Stock Splits and Informational-based Herding

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Abstract

This paper investigates the relation between institutional herding and stock splits. We use data on buying and selling activity of US institutional investors, from 1994 to 2005. We compute the abnormal correlation of trades among institutional investors in companies that have announced a stock split, compared to nonsplitting firms. The results show a significant level of convergence of behavior, adjusted for common market factors, in both samples. Decomposing the correlation of trades into the contributions of several types of herding, we find significant impact of informational-based herding for splitting companies. The latter also motivates the difference between the two groups. We also observe herding has a significant stabilizing effect on the future returns of splitting companies. These results are consistent with an informational-based hypothesis of stock splits.

Keywords: Herding, Institutional investors, Stock Splits, Informational Herding.

JEL codes: G11, G14, G20.

1 Introduction

Herding among institutional investors is a delicate phenomenon in financial markets. Particular attention focuses on any potential destabilizing effect of imitative behavior on stock prices. The literature on herding is flourishing with multiple theoretical approaches, often theorized within fully rational setups. However it is still a challenge to reconcile the theoretical literature with its empirical investigation.

Therefore, this paper addresses institutional herding in the specific occurrence of a stock split. Stock splits are a long-investigated but still puzzling phenomenon in the financial markets. Despite their purely "cosmetic" effects on companies, there are mixed evidence of underreaction following its announcement and occurrence (Lakonishok and Vermaelen, 1986, Ikenberry and Ramnath, 2002), and doubts over whether there is and what is the information content the market react to.

There are three main contributions of this paper to both the literature on splits and on herding. It is aim of this paper to investigate whether there is a link between the two phenomena and whether herding has an impact on the abnormal market reaction to the announcement of a stock split. We investigate whether companies that announce stock splits exhibit a systematic abnormal level of herding with respect to the rest of the market. Then, the intensity of the phenomenon could help to explain the abnormal performance observed in the event window around the announcement.

Moreover, this study brings light on the debate between informational or liquidity motivations to split. A second aim of the study is in fact to bring a new understanding on the presence of an information content in the stock splits. However, what is the information content that drives the market at the announcement of stock splits is still a debatable question. Among the many theories on stock splits, a positive reaction of the market at the announcement of a stock split is consistent with good news incorporated in the event. The Signalling hypothesis posits that managers aim to convey favorable private information about the future performance of a company, given costs to false signalling. According to the Attention Hypothesis, splitting companies are underestimated by the market and splits will function to attract the attention of analysts on future good prospects of the companies. Moreover, the Self-selection hypothesis is consistent with a biased underreaction as managers communicate to the market their optimist about future performance of their companies. Else than estimating the abnormal market reaction around the event, some recent literature tries to empirically investigate an information component looking at, for example, changes in the bid-ask spread decomposition (Desai, Nimalendran, and Venkataraman, 1998) , or at the presence of a derivatives market (Chan, Li, and Lin, 2012).

Linking to the empirical evidence of underreaction to stock splits, an abnormal level of herding could accelerate a reaction to the event. The presence of a destabilizing imitative behavior could worsen suboptimal decisions in the functioning of the markets and in the announcement reaction, moving the prices astray even in the absence of information. A stabilizing form of herd behavior, on the other hand, would help prices to aggregate more quickly any informational content that is driven by this event.

From our results, we show a highly significant level of herding in all samples, still only a negligible level of herding among splitting stocks is on average abnormal compared to the rest of the market. However, distinctively from the rest of the market, herding on splitting companies appear to be triggered by informational motivations. Moreover it has a significant stabilizing effect on the future prices of such companies, consistently with both the theoretical literature on herding and the empirical literature on the biased market reaction to splits. In particular, according to the information cascades model developed by Avery and Zemsky (1998), when the market is uncertain about whether the value of the stock has changed from expectations, herding can arise. Moreover, if we add uncertainty on the average accuracy of traders' information, herding can also cause mispricing effects.

The analysis proceeds in these steps. First, we estimate the level of institutional herding among professional investors both in the overall market and in a subsample of companies that have announced at least one stock split in the quarter. The main data for the analysis are stocks holdings of US institutional investors, from 1994 to 2005. We estimate institutional herding as the correlation between trades among financial institutions over two consecutive periods of time (as Sias, 2004). Then, we propose an analysis of the motivations of this behavior according to the theoretical literature. In particular, we explain the difference in crowding between spitting and nonsplitting companies at the light of informational versus liquidity motivations to herd. Finally, we control the estimated measure for a set of factors that, we assume, imply a nonvoluntary correlation and we investigate the stabilizing effect of herding on splitting stocks.

The starting point in the measurement of the convergence of behavior among institutions is the methodology developed by Sias (2004), estimating the intertemporal correlation of the institutional demand. In the presence of herding, the trading actions observed in the previous period will help to explain this period's decisions. We find that the first order serial correlations of the fraction of investors buying the stock are always positive and highly significant in any period.[1] The phenomenon is particularly intense between 1998 and 2001. Restricting the analysis to splitting stocks, we observe at first a negligible difference on average on the herding coefficients over the all period with respect to the nonsplitting sample. However, when we clean our measures for the effect of passive strategies, splitting stocks exhibit significantly higher herding.

In fact, we perform a further analysis in order to account for the influence of factors other than intentional herding.[2] If investors are exposed to similar market conditions, passive trading strategies and correlated information, they could exhibit clustered, but nonvoluntary behavior. We choose to factor out the effect of fundamentals and common public information cleaning the estimated coefficients for the four factors of Carhart (1997): size, book-to-market, market return and momentum. Our empirical evidence shows that these factors are significant determinants of the institutional demand especially for nonsplitting companies, that appear to be more sensitive to market conditions. On the other hand, splitting companies tend to be more actively traded, and therefore herding is less affected by market factors than by intrinsic characteristics.

The variation across time brings also interesting comments. Investors tend to converge slightly more when they trade on splitting companies in the subperiod from 1994 to 2001. This result can be explained by the fact that, consistently with the literature, herding increases in period of crisis, but it increases more for nonsplitting companies. Splitting stocks exhibit a different herding behaviour, as investors do not appear to change the intensity of the imitative phenomenon on these stocks during crisis. This variation over time motivates additional analysis, that brings better results on the difference in herding, especially in terms of informational content of the event.

Thence, the next part of the analysis aims to investigate the motivations behind the observed level of potential herding and the difference between splitting and nonsplitting stocks. We impose and test specific assumptions for four theoretical models of herding, with particular attention on informational-based herding.[3]

[1] As a robustness check, we also use the methodology proposed by Lakonishov, Shleifer and Vishny (1992) that measures the convergent behavior in trading over the same period of time. The results confirm the presence of a correlation among investors decisions.

[2] A challenge in the empirical literature on herding is to clean the measure of clustering and extrapolate the willingness of the individuals to includes others' decisions in their evaluation process. One solution is to factor out the variables that could affect systematically the decisions of all the agents (Lakonishok, Shleifer, and Vishny, 1992).

[3] We propose to use also different sets of variables to identify the presence of specific types of herding. It is an attempt to reach conclusions as accurate as possible on informational herding versus feedback strategies herding. However, it is not an entirely clean test, as both the four different types of herding and the sets of variables used are not completely disjoint one another. The fact, however, that we are comparing two distinct groups, splitting and nonsplitting companies, and that the interest of the analysis is mostly on the difference between groups, could mitigate these limitations. Both samples share the same difficulties and lack of data, therefore we concentrate in extrapolating any interesting difference between the two categories of stocks.

Informational-based herding can arise among Bayesian agents who face decisions in uncertain environments when they rationally ignore their noisy and imperfect private information. We therefore test empirically for the presence of informational-based herding, in the form of informational cascades (Bikhchandani, Hirshleifer, and Welch, 1992, Avery and Zemsky, 1998) and reputational herding (Scharfstein and Stein, 1990, Dasgupta, Prat, and Verardo, 2011b), looking at market or company conditions for imperfect information (Wermers, 1999, Chan, Hwang, Mian, and Mian, 2005). We proxy for critical information using small market capitalization, high dispersion of analysts' forecasts and low analysts' coverage. Our results confirm the presence of informational-based herding, especially for the splitting companies. In particular we see that the difference in herding between splitting and nonsplitting companies is explained predominantly by the dispersion of beliefs among analysts. Once we account for informational factors, the control group exhibits a much higher and strongly significant level of unexplained herding than splitting firms.

We, then, look more carefully to distinguish career and reputation concerns from informational cascades. Noisy environments can also induce rational managers to mimic the investment decisions of other managers in order to maximize their reputations (Scharfstein and Stein, 1990). According to Dasgupta, Prat, and Verardo (2011a), it is more likely to observe reputational herding by independent advisors and investment companies. Therefore, we look at different institutional types and size-groups and the correlation of their trades within the peer group or extra group.[4] We observe a high level of herding inter-group, positively correlated with the size of the investor. In particular, the correlation of behavior is higher for big investors, where we assume reputational concerns are more binding. They also tend to herd more on splitting stocks, while small investors tend to cluster more easily around nonsplitting companies.

Informational-based herding however does not explain all of the correlation, especially for the nonsplitting group. We test therefore for other motivations, such as positive-feedback strategies in the forms of characteristic herding (Falkenstein, 1996, Gompers and Metrick, 2001) and momentum strategies (Bennett, Sias, and Starks, 2003, Grinblatt, Titman, and Wermers, 1995, Wermers, 1999).

According to the former, investors collectively trade the same firms because they are attracted by the same company characteristics. Gompers and Metrick (2001) find evidence that the institutional demand is positively correlated to the liquidity of the stock, size, book-to-market, S&P membership and volatility. Instead, institutional investors tend to avoid investing in stocks with high past returns and high dividends. Regressing the institutional demand on its lag, interacted with the above regressors, we find that those variables have a significant impact on herding on nonsplitting companies. Higher convergence of trades happens around large, more liquid stocks with low past returns stocks.

A specific case of positive feedback strategies is momentum trading, when investors buy stocks with high past returns and vice-versa. Evidence comes from the relation between demand of stocks and past returns (Sias, 2007, Bennett, Sias, and Starks, 2003 and Hong and Stein, 1999). We find that momentum herding has a stronger effect on imitative behavior for nonsplitting companies, as it impacts negatively on the difference in herding between splitting and nonsplitting companies.[5]

[4] Moreover, Scharfstein and Stein (1990), show that reputational concerns are more binding for stable stocks. Therefore, we alternatively look at stable stocks to give an indication of the presence of reputational concerns, proxied by big companies with high coverage from analysts.

[5] A recent work by Green and Hwang (2009) connects the reason to split with a particular form of herding, such as style investing (Barberis and Shleifer, 2003). The authors consider how the market is attentive to the nominal price, therefore investors categorize stocks according to their price. This price-categorization could be one of the possible reason for managers to split their stocks. In our work, we consider a wider spectrum of reasons to herd as

The final step of the analysis is a test of the effect of herding on the future returns of companies. We observe that the imitative behavior for splitting stocks has a strong stabilizing effect on future returns. This result confirms the presence of an informational content in the announcement of the event, which the market reacts to. This is evidenced by the positive relation between institutional demand and consecutive two quarterly returns. Conversely, herding on the overall market and for nonsplitting companies does not have any significant impact on future returns.

Yet, a significant part of the correlation among investors and of the difference between the subsamples is still not explained by these four types, suggesting that further studies can be carried out to better understand other motivations to the phenomenon.

The remainder of this paper ensures as follows. Section 2 describes the methodology we use to detect, measure and motivate herding in our samples. Section 3 describes the data and discusses the main empirical results, whereas Section 4 reports the results of the robustness checks. Section 5 concludes offering some final remarks.

2 Measuring herding

For the empirical verification of herding among institutional investors, we start with the methodology proposed by Sias (2004), and we will improve it afterwards. It consists in estimating the potential level of herding in quarter t as the correlation across companies between the standardized fraction of buyers of stock i in the quarter t on the analogous proportion in the previous period $t-1$:

$$\Delta_{i,t} = \beta_t \Delta_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

where: $\Delta_{i,t} = (P_{i,t} - \overline{P}_t)/\sigma_t$ is the standardized institutional demand for stock i at quarter t; $P_{i,t}$ is the fraction of institutional buyers of stock i at time t; $\overline{P}_t$ and σ_t are the mean and standard deviation in quarter t of the proportions $P_{i,t}$ across companies.

A positive coefficient β_t is consistent with investors following the past aggregate behavior of all the institutions in the market, whereas a negative coefficient implies contrarian behavior. We call this the "Sias' beta" throughout the paper.

We estimate first of all the betas on the overall sample. Then, we replicate the quarterly estimations in each of the two subsamples of splitting and nonsplitting stocks. The institutional demand for splitting (nonsplitting) companies is regressed on the lag demand for all stocks, estimating what we call "general herding", $\beta_t^{(S)}$ ($\beta_t^{(NS)}$). For splitting companies:

$$\Delta_{i,t}^{(S)} = \beta_t^{(S)} \Delta_{i,t-1} + \varepsilon_{i,t}^{(S)} \; i \in S \tag{2}$$

and analogously for the alternative sample:

$$\Delta_{i,t}^{(NS)} = \beta_t^{(NS)} \Delta_{i,t-1} + \varepsilon_{i,t}^{(NS)} \; i \in NS \tag{3}$$

Then, we test the equality of the betas in the two groups.

informational-based and characteristics-based. Price categorization would enter in this latter class, as institutional investors tend to comove towards stocks with higher prices.

As a robustness check, we investigate the difference in herding using a model specification with a binary variable $\delta^S_{i,t}$, interacted with the lag institutional demand. The dummy $\delta^S_{i,t}$ assumes value 1 if the company has announced at least one stock split in the quarter of interest. We regress, thence, the standardized fractions of buyers in period t on the fraction at end-of-quarter $(t-1)$ and on the interacted dummy, as:

$$\Delta_{i,t} = \beta_{0,t}\Delta_{i,t-1} + \beta_{1,t}\delta^S_{i,t}\Delta_{i,t-1} + \epsilon_{i,t} \tag{4}$$

A significant coefficient $\beta_{1,t}$ of the splitting dummy $\delta^S_{i,t}\Delta_{i,t-1}$ represents a significant difference in herding for splitting stocks when compared to the rest of the market.[6]

2.1 Intentional herding

A first issue arises when we consider that the Sias' beta does not provide indication on the intentionality of the imitative behavior. One delicate point for the empirical investigation of herding is, in fact, to distinguish unintentional comovements in the buying and selling decisions due to correlated or fundamental-driven signals.

Therefore, we assume that the determinants of non-intentionally correlated decisions are the market factors as Carhart (1997) (size, book-to-market, market return and one-year momentum factor). We assume they proxy for passive strategies and portfolio changes driven by variations on the fundamental characteristics of the market.

Thus, we estimate a measure of herding "conditional on the market conditions", across companies, regressing the previously estimated betas on the four market factors:

$$\beta_t = \alpha + \gamma_M R_{Mt} + \gamma_{HML} HML_t + \gamma_{SMB} SMB_t + \gamma_{MOM} MOM_t + \epsilon_t \tag{5}$$

where R_{Mt}, HML_t, SMB_t and MOM_t are the returns on value-weighted zero-investment factors that mimic portfolios for, respectively, book-to-market, company size, market returns and momentum, in quarter t.

The coefficients of the factors indicate the loading of the total beta ("Sias' beta") that is attributable to fundamental-driven clustering. While $\widetilde{\beta_t} = (\alpha + \epsilon_t)$ corresponds to the clean measure of intentional beta for the quarter t, that we call "beta adjusted".

As previously, we distinguish between splitting stocks and nonsplitting stocks and regress the model separately in the two samples, respectively:

$$\beta^{(S)}_t = \alpha^{(S)} + \gamma^{(S)}_M R_{Mt} + \gamma^{(S)}_{HML} HML_t + \gamma^{(S)}_{SMB} SMB_t + \gamma^{(S)}_{MOM} MOM_t + \epsilon^S_t \tag{6}$$

and

$$\beta^{(NS)}_t = \alpha^{(NS)} + \gamma^{(NS)}_M R_{Mt} + \gamma^{(NS)}_{HML} HML_t + \gamma^{(NS)}_{SMB} SMB_t + \gamma^{(NS)}_{MOM} MOM_t + \epsilon^{NS}_t \tag{7}$$

[6] For a better understanding, we perform all the analysis in subsamples according to the number of traders, Trd_{it}. We restrict the sample to the securities with at least 10, 20, 50 or 100 traders per quarter respectively. This is an additional test to consider if the securities with too few traders could drive away the results from the true values. Moreover, it homogenizes the samples for the number of investors trading in the company at time t. In Sias (2004), the results of this additional test show that in the group of securities with at least 5 investors, the coefficients are even stronger, while in the other subgroups the number of investors per security does not alter the previous results. In our sample, we already select only stock-quarters with at least three traders.

2.2 Testing for herding motivations

The next step of the analysis is to motivate herding and the difference between splitting and control stocks in the light of the theoretical literature.

We distinguish informational-based theories, such as informational cascades and reputational herding, and positive-feedback theories, such as characteristic herding and momentum trading.[7]

2.2.1 Informational-based herding

Both informational cascades and reputational herding models are based on the underlying hypothesis of partially noisy private signals. Therefore, we consider triggering conditions for noisy information such as small market capitalization, high dispersion of beliefs and low analysts' coverage. The first two following conjectures will detect informational-based herding of any kind, the third conjecture will instead distinguish a reputational component.

Conjecture 1 *In the presence of informational based herding, we expect herding to be higher for small stocks than for big stocks. This difference between small and big companies will detect both informational cascades and reputational concerns.*

This conjecture is consistent with much of the empirical literature, such as Grinblatt, Titman, and Wermers (1995) and Wermers (1999).[8]

Conjecture 2 *In the presence of informational based herding, we expect herding to be higher when the dispersion of beliefs among analysts is higher.*

This conjecture is consistent with the evidence from Chan, Hwang, Mian, and Mian (2005) among individual and institutional investors.

We consider analysts' coverage as a proxy for the public information available to the market. We assume that the higher the public information, the lower weight investors put on their own private signals and, in particular, the higher reputational concerns will be. To account for the effect of reputational herding, we consider the effect of coverage in inter-size groups.

Conjecture 3 *Coverage and the difference in inter-size groups between low and high analyst coverage can detect reputational concerns, as higher when more public information is available to the market.*

This conjecture is consistent with Scharfstein and Stein (1990), for whom, stable stocks are more likely to raise reputational concerns.

In order to model conjectures 1, 2, and 3, we model the Sias' beta as a function of $\mathbf{X}_{i,t-1}$, the matrix of C companies characteristics proxies for informational-based herding:

$$\Delta_{i,t} = \beta_t(\mathbf{X}_{i,t-1})\Delta_{i,t-1} + \epsilon_{i,t} \tag{8}$$

[7] At first, we consider separately each type. Later, a unifying model is constructed in order to distinguish simultaneously the impact of all the above types.

[8] On the contrary, a positive relation between size and herding will confirm the presence of correlated behavior which is caused only as a result of correlated signals received by the investors (Sias, 2004, Hirshleifer, Subrahmanyam, and Titman, 1994).

X_{t-1} includes: $size_{i,t-1}$, measured as the market capitalization of stock i in the quarter $t-1$; $dispersion_{i,t-1}$, as the ratio between the standard deviation of the earnings' forecasts and the standard error of the mean of these estimates, measured in the previous quarter $t-1$; $coverage_{i,t-1}$, as the number of analysts that have published at least a forecast on the company i in $t-1$; and $(coverage * size)_{i,t-1}$, as the number of analysts following the company in the previous quarter among the same size group.

Therefore, we regress the institutional demand on its lag, decomposing the total beta between the effect from the information quality proxies, $X_{i,t-1}$ and other factors:

$$\Delta_{i,t} = \beta_{NIH,t}\Delta_{i,t-1} + \sum_{c=1}^{C} \varphi_{c,t} X_{c,i,t-1}\Delta_{i,t-1} + \epsilon_{i,t} \tag{9}$$

The coefficients $\varphi_{k,t}$ are catching the effect of informational-based herding, in the form of informational cascades ($\varphi_{size,t}$, $\varphi_{dispersion,t}$ and $\varphi_{coverage,t}$) and reputational herding ($\varphi_{coverage*size,t}$).

$\beta_{NIH,t}$ represents the remaining part of the total beta that cannot be attributed to informational contents.

An alternative test for reputational herding is the analysis per type and size of the investor portfolio. We expect reputational concerns to be more relevant when investors share the same trading strategies, the same clients and especially are subject to the same benchmark evaluation. Therefore, we distinguish between convergence of behavior among peer members of the same group, and overall convergence.

Conjecture 4 *In case of reputational concerns, herding between investors belonging to the same class type will be considerably higher compared to the total clustering of decisions among all investors.*

In order to test conjecture 4, we run the analysis in subsamples according to the investor type, and for each group we estimate the betas inter-type and extra-type, respectively "peer herding" and "general herding".

"Peer herding" is detected by $\beta_t^{(p,T)}$, that represents the coefficient between the institutional demand of type T with the past demand of peer investors belonging to the same type T:

$$\Delta_{i,t}^{(T)} = \beta_{0,t}^{(p,T)}\Delta_{i,t-1}^{(T)} + \beta_{1,t}^{(p,T)}\delta_{i,t}^{S}\Delta_{i,t-1}^{(T)} + \epsilon_{i,t}^{(T)} \tag{10}$$

"General herding" is instead represented by $\beta_t^{(T)}$, as the correlation between the demand of investor T with the past demand of all institutions of any type.

$$\Delta_{i,t}^{(T)} = \beta_{0,t}^{(T)}\Delta_{i,t-1} + \beta_{1,t}^{(T)}\delta_{i,t}^{S}\Delta_{i,t-1} + \epsilon_{i,t}^{(T)} \tag{11}$$

Similarly, the size of the investors could give information on the importance of reputational concerns (Lobão and Serra, 2002).

Conjecture 5 *If reputational herding is present, the correlation between trades of investors belonging to the same size class will be considerably higher compared to the clustering of decisions among all investors. In particular, bigger investors will be more reputationally concerned than smaller investors.*

In order to test for Conjecture 5, we identify peer groups according to the size of the fund. Hence, we classify three groups, small, medium and large institutions according to the value of their portfolio and we reallocate the groups at the end of every quarter. The value of the portfolio of manager n is computed as the market value of all the stocks held in his portfolio in quarter t. As previously, we distinguish the correlation with the peer members of the same size class, $\beta_t^{(p,Sz)}$, and the correlation with any other institution, $\beta_t^{(Sz)}$:

$$\Delta_{i,t}^{(Sz)} = \beta_{0,t}^{(p,Sz)}\Delta_{i,t-1}^{(Sz)} + \beta_{1,t}^{(p,Sz)}\delta_{i,t}^{S}\Delta_{i,t-1}^{(Sz)} + \epsilon_{i,t}^{(Sz)} \tag{12}$$

and

$$\Delta_{i,t}^{(Sz)} = \beta_{0,t}^{(Sz)}\Delta_{i,t-1} + \beta_{1,t}^{(Sz)}\delta_{i,t}^{S}\Delta_{i,t-1} + \epsilon_{i,t}^{(Sz)} \tag{13}$$

Looking at the difference for splitting and nonsplitting companies, we test for the following conjecture.

Conjecture 6 *We expect the level of herding due to informational content to be higher for splitting stocks than for the alternative group.*

Conjecture 6 is consistent with both the theory of Avery and Zemsky (1998) and the empirical evidence of underreaction of the market to the announcement of this event (Ikenberry and Ramnath, 2002).

Finally, all the estimated coefficients are then adjusted with the Carhart factors.

2.2.2 Characteristic-based herding

Gompers and Metrick (2001) consider the impact of three main variables on the institution's demand for stocks: prudence or regulations, liquidity of the stocks and the historical returns pattern. In order to isolate the total level of herding by characteristic herding, we control for these variables which mirror the stock characteristics relevant for institutional investors. In particular, we use annual cash dividends per quarter and volatility of the stock as proxies for prudence; market capitalization, price per share and share turnover, for liquidity; and the returns over the previous year, for the historical pattern of returns.

Conjecture 7 *If the beta is due to characteristics preference, the relation between institutional demand and its lag is significantly explained by the variables in Gompers and Metrick (2001). In particular, we expect herding to be positively correlated with size, price, turnover and volatility, and negatively correlated with past returns and cash dividends.*

In order to test for this Conjecture 7, the total beta is modeled as a function of $\mathbf{Z}_{i,t-1}$:

$$\Delta_{i,t} = \beta_t(\mathbf{Z}_{i,t-1})\Delta_{i,t-1} + \epsilon_t \tag{14}$$

where $\mathbf{Z}_{i,t}$ is the vector of the Q characteristics that affect the institutional demand: $dividends_{i,t}$, $volatility_{i,t}$, $size_{i,t}$, $price_{i,t}$, $turnover_{i,t}$, and $momentum_{i,t}$ (as past year returns)

Hence, we regress the institutional demand on its lag, decomposing the relation between the effect of the characteristics of the company i at the quarter $t-1$ and other factors:

$$\Delta_{i,t} = \beta_{NCH,t}\Delta_{i,t-1} + \sum_{q=1}^{Q} \psi_{q,t} Z_{q,i,t-1}\Delta_{i,t-1} + \epsilon_t \tag{15}$$

where: ψ_t is the vector of coefficients of the Q company characteristics, and $\beta_{NCH,t}$ is the remaining part of the Sias' beta that is not attributable to characteristics preference among investors.

We then analyze the impact of the equity ownership and the characteristic herding on the splits and control subsamples.

As before, the estimated betas $\beta_{NCH,t}$ so estimated are then adjusted for the Carhart factors.

2.2.3 Momentum herding

Institutional investors could also herd because they are momentum traders. If investors use momentum strategies, they would tend to buy the same stocks with past high returns and sell the same stocks with past poor performance. The presence of momentum can be seen in the positive relation between the demand for stocks of quarter t and the past returns of the stocks. Thus, we take into consideration the possibility of a confounding effect in the beta coefficient, which comes from the fact that the past demand proxies last quarter returns if there is momentum among investors (Sias, 2004).

Conjecture 8 *If herding is due to momentum trading, the relation between institutional demand and its lag would be explained by the past quarter's returns. Higher past returns would explain higher correlation among investors.*

Following Sias (2007) freely, we model Conjecture 8 decomposing the total correlation between the past returns effect and other factors, adding the lag returns interacted with the lag demand, as:

$$\Delta_{i,t} = \beta_{NMT,t}\Delta_{i,t-1} + \rho_t R_{i,t-1}\Delta_{i,t-1} + \epsilon_{i,t} \tag{16}$$

Therefore, $\beta_{NMT,t}$ is the remaining part of the correlation not explainable by momentum trading.

We replicate the analysis for splitting and nonsplitting companies, and the betas $\beta_{NMT,t}$ are then again adjusted for the Carhart factors.

2.2.4 The unifying model

Finally, we construct a model that simultaneously distinguishes the impact of the four different herding motivations and their effects on splitting and nonsplitting companies.

We model the total beta from Sias as a function of all the previously stated explanatory variables:

$$\beta_t = f(\mathbf{X}_{i,t-1}, \mathbf{Z}_{i,t-1}, R_{i,t-1}) \tag{17}$$

and we regress the following model:

$$\Delta_{i,t}= \beta_{0,t}\Delta_{i,t-1}+\sum_{c=1}^{C}\varphi_{c,t}X_{p,i,t-1}\Delta_{i,t-1}+\sum_{q=1}^{Q}\psi_{q,t}Z_{q,i,t-1}\Delta_{i,t-1}+\rho_t R_{i,t-1}\Delta_{i,t-1}+\epsilon_{i,t} \tag{18}$$

The autocorrelation of the institutional demand is, thence, partitioned in three herding components. We recall that $X_{i,t-1}$ is the matrix of the variables that proxy for informational cascades (size, dispersion of beliefs and analysts coverage) and reputational herding (coverage*size). The coefficients $\varphi_{c,t}$ would detect any informational-based herding. $Z_{i,t-1}$ is the matrix of variables that affect the stock preference of institutional investors (size, price, turnover, standard deviation of returns and past year return). The coefficient $\psi_{q,t}$ accounts therefore for the effect of any characteristic-based herding. $R_{i,t-1}$ is the momentum factor, proxied by the returns in the previous quarter, and the estimated ρ_t represents that part of the total correlation due to momentum strategies.

Then, $\beta_{0,t}$ is the remaining part of the original correlation that cannot be explained by any of the theories we have considered so far. In order to attribute it to an intentional component, we clean it for the common factors that contribute to unintentional correlation, as:

$$\beta_{0,t} = \alpha_0 + \sum_{k=1}^{K}\gamma_k FF_{k,t} + \epsilon_{0,t} \tag{19}$$

where $\widetilde{\beta}_{0,t} = (\widetilde{\alpha}_0 + \widetilde{\epsilon}_{0,t})$ is the "beta adjusted" not explained by the theoretical types under examination.[9]

3 Empirical results

3.1 Data description

In order to investigate institutional herding, we use the Thompson Financial database to access data from the quarterly reports of US stock holdings by financial institutions over a twelve year period. The sample period goes from 1994 to 2005. We consider all types of professional investment companies and advisors who are asked to fill the 13F form according to the SEC regulations. Information about the companies, such as stock splits data, prices and capitalization, are extracted by the CRSP daily database and aggregated per quarter. Data about the dispersion on analysts' forecasts and analysts' coverage is extracted from the I/B/E/S monthly database and again aggregated per quarter.

The overall sample is composed of 1,760 companies, traded by 3,690 investors (Table 1). Other than the availability of data, we clean the sample considering: (i) any manager that holds at least one security for two consecutive quarters and (ii) any stock that has at least three investors trading it during the quarter. This sample represents the overall market, and the level of correlated decisions is our proxy for market herding.

We select two subsamples of splitting and nonsplitting stocks. We define a splitting stock if the company has announced at least one split in the quarter of analysis, according to the CRSP

[9] We need to take into consideration, however, that the splitting sample is, in some quarters, too limited in size for this specification to be reliable enough.

daily database.[10] We have 1,602 announced events by 890 companies, with 2.39 events on average per company. There are 3,252 investors holding at least one of these companies in their portfolios. Nonsplitting stocks are the remaining companies without any split announcements in the quarter.[11]

We discuss some descriptive statistics on investors and companies in the two subsamples of interest. Table 2 reports the average number of companies per investor (C_{nt}) and the average number of traders per company per quarter (Trd_{it}). Splitting stocks tend to have a higher average trading activity, compared to the more limited number of investors trading in nonsplitting stocks. In fact, splitting stocks have an average of nearly 184 investors trading them per quarter (against 147 for the alternative sample), representing 95% of the investors holding these stocks in their portfolios. This difference is consistent with the stock splits literature confirming the higher trading activities on stocks that decide to split.

We evince from this data that traders who invest in splitting stocks are on average bigger institutions, in terms of number of stocks traded in a quarter, C_{nt}. If a splitting company is included in their portfolio, investors tend to hold and trade in a higher number of stocks. We have on average 160 stocks in a portfolio that includes companies that announced stock splits in the quarter, compared to 127 in case of only nonsplitting companies. Moreover, the splitting sample is slightly more homogeneous than the alternative one, in terms of smaller standard deviation and a narrower range of C_{nt}.[12]

Table 3 provides more details of the average number of institutions trading. We classified the number of institutional investors in five types, defined as:

1. banks,
2. insurance companies,
3. investment companies,
4. independent investment advisors, and
5. other institutions, which includes foundations, university endowments, employee stock option plans, internally managed pension funds and individuals who invests others' money.

The Thompson Database classification of the institutional investors is not always precise, especially between investment companies and independent advisors after 1998. In fact, in 1998 two different databases were merged leading to a change in the classification scheme and a massive transition from types 1-4 to 5. Considering the residual nature of this class, we assume no real changes occur to type 5 after 1998 and we revert to the previous association as groups 1 to 4. Instead, we

[10] We consider only one split per quarter per company. Only two companies announced two splits in the same quarter in our database.

[11] The drawback of this definition is that we have a limited number of observations per quarter for the splitting companies' group. As shown in Table 1, we have on average 39 splits per quarter, ranging from a minimum level in the second half of 2002 and maximum in the second quarter of 1998. This distribution of events confirms the empirical literature that considers stock splits as a typical phenomenon of expansive phases.

[12] In unreported results, we have observed the same conclusions using the value of the portfolio held, instead of the number of stocks held.

keep as valid changes between types 1-4 or from 5 to any of the other classes. For new investors who entered the database after 1998 directly as class 5, we keep the observations as correct.[13]

We notice, as expected, a rise through the years in the number of institutions trading in the markets. This observation confirms the growing importance of these investors and the concerns around a change in the "representative investor" in modern markets. The average increase is primarily due to a strong rise in the number of independent advisors and in the residual category of "not defined".

3.2 Sias' beta

The first step in the analysis is the estimation of the autocorrelation coefficient between the standardized fraction of buyers of stock i at end of quarter t and the same fraction at the previous end of quarter $t-1$. We call this estimate the "Sias' beta". We first perform the regressions as in equations (1) for the overall sample, (2) and (3) for the splitting and nonsplitting samples respectively, in the 48 quarters from 1994 to 2005.

The estimated autocorrelations in the market are positive and statistically different from zero for all quarters. This result is consistent with the hypothesis that a level of herding exists in the trading decisions of institutional investors. Table 4 documents that the beta in the overall market is 0.457 on average across all the quarters, and it is highly significant, ranging from 0.346 in 2005 to 0.562 in 2000.

The results from the comparison between splitting and nonsplitting companies are more complex. Both samples exhibit a positive and significant high level of herding throughout the period. The difference in general herding, between splitting and nonsplitting is however negligible and not significant on average. The average estimated coefficient for general herding in the group of interest is very close (0.467) to the alternative sample (0.457), but more volatile across the quarters. However, even if the difference in means is not statistically significant, the median results are clearly higher for splitting companies (0.481 versus 0.448).

Interestingly though, investors tend to comove more on splitting companies in earlier years until 2001, as we can see graphically in Figure 1 (frame a). Yet, in the years after 2001, the trend seems reverted. [14]

This time pattern can be caused by market factors. Once we cleanse the coefficients from common factors that could affect the decision process of institutional investors we are able to approximately discriminate between intentional and unintentional herding. We regress the estimated Sias's betas on the four factors of Carhart (1997) measured quarterly, as equations (5) to (7).

Part b of Table 4 reports the average adjusted coefficients for the three samples. The factors are determinants of the herding phenomenon, but the average betas are still all considerably significant, and continue to represent almost all of the convergence of behavior. On average, the estimated adjusted beta is 0.448, as 98% of the total correlation measured by the average Sias' beta.

[13] This correction is similar in spirit to Sharma (2004) and Sias, Starks, and Titman (2001).

[14] We also investigate the phenomenon in more details, breaking the analysis into three subperiods of four years each: 1994-1997, 1998-2001 and 2002-2005. We observe that the highest level of herding occurs between 1998 and 2001, and the difference between splitting and nonsplitting companies widens and decreases in value through the subperiods. Splitting stocks exhibit higher herding in the first and second subperiods, while nonsplitting stocks have a higher level of correlated behavior in the third subperiod. The tests on the averages are however still not significant. These results are not reported.

The relative difference between splitting and nonsplitting stocks rises once we adjust for common factors, and the test on the means shows that the difference between the samples is significantly different from zero (at 10%). Splitting stocks exhibit a level of correlation that is even higher once adjusted (0.506), while the market factors seem to affect more the trading decisions on herd on nonsplitting companies (0.447). An explanation could be that nonsplitting stocks are more affected by passive strategies. Instead, when investors trade on stocks that have announced at least one event in the quarter, they act actively against the information content in common market factors. This observation could be affected either by the characteristics of splitting stocks, or by private informational content in the split. Therefore, the next part of the analysis aims at distinguishing between these two determinants of this variation over time.

3.3 The Theoretical types of herding

The next step is to examine the contributions of the different theoretical types of herding on the estimated correlation: informational cascades, reputational herding, characteristic herding and momentum trading. Table 5 reports the average estimated coefficients for the variables in the different models.

3.3.1 Informational-based herding

First at all, we check for the presence of informational-based herding (Table 5, model (1)). We recall that we regress the standardized fraction of institutions' buyers on its lag and on the set of variables which proxies for the quality of information available to the market. Thus, the estimated coefficient of the lag institutional demand now represents only that part of the correlation that cannot be explained with informational motivations. We call it the "Non-Informational beta" (Figure 1b).

The lag institutional demand coefficients are always positive and significant for the nonsplitting companies, with the exception of the dispersion of analysts' forecasts. When looking at the signs of the regressors, they do not confirm an informational type of herding, as conjectures 1 to 3, but rather a characteristic-based herding as we will discuss in the next section (part b of Table 5).

Results are different once we analyze splitting firms only (part a of Table 5). The remaining general level of herding is significantly positive only in 10 quarters out of 18, and the mean across quarters is not significant anymore. Therefore, most of the imitative behavior we have evinced for splitting stocks is captured by informational variables and consistent with our conjecture 6. The F tests on the four regressors provide evidence of the significance of these proxies in most of the quarters and the signs of the estimated coefficients confirm the informational conjectures 1 to 3. However, only dispersion of beliefs among analysts is significant at 5%, confirming the view that herding on splitting companies is due to a noisy informational environment and high disagreement in the market.

3.3.2 Characteristic-based and momentum herding

We subsequently test for the presence of other types of herding, especially in the nonsplitting sample (Table 5, model (2)). We check first for characteristic herding, using the proxies for characteristics preference, such as size, price, turnover for company at the end of quarter t-1, annual dividend per quarter and returns in the previous year.

The estimated coefficients of the institutional demand in the overall market will be that part of the Sias' correlation that remains after the attribution of characteristic-based herding (Figure 1c). Plotting them per quarter, we observe that they are positive and significant in 44 quarters for the nonsplitting sample. On average also they are still positive and highly significant, but smaller than both the average Sias' beta and the Non-Informational beta. This is consistent with the existence of characteristic-based herding, as already evinced in model 1. Company characteristics have a significant effect on convergence, the F tests on the regressors mainly reject the null of non-joint significance for all samples, and the signs of the coefficients are consistent with conjecture 7. Thus, we observe a tendency to herd towards large companies, with high price per share, high turnover and high dividends.

For splitting companies, the average remaining betas are still smaller than Sias's beta, however the results are weaker than informational-based herding. The remaining correlation for splitting firms is positive in most of the significant quarters (9 out of 10). The F tests show a joint significance of the regressors in explaining the convergence of behavior, however, only size has a significant and positive coefficient, while all the other variables have signs contrary to our expectations of characteristic-based herding and not significant.

The last type of herding we investigate is momentum trading (Table 5, model (3)). We extrapolate the effect of momentum strategies based on past returns (Figure 1d).

Momentum has a significant effect in the nonsplitting sample. The test on the average coefficient for past returns is strongly significant, confirming such impact. However, the momentum variable is not relevant for the splitting sample, as the past returns seem to be not a significant determinant of herding.

3.4 The stabilizing effect of herding

We conclude by analyzing whether herding has a stabilizing effect on the future performance of the stocks and whether this effect is different between splitting and nonsplitting companies.[15]

A negative relation between demand and subsequent returns will be consistent with a destabilizing effect on prices due to herding. Evidence of a destabilizing role of herding on future returns would confirm the presence of intentional imitative behavior such as irrational or positive feedback strategies. A reversal in the prices after the herding measurement period will be consistent with this hypothesis. Alternatively, either an intentional correlation due to informational motivations or a fundamental-driven correlation will bring the prices closely and quickly towards the true value, concluding for a stabilizing effect (Sias, 2004).

[15] Past literature exhibits a positive relation between institutional demand and same quarter or previous quarter returns and is weakly positive when correlated with future returns (see for example Nofsinger and Sias, 1999; Grinblatt, Titman, and Wermers, 1995 and Sias, 2004).

Therefore, we regress the institutional demand on returns measured in the past quarter, same quarter, and on the two consecutive quarters after the measurement period. The results are reported in Table 6.

Consistently with the literature, we observe a positive relationship between institutional demand and past quarter and same quarter returns for the overall market and for nonsplitting companies. We do not conclude for any similar relationship for the splitting companies.

However, we observe a positive and highly significant relation between institutional demand and returns in the two following quarters for splitting firms (0.3704 and 0.3692 respectively). This is strongly consistent with a stabilizing effect on prices for splitting companies due to herding. According to Sias (2004), such a positive relation is further evidence of the presence of informational-based herding.

3.5 Robustness checks

3.5.1 The splitting dummy model specification

We investigate the difference in herding between splitting and nonsplitting companies also employing another model specification that includes interacted binary variables $\delta^S_{i,t}$. Per each of the three previous models we include a set of dummies interacted with each of the regressors (Table 7).

The dummy coefficient on the lag institutional demand represents the difference in correlation that remains after checking for the theoretical types under analysis. On average, it is not significant and very small as the models were well specified and detecting the differences between splitting and nonsplitting herding, accounting for informational content, characteristics and momentum strategies.

Considering the difference in herding types, we look at the interacted dummies with the proxies for informational-, characteristics and momentum herding. We confirm the previous results, with significant dummy coefficients for dispersion among analysts, size and momentum. In particular, the results can be read confirming a predominance of informational herding for splitting companies, nonetheless there is also a significant and expected positive component of characteristic herding. However, momentum herding is clearly only supported for nonsplitting companies.

3.5.2 Peer-herding versus general-herding

In addition we test whether investing in splitting stocks could be considered as an investment style shared by the investors (as Barberis and Shleifer (2003)). If this is the case, institutions would imitate past trades in the same style more than the trades in all the companies. We therefore define "peer herding" as the correlation between the institutional demand for splitting stocks at time t on the demand for the same portfolio of splitting stocks at $t-1$. This definition distinguishes from the general level of herding we measured so far, as the correlation of the splitting institutional demand on the demand for all stocks in the previous period.

We have "peer herding" among splitting companies estimated as $\beta^{(S)}_{p,t}$ as:

$$\Delta^{(S)}_{i,t} = \beta^{(S)}_{p,t}\Delta^{(S)}_{i,t-1} + \epsilon^{(S)}_{i,t} \tag{20}$$

where S is the set of companies that had announced at least a split in the quarter t, for which stock $i \in S$.

$\Delta_{i,t}^{(S)}$ is computed from the mean and standard deviation of P_{it} among the group of splitting stocks, as: $\Delta_{i,t}^{(S)} = (P_{i,t}^{(S)} - \overline{P}_t^{(S)})/\sigma_t^{(S)}$. Analogously, $\Delta_{i,t-1}^{(S)}$ is computed on the same portfolio of splitting stocks in period $t-1$.

A corresponding definition applies to the nonsplitting companies. "Peer herding" among nonsplitting companies, for which $i \in NS$, is estimated as $\beta_{p,t}^{(NS)}$ as:

$$\Delta_{i,t}^{(NS)} = \beta_{p,t}^{(NS)} \Delta_{i,t-1}^{(NS)} + \epsilon_{i,t}^{(NS)} \tag{21}$$

The same distinction is carried out in all the previous models. Peer herding is computed respectively for informational-based herding, characteristic-based herding and momentum herding, as:

$$\Delta_{i,t}^{(S)} = \beta_{p,ICH,t}^{(S)} \Delta_{i,t-1}^{(S)} + \sum_{c=1}^{C} \varphi_{c,t}^{(S)} \mathbf{X}_{c,i,t-1} \Delta_{i,t-1}^{(S)} + \epsilon_t^{(S)},\ where\ i \in S \tag{22}$$

$$\Delta_{i,t}^{(S)} = \beta_{p,NCH,t}^{(S)} \Delta_{i,t-1}^{(S)} + \sum_{q=1}^{Q} \psi_{q,t}^{(S)} Z_{q,i,t-1} \Delta_{i,t-1}^{(S)} + \epsilon_t^{S},\ where\ i \in S \tag{23}$$

and

$$\Delta_{i,t}^{(S)} = \beta_{p,NMT,t}^{(S)} \Delta_{i,t-1}^{(S)} + \gamma_t^{(S)} R_{i,t-1} \Delta_{i,t-1}^{(S)} + \epsilon_{i,t}^{(S)},\ where\ i \in S \tag{24}$$

Analyzing the (unreported) results, we see that it does not add much understanding to the previous conclusions. Therefore, when trading in splitting stocks, investors observe the trades that happen in all the stocks in the market portfolio, without identifying splitting stocks as a specific investment style.

3.5.3 Analysis per type and size of the investor

Interesting results and significant differences in the two samples are arising from the analysis by type and size of the investors. We investigate the presence of reputational herding in more details looking at homogeneous groups of investors. We consider, as peers, investors either with the same portfolio size or belonging to the same institutional type. In each group separately, we regress the models specified with interacted dummy variables for splitting companies, distinguishing between herding inter-group ("peer-herding") or extra-group ("general herding").

Looking at the size of the investors, we classify three groups according to the value of the managed portfolio. We consider the presence of reputational herding examining both the difference between general and peer herding, and the difference between the restricted samples and the overall sample of investors. Table 8 and Figure 2c report the average coefficients.[16]

The average betas clearly increase with the size of the investor, confirming that bigger institutions herd more. For both large and small investors, a considerable part of the imitative behavior

[16] We restrain from considerations on the general level of herding, reporting the results only in regard to nonsplitting versus splitting stocks.

comes from "peer herding", as inter-group, therefore reputational considerations seem to be a plausible explanation. However, we also find that in any group, the estimated coefficients are smaller than the original beta estimates in the complete set of investors. This means that herding increases when we consider all the interactions among groups of investors, thus, there is a relevant part that cannot be explained by reputational concerns.

Looking at subperiods, the betas are only higher in the years from 1998 to 2001 for the largest investors. Therefore, the higher intensity of the herding phenomenon in the second subperiod seems to be driven by reputational concerns among big investors.

With regards to the difference between splitting and nonsplitting companies, big investors tend to herd more on splitting stocks, while small investors tend to cluster more easily around nonsplitting companies. In fact, the average estimated dummy coefficient is negative (-0.992) and significant for small investors, yet it is positive and significant on average for bigger institutions (0.0513).

This pattern could partly motivate the differences we observe in the three subperiods. In earlier years before 2002, the impact of bigger institutions is particularly strong and herding is slightly higher for splitting companies. The higher herding could then be due to reputational considerations among big investors. In the third period, the average negative difference could be mainly driven by small investors, who herd more intensively on the rest of the market.

We also carry out an analysis per type of investor (Table 9 and Figure 2d)). We see that the investors with the highest level of general correlation are banks and institutions belonging to the residual category of "not defined". Instead, for investment companies and independent advisors, most of the correlation is inter-group. This suggests that reputational considerations may be more binding for mutual funds than for banks.

Considering the dummy coefficients, the result shows a clear difference in the type of herding underlying the correlation. In particular, it reveals that reputational concerns are more binding for nonsplitting companies, as shown for example by the difference in intra-group versus extra-group herding for insurance companies.

Looking at the subperiods, then, we notice that the average results are dragged by the most recent years. In earlier years, insurance companies, investment companies and "not defined" investors show a higher and significant difference to herd on splitting companies. In the third subperiod instead we observe a reverted pattern. Four out of five institutional classes exhibit higher herding for nonsplitting companies.

Summarizing, we confirm the presence of reputational concerns, but it is not predominant over informational cascades. Banks tend to herd more on nonsplitting companies, especially in the third period. Investment companies are among the institutions that herd the least, but they are more influenced by their peer decisions and tend to herd substantially on splitting companies. Moreover, herding on splitting companies versus nonsplitting companies seems to be affected differently by reputational concerns in insurance companies and mutual funds. In particular, they seem to be particularly careful in observing their peers when trading nonsplitting companies.

4 Conclusions

With this empirical paper we aim to contribute to the understanding of stock splits and their market reaction, looking at the impact of herding, or correlated trading decisions, among institutional investors. We supported the presence of informational herding in trades on splitting stocks, providing the evidence that herding exists and it has a stabilizing effect on the future returns of the companies undertaking this event.

We have found evidence of positive and significant convergence of trades in each quarter of analysis. Also, cleaning for intentional behavior, we have found that most of the correlation is not attributable to the four factors, namely size, market return and book-to-market, that proxy for unintentional or spurious herding.

Distinguishing between herding in splitting and nonsplitting companies in the overall case, we do not evince a significant difference on average. However, the difference is positive and significant once we take into account for intentionality of behavior and the four market factors. It shows that splitting companies are less affected by market factors than the control group. Moreover, the difference in correlation decreases over time. We also observe that big companies and investment companies, insurance companies and the residual type are more inclined to herd on splitting companies.

Investigating the motivations to herd, we find evidence consistent with the presence of informational-based herding for splitting companies, and characteristics-based herding for the rest of the markets.

The presence of informational-based herding, especially for splitting companies, is also confirmed by observing the relation between institutional demand and future returns. The positive relation we find between institutional demand for splitting stocks and their future returns in the following two quarters is consistent with a stabilizing effect of herding. On the contrary, we do not report any significant relationship between institutional demand and future returns in the overall market.

In conclusion, our results are consistent with the presence of informational content in the split event and to the underreaction of the market. Still a significant part of the correlation among investors and of the difference between the subsamples is not explained by these four types, suggesting that further studies should be carried out to better understand other motivations to the phenomenon. Moreover, further development of this research will focus on investigating both the change in herding and its impact on the future performance of the company on the days around the announcement of stock splits.

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A Tables and Figures

Table 1: Sample and number of splits statistics

Number of Splits	1,602		
Number of Companies	1,760	*Number of Splitting companies*	890
Number of Investors	3,690		
Number of Splits per quarter		*Number of Splits per company*	
mean	39.05	mean	2.39
std. dev.	13.32	std. dev.	1.27
min	7	min	1
	(in 2002-3)		
max	65	max	8
	(in 1998-2)		
Q1	32	Q1	1
median	39	median	2
Q3	47	Q3	3

[a] This table reports some descriptive statistics on the sample and on the number of splits per quarter and per company, in the period 1994-2005. We consider a splitting company to be any firm that has announced at least one stock split in the quarter of analysis, subject to the availability of all the necessary data and with at least three traders per quarter.

Table 2: Quarterly Number of Companies Traded per Investor, and Number of Investors per Company

	Average number of companies traded, C_{nt}		Average number of active investors, Trd_{it}	
Year	Nonsplitting companies	Splitting companies	Nonsplitting companies	Splitting companies
1994	80.40	127.37	88.85	91.43
1995	86.34	119.85	95.05	119.32
1996	87.95	130.52	95.82	132.18
1997	96.55	132.19	107.58	129.99
1998	97.77	143.41	117.51	148.60
1999	116.24	150.86	129.02	198.36
2000	117.99	168.19	152.30	237.54
2001	111.86	221.00	160.39	235.74
2002	119.13	255.66	172.38	192.35
2003	159.53	180.73	184.77	169.82
2004	163.50	150.06	199.43	200.84
2005	157.04	173.10	205.73	214.12
Overall period	126.96	159.49	147.35	183.92
Mean	126.96	159.49	147.35	183.92
Std. dev.	219.69	214.35	154.51	173.11
Min	1	1	3	3
Max	1,495	1,459	1,327	1,229
Q1	24	45	53	76
Median	55	80	103	132
Q3	116	169	185	234

[b] This table reports, for splitting and for nonsplitting companies, the number of companies traded by institutional investor in a quarter, C_{nt}, and the number of institutions trading in a company per quarter, Trd_{it}. Computed per quarter, they are averaged per year or overall period. We also report some descriptive statistics of the two variables for the overall period, distinguishing the two subgroups. We recall that a splitting company to be any firm that has announced at least one stock split in the quarter of analysis, subject to the availability of all the necessary data and with at least 5 traders per quarter.

Table 3: Average Number of Investors per Institutional Type

Year	Banks	Insurance companies	Investment co. companies	Independent advisors	Not defined	All types
Splitting stocks						
1994	215	73	64	702	69	1,123
1995	214	71	56	803	71	1,215
1996	199	69	91	856	74	1,289
1997	194	73	92	983	76	1,418
1998	203	76	91	1,088	100	1,558
1999	198	66	82	1,140	168	1,654
2000	191	64	84	1,147	234	1,720
2001	180	60	79	1,077	276	1,672
2002	160	52	72	942	352	1,578
2003	166	52	64	938	560	1,780
2004	159	53	66	970	734	1,982
2005	152	47	64	955	865	2,083
Overall	332	99	111	1,646	1,064	3,252
Nonsplitting stocks						
1994	221	78	68	815	78	1,260
1995	216	80	59	927	86	1,368
1996	201	76	97	979	79	1,432
1997	195	79	97	1,124	93	1,588
1998	204	82	95	1,227	128	1,736
1999	200	73	87	1,282	209	1,851
2000	193	67	88	1,310	350	2,008
2001	189	67	84	1,282	376	1,998
2002	173	61	78	1,209	570	2,091
2003	170	61	73	1,083	788	2,175
2004	163	58	71	1,080	984	2,356
2005	156	59	68	1,083	1,179	2,545
Overall	338	104	113	1,758	1,376	3,689

[c] This table reports the average number of investors in a quarter, for the splitting and nonsplitting samples, per year and per institutional type. The institutional type classification is adapted from the Thompson Financial database, correcting from issues arising at the end of 1998. In particular, we do not consider as valid any changes of classification from types 1 - 4 to type 5 that occurred at the end of 1998. In those cases, we keep as fixed until 2005 the category to which the institution was assigned before 1998. Any other changes are considered as correct.

Table 4: Sias' models: level of herding

	Overall market (1)	**Splitting companies** (2)	**Nonsplitting companies** (3)
(a) Sias's beta			
mean	0.457***	0.467***	0.457***
t-stat	(56.66)	(14.87)	(55.97)
min	0.346	-0.095	0.348
max	0.562	0.894	0.564
Q1	0.417	0.318	0.417
median	0.447	0.481	0.448
Q3	0.498	0.590	0.499
Pos. quarters	48	36	48
Neg. quarters	0	0	0
$H_0 : Beta_t^{(S)} = Beta_t^{(NS)}$: t = 0.2920 (0.7714)			
(b) Beta adjusted			
mean	0.448***	0.506***	0.447***
t-stat	(56.79)	(16.76)	(56.12)
$H_0 : \widetilde{Beta}_t^{(S)} = \widetilde{Beta}_t^{(NS)}$: t = 1.8910* (0.0640)			

[f] The table reports the average level of herding from the Sias' models (in the main text, equations 1, 2 and 3). The institutional demand $\Delta_{i,t}$ (as fraction of buyer of stock i at quarter t) is regressed, per each quarter, on the lag institutional demand $\Delta_{i,t-1}$. In Model 1 we regress the demand for all stock in the overall market. Model 2 regresses the demand for splitting companies on the lag demand for all stocks. Analogously, Model 3 regresses the demand for nonsplitting companies on the the lag demand for all stocks. Frame (a) of the table presents the summary statistics of the quarterly estimated coefficients of the lag demand (Sias' Betas). The t-values reported are computed from the standard error of the estimates series. We also report the numbers of quarters in which the estimated coefficients are significant at 10% and either positive or negative. Frame (b) reports the average betas conditional on market conditions (Betas adjusted) in the three models (equations 5 to 7). They are computed as the residuals from the regression of the Sias' betas on the four factors à la Cahart (1997). We finally report, per each frame, the statistics and the p-values of the tests on difference between splitting and nonsplitting samples.
* 10%, ** 5%, *** 1% of significance level.

Table 5: Average Estimated Coefficients for all Models

	(1) *Informational-based*		*(2)* *Characteristic-based*		*(3)* *Momentum*	
a) Splitting companies	mean	t	mean	t	mean	t
$\Delta_{i,t-1}$	-0.2413	(-0.79)	0.2405	(1.63)	0.4278***	(13.02)
$Dispersion_{i,t-1}$	0.4378**	(2.01)				
$Coverage_{i,t-1}$	0.1728	(-1.30)				
$Size * Coverage_{i,t-1}$	0.4031	(0.97)				
$Size_{i,t-1}$	-0.1744	(-0.43)	0.2979***	(4.82)		
$Price_{i,t-1}$			-0.1120	(-1.16)		
$Turnover_{i,t-1}$			-0.0514	(-0.60)		
$StDev.ofreturns_{i,t-1}$			0.1340	(1.25)		
$Returns_{i,t-4}$			0.0172	(0.46)		
$Dividends_{i,t-1}$			-0.0218	(-0.35)		
$Returns_{i,t-1}$					-0.0283	(-1.19)
b) Nonsplitting companies						
$\Delta_{i,t-1}$	0.4155***	(29.15)	0.3721***	(18.7)	0.4660***	(56.34)
$Dispersion_{i,t-1}$	-0.0139	(-1.4)				
$Coverage_{i,t-1}$	0.1071***	(10.93)				
$Size * Coverage_{i,t-1}$	-0.0801***	(-6.25)				
$Size_{i,t-1}$	0.1467***	(11.65)	0.0935***	(15.23)		
$Price_{i,t-1}$			0.0708***	(7.92)		
$Turnover_{i,t-1}$			0.0392***	(3.99)		
$StDev.ofreturns_{i,t-1}$			-0.0211	(-1.19)		
$Returns_{i,t-1}$			0.0035	(0.6)		
$Dividends_{i,t-1}$			0.0115**	(2.09)		
$Returns_{i,t-1}$					0.0530***	(6.74)

[h] The table reports the average standardized coefficients of all the variables used in three herding models. (1) Informational-based models regress the institutional demand $\Delta_{i,t}$ on its lag $\Delta_{i,t-1}$ and a set of proxies for the quality of information, such as size, dispersion, coverage and size*coverage at the previous quarter (in the main text, equations 9). (2) Characteristic-based models regress the institutional demand on its lag and a set of company characteristics, such as size, price, turnover, standard deviation, returns of stocks and quarterly dividends, measured at the previous quarter (equations 15). (3) Momentum models regresses the institutional demand on its lag and the previous year returns (equation 16). They are separately regressed in the splitting and nonsplitting samples. We report in this table the average coefficients, and their significance is attributed estimating the t statistics from the time series of the estimates.
* 10%, ** 5%, *** 1% of significance level.

Table 6: Stabilizing Effects: average coefficients

	mean estimated coefficients	*t*	*min*	*max*
Splitting companies				
$\Delta_{i,t-1}$	0.4057***	(8.63)	-0.3454	1.4248
$Ret_{i,t-1}$	0.0819	(0.37)	-5.0132	3.2220
$Ret_{i,t}$	0.0035	(0.02)	-5.2177	2.8125
$Ret_{i,t+1}$	0.3704***	(2.11)	-1.8904	3.7678
$Ret_{i,t+2}$	0.3692***	(2.06)	-3.5798	3.3968
$Ret_{i,t+4}$	0.1201	(0.63)	-4.1861	3.9397
Nonsplitting companies				
$\Delta_{i,t-1}$	0.4484***	(55.18)	0.3633	0.5552
$Ret_{i,t-1}$	0.2212***	(5.61)	-0.3450	0.8020
$Ret_{i,t}$	0.342***	(9.27)	-0.2119	0.8572
$Ret_{i,t+1}$	-0.0015	(-0.04)	-0.5669	0.6303
$Ret_{i,t+2}$	0.0100	(0.33)	-0.3770	0.4235
$Ret_{i,t+4}$	-0.0337	(-1.17)	-0.4689	0.3463

[m] The table reports the summary statistics of the estimated coefficients in the Stabilizing Models. We regress the institutional demand (as fraction of buyer of stock i at quarter t) on the lag institutional demand for the overall market and past quarter, same quarter, following two quarters and following year returns, separately in the splitting and nonsplitting samples. The t-values reported are computed from the standard error of the estimates series.
* 10%, ** 5%, *** 1% of significance level.

Table 7: Average Estimated Coefficients for all Models (dummy specifications)

	(1) *Informational-based*		*(2)* *Characteristic-based*		*(3)* *Momentum*	
Overall market	mean	t	mean	t	mean	t
$\Delta_{i,t-1}$	0.4116***	(28.68)	0.3671***	(18.52)	0.4655***	(56.47)
$Dispersion_{i,t-1}$	-0.0134	(-1.38)				
$Coverage_{i,t-1}$	0.1095***	(11.05)				
$Size * Cover_{i,t-1}$	-0.0814***	(-6.05)				
$Size_{i,t-1}$	0.1549***	(11.67)	0.1027***	(17.8)		
$Price_{i,t-1}$			0.0726***	(8.02)		
$Turnover_{i,t-1}$			0.0406***	(4.26)		
$StDeviation_{i,t-1}$			-0.0174	(-0.98)		
$Returns_{i,t-4}$			0.003	(0.51)		
$Dividends_{i,t-1}$			0.0109**	(1.98)		
$Returns_{i,t-1}$					0.0534***	(6.72)
$\delta_{i,t} * \Delta_{i,t-1}$	-0.0034	(-0.65)	-0.005	(-1.03)	0.000	(0.00)
$\delta_{i,t} * Dispersion_{i,t-1}$	0.0262***	(2.52)				
$\delta_{i,t} * Coverage_{i,t-1}$	-0.009	(-0.96)				
$\delta_{i,t} * Size * Cover_{i,t-1}$	0.0798	(1.3)				
$\delta_{i,t} * Size_{i,t-1}$	-0.063	(-1.04)	0.0157***	(2.74)		
$\delta_{i,t} * Price_{i,t-1}$			0.0031	(0.31)		
$\delta_{i,t} * Turnover_{i,t-1}$			0.0013	(0.19)		
$\delta_{i,t} * StDeviation_{i,t-1}$			0.0139*	(1.93)		
$\delta_{i,t} * Returns_{i,t-4}$			0.0041	(1.3)		
$\delta_{i,t} * Dividends_{i,t-1}$			-0.0109*	(-1.83)		
$\delta_{i,t} * Returns_{i,t-1}$					-0.0124***	(-2.72)

[i] The table reports the average standardized coefficients of all the variables used in three herding models with dummy specification. (1) Informational-based models regress the institutional demand $\Delta_{i,t}$ on its lag $\Delta_{i,t-1}$, a set of proxies for the quality of information, such as size, dispersion, coverage and size*coverage at the previous quarter, and the set of interacted dummies. (2) Characteristic-based models regress the institutional demand on its lag and a set of company characteristics, such as size, price, turnover, standard deviation, returns of stocks and quarterly dividends, measured at the previous quarter, and the set of interacted dummies. (3) Momentum models regresses the institutional demand on its lag and the previous year returns, and interacted dummies. They are separately regressed in the splitting and nonsplitting samples. We report in this table the average coefficients, and their significance is attributed estimating the t statistics from the time series of the estimates.
* 10%, ** 5%, *** 1% of significance level.

Table 8: Average Beta Coefficients per Size of Institutional Portfolio

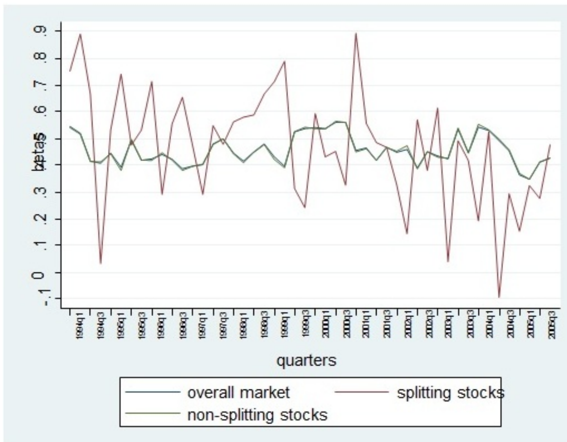
	(a) General herding				(b) Peer herding			
	beta		splitting dummy		beta		splitting dummy	
	mean	t	mean	t	mean	t	mean	t
all period								
small investors	0.3036***	(42.12)	-0.122***	(-3.22)	0.311***	(38.19)	-0.0993***	(-2.74)
medium	0.3883***	(39.4)	-0.0095	(-0.34)	0.3383***	(32.33)	0.0102	(0.37)
big	0.3915***	(37.73)	0.0622*	(1.89)	0.3752***	(34.98)	0.0513	(1.46)
1994-1997								
small investors	0.3123***	(28.22)	-0.0069	(-0.11)	0.2853***	(27.3)	-0.0176	(-0.31)
medium	0.4061***	(33.04)	-0.0539	(-1.16)	0.3525***	(28.45)	-0.0735***	(-2.52)
big	0.3964***	(26.28)	0.1033*	(2.00)	0.3754***	(23.26)	0.1195***	(2.25)
1998-2001								
small investors	0.2973***	(19.12)	-0.1182***	(-2.61)	0.2983***	(24.17)	-0.0591	(-1.48)
medium	0.397***	(19.36)	0.0731	(1.6)	0.3524***	(15.93)	0.0896***	(2.26)
big	0.4281***	(29.08)	0.0963***	(2.61)	0.4149***	(27.43)	0.0676***	(2.35)
2002-2005								
small investors	0.3011***	(27.97)	-0.241***	(-3.22)	0.3494***	(24.2)	-0.221***	(-2.85)
medium	0.3617***	(22.1)	-0.0476	(-0.96)	0.3101***	(17.7)	0.0145	(0.24)
big	0.3499***	(18.42)	-0.0131	(-0.17)	0.3352***	(17.18)	-0.0331	(-0.39)

[k] The table reports the summary statistics of the quarterly standardized coefficients of the lag demand (as Sias' models with dummy specification), estimated separately in subgroups based on the size of the investor portfolio. Institutional demand (as fraction of buyer of stock i at quarter t) is regressed for each group on the lag institutional demand and a dummy for splitting companies interacted with the lag demand itself. We report the average Sias' betas and the splitting dummy coefficients. (a) "General herding" is represented by $\beta_t^{(Sz)}$, as the correlation between the demand of investor Sz with the past demand of all institutions of any portfolio size (equation 13). (b) "Peer herding" is detected by $\beta_t^{(p,Sz)}$, that represents the coefficient between the institutional demand of investor Sz with the past demand of peer investors belonging to the same size class Sz (equation 12). Their significance is attributed estimating the t statistics from the time series of the estimates.
* 10%, ** 5%, *** 1% of significance level.

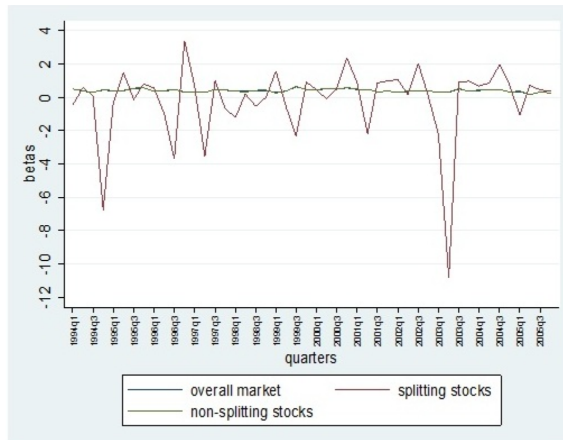
Table 9: Average Beta Coefficients per Institutional Type

	(a) General herding				(b) Peer herding			
	beta		splitting dummy		beta		splitting dummy	
	mean	t	mean	t	mean	t	mean	t
all period								
banks	0.401***	(32.99)	-0.0847***	(-2.44)	0.3343***	(29.99)	-0.0899***	(-2.71)
Insurance co.	0.2407***	(15.86)	0.0507	(1.55)	0.1724***	(12.02)	-0.038	(-1.22)
Investment co.	0.2094***	(12.83)	0.0427	(1.25)	0.1939***	(13.32)	0.031	(0.8)
indip. advisors	0.3119***	(24.6)	0.0114	(0.36)	0.2716***	(16.73)	0.0221	(0.8)
not defined	0.4091***	(30.46)	-0.0554*	(-1.66)	0.3302***	(20.9)	-0.0294	(-0.85)
1994-1997								
banks	0.4264***	(22.82)	-0.0728	(-1.32)	0.3418***	(16.39)	-0.0744	(-1.35)
Insurance co.	0.2264***	(17.89)	0.1071*	(1.83)	0.1626***	(9.93)	-0.043	(-0.74)
Investment co.	0.1953***	(10.07)	0.0467	(0.82)	0.2032***	(13.43)	-0.017	(-0.25)
indip. advisors	0.3585***	(37.62)	0.0109	(0.22)	0.3389***	(30.74)	0.0194	(0.43)
not defined	0.4552***	(21.69)	-0.1282***	(-2.33)	0.379***	(15.77)	-0.0576	(-0.93)
1998-2001								
banks	0.4351***	(21.86)	-0.0184	(-0.49)	0.3757***	(30.51)	-0.0324	(-0.59)
Insurance co.	0.3143***	(10.16)	0.0472	(1.05)	0.2149***	(6.32)	0.0434	(0.99)
Investment co.	0.2789***	(10.58)	0.1171***	(4.57)	0.2649***	(13.5)	0.0381	(0.68)
indip. advisors	0.3533***	(26.87)	0.0075	(0.13)	0.3107***	(25.67)	0.0108	(0.22)
not defined	0.3928***	(17.51)	0.1186***	(2.24)	0.2803***	(11.38)	0.1241***	(2.35)
2002-2005								
banks	0.3415***	(20.17)	-0.1628***	(-2.08)	0.2855***	(16.37)	-0.1629***	(-2.65)
Insurance co.	0.1815***	(8.66)	-0.0022	(-0.03)	0.1398***	(7.93)	-0.1143***	(-2.12)
Investment co.	0.1542***	(5.15)	-0.0358	(-0.45)	0.1138***	(4.61)	0.072	(0.91)
indip. advisors	0.2238***	(10.31)	0.0157	(0.27)	0.1651***	(5.1)	0.0362	(0.69)
not defined	0.3793***	(16.43)	-0.1567***	(-4.00)	0.3312***	(11.44)	-0.1546***	(-3.5)

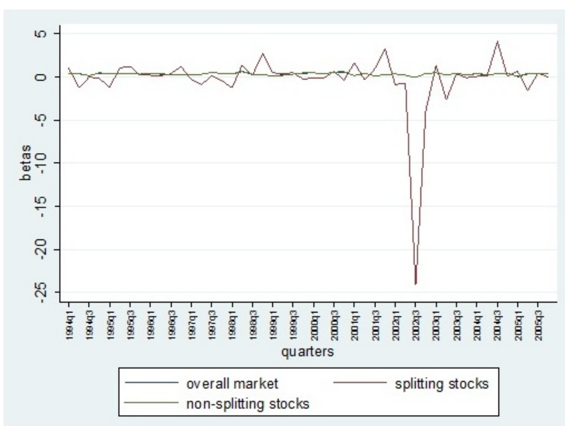
[1] The table reports the summary statistics of the quarterly standardized coefficients of the lag demand (as Sias' models with dummy specification), estimated separately in subgroups based on the type of institutional investors. The classification is updated from the Thompson Database classification. Institutional demand (as fraction of buyer of stock i at quarter t) is regressed for each group on the lag institutional demand and a dummy for splitting companies interacted with the lag demand itself. We report the average Sias' betas and the splitting dummy coefficients. (a) "General herding" is represented by $\beta_t^{(T)}$, as the correlation between the demand of investor T with the past demand of all institutions of any type (equation 11). (b) "Peer herding" is detected by $\beta_t^{(p,T)}$, that represents the coefficient between the institutional demand of type T with the past demand of peer investors belonging to the same type T (equation 10). Their significance is attributed estimating the t statistics from the time series of the estimates.
* 10%, ** 5%, *** 1% of significance level.



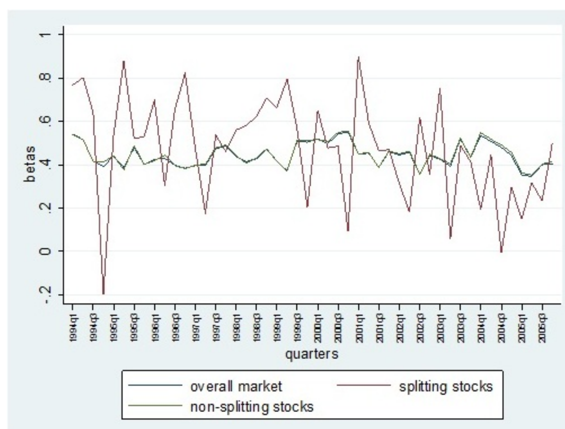
(a) Sias' Betas per Quarter



(b) Non-Informational Betas per Quarter

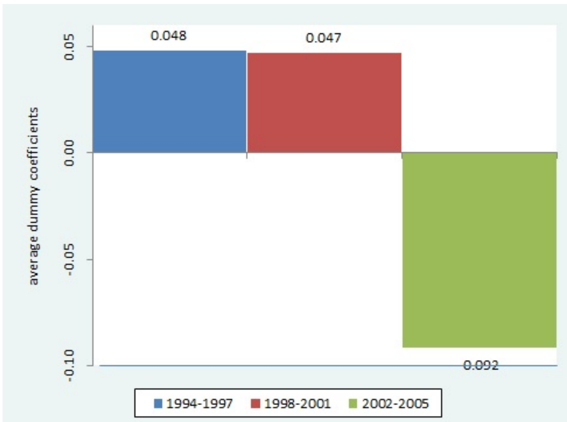


(c) Non-Characteristic-based Betas per Quarter



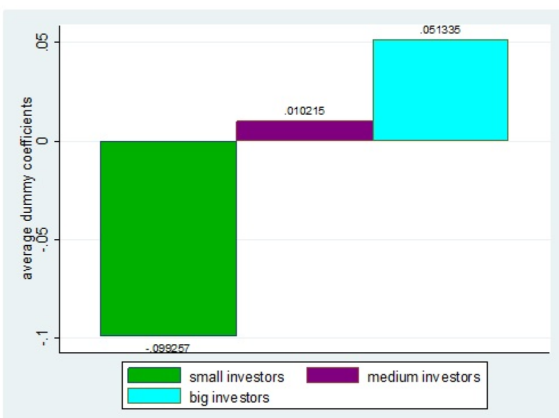
(d) Non-Momentum Betas per Quarter

Figure 1: The graphs show the quarterly estimated coefficients of the institutional demand lag from the first quarter of 1994 to the last quarter of 2005, in four restricted models. Frame (a) reports the Sias's betas, as the institutional lag coefficient in the Sias's models, equations 1 to 3 in the main text. Frame (b) reports the coefficients of the lag institutional demand in the Informational-based models, equation 9. Frame (c) reports the estimated coefficients of the lag demand in the Characteristic-based models, equation 15. Finally, Frame (d) reports the estimates in the Momentum Herding models, equation 16. The regressions are run separately in each quarter and in the three samples: overall market, splitting stocks and non-splitting stocks.

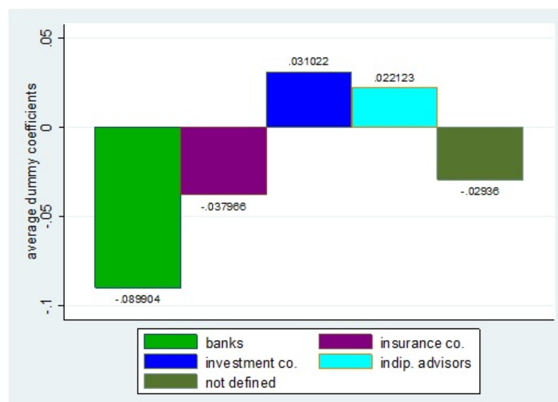


(a) Average Splitting Dummies estimated per subperiod

(b) Average Splitting Dummies estimated per trading activity



(c) Average Splitting Dummies estimated per size of investor portfolio



(d) Average Splitting Dummies estimated per type of investors

Figure 2: The following graphs represent the average splitting dummy coefficients, estimated from the Sias' models with dummy specification. They measure the difference in herding between splitting stocks and nonsplitting firms. They are averaged per: (a) subperiod of four year, (b) trading activity, (c) size of investors, and (d) institutional type.