can help better insulate imitative patterns, as suggested in Bikhchandani and Sharma (2001): the trades originate from a homogeneous and not-too-wide group of private investors located in an emerging market. Indeed, the theoretical predictions found in previous research maintain that herding is more likely to occur when private information is more difficult to obtain and hard to evaluate. Also for the above reason any precedent research focusing on institutional data (Lakonishok et al., 1992 and Grinblatt et al. 1995) might have not picked on this effect.

Another central interest of the analysis is the discrimination between spurious and pure herding. This is attained by matching on a daily basis the trades of the individuals operating physically in the branch and therefore exposed to mutual influence and those

trading separately from a remote location. Three analyses have been conducted on the dataset and namely correlation analysis, clustering analysis and analysis of variance. They all show that different behaviors between the two samples of traders exist. Present traders and not-present traders do not trade in the same way and therefore the conclusion is that pure herding is present.

The low correlations found in the stock picking of the two groups indicate that the movements are not following the same directions. This is further confirmed by the clustering of the unique trades, whereby the measure calculated indicates more aggregated choices in the present group and more dispersed choices in the not-present group. Finally the analysis of variance clearly discriminate the two: a larger variance in the unique trades of the not-present investors is more consistent with portfolio diversification intents, while a much more reduced variance indicates concentration of choices. This is evident for both stock and derivatives.

In conclusion this paper is merely a first step to shed more light into herding and it would benefit from further and more detailed statistical testing as well as a wider data span. Besides the consideration of additional micro-information could also bring precious insights on the mechanics of networking: such as the times of trades, the observation of the choices of the habitual traders or high-reputation traders in the present group. Notwithstanding the above limitations, the present research still presents some explicit answers to the many question marks surrounding the decision processes on private financial markets. Finally, the research offers an affirmative answer to the central inquiring to the possibility of highlighting behavior in the choices made by private investors

Annex I Correlations

Table 1.a - Stocks

Stock Correlation ASH			
	Bear	Bull	Total
1-Oct	0	0	0
2-Oct	0	0	0
3-Oct	0.0650467	0.2128040	0.2329692
4-Oct	0.1218960	0.3160141	0.26180651
5-Oct	0.2445163	0.3902281	0.355607763
6-Oct	0.0320785	0.6452534	0.616810559
7-Oct	0	0	0
8-Oct	0	0	0
9-Oct	0.0621647	0.4405669	0.346674169
10-Oct	0.0655842	0.4936786	0.421413969
11-Oct	0.2304945	0.4241454	0.396881191
12-Oct	0.2990712	0.5563006	0.564338809
13-Oct	0.3168103	0.6494264	0.695133569
14-Oct	0	0	0
15-Oct	0	0	0
16-Oct	0.3415587	0.4883883	0.523345002
17-Oct	0.0750105	0.3164193	0.271913262
18-Oct	0.2799324	0.3877616	0.365439556
19-Oct	0.1281311	0.5796740	0.556142948
20-Oct	0.1783861	0.5848092	0.572650889
21-Oct	0	0	0
22-Oct	0	0	0
23-Oct	0.1377568	0.5809366	0.529293657
24-Oct	0	0	0
25-Oct	0	0	0
26-Oct	0.3052230	0.4177833	0.396047475
27-Oct	0.0929858	0.4476014	0.48339731
28-Oct	0	0	0
29-Oct	0	0	0
30-Oct	-0.0217718	0.3166864	0.415209217
31-Oct	0.1166338	0.5567877	0.576512854
Average	0.1462623	0.4192983	0.4086470
Median	0.0650467	0.3166864	0.3466742

Table 2.a - Stocks

Stock Correlation SANJ			
	Bear	Bull	Total
1-Oct	0	0	0
2-Oct	0	0	0
3-Oct	0.203395095	0.30315281	0.28223071
4-Oct	0.408730623	0.384426973	0.414997081
5-Oct	0.1040691	0.255311851	0.245241182

6-Oct	0.239394558	0.22190224	0.363209389
7-Oct	0	0	0
8-Oct	0	0	0
9-Oct	0.028037619	0.332936578	0.241464471
10-Oct	0.317831243	0.340227567	0.380625265
11-Oct	0.116428777	0.27159784	0.24005426
12-Oct	0.25586296	0.215493815	0.392556435
13-Oct	0.471190079	0.409312869	0.487435121
14-Oct	0	0	0
15-Oct	0	0	0
16-Oct	0.357676333	0.339007723	0.44146887
17-Oct	0.080040084	0.352798231	0.318996529
18-Oct	0.295304368	0.203876555	0.358609628
19-Oct	0.390703856	0.165864636	0.44281348
20-Oct	0.347453701	0.70252915	0.668838058
21-Oct	0.08013357	0.395066299	0.379604676
22-Oct	0	0	0
23-Oct	0.079394846	0.272364352	0.322495903
24-Oct	0	0	0
25-Oct	0	0	0
26-Oct	0.303389144	0.533227338	0.538926115
27-Oct	0.541282149	0.475486877	0.578530071
28-Oct	0	0	0
29-Oct	0	0	0
30-Oct	0.176861333	0.354224135	0.373220989
31-Oct	0.528893853	0.402647293	0.555051857
Average	0.2498067	0.3112566	0.3641317
Median	0.1040691	0.255311851	0.318996529

Table 3.a - Stocks

Stock Correlation BS			
	Bear	Bull	Total
1-Oct	0	0	0
2-Oct	0	0	0
3-Oct	0.2013298	0.271938451	0.240439899
4-Oct	0.393415346	0.336182283	0.350498102
5-Oct	0.30791623	0.06940909	0.239252806
6-Oct	0.21774713	0.384362239	0.307682022
7-Oct	0	0	0
8-Oct	0	0	0
9-Oct	0.058115142	0.372214735	0.263687696
10-Oct	0.076582703	0.184273007	0.135639858
11-Oct	0.267441972	0.208507803	0.243228565
12-Oct	0.087511325	0.201616327	0.146861523
13-Oct	0.411289789	-0.012008598	0.379270936
14-Oct	0	0	0
15-Oct	0	0	0
16-Oct	0.089308717	0.164533132	0.163810536

17-Oct	0.204592601	0.02622258	0.133060353
18-Oct	0.211633506	0.154488692	0.293172115
19-Oct	0.032543034	0.195786798	0.274703227
20-Oct	0.142002871	0.536434763	0.411051007
21-Oct	0	0	0
22-Oct	0	0	0
23-Oct	0.120516921	0.438719983	0.355645932
24-Oct	0	0	0
25-Oct	0	0	0
26-Oct	0.167429907	0.563915562	0.473735978
27-Oct	0.435484489	0.326069333	0.35382488
28-Oct	0	0	0
29-Oct	0	0	0
30-Oct	0.232130459	0.345057026	0.261792998
31-Oct	0.231950475	0.26920076	0.375598351
Average	0.185187734	0.239853522	0.257283656
Median	0.087511325	0.154488692	0.163810536

Table 1.b - Options

Option Correlation ASH			
	Bear	Bull	Total
01-ott	0	0	0.0000000
02-ott	0	0.0000000	0
03-ott	0.6527239	0.8626989	0.909334245
04-ott	0.8272753	0.856828	0.912993484
05-ott	0.6715035	0.7038956	0.825488125
06-ott	0.7164915	0.7941712	0.86321536
07-ott	0	0	0
08-ott	0	0.0000000	0
09-ott	0	0.8312825	0.816004628
10-ott	0.8027356	0.8692790	0.929713571
11-ott	0.7046077	0.868895	0.904016731
12-ott	0	0.815049	0.796464477
13-ott	0	0.8155263	0.823996635
14-ott	0	0	0
15-ott	0	0.0000000	0
16-ott	0.8165594	0.8070300	0.882496714
17-ott	0.8454214	0.7219	0.896081753
18-ott	0.8693104	0.890165	0.939921253
19-ott	0	0.705097	0.699007189
20-ott	0	0.733641	0.817271345
21-ott	0	0	0
22-ott	0	0	0
23-ott	0	0	0
24-ott	0	0	0
25-ott	0	0	0
26-ott	0	0	0
27-ott	0	0.680837	0.683005501

28-ott	0	0	0
29-ott	0	0	0
30-ott	0	0.702553	0.699698537
31-ott	0	0.91845	0.923684811
Average	0.3288871	0.6465381	0.6820188
Median	0.0000000	0.7025532	0.6990072

Table 2.b - Stocks

Option Correlation SANJ			
	Bear	Bull	Total
01-ott	0	0	0
02-ott	0	0	0
03-ott	0.868598256	0.868495242	0.894412913
04-ott	0.594891353	0.950112349	0.943076085
05-ott	0.930679655	0.890336036	0.955400535
06-ott	0.666544297	0.892089631	0.894014826
07-ott	0	0	0
08-ott	0	0	0
09-ott	0.86326932	0.890884663	0.927981233
10-ott	0.853657977	0.838846443	0.915830292
11-ott	0.755425739	0.946825184	0.936356836
12-ott	0.8477504	0.890503342	0.880155264
13-ott	0.944773433	0.853451669	0.92018943
14-ott	0	0	0
15-ott	0	0	0
16-ott	0.885299695	0.818948012	0.922159303
17-ott	0.676832388	0.912503075	0.931558666
18-ott	0.807325945	0.915537692	0.951522862
19-ott	0	0.912385018	0.922085652
20-ott	0.797958325	0.954739074	0.960714083
21-ott	0	0.943074392	0.916408739
22-ott	0	0	0
23-ott	0.64730146	0.903867978	0.887881789
24-ott	0	0	0
25-ott	0	0	0
26-ott	0.853919408	0.938195881	0.953432946
27-ott	0.785996799	0.80706266	0.920054759
28-ott	0	0	0
29-ott	0	0	0
30-ott	0.724211483	0.713973942	0.819152225
31-ott	0.661065181	0.853328348	0.880870269
Median	0.661065181	0.853328348	0.894014826
Average	0.674547672	0.797718392	0.829373808

Table 3.b - Stocks

Option Correlation BS			
	Bear	Bull	Total
01-ott	0	0	0

02-ott	0	0	0
03-ott	0	0.813653	0.812925
04-ott	0.658892	0.63798	0.790336
05-ott	0.624724	0.624724	0.813225
06-ott	0.642495	0.650299	0.791976
07-ott	0	0	0
08-ott	0	0	0
09-ott	0.817104	0	0.845782
10-ott	0.658892	0.817104	0.858594
11-ott	0	0.863512	0.759004
12-ott	0	0	0
13-ott	0	0.786434	0.807315
14-ott	0	0	0
15-ott	0	0	0
16-ott	0.63798	0.631986	0.75843
17-ott	0	0	0
18-ott	0.699882	0	0.757622
19-ott	0.829446	0.813225	0.875298
20-ott	0	0	0
21-ott	0	0	0
22-ott	0	0	0
23-ott	0	0	0
24-ott	0	0	0
25-ott	0	0	0
26-ott	0.66272	0.69437	0.680509
27-ott	0	0	0
28-ott	0	0	0
29-ott	0	0	0
30-ott	0	0	0
31-ott	0	0	0
Average	0.296768	0.349204	0.45481
Median	0	0	0

Annex II Clustering

Table 1.c -Stocks

StockClustering of ASH

	Bear PR max value/ total	Bear NOT PR max value/ total	Bull PR max value/ total	Bull NOT PR max value/ total	TOT PR max value/ total	TOT NOT PR max value/ total
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0.222222222	0.069767442	0.088888889	0.048387097	0.074074074	0.038095238
04-ott	0.111111111	0.046153846	0.114285714	0.108108108	0.090909091	0.057553957
05-ott	0.066666667	0.106060606	0.071428571	0.05	0.046511628	0.048192771
06-ott	0.142857143	0.049180328	0.083333333	0.053030303	0.061728395	0.03626943
07-ott	0	0	0	0	0	0

08-ott	0	0	0	0	0	0
09-ott	0.090909091	0.075471698	0.075949367	0.088709677	0.059405941	0.062146893
10-ott	0.076923077	0.028985507	0.093023256	0.052238806	0.089285714	0.039408867
11-ott	0.076923077	0.076923077	0.1	0.076923077	0.079365079	0.044871795
12-ott	0.0625	0.06779661	0.106382979	0.049180328	0.079365079	0.038674033
13-ott	0.086956522	0.090909091	0.068965517	0.076271186	0.054545455	0.046153846
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.086956522	0.057971014	0.057971014	0.053571429	0.043478261	0.038674033
17-ott	0.166666667	0.096153846	0.072727273	0.051282051	0.06557377	0.046153846
18-ott	0.2	0.090909091	0.088235294	0.090909091	0.06122449	0.062937063
19-ott	0.166666667	0.057692308	0.085714286	0.075757576	0.106382979	0.050847458
20-ott	0.090909091	0.071428571	0.119047619	0.074626866	0.094339623	0.055045872
21-ott	0	0.083333333	0	0.160714286	0	0.108695652
22-ott	0	0	0	0	0	0
23-ott	0.125	0.125	0.178571429	0.090909091	0.138888889	0.071428571
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	0.166666667	0.105263158	0.136363636	0.086956522	0.088235294	0.063492063
27-ott	0.222222222	0.067567568	0.16	0.075630252	0.117647059	0.046632124
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	0.166666667	0.112676056	0.055555556	0.065934066	0.045454545	0.061728395
31-ott	0.142857143	0.072463768	0.06557377	0.066037736	0.053333333	0.045714286
SUM	2.471680554	1.551706919	1.822017504	1.495177547	1.449748699	1.062716194

Table 2.c - Stocks

Stock Clustering of SANJ

	Bear PR max value/ total	Bear NOT PR max value/ total	Bull PR max value/ total	Bull NOT PR max value/ total	TOT PR max value/ total	TOT NOT PR max value/ total
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0.15	0.050847458	0.1	0.1	0.08	0.054263566
04-ott	0.1	0.1	0.117647059	0.058139535	0.074074074	0.044117647
05-ott	0.071428571	0.045454545	0.114285714	0.046511628	0.064935065	0.036697248
06-ott	0.071428571	0.040540541	0.066666667	0.076923077	0.051724138	0.035971223
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0.117647059	0.039215686	0.129032258	0.059701493	0.083333333	0.033898305
10-ott	0.105263158	0.038461538	0.064516129	0.047619048	0.04	0.034782609
11-ott	0.111111111	0.086956522	0.086956522	0.085365854	0.06	0.0546875
12-ott	0.096774194	0.030927835	0.066666667	0.048780488	0.065217391	0.02173913
13-ott	0.131578947	0.115942029	0.12	0.075471698	0.079365079	0.06557377
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.130434783	0.078947368	0.074074074	0.042857143	0.06	0.037037037
17-ott	0.095238095	0.068965517	0.090909091	0.0625	0.0625	0.038961039
18-ott	0.125	0.070175439	0.166666667	0.094339623	0.083333333	0.045454545

19-ott	0.088235294	0.051282051	0.095238095	0.065789474	0.054545455	0.052173913
20-ott	0.09375	0.087719298	0.185185185	0.277777778	0.084745763	0.135135135
21-ott	0.1	0.137931034	0.166666667	0.166666667	0.136363636	0.092307692
22-ott	0	0	0	0	0	0
23-ott	0.111111111	0.060606061	0.25	0.0625	0.1	0.049382716
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	0.103448276	0.06122449	0.117647059	0.102564103	0.065217391	0.045454545
27-ott	0.097560976	0.098765432	0.130434783	0.078431373	0.078125	0.060606061
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	0.090909091	0.056603774	0.111111111	0.054545455	0.075	0.037037037
31-ott	0.181818182	0.140625	0.157894737	0.072463768	0.12195122	0.067669173
SUM	2.172737419	1.461191618	2.411598483	1.678948201	1.520430879	1.042949892

Table 3.c - Stocks

Stock Clustering of BS

	Bear PR	Bear NOT PR	Bull PR	Bull NOT PR	TOT PR	TOT NOT PR
	max value/ total	max value/ total	max value/ total	max value/ total	max value/ total	max value/ total
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0.103448276	0.137931034	0.130434783	0.148148148	0.076923077	0.071428571
04-ott	0.214285714	0.076923077	0.147058824	0.152173913	0.104166667	0.097222222
05-ott	0.115384615	0.142857143	0.142857143	0.24137931	0.106382979	0.102564103
06-ott	0.125	0.129032258	0.172413793	0.166666667	0.081967213	0.072727273
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0.117647059	0.181818182	0.142857143	0.08	0.088888889	0.085106383
10-ott	0.121212121	0.086956522	0.117647059	0.125	0.08	0.051282051
11-ott	0.16	0.111111111	0.130434783	0.21875	0.083333333	0.073684211
12-ott	0.181818182	0.166666667	0.2	0.117647059	0.113207547	0.113207547
13-ott	0.129032258	0.094339623	0.111111111	0.142857143	0.1	0.074626866
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.15	0.15	0.148148148	0.176470588	0.127659574	0.081081081
17-ott	0.111111111	0.128205128	0.217391304	0.304347826	0.12195122	0.112903226
18-ott	0.083333333	0.1	0.1	0.1875	0.068181818	0.065217391
19-ott	0.166666667	0.142857143	0.115384615	0.095238095	0.078947368	0.071428571
20-ott	0.15	0.083333333	0.2	0.172413793	0.125	0.094339623
21-ott	0	0.111111111	0	0.128571429	0	0.102272727
22-ott	0	0	0	0	0	0
23-ott	0.333333333	0.2	0.210526316	0.111111111	0.181818182	0.071428571
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	0.125	0.111111111	0.15	0.137931034	0.107142857	0.071428571
27-ott	0.210526316	0.352941176	0.307692308	0.08	0.125	0.258064516
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0

30-ott	0.230769231	0.117647059	0.1875	0.147058824	0.137931034	0.078431373
31-ott	0.111111111	0.125	0.125	0.181818182	0.117647059	0.105263158
SUM	2.939679328	2.749841678	3.056457329	3.115083122	2.026148818	1.853708036

Table 1.d -Options

Option Clustering of ASH

	Bear PR max value/ total	Bear NOT PR max value/ total	Bull PR max value/ total	Bull NOT PR max value/ total	TOT PR max value/ total	TOT NOT PR max value/ total
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	1	0.230769231	0.333333333	0.166666667	0.25	0.11627907
04-ott	0.5	0.111111111	0.333333333	0.176470588	0.2	0.153846154
05-ott	1	0.176470588	1	0.095238095	0.5	0.084745763
06-ott	1	0.111111111	0.5	0.090909091	0.333333333	0.078431373
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0	0.125	0.5	0.125	0.5	0.125
10-ott	0.333333333	0.3125	0.333333333	0.096774194	0.166666667	0.106382979
11-ott	1	0.210526316	0.333333333	0.117647059	0.25	0.150943396
12-ott	0	0.578947368	0.5	0.136363636	0.5	0.238095238
13-ott	0	0.258064516	0.5	0.088235294	0.5	0.138461538
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.5	0.227272727	0.5	0.15	0.25	0.129032258
17-ott	0.333333333	0.222222222	1	0.083333333	0.25	0.111111111
18-ott	0.333333333	0.2	0.25	0.117647059	0.142857143	0.113636364
19-ott	0	0.1	1	0.2	1	0.125
20-ott	1	0.235294118	1	0.071428571	0.5	0.133333333
21-ott	0	0.4	0	0.333333333	0	0.272727273
22-ott	0	0	0	0	0	0
23-ott	0	0.157894737	0	0.185185185	0	0.173913043
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	0	0.142857143	0	0.152173913	0	0.147058824
27-ott	0	0.238095238	1	0.113636364	1	0.107692308
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	0	0.157894737	1	0.090909091	1	0.079365079
31-ott	0	0.153846154	0.2	0.081081081	0.2	0.1
SUM	7	4.349877317	10.28333333	2.672032555	7.542857143	2.685055103

Table 2.d -Options

Clustering of SANJ

	Bear PR max value/ total	Bear NOT PR max value/ total	Bull PR max value/ total	Bull NOT PR max value/ total	TOT PR max value/ total	TOT NOT PR max value/ total
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0.5	0.3	0.333333333	0.173913043	0.4	0.121212121

04-ott	1	0.5	0.375	0.208333333	0.444444444	0.192307692
05-ott	0.285714286	0.130434783	0.25	0.093023256	0.181818182	0.075757576
06-ott	1	0.2	0.25	0.121212121	0.4	0.083333333
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0.666666667	0.166666667	0.25	0.075	0.285714286	0.068965517
10-ott	0.666666667	0.142857143	0.333333333	0.102564103	0.333333333	0.108695652
11-ott	1	0.2	0.4	0.142857143	0.454545455	0.140350877
12-ott	1	0.285714286	0.25	0.053571429	0.555555556	0.071428571
13-ott	0.4	0.222222222	0.333333333	0.08	0.375	0.058823529
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.2	0.136363636	0.5	0.057142857	0.285714286	0.070175439
17-ott	1	0.15	0.285714286	0.054054054	0.25	0.070175439
18-ott	0.333333333	0.222222222	0.2	0.136363636	0.125	0.096774194
19-ott	0	0.166666667	0.5	0.214285714	0.5	0.2
20-ott	1	0.2	0.125	0.153846154	0.222222222	0.138888889
21-ott	0	0.5	1	0.555555556	1	0.454545455
22-ott	0	0	0	0	0	0
23-ott	1	0.166666667	0.25	0.125	0.4	0.105263158
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	0.5	0.147058824	0.25	0.121212121	0.166666667	0.134328358
27-ott	0.5	0.307692308	0.5	0.081081081	0.25	0.08
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	1	0.153846154	1	0.105263158	0.5	0.0625
31-ott	1	0.2	0.666666667	0.130434783	0.5	0.090909091
SUM	13.05238095	4.498411577	8.052380952	2.784713542	7.63001443	2.424434891

Table 3.d -Options

Clustering of BS

	Bear PR max value/ total	Bear NOT PR max value/ total	Bull PR max value/ total	Bull NOT PR max value/ total	TOT PR max value/ total	TOT NOT PR max value/ total
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0	0.5	0.5	0.142857143	0.5	0.111111111
04-ott	0.5	0.5	1	0.2	0.333333333	0.285714286
05-ott	1	0.25	1	0.25	0.5	0.125
06-ott	1	0.285714286	1	0.25	0.5	0.2
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0.25	0.5	0	0.5	0.25	0.25
10-ott	0.5	0.5	0.5	0.25	0.25	0.166666667
11-ott	0	0.25	1	0.5	1	0.166666667
12-ott	0	0.125	0	0.1	0	0.055555556
13-ott	0	0.2	1	0.25	1	0.222222222
14-ott	0	0	0	0	0	0

15-ott	0	0	0	0	0	0
16-ott	1	0.2	1	0.333333333	0.5	0.181818182
17-ott	0	1	0	0.142857143	0	0.25
18-ott	0.5	0.333333333	0	0.25	0.5	0.142857143
19-ott	0.5	0.5	0.5	0.125	0.5	0.2
20-ott	0	0.4	0	0.125	0	0.153846154
21-ott	0	0	0	1	0	1
22-ott	0	0	0	0	0	0
23-ott	0	0.333333333	0	0.4	0	0.25
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	1	0.208333333	1	0.294117647	1	0.243902439
27-ott	0	0.25	0	0.222222222	0	0.153846154
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	0	0.2	0	0.166666667	0	0.181818182
31-ott	0	0.2	0	0.166666667	0	0.181818182
SUM	6.25	6.735714286	8.5	5.668720822	6.833333333	4.522842943

Annex III Analysis of variance

Table 1.e – Stocks

VARIANCE ASH

	Bear PR	Bear NOTPR	Bull PR	Bull NOT PR	Trades PR	Trades NOT PR
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0.012339903	0.059853772	0.089040571	0.112733594	0.105060807	0.197055094
04-ott	0.01007746	0.095278268	0.065176266	0.189833065	0.080652525	0.334411085
05-ott	0.04183603	0.143753355	0.106851241	0.186312856	0.152430282	0.354264508
06-ott	0.03450418	0.086872715	0.156031904	0.364606181	0.200782283	0.44624411
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0.031055551	0.076726232	0.266909528	0.416997725	0.284549253	0.433289725
10-ott	0.014489864	0.081018483	0.118677301	0.420487256	0.11791507	0.544196292
11-ott	0.014489864	0.13600225	0.123501291	0.289188844	0.136234631	0.42858001
12-ott	0.017772324	0.096229261	0.106904926	0.367852852	0.11905245	0.543861218
13-ott	0.032129253	0.158711046	0.27426183	0.405279035	0.31650803	0.63655502
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.02986681	0.121742465	0.148891786	0.287133471	0.182959324	0.450889746
17-ott	0.006741315	0.091566327	0.108124345	0.146069484	0.104484107	0.252131253
18-ott	0.023468057	0.101337015	0.057345911	0.257069816	0.082724372	0.404572214
19-ott	0.017915484	0.080254109	0.069701153	0.17995245	0.10584576	0.314984848
20-ott	0.012288775	0.065618529	0.097292737	0.146977018	0.113013123	0.263328839
21-ott	0	0	0	0	0	0
22-ott	0	0	0	0	0	0

23-ott	0.008967968	0.055252192	0.066871181	0.152803129	0.077069511	0.239720194
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	0.017915484	0.114625355	0.037842882	0.189615768	0.050740231	0.323385708
27-ott	0.012339903	0.126484649	0.047843649	0.369908224	0.06088454	0.580059806
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	0.015653041	0.159846103	0.107132449	0.167016898	0.1273078	0.382123643
31-ott	0.02011146	0.112692691	0.134384027	0.263918501	0.153364749	0.427768359
average	0.017807749	0.093517372	0.103942142	0.233988389	0.122456136	0.359877222

Table 2.e – Stocks

VARIANCE SANJ

	Bear PR	Bear NOTPR	Bull PR	Bull NOT PR	Trades PR	Trades NOT PR
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0.028900478	0.080392157	0.053148248	0.15889511	0.094089526	0.255878518
04-ott	0.026638035	0.091827083	0.061870798	0.178329115	0.091295345	0.299887517
05-ott	0.065618529	0.084929826	0.08101337	0.064378659	0.172285707	0.164677762
06-ott	0.03293453	0.126484649	0.04183603	0.13600225	0.08846026	0.30675154
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0.023386252	0.072467214	0.051939055	0.124352583	0.078502953	0.212971342
10-ott	0.02329422	0.064417005	0.042889281	0.111442595	0.066940205	0.185584273
11-ott	0.03866094	0.076480814	0.032129253	0.172400746	0.078252422	0.268650459
12-ott	0.049676611	0.136163305	0.016680727	0.046493852	0.071955927	0.201901986
13-ott	0.081864662	0.162466447	0.045581205	0.092563336	0.149904134	0.26151801
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.03665414	0.061502671	0.03866094	0.113646241	0.085039753	0.200023008
17-ott	0.027716849	0.03851778	0.012288775	0.073978066	0.046202418	0.122511951
18-ott	0.042250173	0.082951147	0.046775059	0.103875553	0.101127387	0.208515479
19-ott	0.059608354	0.053485697	0.027716849	0.141938288	0.092287241	0.228570698
20-ott	0.057514636	0.114625355	0.081647366	0.319802132	0.15505279	0.458232993
21-ott	0	0	0	0	0	0
22-ott	0	0	0	0	0	0
23-ott	0.024472736	0.044988113	0.022440371	0.067190735	0.050885804	0.130753892
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	0.04530511	0.072722857	0.030173582	0.073847688	0.087793031	0.159784748
27-ott	0.07816806	0.223514073	0.038916584	0.081516987	0.141823248	0.317094869
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	0.033317995	0.092563336	0.024472736	0.092287241	0.06130327	0.195498121
31-ott	0.044630212	0.1757599	0.03008155	0.133054682	0.087217834	0.342774241
average	0.039076787	0.088393306	0.037155323	0.108856946	0.08573425	0.2153134

Table 3.e – Stocks

VARIANCE BS	Bear PR	Bear NOTPR	Bull PR	Bull NOT PR	Trades PR	Trades NOT PR
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0.054354884	0.047567554	0.038916584	0.056760488	0.116453204	0.106851241
04-ott	0.031423678	0.035335021	0.089020119	0.166978552	0.128276708	0.203780965
05-ott	0.046647238	0.174532812	0.036766623	0.079241762	0.106904926	0.284078534
06-ott	0.064301966	0.049676611	0.083766649	0.042250173	0.161533349	0.092287241
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0.021123808	0.044630212	0.062346294	0.034268988	0.08225324	0.077493162
10-ott	0.072137434	0.02986681	0.025648695	0.020034767	0.10992663	0.04896081
11-ott	0.052368535	0.272076079	0.041179027	0.143487486	0.110177161	0.41267224
12-ott	0.119648746	0.104678273	0.047000026	0.021123808	0.203423064	0.126499987
13-ott	0.072301046	0.1219751	0.01007746	0.017849017	0.095239921	0.149239461
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.033425365	0.031162921	0.065810262	0.030173582	0.120479587	0.067254646
17-ott	0.031260066	0.082897461	0.050228801	0.072853235	0.094005164	0.153457576
18-ott	0.033200399	0.057673134	0.028900478	0.024559654	0.076710893	0.083268144
19-ott	0.017915484	0.03450418	0.053434568	0.025454406	0.072814889	0.061093642
20-ott	0.033425365	0.037725286	0.047000026	0.065667101	0.092977478	0.11518777
21-ott	0	0.026735179	0	0	0	0
22-ott	0	0	0	0	0	0
23-ott	0.003382161	0.023468057	0.041393767	0.054498044	0.044630212	0.081455633
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	0.008967968	0.03866094	0.033425365	0.049829997	0.044246747	0.095539024
27-ott	0.039131324	0.740695861	0.032589411	0.034268988	0.071089296	0.779668686
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	0.021277194	0.188659662	0.035871872	0.070920572	0.065667101	0.267244421
31-ott	0.026735179	0.037725286	0.022297211	0.085712094	0.070920572	0.121412685
average	0.03728704	0.102548155	0.040270154	0.052187272	0.088939531	0.158449803

Table 1.f – Options

VARIANCE ASH	Bear PR	Bear NOTPR	Bull PR	Bull NOT PR	Trades PR	Trades NOT PR
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0.00862069	0.204722639	0.025412294	0.454272864	0.033583208	0.722263868
04-ott	0.017091454	0.184407796	0.025412294	0.643778111	0.041604198	1.11904048
05-ott	0.00862069	0.195727136	0.00862069	0.476461769	0.017091454	0.791229385
06-ott	0.00862069	0.167016492	0.017091454	0.327061469	0.025412294	0.64850075
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0	0.137331334	0.017091454	0.154722639	0.017091454	0.392803598
10-ott	0.025412294	0.311244378	0.025412294	0.336656672	0.049475262	0.677886057

11-ott	0.00862069	0.277286357	0.025412294	0.556821589	0.033583208	1.189430285
12-ott	0	1.094677661	0.017091454	0.88095952	0.017091454	2.719865067
13-ott	0	0.858395802	0.017091454	0.417691154	0.017091454	1.431109445
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.017091454	0.502848576	0.017091454	0.749625187	0.033583208	1.746626687
17-ott	0.025412294	0.306146927	0.00862069	0.494152924	0.033583208	1.172713643
18-ott	0.025412294	0.096851574	0.033583208	0.539430285	0.057196402	0.724437781
19-ott	0	0.178710645	0.00862069	0.283058471	0.00862069	0.662668666
20-ott	0.00862069	0.282683658	0.00862069	0.289055472	0.017091454	0.796026987
21-ott	0	0	0	0.084257871	0	0
22-ott	0	0	0	0	0	0
23-ott	0	0.225112444	0	0.441004498	0	1.076161919
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	0	1.173613193	0	0.989205397	0	3.933133433
27-ott	0	0.375637181	0.00862069	0.828785607	0.00862069	1.57023988
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	0	0.207721139	0.00862069	0.550524738	0.00862069	0.92856072
31-ott	0	0.135157421	0.041604198	0.462593703	0.041604198	0.751724138
average	0.00731063	0.329299636	0.014953238	0.470279146	0.021949739	1.097829657

Table 2.f – Options

VARIANCE SANJ

	Bear PR	Bear NOTPR	Bull PR	Bull NOT PR	Trades PR	Trades NOT PR
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0.017091454	0.131634183	0.025412294	0.299475262	0.058995502	0.431409295
04-ott	0.00862069	0.050974513	0.116941529	1.305547226	0.176536732	1.327736132
05-ott	0.074587706	0.282083958	0.033583208	0.461394303	0.121364318	0.873463268
06-ott	0.00862069	0.183133433	0.033583208	0.483583208	0.058995502	0.731634183
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0.042803598	0.236581709	0.033583208	0.419190405	0.074587706	0.773913043
10-ott	0.042803598	0.057196402	0.025412294	0.607721139	0.066866567	0.745727136
11-ott	0.00862069	0.200524738	0.183808096	0.71994003	0.260494753	1.20862069
12-ott	0.215517241	0.228785607	0.033583208	0.547526237	0.246101949	0.884857571
13-ott	0.058995502	0.253973013	0.025412294	0.543028486	0.116941529	0.818590705
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.041604198	0.276761619	0.017091454	0.334257871	0.074587706	0.704272864
17-ott	0.00862069	0.213493253	0.074587706	0.375637181	0.082158921	0.652098951
18-ott	0.025412294	0.08958021	0.041604198	0.224587706	0.064767616	0.354047976
19-ott	0	0.049475262	0.101649175	0.194002999	0.101649175	0.300449775
20-ott	0.00862069	0.096851574	0.064767616	0.349325337	0.08958021	0.581109445
21-ott	0	0	0	0	0	0
22-ott	0	0	0	0	0	0
23-ott	0.00862069	0.049475262	0.033583208	0.375412294	0.058995502	0.483058471
24-ott	0	0	0	0	0	0

25-ott	0	0	0	0	0	0
26-ott	0.050974513	0.539430285	0.082158921	0.431409295	0.128335832	1.68958021
27-ott	0.017091454	0.204722639	0.017091454	0.358245877	0.033583208	0.612593703
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	0.00862069	0.117766117	0.00862069	0.190329835	0.017091454	0.323238381
31-ott	0.00862069	0.096851574	0.042803598	0.247301349	0.050974513	0.361844078
average	0.031230813	0.159966445	0.04739416	0.403234097	0.089648033	0.65991647

Table 3.f – Options

VARIANCE BS

	Bear PR	Bear NOTPR	Bull PR	Bull NOT PR	Trades PR	Trades NOT PR
01-ott	0	0	0	0	0	0
02-ott	0	0	0	0	0	0
03-ott	0	0.017091454	0.017091454	0.057196402	0.017091454	0.072188906
04-ott	0.017091454	0.017091454	0.00862069	0.041604198	0.025412294	0.074587706
05-ott	0.00862069	0.033583208	0.00862069	0.033583208	0.017091454	0.064767616
06-ott	0.00862069	0.074587706	0.00862069	0.082158921	0.017091454	0.217916042
07-ott	0	0	0	0	0	0
08-ott	0	0	0	0	0	0
09-ott	0.033583208	0.017091454	0	0.017091454	0.033583208	0.033583208
10-ott	0.017091454	0.017091454	0.017091454	0.033583208	0.033583208	0.049475262
11-ott	0	0.033583208	0.00862069	0.017091454	0.00862069	0.049475262
12-ott	0	0.064767616	0	0.07946027	0	0.132233883
13-ott	0	0.041604198	0.00862069	0.033583208	0.00862069	0.08958021
14-ott	0	0	0	0	0	0
15-ott	0	0	0	0	0	0
16-ott	0.00862069	0.041604198	0.00862069	0.066866567	0.017091454	0.138755622
17-ott	0	0.00862069	0	0.057196402	0	0.082158921
18-ott	0.017091454	0.025412294	0	0.033583208	0.017091454	0.057196402
19-ott	0.017091454	0.017091454	0.017091454	0.064767616	0.050974513	0.114242879
20-ott	0	0.058995502	0	0.064767616	0	0.16994003
21-ott	0	0	0	0	0	0
22-ott	0	0	0	0	0	0
23-ott	0	0.025412294	0	0.058995502	0	0.099550225
24-ott	0	0	0	0	0	0
25-ott	0	0	0	0	0	0
26-ott	0.00862069	0.530734633	0.00862069	0.334857571	0.034482759	1.500074963
27-ott	0	0.033583208	0	0.08958021	0	0.117766117
28-ott	0	0	0	0	0	0
29-ott	0	0	0	0	0	0
30-ott	0	0.041604198	0	0.049475262	0	0.103973013
31-ott	0	0.041604198	0	0.049475262	0	0.103973013
average	0.006496752	0.054340687	0.0053152	0.060234169	0.013368316	0.155782823

Bibliography

Bikhchandani, S. & Sharma, S. (2001) Herd behavior in financial markets, *IMF Staff Papers*, Vol. 47, No. 3, Pp. 279-310

Bikhchandani, S. Hirshleifer, D. & Ivo Welch (1992) A theory of fads, fashion, custom and cultural change as informational cascades, *The Journal of Political Economy*, Vol. 100, No. 5, pp. 992-1026

Borensztein, E. & Gelos, G. (2000) A panic-prone pack? The behavior of emerging markets and mutual funds. International Monetary Fund Working Paper Vol. 50, Issue 1, Washington

Cote, J. & Sanders D. (1997) Herding behavior: explanations and implications, *Behavioral Research in Accounting*, Vol. 9, pp. 20-45

Devenow, A. & Welch, I. (1996) Rational herding in financial economics, *European Economic Review* No. 40, pp 603-615

Drehmann, M. Oechssler, J. & Roider A. (2005) Herding and contrarian behavior in Financial markets: an Internet experiment, *The American Economic Review*, pp. 1403-pp.1426

Grinblatt, M. Titman S. & Wermers R. (1995) Momentum investment strategies, portfolio performance and herding: a study of mutual fund behavior, American Economic Review, 85, pp 1088-1105

Henker, J. Henker, T. & Mitsios Anna (2003) Do investors herd intraday in the Australian equities market? University of New South Wales, Sydney, Australia, Retrieved June 30, 2007, from http://wwwdocs.fce.unsw.edu.au/banking/workpap/wp%2009%202004.pdf

Hwang, S. & Salmon, M. (2001) A new measure of herding and empirical evidence. Retrieved June 30, 2007, from http://www2.warwick.ac.uk/fac/soc/wbs/research/wfri/wpaperseries/wp01-03.pdf

Keller, G. & Warrack, B. (2003) Statistics for Management and Economics, Brooks/Cole, Thomson Learning, Pacific Grove

Lakonishok, J. Shleifer, A. & Vishny R. W. (1992) The impact of institutional trading on stocks prices, Journal of Financial Economics, No. 312, pp. 23-43

Metzger, W. J. (2002) Statistical Methods in Data Analysis, Experimental High Energy Physics Group, HEN-343, Faculteit der Natuurwetenschappen, Wiskunde en Informatica

Ozsoylev, H. N. (2003) Knowking thy neighbor: rational expectations and social interaction in financial markets. Retrieved June 12 2007 from http://cf.uba.uva.nl/nl/handl/googlescholar/

Patterson, D. & Sharma V. (2006) Do *traders follow other traders at the NYSE*? Retrieved June 30, 2007, from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=712401

Welch, I. (2000) Herding among security analysts, Journal of Financial Economics, 58, 369-396

Wermers, R. (1999) Mutual fund trading and impact on stock prices, Journal of Finance, Vol. 2, 54, pp. 581-622