When is Herding not Herding?

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Abstract

This paper tests for herding effects in the prices of all S&P100 constituent stocks for the period between 1989 and 2011. We find herding only for the extremely volatile period related to the global financial crisis. This finding is robust to time-variation in slope coefficients, and to various sub-samples of stocks (value vs. growth, large vs. smaller). The paper shows that when the HML and SMB factors are included in the regressions, they pick-up the effect of the herding term, i.e. that what was thought to be herding in the paper (literature) is (may be) linear investor reaction to common fundamental risk factors.

Keywords: Herding, HML, SMB, S&P100, Kalman-filter, Financial crisis.

JEL Classification: G15

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Abstract

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1. Introduction

During the past two decades, financial markets have experienced episodes of significant financial market volatility. Events in different regions, such as the Russian debt moratorium and the collapse of the LTCM hedge fund, the Asian crisis in the late 1990s, the burst of the dot-com bubble, the subprime crisis in the US, and the recent European debt crisis, due to the interdependencies of global financial markets all result to global financial turmoil and extreme asset price movements. At the same time, empirical studies have indicated that during periods of extreme volatility investors (institutional and private) may herd, i.e. may imitate each other's actions, move in the same direction, and their trading activity may be correlated. For example, Christie and Huang (1995) argue that herding may be particularly prevalent during periods of extreme market movements since during these times investors may most likely suppress their own beliefs in favor of the market consensus.

According to Devenow and Welch (1996) herding may be approached either from a non-rational point of view (e.g. investors do not engage in rational analysis and follow one another blindly), a rational point of view (e.g. herding stems from payoff externalities and optimal decision-making being distorted by issues such as information asymmetry), or a near-rational view (e.g. investors may use heuristic rules). Banerjee (1992), for example, presents a model where each decision maker looks at the decisions made by previous decision makers and argues that this is rational since other decision makers may have some information that is important, while Nofsinger and Sias (1999) find no evidence that institutional herding is irrational. In addition, Froot, Scharfstein, and Stein (1992) show that if speculators have short horizons they may herd on the same information trying to learn what other

informed investors know, and that there may be multiple herding equilibria (for a detailed review see Hirshleifer and Teoh, 2003). This paper contributes to the above literature by examining new aspects relating to herding behavior in US stocks.

The contribution of the paper to the literature is threefold. Firstly, in contrast to previous published studies that employ a static OLS methodology, we allow for herding effects to be time-varying. The rationale is that if herding is more prevalent during periods of extreme market movements (Christie and Huang, 1995), then it is not static, and by allowing for this variation, we explore whether previous results depend on the assumption of constant herding behavior.[1] Furthermore, there is considerable evidence suggesting that estimated betas of unconditional capital asset pricing models exhibit significant time-variation (Ghysels, 1998), or that the variation through time in expected returns is a relatively large fraction of return variances and that the degree of variation in returns also changes systematically over time (Conrad and Kaul, 1988).[2] To this end, we apply the Kalman-Filter approach to estimate slope coefficients.

Secondly, our paper is complementary to that of Chang, Cheng, and Khorana (2000) whose model ignores the evidence in the literature that other fundamental risk factors determine the cross-section of stock returns. More specifically, our paper augments their model with the Fama and French HML and SMB factors (e.g. Fama and French, 1993, 1995), which are often hypothesized to act as state variables in the context an intertemporal capital asset pricing model. For instance, Liew and Vassalou

[1] The Kalman-Filter approach has been used in many studies in the past to estimate from interest rate behavior and term structure models to macro models of monetary policy, investor sentiment, and the variability of contrarian profits (Jegadeesh and Pennacchi, 1996; Babbs and Nowman, 1999; Söderlind, 1999; Brown and Cliff, 2004; Antoniou, Galariotis, and Spyrou, 2006; among others).

[2] Note that time-variation in betas may be an international phenomenon: Koutmos, Lee, and Theodossiu (1994) find that time-dependency for market betas for many of the markets examined (see also, Groenewold and Fraser, 1999). Bos and Newbold (1984) argue that time-variation in systematic risk may arise from either microeconomic or macroeconomic factors; their empirical tests also indicate stochastic systematic risk (see also, Ferson, Kandel, and Stambaugh, 1987).

(2000), construct such return-based factors for ten developed markets, and find evidence that the HML and SMB portfolios are related to future growth in the real economy, i.e. a risk-based explanation is supported for the performance of these return factors. By ignoring this, the Chang, Cheng, and Khorana (2000) model that employs the market portfolio to test for herding effects, can be incorrectly picking up these effects and present them as herding behavior when in fact they may simply be a linear investor reaction to fundamental risk factors. Finally, we examine whether investment style plays a role in herding behavior and for all the above examine a very long sample period that includes all recent episodes of global volatility and the global meltdown.

Our results initially suggest that herding is evident only during the recent 2007-2008 global financial crisis period. The use of a Kalman filter procedure to account for time-variation in slope coefficients suggests that this result is robust to time variation in slope coefficients. When, however, the HML and SMB factors are included in the regressions they pick-up the effect of the non-linear term which is no longer statistically significant. In other words, as hypothesized earlier, what appears as herding in all static approaches may actually be a linear investor reaction to common fundamental risk factors ignored by the extant herding literature. Therefore the results further contribute to the literature by offering a possible explanation for the finding that herding is irrationally stronger during volatile periods (see Economou, Kostakis, and Philippas, 2011; Tan, Chiang, Mason, and Nelling, 2008; Caparrelli, D'Arcangelis, and Cassuto, 2004; Christie and Huang, 1995 etc.), when it may actually be a rational reaction to risk. At the same time the results allow for other potential explanations and are in line with Devenow and Welch's (1996) proposition,

and Gleason, Mathur, and Peterson's (2004) findings, giving empirical support to the theoretical proposition of Banerjee (1992).

2. Previous Studies

In an early important study, Lakonishok, Shleifer, and Vishny (1992) use US data on 769 tax-exempt funds to examine herding and positive-feedback trading. They find that pension fund managers do not strongly engage in either herding or positive-feedback trading, although they do find some evidence of herding for smaller stocks, with no destabilising effect on stock prices. Grinblatt, Titman, and Wermers (1995) examine the US mutual fund industry for momentum and herding behaviour and find evidence consistent with momentum but not herding; Christie and Huang (1995) also find evidence inconsistent with the presence of herding during periods of large price movements. Wermers (1999) also finds little evidence of herding by US mutual funds in the average stock; however, the results suggest a much higher level of herding in trades of small stocks and in trading by growth-oriented funds. In other words the early evidence only weakly supports the notion that funds tend to buy and sell the same stocks at the same time. Note that Nofsinger and Sias (1999) find a positive relation between annual changes in institutional ownership and returns in the USA markets. This, they suggest, may be due to either higher positive-feedback trading of institutional investors compared to individual investors or due to the higher impact on prices of institutional herding compared to individual investor herding. They find evidence that both factors play a role in explaining the relation.

More recently Sias (2004) finds that institutional investors tend to follow each other in buying and selling the same securities and their own lag trades, and that they tend to follow momentum strategies, although little of their herding results from momentum trading. Sias argues that the results are most consistent with the hypothesis that institutions herd as a result of inferring information from each other's trades. Li and Yung (2004) examine US institutional herding in the ADR market and find a significant positive relation between changes in institutional ownership and ADR returns that persists even after they control for momentum. Gleason, Mathur, and Peterson (2004) use intraday data on sector Exchange Traded Funds (ETFs) traded on the American Stock Exchange and find that investors do not herd during periods of extreme market movements using ETFs. Choi and Sias (2009) find strong empirical evidence of US institutional industry herding: there is a cross-sectional correlation between the fraction of institutional traders buying an industry one quarter and the fraction buying the previous quarter of, on average, 39%. They also show that institutional industry herding stems from managers' decisions, is behind institutional industry momentum trading, is more pronounced in smaller and more volatile industries, and may drive industry market values away from fundamentals.

Other studies examine institutional investor herding in international markets. For example, Wylie (2005) finds that there is only a modest amount of UK equity fund manager herding and only for extreme capitalisation individual stocks, with little herding detected for other capitalisations or stocks aggregated by industry. Kim and Nofsinger (2005) find a lower level of institutional herding in Japan than the US. This seems to depend on economic conditions and the regulatory environment, while herding appears to have a more significant impact on price movements. Iihara, Kato and Tokunaga (2001) earlier found similar results on the impact of herding on stock

prices in Japan, while using the yearly change in ownership as a proxy for investor herding they also find that both institutional and foreign investors herd. Chang and Dong (2006) show that in Japan both institutional herding and firm earnings are positively related to idiosyncratic volatility. Walter and Weber (2006) find evidence of herding and positive feedback trading by German mutual fund managers, with a significant portion of herding being related to spurious herding as a consequence of changes in benchmark index composition. Voronkova and Bohl (2005) show that Polish pension fund managers are to a greater extent involved in herding and positive feedback trading than managers in mature markets. Looking at other types of investors as well, Economou, Kostakis, and Philippas (2011) test for herding effects in the Portuguese, Italian, Spanish and Greek market, and find they become more intense during the recent global financial crisis of 2007-2008. Caparrelli, D'Arcangelis, and Cassuto (2004) focus on Italy and support the finding that herding is present in extreme market conditions. Chang, Cheng, and Khorana (2000) examine a number of markets and find no evidence of herding for the US and Hong Kong, partial evidence of herding in Japan, and significant evidence of herding for South Korea and Taiwan. Furthermore, they find that it is macroeconomic information rather than firm-specific information that tends to have a more significant impact on investor behavior in markets that exhibit herding.

3. Data and Testing Methodology

A common metric of herding behaviour for empirical testing is the one proposed by Lakonishok, Shleifer, and Vishny (1992; LSV hereafter). LSV compute

herding as the proportion of net buyers (money managers who increase their holdings in a stock during a given quarter) relative to the total money managers who trade that stock less an adjustment factor that declines as the number of money managers active in that stock rises. If no herding exists the expected value of this metric should not vary from period to period; in the presence of herding there should be significant cross-sectional variation in this measure. This measure of herding is standard in earlier empirical literature (e.g. Lakonishok, Shleifer, and Vishny, 1992; Grinblatt, Titman, and Wermers, 1995; Wermers, 1999; Wylie, 2005; among others).

Christie and Huang (1995) propose the cross-sectional standard deviation of returns as a metric of herd behavior. They argue that when individual returns herd around the market consensus then dispersions should be relatively low. By contrast, when stocks differ in their sensitivity to market movements, rational asset pricing suggests that dispersions will increase (see also, Hwang and Salmon, 2004). Chang, Cheng, and Khorana (2000) propose an approach similar in spirit to Christie and Huang (1995) to measure herding behavior. They argue that if investors tend to follow aggregate market behavior during periods of large average price movements, then the linear and increasing relation between dispersion and market return will no longer hold and it can become non-linearly increasing or even decreasing. Thus, they utilize a non-linear regression specification to estimate the relation between the cross-sectional absolute deviation of returns and the market return.

This paper starts by employing a methodology similar to that suggested by Chang, Cheng, and Khorana (2000). More specifically, for each stock i of the N stocks and for each day t we calculate the difference of the stock's return (R_{it}) and the market return (R_{mt}) and then estimate the Cross Sectional Absolute Deviation (CSAD) as:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{it} - R_{mt}\right| \tag{1}$$

To detect herding activity we estimate a non-linear (OLS) regression:

$$CSAD_t = \beta_0 + \beta_1\left|R_{mt}\right| + \beta_2 R_{mt}^2 + e_t \tag{2}$$

In the case of herding the coefficient on the non-linear term will be negative and statistically significant (for more details see Chang, Cheng, and Khorana, 2000; Gleason, Mathur, and Peterson, 2004).

For the empirical analysis we use daily prices for all S&P100 constituent stocks between October 1989 and April 2011. The S&P 100 index is a subset of the S&P 500 index and includes 100 leading U.S. stocks with exchange-listed options and an adjusted Market Capitalization of approximately 7,455.80 $ billion, as of January 2012 (see www.standardandpoors.com); the constituent stocks represent approximately 45% of the market capitalization of the U.S. equity markets. Returns are defined as the first difference of the log price levels. We also use four sub-samples of stocks based on the Book-to-Market ratio (B/M) and market capitalization (MV): each year stocks are ranked on their B/M (MV) ratio and are assigned to a High BM (MV) sub-sample or a Low B/M (MV) sub-sample. This way we obtain a sub-sample with “growth” (Low B/M), “value” (High B/M), “big” (High MV), and “small” (Low MV) stocks. Since the S&P100 index contains, by definition, the largest stocks in the U.S. markets, sorting stocks on market capitalization to obtain “small” and “large” stocks may add little to the analysis. Note, however, that there is a large dispersion in market values, thus we include in the analysis the sub-samples based on MV and term

the low capitalization stocks as “smaller” rather than “small” stocks (the average constituent stock has a market capitalization of 74.56 $ billion, the largest 417.15 $ billion and the smallest 7.01 $ billion, as of January 2012).

All data are obtained from Datastream International. Furthermore, we also examine three sub-periods as follows: October 1989 to December 2006 (the “before the crisis” period), January 2007 to December 2008 (the “crisis” period), and January 2009 to April 2011 (the “after the crisis” period). The split is arbitrary since one could argue that the global financial crisis in ongoing, however, the 2007-2008 period seems particularly important for US equities since it contains the sub-prime crisis and the Lehman issue. Also, since the “before the crisis” sub-period is relatively long, we repeat the calculations for smaller periods within this sub-period in order to see whether the results are stable over time: the result we obtain for the 1989-2006 period is stable even if shorter periods are evaluated (these results are not reported but are available upon request). Within each sub-period we further split the sample to days with a positive market return (“up” days) and days with a negative market return (“down” days) and study herding separately for “up” and “down” markets.

4. Herding in S&P100 stocks

Table 1 presents results for regression (2) using the S&P500 as the market portfolio, for the full sample period and three sub-periods as follows: Panel A contains the results for the full sample period (February 1989-March 2011), Panel B the results for the first sub-period (February 1989-December 2006), Panel C the results for the second sub-period (January 2006-December 2008, i.e. the “crisis”

period), and Panel D the results for the last sub-period (January 2009-March 2011). Within each Panel the first line presents results for all days, the second line presents results for only days with a negative market return ("down" days), and the third line presents results for only days with a positive market return ("up" days). The first column in the Table lists the periods, the second column the observations used for the regression, the third, fifth and seventh column present the estimated coefficients on the constant, linear and non-linear term, respectively, while the fourth, sixth and eighth column presents the *t*-statistics on the estimated coefficients on the constant, linear and non-linear term, respectively. The rest of the Tables in the paper are arranged in a similar manner.

More specifically, there are 5424 trading days within the full period (Panel A); in 2534 days the market return was negative while in 2890 days the market returns was positive. When all days are used to estimate regression (2) the estimated value of the constant coefficient is 0.0101 with a *t*-statistic of 117.025, the market beta is 0.3639 with a *t*-statistic of 31.55, and the beta on the non-linear term is 1.8434 with a *t*-statistic of 8.339. Note that the coefficient on the non-linear term is positive for all sub-periods except the 2007-2008 period (Panel C) suggesting that herding is more pronounced during the "crisis period". This would be consistent with the expectation that investors follow market beliefs instead of their own beliefs during large volatile periods, leading to herding during such periods. However, while the estimated coefficient for all days is negative at -0.0636, it has an insignificant *t*-statistic of -0.1664. A closer look indicates that the coefficient is negative *and* statistically significant (*t*-statistic: -2.6609) only during the "up" market days of the extreme volatile period of 2007-2008 and not for the down market days. We see therefore that during such extreme periods the herding occurs on the upside moves only, indicating

that although there is similar behavior of stocks during volatile periods, this actually occurs on the good days of such periods suggesting that, consistent with the theory, portfolio diversification is very (not very) useful when needed (not needed) i.e. in bad (good) days of volatile markets. This shows that there is herding only during very extreme market periods but even so it is not damaging for risk managers. In addition this indirectly shows that is extreme volatile down markets the price may not be falling to reflect fundamental information, and the herding is hence "spurious" (Bikhchandani and Sharma, 2000) which is a question we address later. Had we ignored the non-linear term (as done in the extant literature with exceptions such as Gleason, Mathur, and Peterson, 2004) and the distinction between up and down markets, the herding itself would have not been picked up, and in addition this critical market performance related difference would have not been picked up as is the case for example in Demirer and Kutan (2006). Our result overall is consistent with Gleason, Mathur, and Peterson (2004) in the fact that herding is not a phenomenon of extreme down markets and it seems to exist only in one of many volatile market periods.

[Insert Table 1 about here]

In order to examine whether the choice of the market portfolio affects the results, we re-estimate equation (2) using the S&P100 as the market portfolio. The results are presented in Table 2 and are nearly identical to the results in Table 1: The coefficient on then non-linear term is negative (-1.394) and statistically significant (*t*-statistic: -2.759) only during the crisis period and only during days with a positive market return. All estimations in the rest of the paper are repeated with both portfolios (S&P100, S&P500) as market portfolios, yet we report only the S&P100 findings as results are the same for both portfolios (S&P500 results are available upon request).

[Insert Table 2 about here]

Tables 3 and 4 report results for two sub-sample of stocks: smaller stocks (Table 3) and large stocks (Table 4) in order to investigate whether herding is more pronounced in smaller capitalization stocks as some previous studies indicate (Lakonishok, Shleifer, and Vishny, 1992; Wermers, 1999; among others). As above, the only period where herding seems to take place is during the crisis and only during the "up" days: the coefficient on the non-linear term is -1.1430 (*t*-statistic: -2.070) for smaller stocks (Table 3, Panel C), and -1.6368 (*t*-statistic: -3.107) for large stocks (Table 4, Panel C). Therefore the size of the stock does not play a role here. Tables 5 and 6 report results for two further sub-samples of stocks: growth (Low B/M ratio, Table 5) and value stocks (High B/M ratio, Table 6). Note that this sample division also gives nearly identical results to the ones presented above: the only period where herding seems to take place is during the crisis and only for "up" days. One could argue that larger firms and value firms seem to have a somewhat higher loading on the no-linear factor, and that perhaps these two should be addressed simultaneously in case there is any cancelling out or other effects that lead to no real difference of the findings here, which we perform at a later stage.

[Insert Tables 3, 4, 5, and 6 about here]

5. Does Time-Variation in Slope Coefficients Affect the Results?

As discussed in the introduction there is considerable evidence suggesting that betas exhibit time-variation (Ghysels, 1998; Conrad and Kaul, 1988; Koutmos, Lee, and Theodossiu, 1994; Groenewold and Fraser, 1999; among others) and that variation may arise from various microeconomic or macroeconomic factors (Bos and

Newbold, 1984). Note that this may be related to spurious herding, yet our specification in (2) is static as in the extant literature, and to deal with this, we employ the Kalman filter that takes into account for the time-varying nature of the slope coefficients. This has been done in other areas, for instance, Antoniou, Galariotis, and Spyrou (2006) show that time-variation in systematic risk significantly affects long-term contrarian profits in the UK: with returns defined as systematic-risk-adjusted assuming constant risk, long-term contrarian profits were economically and statistically significant; when, however, a Kalman filter procedure was employed the profitability of contrarian strategies was significantly reduced. Thus, in order to deal with the potential problem of time-variation in slope coefficients, we employ a Kalman-Filter approach to estimate the model, allowing slope coefficients to be time-varying. This approach has been used by many studies before in different areas (see, Jegadeesh and Pennacchi, 1996; Babbs and Nowman, 1999; Söderlind, 1999; Brown and Cliff, 2004; among others).

The Kalman filter is an algorithm that generates minimum mean square error forecasts in a state space model, and assuming Gaussian errors allows it to compute the log-likelihood function of the model (using maximum likelihood methods). The state space form comprises two equations: a measurement equation and a transition equation. More specifically, the state space representation can be represented as:

$$y_t = H\xi_t + Ax_t + \mu_t \tag{3}$$

$$\xi_{t+1} = F\xi_t + Bx_{t+1} + \nu_{t+1} \tag{4}$$

In (3) and (4), i.e. the observation equation and the state equation respectively, y_t is a $n \times 1$ vector of observed variables, ξ_t is a $r \times 1$ vector of state variables, x_t is a $k \times 1$ vector of exogenous variables, and H, A and F are coefficient matrices ($n \times r$, $n \times k$, $r \times r$, respectively). μ_t and v_t are vectors of residuals ($n \times 1$, $r \times 1$, respectively), with a covariance matrix Cov(μ_t, v_t) = 0. The observation equation and the state equation can be estimated by the Kalman filter algorithm.

Thus, we employ the Kalman filter procedure to (3) where $\beta_{i,t} = \beta_{i,t-1} + v_{t,t}$; in the Kalman filter algorithm the time varying parameters are generated stochastically by the state or transition equation, that is, b_{it} evolves as a random walk process. The intuition behind this specification is that beta change in response to new information (see Wang, 2003, for more details). Tables 7 to 11 present the same results as earlier but equation (2) is estimated with a Kalman-Filter procedure, which allows the coefficients to vary over-time. Table 7 presents results for the all-stock sample; Tables 8 and 9 present the results for the smaller and large stocks respectively, while Tables 10 and 11 present the results for the growth and value stocks, respectively. Note that the findings are similar to the findings in Tables 1-6: the only period where the estimated co-efficient on the non-linear term is negative and statistically significant is during the crisis and only during the "up" days. Therefore the results so far are robust to time variation in slope coefficients

[Insert Tables 7, 8, 9, 10, and 11 about here]

6. A Rational Explanation?

As discussed in the introduction, the finding of herding during the crisis period may not necessarily suggest non-rational investor behaviour; models that are based on payoff externalities, principal-agent relations, and cascades indicate that inferring information from the actions of other agents may be an optimal decision. Furthermore, the negative and statistically significant coefficient on the non-linear term that is often interpreted as evidence of herding behavior may capture a uniform investor reaction to significant information arrival. In order to investigate this issue further, we include in the regressions the Fama and French (1993, 1995, and 1996) factors (HML and SMB). The intuition is that, since these factors are hypothesized that they act as state variables in the context of an intertemporal capital asset pricing model (Fama and French, 1993, 1995) and that they are related to future growth in the real economy (Liew and Vassalou, 2000), the inclusion of these factors in the model will reveal whether investors herd due to biased beliefs or react to significant fundamental information. The factors are collected from French's site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french) where more details on the construction of the portfolios can be found.

We estimate the following regression for the sample portfolios for the full sample period and during the crisis period (since during the latter period we find evidence of herding):

$$CSAD_t = \beta_0 + \beta_1 |R_{mt}| + \beta_2 R_{mt}^2 + \beta_3 HML_t + \beta_4 SMB_t + e_t \tag{5}$$

The results are presented in Table 12 and are revealing: when the HML and the SMB portfolios are included the coefficient on the non-linear term is no more statistically significant. More specifically, Panel A in Table 12 presents the estimated

slope coefficients and their corresponding *t*-statistics from regression (5) for the full sample period and all stocks (column 2), value stocks (column 3), growth stocks (column 4), large stocks (column 5), and smaller stocks (column 6). Note that the only sub-sample of stocks for which non-linearity is still present when the Fama and French factors are included in the model is the growth portfolio for the full sample period (*t*-statistic: 5.1406). The HML and SMB factors have a statistically significant (and positive) slope coefficient for all sub-samples of stocks. Panel B presents the same results for the crisis period and the "up" days only, where evidence of herding is detected in the previous sections: for no sub-sample of stocks is the slope coefficient on the non-linear term statistically different from zero. Note that the results are similar for other sub-periods as well (not reported here for the economy of the paper, yet available upon request), suggesting that the inclusion of the HML and the SMB factors absorb the significance of the non-linear term, and consistent with the extant literature there is no evidence of herding once this is considered, i.e. there was spurious herding when not considering the state variables.

[Insert Table 12 about here]

7. Conclusion

Using a long sample period and all S&P100 constituent stocks we test for herding behavior utilizing that Chang, Cheng, and Khorana (2000) approach to measure herding. We find evidence of herding during the crisis period of 2007-2008 for various sub-samples of stocks. The use of a Kalman filter procedure to account for time-variation in slope coefficients does not affect the results. When, however, the

HML and SMB factors are included in the regressions they pick-up the effect of the non-linear term which is no longer statistically significant; this indicates that what appears as herding especially in extreme market periods in the literature may have actually been a linear investor reaction to fundamental risk factors.

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Table 1
Full sample, S&P 500 as the benchmark portfolio.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5424	0.0101	117.0250	0.3639	31.5518	1.8435	8.3395
02/10/1989-29/04/2011 (all - Down Market, , Rm<0)	2534	0.0105	81.3106	0.3120	18.3900	2.4235	7.5236
02/10/1989-29/04/2011 (all - Up Market, , Rm>0)	2890	0.0098	84.3367	0.4120	26.3010	1.3614	4.4886
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4336	0.0108	106.9101	0.3183	18.7165	2.1437	4.4383
02/10/1989-29/12/2006 (before the crisis - Down Market)	2042	0.0110	75.2565	0.3110	13.3885	1.0730	1.7359
02/10/1989-29/12/2006 (before the crisis - Up Market)	2294	0.0108	76.1319	0.2894	11.3009	4.5434	5.8028
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	503	0.0072	23.7843	0.5546	19.0211	-0.0636	-0.1665
03/01/2007-31/12/2008 (during the crisis - Down Market)	240	0.0081	16.6720	0.4465	10.0483	1.3160	2.2054
03/01/2007-31/12/2008 (during the crisis - Up Market)	263	0.0065	17.2561	0.6581	17.2907	-1.2817	-2.6610
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	585	0.0072	28.9497	0.4801	13.8973	1.8429	2.2821
02/01/2009-29/04/2011 (after the crisis - Down Market)	*252*	0.0075	18.2444	0.4300	7.2273	2.9958	2.0426
02/01/2009-29/04/2011 (after the crisis - Up Market)	333	0.0070	22.4119	0.5114	11.9792	1.2087	1.2693

This table presents OLS results for the all-stock sample for the following non-linear regression: $CSAD_t = \beta_0 + \beta_1 |R_{mt}| + \beta_2 R_{mt}^2 + e_t$, where CSAD is the Cross Sectional Absolute Deviation and R_{mt} is the market return. "Down Market" and "Up Market" denotes days with a negative and positive market return respectively.

Table 2
Full sample, S&P 100 as the benchmark portfolio.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5425	0.0100	114.8974	0.3793	32.5792	1.6873	7.3848
02/10/1989-29/04/2011 (all - Down Market, Rm<0)	2562	0.0103	79.8231	0.3383	19.8140	2.0981	6.2679
02/10/1989-29/04/2011 (all - Up Market, Rm>0)	2863	0.0098	82.7006	0.4183	26.3535	1.3481	4.3228
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4335	0.0107	105.6036	0.3409	20.8414	1.6774	3.7988
02/10/1989-29/12/2006 (before the crisis - Down Market)	2063	0.0107	74.2900	0.3491	15.6571	0.3984	0.6982
02/10/1989-29/12/2006 (before the crisis - Up Market)	2272	0.0108	75.4707	0.3006	12.2969	4.0935	5.8417
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	504	0.0073	23.9830	0.5576	18.6628	-0.0237	-0.0588
03/01/2007-31/12/2008 (during the crisis - Down Market)	248	0.0082	17.5998	0.4369	9.7194	1.5960	2.5327
03/01/2007-31/12/2008 (during the crisis - Up Market)	256	0.0065	16.6941	0.6710	17.0856	-1.3943	-2.7595
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	586	0.0072	28.6223	0.5076	13.8543	1.4755	1.6720
02/01/2009-29/04/2011 (after the crisis - Down Market)	251	0.0073	17.2246	0.4904	7.5941	2.0705	1.2360
02/01/2009-29/04/2011 (after the crisis - Up Market)	335	0.0072	22.6837	0.5128	11.2374	1.2463	1.2065

See notes to Table 1.

Table 3
Smaller stocks.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5425	0.0112	115.2741	0.4109	31.7655	2.5657	10.1071
02/10/1989-29/04/2011 (all - Down Market, Rm<0)	2562	0.0115	78.8903	0.3669	19.0586	3.2039	8.4874
02/10/1989-29/04/2011 (all - Up Market, Rm>0)	2863	0.0109	84.1652	0.4518	25.9645	2.0019	5.8558
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4336	0.0120	110.0992	0.3743	21.2455	1.4670	3.0845
02/10/1989-29/12/2006 (before the crisis - Down Market)	2063	0.0121	77.2117	0.3696	15.2598	0.5753	0.9281
02/10/1989-29/12/2006 (before the crisis - Up Market)	2272	0.0120	78.4511	0.3532	13.4883	3.2610	4.3440
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	504	0.0071	20.4970	0.6815	20.1239	0.2460	0.5389
03/01/2007-31/12/2008 (during the crisis - Down Market)	248	0.0080	14.7259	0.5631	10.6795	1.9588	2.6497
03/01/2007-31/12/2008 (during the crisis - Up Market)	256	0.0063	14.6886	0.7847	18.2821	-1.1430	-2.0698
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	586	0.0074	25.0035	0.6839	15.8121	0.1374	0.1319
02/01/2009-29/04/2011 (after the crisis - Down Market)	251	0.0074	14.8072	0.6580	8.5510	1.6638	0.8335
02/01/2009-29/04/2011 (after the crisis - Up Market)	335	0.0076	20.4025	0.6742	12.6770	-0.3071	-0.2551

This table presents OLS results for the small-stock sample. S&P 100 is used as the benchmark portfolio. See also notes to Table 1.

Table 4
Large stocks.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5425	0.0089	99.5188	0.3476	29.1886	0.8245	3.5278
02/10/1989-29/04/2011 (all - Down Market, Rm<0)	2562	0.0091	70.4025	0.3094	18.0340	1.0120	3.0086
02/10/1989-29/04/2011 (all - Up Market, Rm>0)	2863	0.0087	70.4823	0.3849	23.3499	0.7062	2.1807
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4335	0.0094	87.8066	0.3075	17.8053	1.8929	4.0602
02/10/1989-29/12/2006 (before the crisis - Down Market)	2063	0.0093	61.9593	0.3284	14.0877	0.2305	0.3863
02/10/1989-29/12/2006 (before the crisis - Up Market)	2272	0.0096	62.9099	0.2482	9.5408	4.9253	6.6055
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	504	0.0076	25.1919	0.4342	14.8036	-0.2818	-0.7128
03/01/2007-31/12/2008 (during the crisis - Down Market)	248	0.0083	19.4296	0.3111	7.4996	1.2489	2.1478
03/01/2007-31/12/2008 (during the crisis - Up Market)	256	0.0068	16.6263	0.5579	13.6271	-1.6368	-3.1073
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	586	0.0070	29.7598	0.3323	9.7349	2.8135	3.4219
02/01/2009-29/04/2011 (after the crisis - Down Market)	251	0.0071	18.3469	0.3235	5.4691	2.4919	1.6238
02/01/2009-29/04/2011 (after the crisis - Up Market)	335	0.0069	22.9101	0.3524	8.1940	2.7950	2.8711

This table presents OLS results for the large-stock sample. S&P 100 is used as the benchmark portfolio. See also notes to Table 1.

Table 5
Growth (Low B/M) stocks.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5425	0.0097	109.3780	0.3450	29.2057	1.5040	6.4876
02/10/1989-29/04/2011 (all - Down Market, Rm<0)	2562	0.0099	77.2145	0.3046	17.8551	1.7999	5.3815
02/10/1989-29/04/2011 (all - Up Market, Rm>0)	2863	0.0095	77.5971	0.3839	23.5197	1.2798	3.9903
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4335	0.0106	98.8427	0.2982	17.2646	2.3147	4.9639
02/10/1989-29/12/2006 (before the crisis - Down Market)	2063	0.0105	69.7893	0.3155	13.4974	0.6019	1.0063
02/10/1989-29/12/2006 (before the crisis - Up Market)	2272	0.0108	70.8451	0.2400	9.2620	5.4847	7.3839
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	504	0.0069	32.7156	0.4683	22.6248	0.2836	1.0166
03/01/2007-31/12/2008 (during the crisis - Down Market)	248	0.0075	24.5760	0.3776	12.7966	1.5510	3.7494
03/01/2007-31/12/2008 (during the crisis - Up Market)	256	0.0064	22.3748	0.5524	19.2796	-0.7820	-2.1211
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	586	0.0054	38.1056	0.4870	23.6663	1.3041	2.6311
02/01/2009-29/04/2011 (after the crisis - Down Market)	251	0.0054	23.0520	0.4774	13.3254	1.4019	1.5084
02/01/2009-29/04/2011 (after the crisis - Up Market)	335	0.0054	29.8623	0.4978	19.2513	1.1978	2.0461

This table presents OLS results for the Low B/M stock sample. S&P 100 is used as the benchmark portfolio. See also notes to Table 1.

Table 6
Value (High B/M) stocks.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5425	0.0102	100.0090	0.3971	29.1925	1.7267	6.4675
02/10/1989-29/04/2011 (all - Down Market, Rm<0)	2562	0.0105	69.0138	0.3493	17.3340	2.3375	5.9171
02/10/1989-29/04/2011 (all - Up Market, Rm>0)	2863	0.0099	72.4266	0.4421	24.0505	1.1982	3.3177
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4335	0.0107	96.3690	0.3671	20.5261	1.1889	2.4624
02/10/1989-29/12/2006 (before the crisis - Down Market)	2063	0.0107	67.9744	0.3638	14.8969	0.3771	0.6034
02/10/1989-29/12/2006 (before the crisis - Up Market)	2272	0.0107	68.1999	0.3472	12.9581	2.8138	3.6630
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	504	0.0077	17.2608	0.6223	14.3211	-0.4635	-0.7913
03/01/2007-31/12/2008 (during the crisis - Down Market)	248	0.0089	12.8183	0.4590	6.8562	1.6739	1.7836
03/01/2007-31/12/2008 (during the crisis - Up Market)	256	0.0066	11.8046	0.7775	13.9616	-2.2841	-3.1879
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	586	0.0087	22.4457	0.4642	8.1972	2.2288	1.6340
02/01/2009-29/04/2011 (after the crisis - Down Market)	251	0.0089	13.4469	0.4374	4.3018	3.1765	1.2043
02/01/2009-29/04/2011 (after the crisis - Up Market)	335	0.0087	17.9604	0.4691	6.7638	1.8975	1.2086

This table presents OLS results for the High B/M stock sample. S&P 100 is used as the benchmark portfolio. See also notes to Table 1.

Table 7
Full sample, S&P 100 as the benchmark portfolio, Kalman Filter procedure.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5425	0.0100	114.8974	0.3793	32.5792	1.6873	7.3848
02/10/1989-29/04/2011 (all - Down Market, Rm<0)	2562	0.0103	79.8231	0.3383	19.8140	2.0981	6.2679
02/10/1989-29/04/2011 (all - Up Market, Rm>0)	2863	0.0098	82.7006	0.4183	26.3535	1.3481	4.3228
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4335	0.0107	105.6036	0.3409	20.8414	1.6774	3.7988
02/10/1989-29/12/2006 (before the crisis - Down Market)	2063	0.0107	74.2900	0.3491	15.6571	0.3984	0.6982
02/10/1989-29/12/2006 (before the crisis - Up Market)	2272	0.0108	75.4707	0.3006	12.2969	4.0935	5.8417
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	504	0.0073	23.9830	0.5576	18.6628	-0.0237	-0.0588
03/01/2007-31/12/2008 (during the crisis - Down Market)	248	0.0082	17.5998	0.4369	9.7194	1.5960	2.5327
03/01/2007-31/12/2008 (during the crisis - Up Market)	256	0.0065	16.6941	0.6710	17.0856	-1.3943	-2.7595
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	586	0.0072	28.6223	0.5076	13.8543	1.4755	1.6720
02/01/2009-29/04/2011 (after the crisis - Down Market)	251	0.0073	17.2246	0.4904	7.5941	2.0705	1.2360
02/01/2009-29/04/2011 (after the crisis - Up Market)	335	0.0072	22.6837	0.5128	11.2374	1.2463	1.2065

This table presents results for the all-stock sample with a time-varying procedure (Kalman-Filter). S&P 100 is used as the benchmark portfolio. See also notes to Table 1.

Table 8
Large stocks, Kalman Filter procedure.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5425	0.0089	99.5188	0.3476	29.1886	0.8245	3.5278
02/10/1989-29/04/2011 (all - Down Market, Rm<0)	2562	0.0091	70.4025	0.3094	18.0340	1.0120	3.0086
02/10/1989-29/04/2011 (all - Up Market, Rm>0)	2863	0.0087	70.4823	0.3849	23.3499	0.7062	2.1807
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4335	0.0094	87.8066	0.3075	17.8053	1.8929	4.0602
02/10/1989-29/12/2006 (before the crisis - Down Market)	2063	0.0093	61.9593	0.3284	14.0877	0.2305	0.3863
02/10/1989-29/12/2006 (before the crisis - Up Market)	2272	0.0096	62.9099	0.2482	9.5408	4.9253	6.6055
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	504	0.0076	25.1919	0.4342	14.8036	-0.2818	-0.7128
03/01/2007-31/12/2008 (during the crisis - Down Market)	248	0.0083	19.4296	0.3111	7.4996	1.2489	2.1478
03/01/2007-31/12/2008 (during the crisis - Up Market)	256	0.0068	16.6263	0.5579	13.6271	-1.6368	-3.1073
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	586	0.0070	29.7598	0.3323	9.7349	2.8135	3.4219
02/01/2009-29/04/2011 (after the crisis - Down Market)	251	0.0071	18.3469	0.3235	5.4691	2.4919	1.6238
02/01/2009-29/04/2011 (after the crisis - Up Market)	335	0.0069	22.9101	0.3524	8.1940	2.7950	2.8711

This table presents results for the large-stock sample with a time-varying procedure (Kalman-Filter). S&P 100 as the benchmark portfolio. See also notes to Table 1.

Table 9
Smaller stocks, Kalman Filter procedure.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5425	0.0112	115.2741	0.4109	31.7655	2.5657	10.1071
02/10/1989-29/04/2011 (all - Down Market, Rm<0)	2562	0.0115	78.8903	0.3669	19.0586	3.2039	8.4874
02/10/1989-29/04/2011 (all - Up Market, Rm>0)	2863	0.0109	84.1652	0.4518	25.9645	2.0019	5.8558
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4335	0.0120	110.0992	0.3743	21.2455	1.4670	3.0845
02/10/1989-29/12/2006 (before the crisis - Down Market)	2063	0.0121	77.2117	0.3696	15.2598	0.5753	0.9281
02/10/1989-29/12/2006 (before the crisis - Up Market)	2272	0.0120	78.4511	0.3532	13.4883	3.2610	4.3440
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	504	0.0071	20.4970	0.6815	20.1239	0.2460	0.5389
03/01/2007-31/12/2008 (during the crisis - Down Market)	248	0.0080	14.7259	0.5631	10.6795	1.9588	2.6497
03/01/2007-31/12/2008 (during the crisis - Up Market)	256	0.0063	14.6886	0.7847	18.2821	-1.1430	-2.0698
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	586	0.0074	25.0035	0.6839	15.8121	0.1374	0.1319
02/01/2009-29/04/2011 (after the crisis - Down Market)	251	0.0074	14.8072	0.6580	8.5510	1.6638	0.8335
02/01/2009-29/04/2011 (after the crisis - Up Market)	335	0.0076	20.4025	0.6742	12.6770	-0.3071	-0.2551

This table presents results for the small-stock sample with a time-varying procedure (Kalman-Filter). S&P 100 as the benchmark portfolio. See also notes to Table 1.

Table 10
Growth (Low B/M) stocks, Kalman Filter procedure.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5425	0.0097	109.3780	0.3450	29.2057	1.5040	6.4876
02/10/1989-29/04/2011 (all - Down Market, Rm<0)	2562	0.0099	77.2145	0.3046	17.8551	1.7999	5.3815
02/10/1989-29/04/2011 (all - Up Market, Rm>0)	2863	0.0095	77.5971	0.3839	23.5197	1.2798	3.9903
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4335	0.0106	98.8427	0.2982	17.2646	2.3147	4.9639
02/10/1989-29/12/2006 (before the crisis - Down Market)	2063	0.0105	69.7893	0.3155	13.4974	0.6019	1.0063
02/10/1989-29/12/2006 (before the crisis - Up Market)	2272	0.0108	70.8451	0.2400	9.2620	5.4847	7.3839
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	504	0.0069	32.7156	0.4683	22.6248	0.2836	1.0166
03/01/2007-31/12/2008 (during the crisis - Down Market)	248	0.0075	24.5760	0.3776	12.7966	1.5510	3.7494
03/01/2007-31/12/2008 (during the crisis - Up Market)	256	0.0064	22.3748	0.5524	19.2796	-0.7820	-2.1211
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	586	0.0054	38.1056	0.4870	23.6663	1.3041	2.6311
02/01/2009-29/04/2011 (after the crisis - Down Market)	251	0.0054	23.0520	0.4774	13.3254	1.4019	1.5084
02/01/2009-29/04/2011 (after the crisis - Up Market)	335	0.0054	29.8623	0.4978	19.2513	1.1978	2.0461

This table presents results for the Low B/M stock sample with a time-varying procedure (Kalman-Filter). S&P 100 as the benchmark portfolio. See also notes to Table 1

Table 11
Value (High B/M) stocks, Kalman Filter procedure.

Sample Period	# of trading days	β_0	*t*-statistic β_0	β_1	*t*-statistic β_1	β_2	*t*-statistic β_2
PANEL A							
02/10/1989-29/04/2011 (all)	5425	0.0102	100.0090	0.3971	29.1925	1.7267	6.4675
02/10/1989-29/04/2011 (all - Down Market, Rm<0)	2562	0.0105	69.0138	0.3493	17.3340	2.3375	5.9171
02/10/1989-29/04/2011 (all - Up Market, Rm>0)	2863	0.0099	72.4266	0.4421	24.0505	1.1982	3.3177
PANEL B							
02/10/1989-29/12/2006 (before the crisis - all)	4335	0.0107	96.3690	0.3671	20.5261	1.1889	2.4624
02/10/1989-29/12/2006 (before the crisis - Down Market)	2063	0.0107	67.9744	0.3638	14.8969	0.3771	0.6034
02/10/1989-29/12/2006 (before the crisis - Up Market)	2272	0.0107	68.1999	0.3472	12.9581	2.8138	3.6630
PANEL C							
03/01/2007-31/12/2008 (during the crisis - all)	504	0.0077	17.2608	0.6223	14.3211	-0.4635	-0.7913
03/01/2007-31/12/2008 (during the crisis - Down Market)	248	0.0089	12.8183	0.4590	6.8562	1.6739	1.7836
03/01/2007-31/12/2008 (during the crisis - Up Market)	256	0.0066	11.8046	0.7775	13.9616	-2.2841	-3.1879
PANEL D							
02/01/2009-29/04/2011 (after the crisis - all)	586	0.0087	22.4457	0.4642	8.1972	2.2288	1.6340
02/01/2009-29/04/2011 (after the crisis - Down Market)	251	0.0089	13.4469	0.4374	4.3018	3.1765	1.2043
02/01/2009-29/04/2011 (after the crisis - Up Market)	335	0.0087	17.9604	0.4691	6.7638	1.8975	1.2086

This table presents results for the High B/M stock sample with a time-varying procedure (Kalman-Filter). S&P 100 as the benchmark portfolio. See also notes to Table 1.

Table 12
Rational Herding.

	All stocks	Value stocks	Growth stocks	Large stocks	Smaller stocks
PANEL A: all trading days					
β_0	0.0074	0.0078	0.0077	0.0072	0.0076
t-statistic	24.957	18.143	29.237	20.990	26.676
β_1	0.5384	0.5910	0.3581	0.6650	0.4125
t-statistic	18.522	14.043	13.775	19.861	14.705
β_2	0.4763	0.3330	1.8342	0.6669	0.2969
t-statistic	1.1939	0.5766	5.1406	1.4513	0.7712
β_3	0.0014	0.0021	0.0010	0.0010	0.0017
t-statistic	5.4443	5.6882	4.2282	3.4758	7.1270
β_4	0.0007	0.0012	0.0004	0.0008	0.0006
t-statistic	2.6783	3.2055	1.8332	2.6415	2.4049
PANEL B: up days					
β_0	0.0067	0.0068	0.0073	0.0070	0.0064
t-statistic	18.775	13.667	22.248	19.435	15.812
β_1	0.5968	0.6584	0.4110	0.4748	0.7195
t-statistic	15.589	12.295	11.597	12.309	16.537
β_2	-0.469	-0.752	0.8262	-0.661	-0.268
t-statistic	-0.950	-1.088	1.8059	-1.327	-0.477
β_3	0.0021	0.0033	0.0014	0.0025	0.0017
t-statistic	6.2987	7.0014	4.4698	7.4078	4.5165
β_4	0.0006	0.0011	0.0003	0.0005	0.0007
t-statistic	1.7140	2.2440	1.0595	1.3223	1.8489

This table presents results for: $CSAD_t = \beta_0 + \beta_1 |R_{mt}| + \beta_2 R_{mt}^2 + \beta_3 HML_t + \beta_4 SMB_t + e_t$ with the S&P 100 as the benchmark portfolio. See also notes to Table 1.