Chapter 11.

DO INVESTORS HERD DURING EXTREME PERIODS IN THIN MARKETS? EVIDENCE FROM BANJA LUKA[1]

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Abstract

A large amount of studies has attempted to trace the presence of herding during extreme periods at the cross-sectional level by associating herding with the reduction in the cross-sectional dispersion of returns around the market average. In this paper we address the issue of whether the estimation of herding on the premises of such frameworks is robust to the thin trading bias whose presence is particularly prevalent in emerging markets. Our study is undertaken in the context of the Banja Luka stock exchange which is one of the world's most recently established markets. Results indicate that herding is insignificant during extreme return periods with its insignificance persisting even after controlling for thin trading.

Key words: Herding, Thin Trading, Extreme Markets, Banja Luka

1. Introduction

The issue of whether extreme market periods are characterized by herd behavior has been at the forefront of considerable research. Originally motivated by the popular Finance literature (Galbraith 1994) which illustrated the "animal instincts" in traders' behavior during major episodes in financial history, several studies have developed empirical frameworks, both linear as well as non-linear, aiming at addressing this issue. The key feature of these studies is their belief that herding can be reflected in the cross-section of asset returns, in the sense that a lower (cross-sectional) dispersion of returns would indicate that assets herd towards the market average. The development of such models led to a series of researches conducted on the premises of both developed as well as developing capital markets with evidence on the existence of herding being rather mixed.

The present study contributes to the extant literature on the subject by examining herding during extreme periods in the context of one of the world's youngest stock exchanges, that of Banja Luka. Contrary to most studies in the field that restrict their scope in the demonstration of whether or not herding is significant during extreme markets, we extend the scope of our investigation by trying to

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establish whether the significance of the estimated herding remains robust to the thin trading bias. We believe this issue to be a serious one, more so since thin trading has been found to exert an effect over empirical estimations in emerging markets which are normally characterized by lower liquidity levels relative to their mature counterparts (Antoniou et al 1997).

The rest of the paper is organized as follows: section 2 provides an overview of the herding literature, while section 3 delineates the evolution of the Banja Luka capital market; section 4 discusses the data (4.1), the methodology employed (4.2) and presents some descriptive statistics (4.3). Section 5 discusses the results and concludes.

2. Herd behaviour

Individuals form herds when they align their behaviour to a mode of collective conduct following the "interactive observation" of the *actions* and the *payoffs* (arising from those actions) of their peers (Hirshleifer and Teoh 2003). Behavioural finance has associated herding with the intentional sidelining of investors' private information in favor of the observable "consensus" irrespective of fundamentals (Hwang and Salmon 2004). From a behavioural perspective, several psychological biases have been found to contribute to herd behaviour, including conformity (Hirshleifer 2001), congruity and cognitive dissonance (Prast 2000), the home-bias (Feng and Seasholes 2004) and rumour (Buckner 1965). On the rational side, investors may well choose to herd if they perceive herding as a means of extracting informational payoffs (Devenow and Welch 1996). An investor, for example, who is uninformed, or who believes others to be better informed may decide to imitate others' actions if she deems them to be informative. Such a situation has been found to be particularly relevant to finance professionals (e.g. fund managers or financial analysts) whose performance is subject to periodic evaluation on a relative basis, i.e. their performance is compared to that of their peers. Under these circumstances, it is reasonable to assume that principal-agent issues arise, since their professional prospects are heavily dependent upon their employers' assessment of their performance and it is precisely in the above that herding comes into play. As Scharfstein and Stein (1990) and Trueman (1994) have noted, low ability/reputation professionals have every interest in copying the behaviour of their "good" peers in order to improve their professional image, thus "jamming" the assessment process.

Irrespective of the sources (rational; psychological) underlying herding, if many investors decide to ignore their private signals and free-ride on the informational content of others' actions, this is expected to foster the creation of informational cascades (Banerjee 1992; Bikhchandani et al 1992) that can hamper a market's informational efficiency (since imitation tends to slow down the incorporation of individuals' private information in the public information pool) and potentially lead to wild deviations of prices from fundamentals. The latter has constituted a key argument featuring in the popular Finance literature which has widely preoccupied itself with the interpretation of major financial episodes in history by invoking investors' "animal instincts" (e.g. Galbraith 1994).

Academic researchers have only recently embarked during the last two decades in a voluminous effort to delineate investors' behaviour around major financial events. Using transactions-data they have managed to anatomize the behaviour of investors at the micro-level in the context of well-known financial crises, such as the 1997 Asian one (e.g. Choe et al 1999; Kim and Wei 2002a, 2002b). The difficulty, however, in obtaining micro-data (due to their proprietary and sensitive nature) led other researchers to pursue the relationship between herding and extreme market returns on the premises of aggregate data. This strand of research identified herding at the market-wide level with the reduction of the cross-sectional dispersion of stock returns during "extreme" periods and culminated in an equally prolific output of studies (e.g. Caporale et al 2008; Caparelli et al 2004; Chang et al 2000; Christie and Huang 1995; Demirer and Kutan 2006; Gleason et al 2003; Gleason et al 2004; Henker et al 2006) employing both linear as well as nonlinear frameworks.

Our study contributes to the extant literature on the empirical identification of herd behaviour during extreme periods at the aggregate level by investigating the issue in the context of the Banja Luka stock exchange which is one of the most recently founded markets in the world and has never before been the focus of academic research. A key distinguishing feature of our work relates to it considering the effect of thin trading over herding estimations. Emerging markets are typified by relatively lower liquidity compared to their developed counterparts, a fact that can be ascribed to factors curtailing investors' participation in such markets, including entry restrictions (e.g. for foreign investors), trading restrictions (e.g. margin trading and short-sales' constraints), market frictions (e.g. high transaction costs) as well as overall macroeconomic conditions (e.g. when the country's average income is low). As the matching (and, hence execution) of orders becomes slower under these conditions, order-imbalances develop on either the buy- or the sell-side, thus interfering with the trading process that is now characterized by thinner volumes and stale prices (Kim and Rhee 1997). Although thin trading has been found to bear serious implications over empirical estimations in a series of emerging markets' studies (Antoniou et al 1997; Siriopoulos et al 2001), its impact over herding estimates during extreme market states has been widely overlooked and, in view of this, we believe our study to fill an important gap in the relevant literature.

3. The Banja Luka Stock Exchange

Both entities (Federation of Bosnia and Herzegovina; Serb Republic of Bosnia) in Bosnia and Herzegovina have created their own modern capital market infrastructure with separate stock exchanges in Sarajevo (SASE) and Banja Luka (BLSE), respectively. The two exchanges have similar histories and represent good intentions towards the creation of financial markets in Bosnia and Herzegovina. The Banja Luka Stock Exchange (BLSE) was established in May 2001 following an *ad hoc* agreement among eight banks and one brokerage house and its evolution has been strongly linked to the privatization process in the Serb Republic of Bosnia. Socio-economic trends in the region were characterized by the active role of the government in implementing reforms necessary to step up the transition process towards a market economy and it is through this prism that the establishment of modern stock market infrastructure has to be viewed. The Banja Luka Stock Exchange started trading in March 2002 and it has experienced a meteoric growth, with the number of listed companies rising from 48 (March 2002) to almost a thousand by 2009. Following a period of initial tranquillity, the market's activity surged during 2006, catapulting the main index (BIRS) to over 5200 points in mid-April 2007 (from an all-time low until then of 898 points in July 2002). Although its turnover documented a noteworthy increase from Bosnian Marka or BAM7 million ($5 million) in 2002 to a record high of BAM742 million ($ 558 million) in 2007, the market itself is notably thin as evidenced by its very low turnover ratio (4.21 percent). The high concentration of trading activity further contributes to the thinness of the market, as the volume of trade is frequently dominated by a few major stocks. In 2009, for example, *Telekom Srpske* and *AD Bosanski Brod* dominated investors' interest accounting for 14.6 and 6.7 percent, respectively, of the turnover.

4. Data and methodology

4.1. Data

Our data includes daily closing prices of the historical constituents of the BIRS index which is the main index of the Banja Luka Stock Exchange. The data covers the period beginning 17 May 2004 when the BIRS was launched and ending 9 June 2009 and was obtained from the Banja Luka Stock Exchange website (http://www.blberza.com). The BIRS currently (July 2009) accommodates 30 stocks in its composition, while according to its historical revisions obtained from the market's website, the total number of stocks that have been included at any point during that period (including the July-composition) in the index equals 39.

4.2. Methodology

We shall now introduce the empirical designs upon which the examination of herd behaviour during extreme periods has been based. The crux of the argument there was the identification of herding with the level of dispersion of stock returns from the market average. Put it this way, a low dispersion would indicate that assets converged to their cross-sectional mean, i.e. herded towards some sort of market consensus. To test for herding during extreme periods on the basis of this context, researchers had to devise empirical frameworks that would allow for the formalization of the relationship between herding and market returns.

In the seminal paper on the subject, Christie and Huang (1995) proposed the following linear specification:

$$CSSD_t = a_0 + a_1 D_t^{UP} + a_2 D_t^{DOWN} + \varepsilon_t \tag{1}$$

CSSD here denoted the cross-sectional standard deviation of individual stock returns around their cross-sectional average which was calculated as $\sqrt{\frac{\sum_{i=1}^{n}(r_{i,t}-\overline{r_t})^2}{n-1}}$, where $r_{i,t}$ is the return of security i at period t and $\overline{r_t}$ the cross-sectional average of n-stocks' returns during period t. The two dummies in regression (1) were employed as proxies for "extreme" periods and corresponded to the tails of the market-return distribution. More specifically, D_t^{UP} = 1, if the market return on day t falls in the extreme upper tail, zero otherwise; and D_t^{DOWN} = 1, if the market return on day t falls in the extreme lower tail, zero otherwise. Since herding was taken to be reflected in a decline of the returns' dispersion, the presence of herding during "extreme" positive or negative markets would be indicated by the coefficients of the dummies (a_1, a_2) assuming negative signs. In the present context, we shall define as "extreme" the observations lying one, two and three standard deviations from the market average, in line with Christie and Huang (1995).

Chang et al (2000) argued that in the presence of herding, the relationship between the cross-sectional return-dispersion and market returns during extreme periods can assume a nonlinear form and proposed the following test:

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP}\left|R_{m,t}^{UP}\right| + \gamma_2^{UP}\left(R_{m,t}^{UP}\right)^2 + \varepsilon_t \tag{2}$$

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN}\left(R_{m,t}^{DOWN}\right)^2 + \varepsilon_t \tag{3}$$

In the above set of regressions, the CSAD is the cross-sectional absolute deviation of returns calculated as $\frac{1}{N}\sum_{i=1}^{N}\left|\beta_i - \beta_p\right|\left|r_{i,t} - r_f\right|$, where β_i represents the systematic risk of the individual security i, β_p reflects the systematic risk of the market portfolio, $r_{i,t}$ is the return of the individual security i at time t, r_f is the risk free rate, and N is the number of securities in the market portfolio. As Henker et al (2006) illustrated, the CSAD can equivalently be expressed as $\frac{1}{N}\sum_{i=1}^{N}\left|r_{i,t} - r_{p,t}\right|$, where $r_{i,t}$ is the return of the individual security i at time t, $r_{p,t}$ is the return of the market portfolio at time t and N is the number of securities in the market portfolio. Finally, the $R_{m,t}$ in equations (2) and (3) is the equal-weighted market portfolio return and the UP/DOWN superscripts denote up/down market days. As herding is assumed here to be related to market nonlinearities, we are particularly interested in the γ_2-coefficient. In view of what we mentioned above, a negative and statistically significant estimate for γ_2 would be suggestive of the presence of significant herding. The reasoning behind the Chang et al (2000) specification draws upon the concept of "directional asymmetry" introduced by McQueen et al (1996). According to this, the arrival of bad macroeconomic news in the market leads all stocks to react *in tandem*; conversely, when good macroeconomic news hits the market, larger stocks tend to respond first with smaller stocks following them with a lag. In the presence of directional asymmetry, the dispersion of returns around the market average would be expected to be smaller during down-markets as opposed to up-markets.

In this study we employ both the Christie and Huang (1995) and the Chang et al (2000) models to gauge the presence of herding during extreme market periods. However, the fact that the Banja Luka stock exchange is an emerging one, raises the issue of thin trading that typifies such markets and introduces biases in empirical estimations conducted on their premises (e.g. Antoniou et al, 1997). To that end, we extend the existing work in the literature by undertaking two *ad hoc* robustness tests. The first one is based on an established method which was developed by Miller et al (1994), who demonstrated that the correction for thin trading can be accomplished using an AR (1) process, as follows:

$$R_t = a_1 + a_2 R_{t-1} + e_t \tag{4}$$

where R_t is the individual stock return at time *t*; R_{t-1} is the individual stock return at time *t-1* and e_t is the error term. Realized returns can then be adjusted as follows:

$$R_t^{adj} = \frac{e_t}{(1 - a_2)} \tag{5}$$

where R_t^{adj} is the return at time *t* after thin trading has been taken into account. Antoniou et al. (1997) pointed out that an assumption underlying the Miller et al. (1994) approach is that the adjustment for thin trading is taken to be constant throughout time. They argued that this assumption may be inappropriate when dealing with emerging markets as they may well accommodate substantial windows of trading inertia. As this is the case with the Banja Luka market, equation (4) is estimated recursively. Once returns are adjusted for thin trading, they are used to re-estimate herding in the Christie and Huang (1995) and Chang et al (2000) models. The second approach aims at estimating the presence of herding taking into account trading inactivity. In the presence of thin trading, stocks fail to trade every consecutive day, thus leading their prices to exhibit pockets of inertia. As a result, when daily returns are calculated, one comes across multiple zero observations in their time series. To counter the impact of this over our estimates, we repeat our herding estimations excluding from our sample all zero-return observations, so that our estimates will now be based upon actually traded stocks only. As table 1 shows, the average number of active stocks per day equals 7.3, yet the average number of total stocks (active and inactive) per day in the BIRS is almost 19 during our sample period. In other words, little over a third of the BIRS-stocks are actively traded each day.

4.3. Descriptive statistics

Table 1 presents some descriptive statistics related to the cross-sectional standard (CSSD) and absolute (CSAD) dispersions of returns when raw returns are used, when returns are adjusted for thin trading and when trading inactivity is taken into account. As the table shows, both the CSAD and CSSD assume their lowest values for their sample mean and standard deviation before returns have been corrected for thin trading and before trading inactivity has been taken into account. This is something perhaps to be expected as in a market as thinly traded as the Banja Luka one, individual stocks' series would include a number of zero-observations, thus rendering the dispersion of stocks' returns around their mean smaller and (as a result) its average and standard deviation to appear reduced. An interesting pattern is revealed as regards the average daily number of stocks prior to after controlling for market inactivity. Although the average daily number of stocks calculated on the premises of the full composition of the BIRS during our sample period equals almost 19, it drops abruptly to 7 once actively traded stocks are taken into consideration, thus being reflective of the illiquid conditions surrounding the Banja Luka market. The near-zero (less than -0.01 percent) BIRS-average return is again indicative of the course of the market during the 17/5/2004 – 9/6/2009 period (see Figure 1), as the BIRS skyrocketed from around 1100 points in May 2004 to over 5000 in December 2007 only to begin its descending course enter 2008 and reach below 1000 points in early June 2009.

5. Results – Concluding remarks

We begin the discussion of our results with the presentation of our estimations from the Christie and Huang (1995) model. Table 2 presents the results when extreme returns are taken to lie one (Panel A), two (Panel B) or three (Panel C) standard deviations from the BIRS-average of our sample period. As table 2 indicates, the intercept term (α_0) reflective of the average CSSD in a stagnant market remains significantly (1 percent level) positive throughout all our results, with its estimates however assuming higher values when returns have been adjusted for thin trading and when trading inactivity has been taken into account. Regarding the estimates of the dummy variables' coefficients, they are suggestive of the absence of herding, as they are all found to be positive (with the exception of a_2 in Panel C when returns are adjusted for thin trading), while their significance appears robust (1 percent level) before adjusting returns for thin trading or taking trading inactivity into account. Adjusting returns for thin trading leads the a_1, a_2 coefficients to become insignificant (with the sole exception of α_1 in panel B), while taking trading inactivity into account renders the a_2 coefficient insignificant in panels B and C. Perhaps more interestingly, the values of α_1 appear to be consistently higher compared to α_2 (with the exception of Panel A prior to adjusting for thin trading or taking trading inactivity into account). This implies that although the dispersion of returns around their mean increases during both upside and downside extreme periods, this increase is lower for extreme downside returns, which indicates a greater similarity in the behaviour of returns during extreme negative periods compared to extreme positive ones.

Table 3 presents the estimates obtained for the Chang et al. (2000) model. Much like with the results from the Christie and Huang (1995) model, the intercept is found to be significantly (1 percent level) positive for all estimations with its value rising dramatically when returns have been adjusted for thin trading and when trading inactivity has been taken into account. Regarding the γ_1 coefficient, it is also found to be significantly (1 percent level) positive for all tests, thus being suggestive of a positive linear relationship between the cross-sectional absolute dispersion and the absolute value of the BIRS-average. An interesting feature of our results relates to the fact that adjusting for thin trading and taking trading inactivity into account leads to consistently lower γ_1 estimates, thus indicating that the above documented positive linear relationship between the cross-sectional absolute dispersion and the $R_{m,t}$ becomes weaker (i.e. the dispersion increases at a decreasing rate) when controlling for market illiquidity. Contrary to the directional asymmetry argument of McQueen et al (1996), we notice that there seems to be a general trend for γ_1^{DOWN} to be greater than γ_1^{UP}. This means that dispersions increase at a lower rate during periods of market upswings compared to periods of negative market returns; the F_1 test statistic used to test the null hypothesis $\gamma_1^{UP} = \gamma_1^{DOWN}$ shows that the null hypothesis is indeed rejected at the 1 percent level of significance with the exception of the case where returns are adjusted for thin trading. With regards to γ_2, it is found to exhibit consistency in its pattern during up versus down markets; more specifically, γ_2^{UP} is found to be always positive while the sign of γ_2^{DOWN} appears always negative. The above are reflective of a positive (negative) nonlinear relationship between the cross-sectional absolute dispersion and the $R_{m,t}$ during market upswings (slumps) whose significance

(1 percent level) appears more pronounced during market upswings (the significance of γ_2^{DOWN} is manifested only once trading inactivity has been taken into account, which is where we find the sole estimate in our results indicative of herding significance). It is further interesting to observe that correcting for thin trading or taking trading inactivity into account leads to a substantial depression of the γ_2 coefficient's values in absolute terms, thus indicating that any nonlinearities documented in the relationship between the cross-sectional absolute dispersion and the $R_{m,t}$ tend to evaporate when controlling for market illiquidity. The F_2 test statistic used to test the null hypothesis $\gamma_2^{UP} = \gamma_2^{DOWN}$ shows that the null hypothesis is indeed rejected at the 1 percent level of significance with the exception of the case where returns are adjusted for thin trading. The fact that both γ_1 and γ_2 appear notably depressed once returns have been adjusted for thin trading and once trading inactivity has been taken into account brings forth the issue of the impact of thin trading over linear and nonlinear estimations. Evidence from the literature indicates that thin trading tends to amplify both linear (Antoniou et al 1997; Siriopoulos et al 2001) and nonlinear dynamics (Solibakke 2001, 2005) in the return-generation process thus introducing biases into empirical estimations that tend to be reduced once adjustments for thin trading are implemented and this is precisely what we are witnessing in table 3. All in all, as our results from table 3 show, the herding hypothesis is largely refuted on the premises of the Chang et al (2000) approach.

It is evident from the empirical evidence depicted thus far that extreme return-periods (as defined in the two models employed above) do not accommodate significant herding in the context of the BIRS-portfolio in the Banja Luka market. We believe that the absence of herding here should be viewed by taking the conditions of the market itself into consideration. Since a herd's significance is a function of the accrued participation it attracts (Bikhchandani et al 1992), it is reasonable to assume that the significance of herding at the market-wide level will be a straight function of the market's overall trading activity. With about a third of the BIRS stocks being actively traded every day on average, it is obvious that investors' participation in the Banja Luka stock exchange is unable to reach levels high enough to generate the turnover necessary to move prices market-wide. This reality is further exacerbated by the fact that the Serb Republic of Bosnia bears a low average income that inhibits the wider involvement of retail traders in their country's stock market. From a herding perspective, the manifestation of herding under such circumstances will depend upon the ability/opportunity to trade, since if a herd is to develop, for example, on the buy-side, it will be able to express itself in the market only when there are enough traders on the sell-side to allow the buy-herd members to transact. Thus, even if herding does indeed exist in the market, its actual magnitude will fail to be revealed due to the order-matching difficulties induced by thin trading and this will naturally bear an adverse effect over its significance. However, it could well be the case that even if only about a third of all BIRS-stocks are actively traded each day, those that are actively traded do in fact exhibit co-movement in their behaviour. To explore this possibility, we split the actively traded stocks each day into "winners" and "losers" contingent upon whether their daily return is positive or negative. Results are reported in table 1 and provide us with no evidence in support of any systematic co-movement, since as the table indicates, the average daily number of winners is 3.5 and that of losers is 3.8. Concurrently, it appears that on average the number of stocks advancing each day is more or less similar to the number of stocks declining, thus providing an additional argument in support of the herding insignificance at the market-wide level reported in our empirical findings. If indeed herding exists under these circumstances, it will have to be traced at the individual stock level using investors' transaction-data, which unfortunately are not available here. The robustness of herding absence to thin trading during extreme markets constitutes a key contribution of the present paper to research. Using two established herding specifications we demonstrated that extreme periods need not necessarily accommodate market-wide herding in an illiquid market setting; indeed, it may well be the case that the "extremities" observed in such market's indices are the byproduct of the extreme movements of a few individual stocks with sufficient interest from both sides (buy/sell) of the market rather than the market as a whole.

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Appendix

Figure 1. BIRS-chart (17/5/2004 – 9/6/2009).

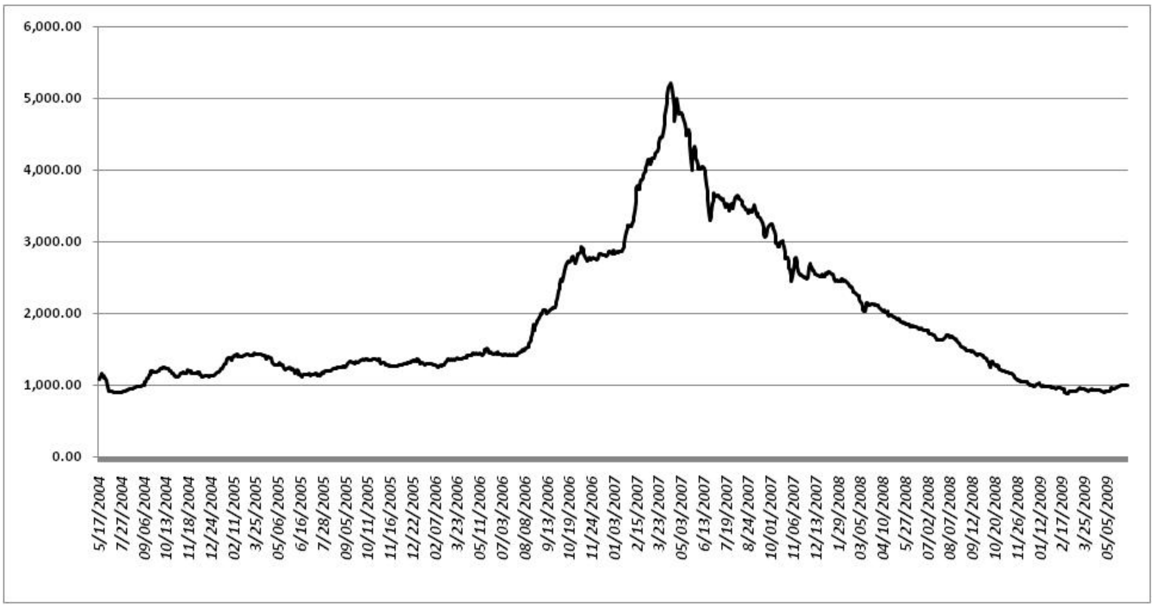

Table 1. Sample Descriptive Statistics (sample period: 17/5/2004 – 9/6/2009).

	Raw returns		Returns adjusted for thin trading		Accounting for trading inactivity	
	Mean	**Standard deviation**	**Mean**	**Standard deviation**	**Mean**	**Standard deviation**
CSAD	0.0193	0.0135	0.0369	0.0247	1.2901	0.9539
CSSD	0.0282	0.0219	2.8136	1.9500	0.0444	0.0353
Average daily number of stocks	18.9		18.9		7.3	
Average daily number of winners	3.5					
Average daily number of losers	3.8					
BIRS average return	-0.000075					

Table 2. Regression results for the Christie and Huang (1995) model.

	α_0	a_1	a_2	Adjusted R^2
Panel A: ±1 standard deviation from average				
Raw returns	0.02838	0.0125	0.0126	0.063
	(40.48)*	(6.50)*	(6.44)*	
Returns adjusted for thin trading	1.2610	0.0956	0.0347	0.001
	(62.76)*	(1.73)	(0.62)	
Accounting for trading inactivity	0.0468	0.0108	0.0097	0.015
	(40.12)*	(3.36)*	(3.03)*	
Panel B: ±2 standard deviations from average				
Raw returns	0.0301	0.0225	0.0179	0.051
	(47.18)*	(6.09)*	(4.92)*	
Returns adjusted for thin trading	1.2656	0.3281	0.0473	0.007
	(69.94)*	(3.08)*	(0.46)	
Accounting for trading inactivity	0.0483	0.0210	0.0095	0.011
	(45.70)*	(3.42)*	(1.57)	
Panel C: ±3 standard deviations from average				
Raw returns	0.0307	0.0421	0.0196	0.046
	(49.04)*	(6.83)*	(2.71)*	
Returns adjusted for thin trading	1.2752	0.1201	-0.0254	-0.001
	(71.65)*	(0.69)	(-0.12)	
Accounting for trading inactivity	0.0486	0.0538	0.0110	0.025
	(47.25)*	(5.31)*	(0.93)	

This table reports the estimated coefficients of the following regression (t-statistics in brackets; * = indicates significance at the 1 percent level): $CSSD_t = a_0 + a_1 D_t^{UP} + a_2 D_t^{DOWN} + \varepsilon_t$

Table 3. Regression results for the Chang et al. (2000) model.

	Up-market model				Down-market model				Test statistics	
	α	γ_1^{UP}	γ_2^{UP}	Adjusted R^2	α	γ_1^{DOWN}	γ_2^{DOWN}	Adjusted R^2	F_1	F_2
Raw returns	0.0099 (14.36)*	1.0022 (10.39)*	7.5608 (3.19)*	0.645	0.0082 (14.26)*	1.2943 (15.09)*	-2.8705 (-1.44)	0.616	11.30	27.22
Returns adjusted for thin trading	0.4522 (16.96)*	0.9983 (24.39)*	0.0144 (1.47)	0.827	0.5475 (21.09)*	1.0104 (24.42)*	-0.0109 (-0.99)	0.820	1.31	4.26 x 10^{-16}
Accounting for trading inactivity	0.0279 (17.31)*	0.2316 (2.85)*	4.0744 (6.74)*	0.414	0.0241 (15.04)*	0.5999 (7.48)*	-1.8310 (-2.62)*	0.169	21.07	71.15

This table reports the estimated coefficients of the following set of regressions (t-statistics in brackets):

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP} \left|R_{m,t}^{UP}\right| + \gamma_2^{UP} \left(R_{m,t}^{UP}\right)^2 + \varepsilon_t$$

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN} \left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN} \left(R_{m,t}^{DOWN}\right)^2 + \varepsilon_t$$

F_1 and F_2 statistics test respectively the following null hypotheses: $\gamma_1^{UP} = \gamma_1^{DOWN}$ and $\gamma_2^{UP} = \gamma_2^{DOWN}$; * = indicates significance at the 1 percent level.