



## Market stress and herding

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### Abstract

We propose a new approach to detecting and measuring herding which is based on the cross-sectional dispersion of the factor sensitivity of assets within a given market. This method enables us to evaluate if there is herding towards particular sectors or styles in the market including the market index itself and critically we can also separate such herding from common movements in asset returns induced by movements in fundamentals. We apply the approach to an analysis of herding in the US and South Korean stock markets and find that herding towards the market shows significant movements and persistence independently from and given market conditions and macro factors. We find evidence of herding towards the market portfolio in both bull and bear markets. Contrary to common belief, the Asian Crisis and in particular the Russian Crisis reduce herding and are clearly identified as turning points in herding behaviour.

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### 1. Introduction

Herding arises when investors decide to imitate the observed decisions of others or movements in the market rather than follow their own beliefs and information. Such behaviour may be seen to be individually rational on a number of grounds although it may not necessarily lead to efficient market outcomes. Herding can be rational in a utility-maximising sense, for instance, when it is thought that other participants in the market are better-informed or as in [Avery and Zemsky \(1998\)](#) where there is uncertainty as to the average accuracy of traders' information so that market participants hold mistaken but

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rational beliefs that most traders possess accurate information. Other sources considered in the literature arise when deviating from the consensus is potentially costly as, for example, in the remuneration of fund managers.<sup>1</sup>

The suppression of private information as herding gathers pace may lead to a situation in which the market price fails as a sufficient statistic to reflect all relevant fundamental information—a process which moves the market towards inefficiency in an information cascade as social learning completely breaks down (Banerjee, 1992; Bikhchandani et al., 1992).<sup>2</sup> The sequential nature of information flow and action is crucial in this argument as is the assumption that the price is fixed. Avery and Zemsky (1998) show, in a theoretical analysis which extends the model used in Bikhchandani et al. (1992) by allowing the market price to be endogenous and where informed traders are rational actors and prices incorporate all publicly available information, that information cascades are impossible and herd behaviour can cause no long-term mispricing of assets. However, when the market is uncertain as to whether the value of the asset has changed from its initial expected value they show herding can reappear. The effect of this herding, however, is bounded and the impact on pricing may be small if the bound is tight. Finally when they add uncertainty about the average accuracy of trader's information, herd behaviour can become dominant and the extreme effects of herding in terms of mispricing can arise leading to bubbles and subsequent crashes. Herding cannot therefore be ruled out on the basis of theoretical analysis and we need to rely on empirical evidence to determine the importance of herding in practice.

Herding as a form of correlated behaviour can be in principle separated from what Bikhchandani and Sharma (2001) refer to as “spurious” or unintentional herding where independent individuals decide to take similar actions induced by the movement of fundamentals. The terminology in this area can be difficult and at times unintuitive. We will, in what follows, try to retain simplicity and use the term herding in its common pejorative sense which implies the suppression of private information and imitation without reference to fundamentals. Without being specific, we view this form of herding as related to market sentiment which we note is naturally a latent and unobservable process. We will refer to common actions taken by independent agents following fundamental signals simply as fundamentals adjustment.

Leaving aside issues of what may be rational or irrational motives for herding, it is clearly important to be able to discriminate empirically between these two cases of common or correlated movements within the market; one of which potentially leads to market inefficiency whereas the other simply reflects an efficient reallocation of assets on the basis of common fundamental news. Since both motivations represent collective movements in the market towards some position or view and hence a preference towards

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<sup>1</sup> See Banerjee (1992), Bikhchandani et al. (1992), and Welch (1992) for information-based herding, Scharfstein and Stein (1990) for reputation-based herding, and Brennan (1993), and Roll (1992) for compensation-based herding. Studies of herd behaviour are in principle closely related to the study of contagion, see Eichengreen et al. (1998) and Bae et al. (2003) for example.

<sup>2</sup> There is considerable experimental evidence from social psychology on the behaviour of individuals in groups which demonstrate this suppression of individual opinion to group opinion, see for instance Asch (1953), Deutsch and Gerard (1955) and Turner et al. (1987).

some class of assets, it has not been easy to develop statistical methods that discriminate between these two cases and that is one principal objective of this paper.

We develop a new approach to measuring herding based on observing deviations from the equilibrium beliefs expressed in CAPM prices. By conditioning on the observed movements in fundamentals, we are able to separate adjustment to fundamentals news from herding due to market sentiment and hence extract the latent herding component in observed asset returns. Our approach is similar to [Christie and Huang's \(1995\)](#) to the extent that we exploit the information held in the cross-sectional movements of the market. However, we focus on the cross-sectional variability of factor sensitivities rather than returns, and thus our measure is free from the influence of idiosyncratic components. Our measure captures market-wide herding when market beliefs converge on particular assets or asset classes rather than herding by individuals or a small group of investors. It is also relatively easy to calculate since it is based on observed returns data, whilst other measures proposed by [Lakonishok et al. \(1992\)](#) or [Wermers \(1995\)](#) for instance, need detailed records of individual trading activities which may not be readily available in many cases.

For a one-factor model where the factor is market returns, the measure of herding is simply calculated from the relative dispersion of the betas for all the assets in the market. When there is herding “towards the market portfolio”, the cross-sectional variance of the estimated betas will decrease so that investors herd around the consensus of all market participants (“the market”) as reflected in the market index. When considering herding towards the market, we take the underlying movement in the market itself as given and hence capture adjustments in the structure of the market due to herding rather than adjustments in the market. This may be termed market wide herding and allows us to measure movements in sentiment/herding within the market which may follow a different path from the market itself, see [Richards \(1999\)](#) and [Goyal and Santa-Clara \(2003\)](#). Market sentiment is for instance often believed to change with little or no apparent movement in the market itself. The use of linear factor models can also provide additional insights into other directions towards which the market may herd based on different factors in addition to the market factor, such as growth and value, country- or sector-specific factors.

We have applied our approach to the US and South Korean stock markets and found that herding towards the market shows significant movements and persistence independently from and given market conditions as expressed in return volatility and the level of the market return. Macro-factors are found to offer almost no help in explaining these herding patterns. We also find evidence of herding towards the market portfolio both when the market is rising and when it is falling. The Asian Crisis and in particular the Russian Crisis are clearly identified as turning points in herding behaviour. Contrary to common belief, these crises appear to stimulate a return towards efficiency rather than an increased level of herding; during market stress investors turn to fundamentals rather than overall market movements. If we compare these results with those of [Christie and Huang \(1995\)](#) who find no evidence of herding during market crises, our approach provides much more detailed analysis of the dynamic evolution of herding before, after and during a crisis. Our results are not inconsistent with [Christie and Huang \(1995\)](#) in the sense that during market crises herding begins to disappear. However, we find herding when the market is quiet and investors are confident of the direction in which markets are heading; results which cannot be found in [Christie and Huang \(1995\)](#).

We have also examined herding towards size and value factors and found significant evidence of herding towards value at different times in the sample within the US market but particularly since January 2001. We have been able to examine herding relationships across the two markets and between the different herding objectives and find some common patterns but far from perfect co-movements. Briefly, within a market, herding towards the different factors is correlated, but between the US and South Korean markets we find little or no evidence of co-movement in herding. These results suggest that market sentiment does not necessarily transfer internationally.

## 2. Herding and its measurement

In [Christie and Huang \(1995\)](#), the cross-sectional standard deviation of individual stock returns is calculated and then regressed on a constant and two dummy variables designed to capture extreme positive and negative market returns. They argue that during periods of market stress rational asset pricing would imply positive coefficients on these dummy variables, while herd behaviour would suggest negative coefficients. However, market stress does not necessarily imply that the market as a whole should show either large negative or positive returns. For example, we have seen periods with large swings in both the Dow Jones and the NASDAQ (reflecting the weight given to the old and new economies in investor sentiment) while the market for stocks as a whole has not shown any dramatic change in the aggregate. In this case, without any large movement in the whole market we may still observe considerable reallocation towards particular sectors. Thus, defining herding as only arising when there are large positive or negative returns will exclude these important examples of herd behaviour. The introduction of dummy variables is itself crude since the choice of what is meant by “extreme” is entirely subjective. Moreover, since the method does not include any device to control for movements in fundamentals it is impossible to conclude whether it is herding or independent adjustment to fundamentals that is taking place and therefore whether or not the market is moving towards a relatively efficient or an inefficient outcome. Another problem with using the cross-sectional standard deviation of individual stock returns is that it is not independent of time series volatility. [Goyal and Santa-Clara \(2003\)](#) and [Hwang and Satchell \(2002\)](#) show that cross-sectional volatility and time series volatility are theoretically and empirically significantly positively correlated and the uncertainty of return predictability (volatility measured over time horizon) moves together with cross-sectional standard deviation of individual stock returns. Hence, even if we find a negative relationship between the cross-sectional standard deviation of individual stock returns and the dummy variables, we could not be sure whether it originates from changes in volatility (measured over time) or herding.

### 2.1. CAPM in the presence of herding

The type of herding behaviour in which we are interested is however similar to that in [Christie and Huang \(1995\)](#); we wish to monitor, through the cross-sectional behaviour of assets, the actions of investors who follow the performance of the market (or other signals

such as macroeconomic factors or styles) and are led to buy or sell particular assets at the same time.<sup>3</sup> This is different from the usual definition of herding in which the behaviour of a subgroup of investors follow each other by buying and selling the same assets at the same time. In our concept of herding, individuals follow market views about either the market index itself or particular sectors or styles. This market-based notion of herding is as important as the usual definition since both forms of herd behaviour lead to the mispricing of individual assets as equilibrium beliefs are suppressed.

Herding leads to mispricing as rational decision making is disturbed through the use of biased beliefs and hence biased views of expected returns and risks. To see how herding biases the risk–return relationship, we first consider what could happen when herding exists in the conventional CAPM. When investors herd towards the performance of the market portfolio, the CAPM betas for individual assets will be biased away from their equilibrium values, making the cross-sectional dispersion of the individual betas smaller than it would be in equilibrium. If all returns were expected to be equal to the market return, all betas would take the same value of one and the cross-sectional variance would be zero.

Consider the following CAPM in equilibrium,

$$E_t(r_{it}) = \beta_{imt}E_t(r_{mt}). \quad (1)$$

where  $r_{it}$  and  $r_{mt}$  are the excess returns on asset  $i$  and the market at time  $t$ , respectively,  $\beta_{imt}$  is the systematic risk measure, and  $E_t(\cdot)$  is conditional expectation at time  $t$ . In equilibrium, given the view of the market ( $E_t(r_{mt})$ ), we only need  $\beta_{imt}$  in order to price an asset  $i$ .

The conventional CAPM assumes that  $\beta_{imt}$  does not change over time. However, there is considerable empirical evidence that the betas are in fact not constant, see Harvey (1989), Ferson and Harvey (1991, 1993), and Ferson and Korajczyk (1995) for example. The empirical evidence on the variation in betas does not however suggest that betas are changing over time in equilibrium. On the contrary, we would argue that a significant proportion of the time-variation reflects changes in investor sentiment and that while equilibrium betas may change over time they will generally vary very slowly as firms evolve.<sup>4</sup> That is, the empirical evidence of time-varying betas may derive from behavioural anomalies such as herding, rather than from fundamental changes in  $\beta_{imt}$ , or the equilibrium relationship between  $E_t(r_{mt})$  and  $E_t(r_{it})$ . Of course changes in the equilibrium betas could come about if a firm changed its capital structure substantially, for example, to become highly geared or if its main business area moved from, say, manufacturing to the service sector. However, these changes are likely to be rare and it is unlikely that they would arise within a short time interval. In addition, Ghysels (1998) shows that it is difficult to use the commonly adopted models for time-varying betas and we have no statistical model that appears to capture the time variation in betas correctly. He argues that

<sup>3</sup> Although we explain herd behaviour at the market level, the concept could easily be applied to any subgroup of assets or sectors.

<sup>4</sup> In equilibrium, time-variant betas are possible with some assumptions on probability density functions and investors' attitudes towards risk. However we prefer a behavioural interpretation where statistically significant changes in betas reflect changes in market sentiment rather than a time-varying equilibrium unless there are changes in fundamentals. In this sense our approach is different from Wang (2003) who explains asset prices with time-varying betas in equilibrium.

betas change very slowly over time and concludes that it is better to use a constant beta assumption in pricing.

How do the betas become biased when herding occurs? When investors' beliefs shift so as to follow the performance of the overall market more than they should in equilibrium, they disregard the equilibrium relationship ( $\beta_{imt}$ ) and move towards matching the return on individual assets with that of the market. In this case, we say herding towards the market (performance) takes place. For example, when the market increases significantly, investors will often try to buy underperforming assets (relative to the market) and sell overperforming assets. Suppose the market index increases by 20%. Then we would expect a 10% increase for any asset with a beta of 0.5 and 30% increase for an asset with a beta of 1.5 in equilibrium. However, when there is herding towards the market portfolio, investors would buy the asset with a beta of 0.5 since it appears to be relatively cheap compared to the market and thus its price would increase. On the other hand, investors would sell an asset with a beta of 1.5 since the asset would appear to be relatively expensive compared to the market. This behaviour would also take place when market goes down significantly. We can also think of the opposite form of behaviour, or cases of adverse herding, when high betas (betas larger than one) become higher and low betas (betas less than one) become lower. In this case, individual returns become more sensitive for large beta stocks but less sensitive for low beta stocks. This represents mean reversion towards the long term equilibrium  $\beta_{imt}$ , and in fact adverse herding must exist if herding exists since there must be some systematic adjustment back towards the equilibrium CAPM from mispricing both above and below equilibrium.

Could this kind of herding happen in the market? Macro-trading and investment rules based on macro predictability, as discussed for instance in [Burstein \(1999\)](#), have become recognised investment strategies. When macroeconomic signals convince investors, in either a positive or negative way, that the market is "easy" to forecast, they might overreact and become too optimistic or pessimistic compared to the equilibrium risk–return relationship.<sup>5</sup> In this situation, we would expect to find investors who are looking for "undervalued" or "overvalued" equities relative to "the market" (or sector, or other equities in the same sector) increasing the plausibility of mispricing and herding towards the market. On the other hand, when sudden unexpected shocks occur, the market becomes "difficult" in the sense that nobody is sure where it is heading. Then investors could return towards the fundamental values of firms (via adverse herding) and asset prices then return towards the long-term equilibrium risk–return relationship.

## 2.2. A new measure of herding

When there is herding towards the market portfolio and the equilibrium CAPM relationship no longer holds, both the beta and the expected asset return will be biased. We assume that  $E_t(r_{mt})$  is set by a common market-wide view and the investor first forms a

<sup>5</sup> There is substantial evidence on this sort of behavioural anomaly in financial markets, see for instance, [Arnold \(1986\)](#), [Lux \(1997\)](#), [Kahneman and Tversky \(1973\)](#), [Amir and Ganzach \(1998\)](#), and [Shiller \(2003\)](#), and similar references in the over-reaction and under-reaction and positive feedback investment strategy literature, reviewed for instance in [Shleifer \(2000\)](#).

view of the market as a whole and then considers the value of the individual asset. So in effect we assume investors' behaviour is conditional on  $E_t(r_{mt})$  and therefore the empirically observed  $\beta_{imt}$  will be biased, at least in the short run, given  $E_t(r_{mt})$ .<sup>6</sup>

Instead of the equilibrium relationship (Eq. (1)), we assume the following relationship holds in the presence of herding towards the market;

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1), \quad (2)$$

where  $E_t^b(r_{it})$  and  $\beta_{imt}^b$  are the market's biased short run conditional expectation on the excess returns of asset  $i$  and its beta at time  $t$ , and  $h_{mt}$  is a latent herding parameter that changes over time,  $h_{mt} \leq 1$ , and conditional on market fundamentals.<sup>7</sup>

When  $h_{mt} = 0$ ,  $\beta_{imt}^b = \beta_{imt}$  so there is no herding and the equilibrium CAPM applies. When  $h_{mt} = 1$ ,  $\beta_{imt}^b = 1$  which is the beta on the market portfolio and the expected excess return on the individual asset will be the same as that on the market portfolio. So  $h_{mt} = 1$  suggests perfect herding towards the market portfolio in the sense that all the individual assets move in the same direction with the same magnitude as the market portfolio. In general, when  $0 < h_{mt} < 1$ , some degree of herding exists in the market determined by the magnitude of  $h_{mt}$ .

Consider the situation described in the previous section. We can now explain the relationship between the true and biased expected excess returns on asset  $i$  and its beta. For an equity with  $\beta_{imt} > 1$  and thus  $E_t(r_{it}) > E_t(r_{mt})$ , the equity "is herded" towards the market so that  $E_t^b(r_{it})$  moves closer to  $E_t(r_{mt})$  and  $E_t(r_{it}) > E_t^b(r_{it})$ . Therefore, the equity looks less risky than it should, suggesting  $\beta_{imt}^b < \beta_{imt}$ . On the other hand, for an equity with  $\beta_{imt} < 1$  and thus  $E_t(r_{it}) < E_t(r_{mt})$ , the equity "is herded" towards the market when  $E_t^b(r_{it})$  moves closer to  $E_t(r_{mt})$  so that  $E_t(r_{it}) < E_t^b(r_{it}) < E_t(r_{mt})$ . The equity looks riskier than it should, suggesting  $\beta_{imt}^b > \beta_{imt}$ . For an equity whose  $\beta_{imt} = 1$ , the equity is neutral to herding. As discussed above, the existence of herding implies the existence of adverse herding, which is explained by allowing  $h_{mt} < 0$ . In this case, for an equity with  $\beta_{imt} > 1$ ,  $E_t^b(r_{it}) > E_t(r_{it}) > E_t(r_{mt})$ , whereas for an equity with  $\beta_{imt} < 1$ ,  $E_t^b(r_{it}) < E_t(r_{it}) < E_t(r_{mt})$ .

### 2.3. Models for measuring herding

While herding towards the market portfolio can be captured by  $h_{mt}$ , both  $\beta_{imt}$  and  $h_{mt}$  are unobserved and it is not immediately obvious how to measure  $h_{mt}$ , particularly if the true beta,  $\beta_{imt}$ , is not constant. Since the form of herding we discuss represents market-wide behaviour and Eq. (2) is assumed to hold for all assets in the market, we should calculate the level of herding using all assets in the market rather than a single asset, thereby removing the effects of idiosyncratic movements in any individual  $\beta_{imt}^b$ .

<sup>6</sup> In passing, this implies that our measure of herding should not be not affected by changes in equity premium.

<sup>7</sup> Notice that even if the expected market returns are themselves biased, our measure still calculates the level of the cross-sectional dispersion of the betas within the biased expected market returns. We assume that our investors' herding behaviour is calculated conditional on  $E_t(r_{mt})$  regardless of any bias in  $E_t(r_{mt})$ .

Since the cross-sectional mean of  $\beta_{imt}^b$  (or  $\beta_{imt}$ ) is always 1,<sup>8</sup> we have

$$\begin{aligned} \text{Std}_c(\beta_{imt}^b) &= \sqrt{E_c((\beta_{imt} - h_{mt}(\beta_{imt} - 1) - 1)^2)} \\ &= \sqrt{E_c((\beta_{imt} - 1)^2)(1 - h_{mt})} \\ &= \text{Std}_c(\beta_{imt})(1 - h_{mt}), \end{aligned} \tag{3}$$

where  $E_c(\cdot)$  and  $\text{Std}_c(\cdot)$  represent the cross-sectional expectation and standard deviation, respectively. The first component is the cross-sectional standard deviation of the equilibrium betas and the second is a direct function of the herding parameter.

While we minimize the impact of idiosyncratic changes in  $\beta_{imt}$  by calculating  $\text{Std}_c(\beta_{imt})$  using a large number of assets, we allow  $\text{Std}_c(\beta_{imt})$  to be stochastic in order to be able monitor movements in the equilibrium beta. However, as discussed above, we do not expect the market wide  $\text{Std}_c(\beta_{imt})$  to change significantly within any short time scale unless the structure of companies within the market changed dramatically. Therefore, we assume that  $\text{Std}_c(\beta_{imt})$  does not exhibit any systematic movement and that changes in  $\text{Std}_c(\beta_{imt}^b)$  over a short time interval can therefore be attributed to changes in  $h_{mt}$ .

2.3.1. The state space model

To extract  $h_{mt}$  from  $\text{Std}_c(\beta_{imt}^b)$ , we first take logarithms of Eq. (3);

$$\log[\text{Std}_c(\beta_{imt}^b)] = \log[\text{Std}_c(\beta_{imt})] + \log(1 - h_{mt}).$$

Using our assumptions on  $\text{Std}_c(\beta_{imt})$ , we may write

$$\log[\text{Std}_c(\beta_{imt})] = \mu_m + v_{mt}, \tag{4}$$

where  $\mu_m = E[\log[\text{Std}_c(\beta_{imt})]]$  and  $v_{mt} \sim iid(0, \sigma_{mv}^2)$ , and then

$$\log[\text{Std}_c(\beta_{imt}^b)] = \mu_m + H_{mt} + v_{mt},$$

where  $H_{mt} = \log(1 - h_{mt})$ . We now allow herding,  $H_{mt}$ , to evolve over time and follow a dynamic process; for instance if we assume a mean zero AR(1) process, this gives us,

(Model 1)

$$\log[\text{Std}_c(\beta_{imt}^b)] = \mu_m + H_{mt} + v_{mt}, \tag{5}$$

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where  $\eta_{mt} \sim iid(0, \sigma_{m\eta}^2)$ . This is now a standard state-space model similar to those used in stochastic volatility modelling which can be estimated using the Kalman filter.

<sup>8</sup> The cross-sectional expectation is equivalent to taking expectations over all assets at one point in time rather than over some time horizon. For example, the cross-sectional expectation of individual asset returns at time  $t$  will give the market return at time  $t$ . Note that when we take the cross-sectional expectation on both sides of Eq. (1), we find that the cross-sectional expectation of  $\beta_{imt}$  is 1. This is true regardless of whether  $\beta_{imt}$  is biased or not.



Although  $\mu_m$  and  $v_{mt}$  in the measurement equation are potentially interesting, our principal focus is on the dynamic pattern of movements in the latent state variable,  $H_{mt}$ , the state equation. When  $\sigma_{m\eta}^2 = 0$ , Model 1 becomes

$$\log[\text{Std}_c(\beta_{imt}^b)] = \mu_m + v_{mt}$$

and there is no herding, i.e.,  $H_{mt} = 0$  for all  $t$ . A significant value of  $\sigma_{m\eta}^2$  can therefore be interpreted as the existence of herding and a significant  $\phi$  supports this particular autoregressive structure. One restriction is that the herding process,  $H_{mt}$ , should be stationary since we would not expect herding towards the market portfolio to be an explosive process, hence we require  $|\phi_m| \leq 1$ .

### 2.3.2. Herding measurement conditioning on macro and market variables

As explained above, we expect  $\text{Std}_c(\beta_{imt}^b)$  to change over time in response to the level of herding in the market. However, an important question remains as to whether the herd behaviour extracted from  $\text{Std}_c(\beta_{imt}^b)$  is robust in the presence of variables reflecting the state of the market, in particular the degree of market volatility or the market returns as well as potentially variables reflecting macroeconomic fundamentals. If  $H_{mt}$  becomes insignificant when these variables are included then changes in the  $\text{Std}_c(\beta_{imt}^b)$  could be explained by changes in these fundamentals rather than herding. The framework set up above allows us to take into account the effect of these variables and condition on them while determining the degree of latent herding behaviour through  $H_{mt}$ .

The first alternative model we consider therefore includes market volatility and returns as independent variables in the measurement equation, thus we have the following model (Model 2)

$$\log[\text{Std}_c(\beta_{imt}^b)] = \mu_m + H_{mt} + c_{m1} \log \sigma_{mt} + c_{m2} r_{mt} + v_{mt}, \quad (6)$$

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt}.$$

where  $\log \sigma_{mt}$  and  $r_{mt}$  are market log-volatility and return at time  $t$ .<sup>9</sup>

Two more cases we investigate are given by adding the size (small minus big, SMB) and book-to-market (high minus low, HML) factors of Fama and French (1993), and macroeconomic variables as further independent variables in Eq. (6). Model 3 is then written,

(Model 3)

$$\begin{aligned} \log[\text{Std}_c(\beta_{imt}^b)] &= \mu_m + H_{mt} + c_{m1} \log \sigma_{mt} + c_{m2} r_{mt} + c_{m3} \text{SMB}_t + c_{m4} \text{HML}_t + v_{mt}, \\ H_{mt} &= \phi_m H_{mt-1} + \eta_{mt}. \end{aligned} \quad (7)$$

and by adding macroeconomic variables we get,

(Model 4)

$$\begin{aligned} \log[\text{Std}_c(\beta_{imt}^b)] &= \mu_m + H_{mt} + c_{m1} \log \sigma_{mt} + c_{m2} r_{mt} + c_{m5} \text{DP}_t + c_{m6} \text{RTB}_t + c_{m7} \text{TS}_t \\ &\quad + c_{m8} \text{DS}_t + v_{mt}, \\ H_{mt} &= \phi_m H_{mt-1} + \eta_{mt}, \end{aligned} \quad (8)$$

<sup>9</sup> The monthly market volatility,  $\sigma_{mt}$ , is calculated below using squared daily returns as in Schwert (1989).

where  $DP_t$  is the dividend price ratio,  $RTB_t$  is the relative treasury bill rate,  $TS_t$  is the term spread, and  $DS_t$  is the default spread. We choose these four macroeconomic variables following previous studies such as those of [Chen et al. \(1986\)](#), [Fama and French \(1988, 1989\)](#) and [Ferson and Harvey \(1991\)](#).<sup>10</sup>

#### 2.4. Estimating the cross-sectional standard deviation of the betas

We calculate the standard OLS estimates of the betas using daily data over monthly intervals in both the standard market model and the Fama and French three factor model. After estimating  $\hat{\beta}_{imt}^b$ , we obtain the cross-sectional standard deviation of the betas on the market portfolio  $\widehat{\hat{\beta}}_{imt}^b$  as

$$\text{Std}_c(\widehat{\hat{\beta}}_{imt}^b) = \sqrt{\frac{\sum_{i=1}^{N_t} (\hat{\beta}_{imt}^b - \overline{\hat{\beta}}_{imt}^b)^2}{N_t}}, \quad (9)$$

where  $\overline{\hat{\beta}}_{imt}^b = \frac{1}{N_t} \sum_{i=1}^{N_t} \hat{\beta}_{imt}^b$  and  $N_t$  is the number of equities in the month  $t$ . The estimates of the betas used in this calculation will naturally include an estimation error that will make our estimates of the cross-sectional standard deviations of the betas noisy to some degree and we need to consider how this is likely to impact on our results below. The OLS estimate of  $\hat{\beta}_{imt}^b$  can be written as

$$\hat{\beta}_{imt}^b = \beta_{imt}^b + \delta_{imt},$$

where  $\delta_{imt}$  is the purely random sampling or estimation error. To see the effects of the estimation error, we first note that the cross-sectional expectation of the OLS estimated betas is unbiased;

$$\begin{aligned} E_c[\hat{\beta}_{imt}^b] &= E_c[\beta_{imt}^b + \delta_{imt}] \\ &= E_c[\beta_{imt}^b] \end{aligned}$$

since  $E_c[\delta_{imt}] = 0$ . Therefore, the cross-sectional standard deviations of betas,  $\text{Std}_c(\hat{\beta}_{imt}^b)$ , is given by

$$\begin{aligned} \text{Std}_c(\hat{\beta}_{imt}^b)^2 &= E_c[(\hat{\beta}_{imt}^b - E_c[\hat{\beta}_{imt}^b])^2] \\ &= E_c[(\beta_{imt}^b + \delta_{imt} - E_c[\beta_{imt}^b])^2] \\ &= \text{Std}_c(\beta_{imt}^b)^2 + E_c[\delta_{imt}^2] \end{aligned}$$

<sup>10</sup> We also investigated several variations of (8), but the essential results are unchanged.

since  $E_c[(\hat{\beta}_{imt}^b - E_c[\hat{\beta}_{imt}^b])\delta_{imt}] = 0$ , i.e., the estimation errors are not cross-sectionally correlated with the betas. The OLS estimates of betas suggest  $\text{Std}_c(\hat{\beta}_{imt}^b) > \text{Std}_c(\beta_{imt}^b)$  since  $E_c[\delta_{imt}^2] > 0$ , and we could write

$$\log[\text{Std}_c(\hat{\beta}_{imt}^b)] = \mu_\delta + \log[\text{Std}_c(\beta_{imt}^b)] + \delta_{mt}$$

where  $\delta_{mt} \sim (0, \sigma_{m\delta}^2)$ .

However, the existence of the estimation error should not be serious when the estimation error is random and uncorrelated with  $v_{mt}$  and  $H_{mt}$ , because the state space model in Eq. (5) becomes

$$\log[\text{Std}_c(\hat{\beta}_{imt}^b)] = \mu_m^s + H_{mt} + v_{mt}^s, \tag{10}$$

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where  $\mu_m^s = E[\log[\text{Std}_c(\beta_{imt}^b)]] + \mu_\delta$  and  $v_{mt}^s \sim iid(0, \sigma_{mv}^2 + \sigma_{m\delta}^2)$ . This suggests that  $\mu_m^s \neq \mu_m$  and  $\text{Var}(v_{mt}^s) > \text{Var}(v_{mt})$  and we cannot identify the true  $\mu_m$ . If we try to compare the level of herding between two markets, for example, this identification issue becomes relevant as  $\mu_m$  is not identifiable. However, the mean zero herding state variable,  $H_{mt}$ , is designed to capture relative changes in herding activity over time, not the absolute level of herding across markets. Eq. (10) shows that under an assumption that the estimation error ( $\delta_{mt}$ ) is not correlated with the error term in the measurement equation ( $v_{mt}$ ) and  $H_{mt}$ , which we believe is not a restrictive assumption, our mean zero herding measure,  $H_{mt}$ , is not itself affected by the estimation error. So the effect of the estimation error,  $\delta_{imt}$ , will be simply to change the level of  $\text{Std}_c(\hat{\beta}_{imt}^b)$  and raise the noise in the state space model in Eq. (5), and thus increase the confidence bands around the estimate of  $H_{mt}$ . However, relative movements in  $H_{mt}$  should not be affected and the presence of the estimation error will only have the effect of making it more difficult to find significant estimates of  $\phi$ . Indeed, finding significant  $\phi$  values using monthly intervals would strongly suggest we would find more significant values if we lengthened the interval over which we computed the initial beta estimates but then we would be less able to capture more rapid movements in herding.

### 2.5. Generalised herding measurement in linear factor models

The measurement of herding towards any other factor can also be investigated using standard linear factor models. Suppose that the excess return  $r_{it}$  on asset  $i$  follows the linear factor model;

$$r_{it} = \alpha_{it}^b + \sum_{k=1}^K \beta_{ikt}^b f_{kt} + \varepsilon_{it}, \quad i = 1, \dots, N \text{ and } t = 1, \dots, T, \tag{11}$$

where  $\alpha_{it}^b$  is an intercept that changes over time,  $\beta_{ikt}^b$  are the coefficients on factor  $k$  at time  $t$ ,  $f_{kt}$  is the realised value of factor  $k$  at time  $t$ , and  $\varepsilon_{it}$  is mean zero with variance  $\sigma_\varepsilon^2$ . As in

conventional linear factor models, the excess market return is one of the factors.<sup>11</sup> The factors in Eq. (11) may be specific risk factors or designed to account for particular anomalies, for instance, the factors can correspond to countries, industries, currencies, styles, macroeconomic variables or other persistent features.

The superscript b on the betas indicates that these correspond to the biased betas under herding. Herding towards factor  $k$  at time  $t$ ,  $h_{kt}$ , can then be captured by

$$\beta_{ikt}^b = \beta_{ikt} - h_{kt}(\beta_{ikt} - E_c[\beta_{ikt}]), \quad (12)$$

where  $E_c[\beta_{ikt}]$  is cross-sectional expected beta for factor  $k$  at time  $t$ . Again when  $h_{kt}=0$ , there is no herding and  $\beta_{ikt}^b = \beta_{ikt}$  and thus individual asset returns are priced on the factor as they are in the long run. We have perfect herding when  $h_{kt}=1$ . In this case,  $\beta_{ikt}^b = E_c[\beta_{ikt}]$  for all  $i$ , the betas on factor  $k$  for all the individual assets take the same value  $E_c[\beta_{ikt}]$  implying that all the assets will respond in unison given changes in the factor. Thus with the same assumptions as behind Eq. (5), we have

$$\log[\text{Std}_c(\beta_{ikt}^b)] = \mu_k + H_{kt} + v_{kt}, \quad (13)$$

$$H_{kt} = \phi_k H_{kt-1} + \eta_{kt},$$

where  $\mu_k = E[\log[\text{Std}_c(\beta_{ikt})]]$ ,  $v_{kt} \sim iid(0, \sigma_{kv}^2)$ ,  $\eta_{kt} \sim iid(0, \sigma_{k\eta}^2)$  and  $H_{kt} = \log(1 - h_{kt})$ . As in the case of herding towards the market index above, we can develop equivalent additional models that specifically condition on market and macro-factors.

### 3. Data

Empirical studies of herding in advanced and emerging markets have found mixed evidence regarding herding during crises and also differences in herd behaviour between bear and bull markets, see [Hirshleifer and Teoh \(2003\)](#). Using the framework developed above, we now address both these issues using daily data from 1 January 1993 to 30 November 2002 to investigate herding in the US and South Korean stock markets.<sup>12</sup> The period covers the 1997 Asian crisis and the 1998 Russian crisis as well as the bull market up to early 2000 and the recent bear market. The comparison of herd behaviour in advanced markets with that in an emerging market is interesting given their structural and institutional differences.<sup>13</sup> We have calculated the herd measures using the constituents of the S&P500 index for the US market (500 stocks) and 657 ordinary stocks included in the KOSPI index of the South Korean market. To calculate the excess returns, we use 3-month

<sup>11</sup> Note that the linear factor model we use does not require that the market is in equilibrium or efficient.

<sup>12</sup> We have also examined herding in the UK stock market and found that herd behaviour in the FTSE is similar in many respects to that in the S&P500 but quite different from that in the South Korean market. The detailed results on the UK case can be obtained from the authors.

<sup>13</sup> See [Bekaert et al. \(1997\)](#) for example, for an extensive discussion of emerging markets.

Table 1  
 Properties of daily excess market returns and Fama–French’s SMB and HML factor returns: 1 January 1993–30 November 2002

	Market Excess Return	SMB	HML
(A) Properties of monthly factor returns in the US market (2499 observations)			
Mean	0.029	0.003	0.020
Standard Deviation	1.088	0.608	0.688
Skewness	–0.097	–0.445*	–0.031
Excess Kurtosis	4.076*	4.640*	4.533*
<i>Correlation matrix</i>			
Market Excess Return	1.000		
SMB	–0.109	1.000	
HML	–0.615*	–0.253*	1.000
(B) Properties of daily factor returns in the South Korean market (2433 observations)			
Mean	0.002	–0.004	0.065
Standard Deviation	2.272	1.571	1.172
Skewness	0.068	–0.236*	0.651*
Excess Kurtosis	3.176*	2.335*	8.017*
<i>Correlation matrix</i>			
Market Excess Return	1.000		
SMB	–0.443*	1.000	
HML	–0.443*	0.205*	1.000

For the US SMB and HML data, we used the Fama–French daily factor returns. For the period of 1 February 2002 to 30 November 2002, we calculated the factor returns using S&P500. The South Korean SMB and HML data were calculated using and 657 KOSPI constituents using the same method in Fama and French (1993).

\*Represents significance at 5% level.

treasury bills for the US market, whereas for the South Korean market, 1-year Korea Industrial Financial Debentures.<sup>14</sup>

Since early 1990, styles have been used as an important investment strategy and it is interesting to investigate if stock markets have in fact herded towards these factors. While different choices of style exist, we decided (for comparability with the existing literature) to use Fama and French’s SMB and HML for the US market. Daily factors are not available for the South Korean market for the 10-year period, although shorter daily or longer monthly factor data are available. So for the South Korean Market we calculated the SMB and HML factors with the 657 ordinary stocks using the same method as described in Fama and French (1993).

Table 1 reports some statistical properties of the excess market returns and the SMB and HML returns in the two markets. For the sample period, all the excess market returns are leptokurtic and thus non-gaussian. The standard deviation of the South Korean excess market returns is around twice as large as those of the US market. Given the low return–high risk (measured by standard deviation), the South Korean market might seem

<sup>14</sup> Because of the underdevelopment of the fixed income market in South Korea, there is no treasury bill available during our sample period.

unattractive to foreign investors. However, the inclusion of a market with these characteristics can still expand the mean variance efficient frontier and can be considered worthy of inclusion in a global portfolio.

The two factor returns, HML and SMB, also show non-gaussianity being leptokurtic and an interesting result is that SMB has significant negative skewness for both countries. In addition, all factor returns have means that are insignificantly different from zero, suggesting that these “hedge” funds do not produce significant positive or negative returns over short horizons. However, the South Korean HML has a daily mean return of 0.065% implying more than 16% a year, with a large kurtosis. Most of the large positive returns in HML in fact happened after mid-1998 when the South Korean market stabilised and confidence in its economy was regained after the Asian crisis (see Fig. 4C).

We can also see that there is some correlation between the three factors. For the US market, a large negative correlation exists between the excess market return and HML, whereas for the South Korean market the excess market return is negatively correlated with both SMB and HML. Unless we use a statistical method such as factor analysis to construct factors, some correlation between the factors within the sample is inevitable given that we use firm specific characteristics to construct the factors.<sup>15</sup>

#### 4. Empirical results

Our first step is to estimate the betas and calculate the cross-sectional standard deviation of the estimated betas to be used in the state space models. With around 10 years of daily data, we need to decide at what frequency we wish to apply the state space modelling in order to detect herding. By taking a larger sample period or interval to estimate the betas, we reduce the estimation error in our beta estimates but at the same time this will reduce the number of observations that can be used in the state space models to monitor movements in  $H_{mt}$ . We decided not to use overlapping intervals given the implied statistical difficulties and problems of interpretation, but instead experimented with different sample sizes trading off the ability to closely monitor changes in  $H_{mt}$  with precision in estimation. Our final choice of using 1-month's data at a time to estimate the betas gave us reliable estimates together with an ability to model reasonably rapid changes in  $H_{mt}$ .

We estimate the standard OLS estimates of the betas using daily data over monthly intervals in both the standard market model and the Fama and French three factor model (from now on the FF model);

$$r_{it_d} = \alpha_{it}^b + \beta_{imt}^b r_{mt_d} + \varepsilon_{it_d}, \quad (14)$$

$$r_{it_d} = \alpha_{it}^b + \beta_{imt}^b r_{mt_d} + \beta_{iS\&T}^b \text{SMB}_{t_d} + \beta_{iH\&T}^b \text{HML}_{t_d} + \varepsilon_{it_d}, \quad (15)$$

<sup>15</sup> We use factor mimicking portfolios, such as SMB and HML because we can easily interpret them. The use of statistical factor analysis leads to factors that are statistically justified but difficult to interpret and this is important in our case since we want to understand the economic nature of the factor towards which the market may herd.

where the subscript  $t_d$  indicates daily data  $d$  for the given month  $t$ . These estimated betas are then used to construct a monthly times series of the cross-section standard deviations of the betas.

#### 4.1. Properties of the cross-sectional standard deviation of the betas

Table 2 reports some statistical properties of the estimated cross-sectional standard deviations of the betas on the market portfolio. The first two columns of Table 2 show  $\text{Std}_c(\hat{\beta}_{imt}^b)$  is significantly different from zero and like other volatility series positively skewed, regardless of whether the market model or the FF model is used to compute the betas.<sup>16</sup> While none of the  $\text{Std}_c(\hat{\beta}_{imt}^b)$  shows significant kurtosis the Jarque–Bera statistics for normality show that most of them are not Gaussian. The correlations between the  $\text{Std}_c(\hat{\beta}_{imt}^b)$  calculated using the market model and the FF model are not particularly high, especially in the South Korean case. Thus, we may find differences in the herding measures computed from these two linear factor models; an issue we explore below. Finally, the estimated cross-sectional standard deviations of the betas on SMB ( $\text{Std}_c(\hat{\beta}_{iSMB}^b)$ ) and HML ( $\text{Std}_c(\hat{\beta}_{iHML}^b)$ ) also show similar properties; most of them are positively skewed and non-normal. We also report the properties of the logarithms of the estimated cross-sectional standard deviations of the betas in the four right-hand columns of Table 2. The positive skewness in the estimated cross-sectional standard deviations of the betas disappears and the log-cross-sectional standard deviations of betas do not deviate significantly from Gaussianity. Given this, the state space models proposed in Eqs. (5)–(8) can be legitimately estimated using a Kalman filter.

#### 4.2. Herding towards the market portfolio in the US Market

We first investigate  $H_{mt}$  in Model 1 in the first two columns of panel A of Table 3. The results in the first column are obtained using the betas of the market model, whereas those in the second column come from using the betas of the FF model. We can see immediately that  $H_{mt}$  is highly persistent with  $\hat{\phi}_m$  large and significant in both cases and the proportions of signal are also of a similar order of magnitude indicating that herding explains around 40% of the total variability in  $\text{Std}_c(\hat{\beta}_{imt}^b)$ . More importantly, the estimates of  $\sigma_{m\eta}$  (the standard deviation of  $\eta_{mt}$ ) are highly significant and thus we can conclude that there is herding towards the market portfolio.

The results of Models 2 to 4 are reported in columns 3 to 5 of the table. Model 2 also shows strong evidence of herding through  $H_{mt}$  taking into account the level of market volatility and returns as the standard deviation of  $\eta_{mt}$  is significantly different from zero and  $H_{mt}$  is highly persistent with the  $\hat{\phi}_m$  being significant. There is little difference in the estimated  $\hat{\phi}_m$  and the implied  $H_{mt}$  between Models 1 and 2. If we refer back to Eq. (6), we interpret the significance of the two market variables as adjusting the mean level ( $\mu_m$ ) of  $\log[\text{Std}_c(\hat{\beta}_{imt}^b)]$  in the measurement equation not herding activity, so we can examine the

<sup>16</sup> Obviously in the following empirical tests we use  $\text{Std}_c(\hat{\beta}_{imt}^b)$  as calculated above since  $\text{Std}_c(\beta_{imt}^b)$  is not observable.

Table 2  
Properties of the cross-sectional standard deviation of betas on the market returns

	Cross-sectional standard deviation of OLS betas				Log-cross-sectional standard deviation of OLS betas			
	Market model		Fama–French three factor model		Market model		Fama–French three factor model	
	Betas on market returns (A)	Betas on market returns (B)	Betas on SMB	Betas on HML	Betas on market returns (A)	Betas on market returns (B)	Betas on SMB	Betas on HML
<i>(A) US Market</i>								
Mean	0.888	1.241	1.555	1.943	−0.153	0.167	0.408	0.639
Standard Deviation	0.238	0.380	0.407	0.448	0.261	0.323	0.262	0.228
Skewness	0.761*	0.361	0.572*	0.764*	0.140	−0.467	−0.080	−0.092
Excess Kurtosis	0.264	−0.159	0.270	1.381	−0.358	0.104	−0.352	0.555
Jarque–Bera Statistics	11.846*	2.706*	6.856*	21.027*	1.023	4.373	0.742	1.696
Correlation between A and B	0.586				0.618			
<i>(B) South Korean market</i>								
Mean	0.551	1.250	1.038	1.250	−0.615	0.193	0.079	0.193
Standard Deviation	0.111	0.310	0.316	0.310	0.198	0.246	0.224	0.246
Skewness	0.590*	0.651*	2.997*	0.651*	0.071	−0.041	−0.430	−0.041
Excess Kurtosis	0.146	0.477	17.247*	0.477	−0.186	−0.073	0.290	−0.073
Jarque–Bera Statistics	7.020*	9.540*	1652.981*	9.540*	0.272	0.060	4.086	0.060
Correlation between A and B	0.335				0.326			

Betas on factors are calculated with OLS either in market model or Fama–French three factor model. For each month, we used daily data to estimate OLS estimates of the betas on the factors and then these betas were used to obtain cross-sectional standard deviation of betas.

\* Represents significance at 5% level.



degree of herding given the state of the market. It is interesting to note that  $\text{Std}_c(\beta_{imt}^b)$  decreases as market volatility rises but increases with the level of market returns, since log-market volatility and market returns have significant negative and positive coefficients, respectively. So when the market becomes riskier and is falling,  $\text{Std}_c(\beta_{imt}^b)$  decreases, while it increases when the market becomes less risky and rises. Using our definition of herding as a reduction in  $\text{Std}_c(\beta_{imt}^b)$  due to the  $H_{mt}$  process, these results suggest that herd behaviour is significant and exists independently of the particular state of the market. However, it is now easy to see how these results are consistent with and explain many previous empirical studies which argue that “herding” occurs during market crises.

Model 3 includes the SMB and HML factors as explanatory variables with results very similar to those of Models 1 and 2, which is not surprising given that the estimated coefficients on SMB and HML are found not to be significant. The results from the inclusion of the four macroeconomic variables are reported in Model 4. We use the log-dividend price ratio (S&P500 Index) ( $DP_t$ ), the difference between the US 3-month treasury bill rate and its 12-month moving average ( $RTB_t$ ), the relative treasury bill rate, the difference between the US 30-year treasury bond rate and the US 3-month treasury bill rate ( $TS_t$ ) for the term spread and the difference between Moody’s AAA and BAA rated corporate bonds for ( $DS_t$ ) the default spread. None of these are found to be significant except the term spread. More importantly since we find that  $\sigma_{m\eta}$  is significantly non-zero we still find that there is significant herd behaviour in the market although the degree of persistence is lower and significantly different from zero only with an 85% confidence interval instead of the usual 95%.

So with or without these independent variables, we find highly persistent herd behaviour in the market and since  $H_{mt}$  does not seem to vary substantially across the models, we take the results from Model 2 in order to study the properties of herd behaviour in more detail below.<sup>17</sup>

Fig. 1 shows the evolution of our herding measure  $h_{mt}$  ( $= 1 - \exp(H_{mt})$ ) in the US market calculated with the betas of the FF model using Models 1 and 2. We can first see that the largest value of  $h_{mt}$  is far less than one (bounded above and below roughly by 0.5) which indicates that there was never an extreme degree of herding towards the market portfolio during our sample period.<sup>18</sup> In addition, the difference between Models 1 and 2 does not seem to be large enough to change our interpretation of the relative movements in herding. The figure shows several cycles of herding and adverse herding towards the market portfolio as  $h_{mt}$  move around its long-term average of zero over the last 10 years since 1993. While we can find plausible interpretations for these relative movements in  $h_{mt}$  given economic events, we should also note that the confidence intervals shown in Fig. 1 only indicate five periods where herding is significantly different from zero with a 95% confidence interval. These are early 1994, around May 1996, May to September 1999, September 2000 to January 2001 and then from February 2002 to the end of the sample. The first high level or peak in herding can be found around March 1994. The US market

<sup>17</sup> A choice which is supported by the Schwarz information criteria (SIC) in Table 3.

<sup>18</sup> We should note however that this interpretation is conditional on the available sample. If we had been able to carry out this analysis with data starting from say the 1950s onwards then the relative degree of herding over the sample period may have appeared different.

Table 3  
Estimates of state-space models for herding in the US market

## (A) Herding towards the market portfolio

	Cross-sectional variance calculated with market variance of betas calculated with market model (Model 1)	Cross-sectional variance of betas calculated with Fama–French three factor model				Cross-sectional variance of betas calculated with market model (Value Weighted, Model 1)
		No exogenous variables (Model 1)	Excess market return and volatility (Model 2)	Excess market return, volatility, SMB and HML (Model 3)	Excess market return, volatility, and four business cycle-related factors (Model 4)	
$\mu$	−0.114 (0.105)	0.152 (0.085)*	0.064 (0.073)	0.059 (0.085)	−0.265 (0.817)	−0.036 (0.092)
$\phi_m$	0.859 (0.115)*	0.875 (0.080)*	0.845 (0.169)*	0.828 (0.283)*	0.549 (0.379)	0.861 (0.072)*
$\sigma_{mv}$	0.145 (0.025)*	0.212 (0.025)*	0.174 (0.032)*	0.168 (0.051)*	0.146 (0.073)*	0.211 (0.025)*
$\sigma_{m\eta}$	0.114 (0.036)*	0.125 (0.031)*	0.103 (0.055)*	0.108 (0.090)	0.142 (0.092)*	0.144 (0.027)*
log-Vm	–	–	−0.383 (0.067)*	−0.385 (0.082)*	−0.436 (0.075)*	–
$r_m$	–	–	0.012 (0.005)*	0.016 (0.006)*	0.011 (0.004)*	–
SMB	–	–	–	−0.005 (0.006)	–	–
HML	–	–	–	0.006 (0.008)	–	–
DP	–	–	–	–	−0.119 (0.208)	–
RTB	–	–	–	–	0.019 (0.041)	–
TS	–	–	–	–	0.086 (0.042)*	–
DS	–	–	–	–	−0.026 (0.199)	–
Proportion of signal ( $\sigma_{m\eta}$ ) to S.D.(log-CXB)	0.437	0.387	0.320	0.335	0.441	0.447
Maximum likelihood values	20.173	−13.995	10.332	12.228	15.931	−18.313
Schwarz information criteria	−21.231	47.106	8.011	13.777	15.929	55.742

A total number of 2499 daily data from 1 January 1993 to 30 November 2002 is used. For each month, daily factor returns of the month are used to estimate betas of the factors on each stocks, which are used to calculate cross-sectional variance of the betas of the month. Calculation of betas is carried out in the simple market model (the first and the last columns) and in the Fama–French three factor model (middle four columns). The last column shows the case of value weighted cross-sectional variances of betas, whereas we used equally weighted cross-sectional variance of betas for all the other cases. Using this method, we obtain a total number of 119 monthly cross-sectional variances of betas, which is used to estimate several state-space models to extract herding measure. The state-space models estimated can be found in Eq. (5) for Model 1, Eq. (6) for Model 2, Eq. (7) for Model 3, and Eq. (8) for Model 4. S.D.(log-CXB) represents time series standard deviation of log-cross-sectional standard deviation of betas. DP represents dividend price ratio, RTB relative treasury bill rate, TS term spread, and DS default spread, respectively.

\*represents significance at 5% level.

Table 3 (continued)

## (B) Herding towards the size factor (SMB)

	No exogenous variables (Model 1)	Excess market return and volatility (Model 2)	Excess market return, volatility, SMB and HML (Model 3)	Excess market return, volatility, and four business cycle-related factors (Model 4)
$\mu$	0.408 (0.032)*	0.377 (0.031)*	0.380 (0.032)*	0.304 (0.567)
$\phi_S$	0.422 (0.208)*	0.278 (0.225)	0.308 (0.097)*	0.213 (0.101)*
$\sigma_{Sv}$	0.176 (0.059)*	0.072 (0.309)	0.000 (0.001)	0.000 (0.021)
$\sigma_{S\eta}$	0.174 (0.062)*	0.229 (0.104)*	0.234 (0.015)*	0.234 (0.016)*
log-Vm	–	–0.126 (0.057)*	–0.156 (0.058)*	–0.157 (0.071)*
$r_m$	–	0.010 (0.005)*	0.008 (0.006)	0.010 (0.005)*
SMB	–	–	–0.016 (0.005)*	–
HML	–	–	–0.010 (0.007)	–
DP				0.054 (0.143)
RTB				–0.062 (0.050)
TS				0.014 (0.032)
DS				–0.407 (0.192)*
Proportion of signal ( $\sigma_\eta$ ) to S.D.(log-CXB)	0.666	0.874	0.896	0.895
Maximum likelihood values	– 5.446	0.734	3.793	3.939
Schwarz information criteria	30.008	27.207	30.647	39.914

A total number of 2499 daily data from 1 January 1993 to 30 November 2002 is used. For each month, daily factor returns of the month are used to estimate betas of the factors on each stocks, which are used to calculate equally weighted cross-sectional variance of the betas on SMB. Calculation of betas is carried out in the Fama–French three factor model. Using this method, we obtain a total number of 119 monthly cross-sectional variances of betas on SMB, which is used to estimate several state-space models. The state-space models estimated can be found in Eq. (5) for Model 1, Eq. (6) for Model 2, Eq. (7) for Model 3, and Eq. (8) for Model 4. S.D.(log-CXB) represents time series standard deviation of log-cross-sectional standard deviation of betas. DP represents dividend price ratio, RTB relative treasury bill rate, TS term spread, and DS default spread, respectively.

\* represents significance at 5% level.

(continued on next page)

Table 3 (continued)

## (C) Herding towards the value/growth factor (HML)

	No exogenous variables (Model 1)	Excess market return and volatility (Model 2)	Excess market return, volatility, SMB and HML (Model 3)	Excess market return, volatility, and four business cycle-related factors (Model 4)
$\mu$	0.456 (0.130)*	0.482 (0.108)*	0.483 (0.108)*	1.815 (0.555)*
$\phi_H$	0.981 (0.027)*	0.980 (0.028)*	0.980 (0.028)*	0.628 (0.193)*
$\sigma_{Hv}$	0.176 (0.022)*	0.175 (0.021)*	0.175 (0.022)*	0.166 (0.022)*
$\sigma_{H\eta}$	0.049 (0.013)*	0.050 (0.013)*	0.050 (0.013)*	0.080 (0.030)*
log-Vm	–	0.037 (0.041)	0.035 (0.042)	–0.038 (0.050)
$r_m$	–	–0.001 (0.003)	–0.001 (0.003)	–0.001 (0.003)
SMB	–	–	–0.001 (0.004)	–
HML	–	–	–0.001 (0.005)	–
DP	–	–	–	0.218 (0.140)
RTB	–	–	–	0.045 (0.038)
TS	–	–	–	0.078 (0.031)*
DS	–	–	–	0.229 (0.130)*
Proportion of signal ( $\sigma_\eta$ ) to S.D.(log-CXB)	0.212	0.218	0.218	0.348
Maximum likelihood values	22.923	23.232	23.242	28.303
Schwarz information criteria	–26.729	–17.340	–8.904	–8.814

A total number of 2499 daily data from 1 January 1993 to 30 November 2002 is used. For each month, daily factor returns of the month are used to estimate betas of the factors on each stocks, which are used to calculate equally weighted cross-sectional variance of the betas on HML. Calculation of betas is carried out in the Fama–French three factor model. Using this method, we obtain a total number of 119 monthly cross-sectional variances of betas on SMB, which is used to estimate several state-space models. The state-space models estimated can be found in Eq. (5) for Model 1, Eq. (6) for Model 2, Eq. (7) for Model 3, and Eq. (8) for Model 4. S.D.(log-CXB) represents time series standard deviation of log-cross-sectional standard deviation of betas. DP represents dividend price ratio, RTB relative treasury bill rate, TS term spread, and DS default spread, respectively.

\*Represents significance at 5% level.

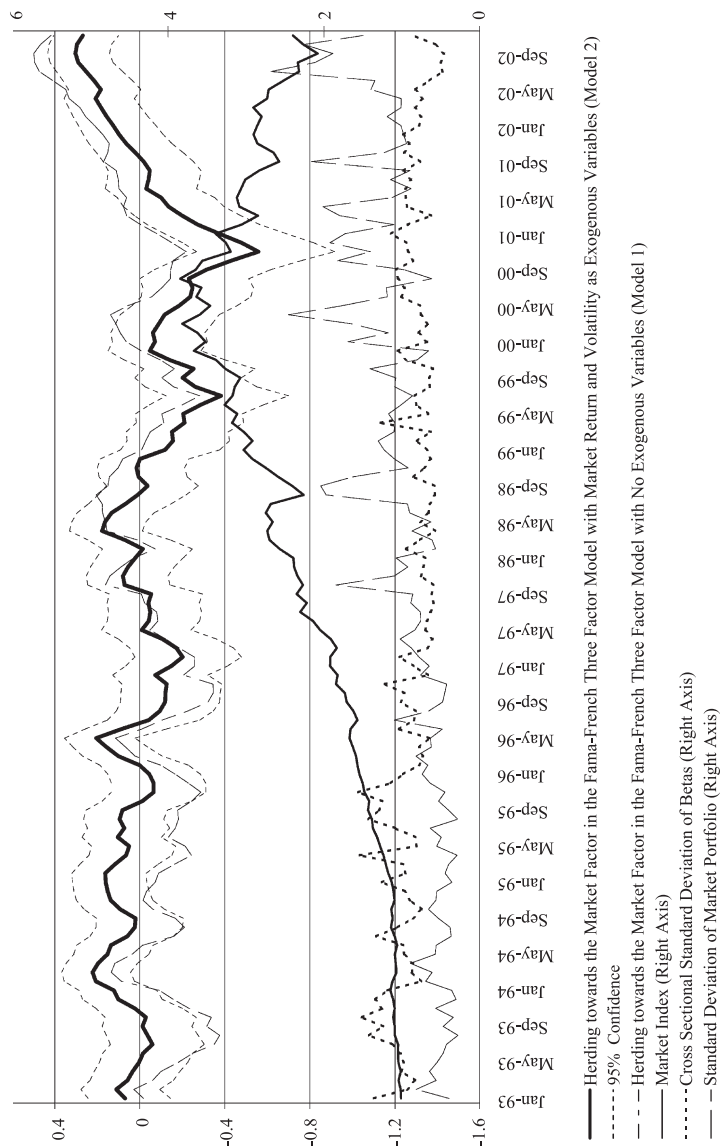


Fig. 1. Herding towards the market portfolio in the US market.

showed an upward trend during 1993 and investors began to herd towards these market movements from the summer of 1993 until the US Federal Reserve (Fed) unexpectedly raised interest rates in 1994. During 1994, the Fed raised interest rates six times from 3% to 5.5% and herding began to decline. A second significant increase in herding occurred around late 1995 which stopped in May 1996 when it reached a level similar to that of 1994 peak.

The figure shows that  $h_{mt}$  has often increased prior to a crisis but closer inspection also shows that herding starts to decrease sometime before the crisis actually occurs. For instance, there are clear movements upwards in  $h_{mt}$  before the Asian Crisis of 1997 and the Russian Crisis of 1998 but some 4 months beforehand in each case, herding, as we measure it, starts to fall. This same pattern is repeated for the market fall in September 2000 except that herding started to fall some nine months beforehand in this case. The figure also shows that the Asian crisis did not have enough impact on the US market to remove herding. In fact, herding was effectively constant during the Asian Crisis and it was only the impact of the Russian crisis that was powerful enough to have a substantial impact in reducing herd behaviour. Note that the US market grew strongly after the Russian crisis until summer 1999 but herding continued to decrease over the same period. The continued increase in equity prices finally convinced investors to start herding again from the summer 1999 to the end of 1999. Herd behaviour then began to disappear from early 2000 before the US market hit its historical high and subsequently fell. Investors then began to lose confidence and the market drifted for several months until the bear market was confirmed. Once the bear market was underway herding has grown from late 2000 until the end of our sample period at the end of 2002. This last movement shows that herding can arise equally in bull markets and bear markets. In fact, the figure shows that during the recent bear market herding appears much more significant. It is also interesting that we find a small decline in herd behaviour after December 1996 when Allan Greenspan made his famous “irrational exuberance” speech but this was not sufficient to remove herding until the two crisis in 1997 and 1998. The event of September 11, 2001 seems to have convinced investors that a bear market was imminent and herding has increased steadily ever since.

#### 4.3. Herding towards size and value factors

We also carried out the same analysis in order to investigate herding towards SMB and HML instead of the market index and report the results in panels B and C of Table 3 and Figs. 2 and 3, respectively. Note that betas for these factors can only be obtained from the FF model in Eq. (15).

We first investigate herding towards SMB ( $H_{St}$ ). Panel B of Table 3 shows that the standard deviations of the herding error ( $\eta_{St}$ ) are significantly non-zero for all of the models, suggesting that there was herd behaviour in the US market, towards SMB. In addition as in the case of herding towards the market index, we find that market volatility and the market return level are significant with negative and positive signs, respectively. The coefficients on the default spread and SMB are significantly negative in Models 3 and 4, respectively, otherwise the coefficients on the macro-factors are not significant. However,  $H_{St}$  is not as persistent and smooth as  $H_{mt}$ , since the signal to noise ratios for  $H_{St}$  are much larger than those for  $H_{mt}$ , explaining nearly 90% of the total variation and the estimated persistence parameters,  $\hat{\phi}_S$  are much smaller than the  $\hat{\phi}_m$ .

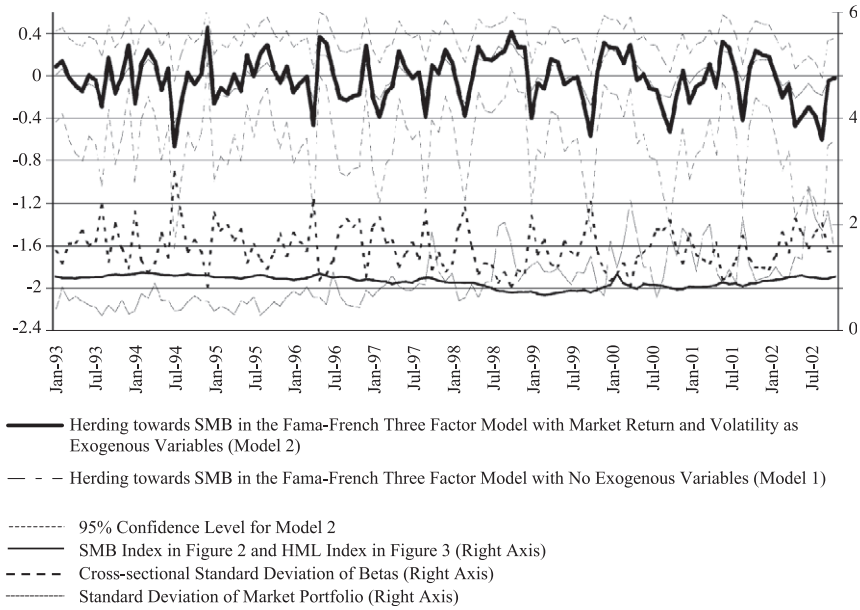


Fig. 2. Herding towards the SMB factor in the US market.

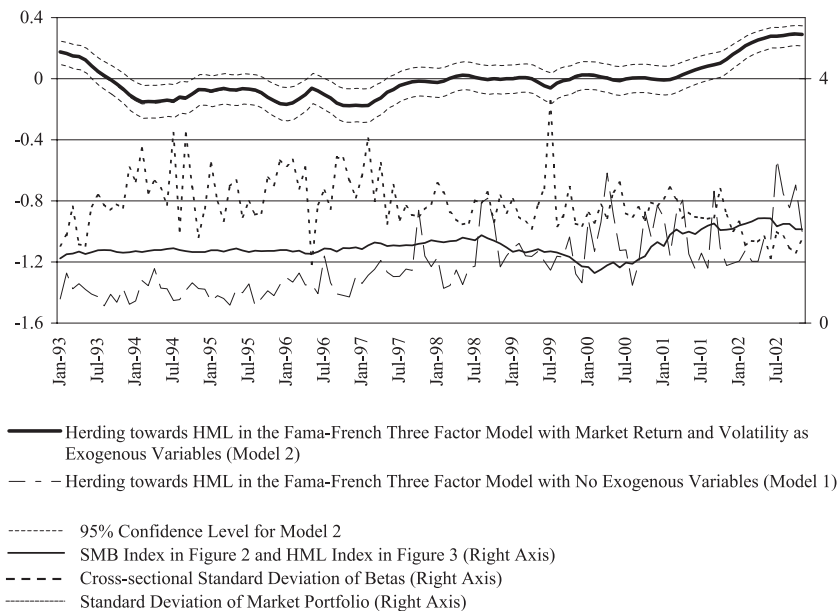


Fig. 3. Herding towards the HML factor in the US market.

Using Model 2 which is again selected by the SIC value, we plot herding towards SMB,  $h_{St} (= 1 - \exp(H_{St}))$ , in Fig. 2. Note that the herding movements towards SMB obtained from Model 1 are not significantly different from those implied by Model 2. As expected,  $h_{St}$  changes frequently over time. Using a 95% confidence level, we can identify a few interesting periods with high levels of  $h_{St}$ . In many cases, the high levels of  $h_{St}$  are coincident with those of  $h_{mt}$  in Fig. 1. These are May–June 1996, August–October 1998, January–April 2000, and June 2001. Thus, when there is herding towards the market portfolio we are also likely to observe herding towards size and vice versa. Interestingly during the recent bear market, we do not find herding towards SMB whereas we do find high levels of  $h_{mt}$ .

Herding towards HML ( $H_{Ht}$ ) on the other hand, shows a quite different pattern. Panel C of Table 3 shows that there is significant herding in the US market towards HML. As opposed to the previous two sets of results,  $\text{Std}_c(\beta_{iHt})$  is now not explained by market volatility or the level of market returns, and  $TS_t$  and  $DS_t$  become significant in explaining  $\text{Std}_c(\beta_{iHt})$ . In addition,  $H_{Ht}$  is highly persistent with a tight error band, suggesting it changes very smoothly. The proportion of signal is also much lower at around 21%. Fig. 3 calculated again with Model 2 confirms that  $h_{Ht} (= 1 - \exp(H_{Ht}))$  changes smoothly over time and seems to show a very different pattern from the two other herding,  $h_{mt}$  and  $h_{St}$ , shown in Figs. 1 and 2. A close look at the figure however reveals that after the Asian crisis, herd behaviour increased and during the recent bear market it increased even more.

#### 4.4. Herding behaviour in the South Korean market

We have carried out the same analysis for the South Korean market and report the results in Table 4 and Fig. 4. We do not report all of our results because in most cases there is little significant difference between the models. As in the US case, we find significant herd behaviour towards the market portfolio in the South Korean market. Herding is highly persistent and the estimates indicate that market volatility and the level of returns are both significant. The South Korean market, however, shows some different patterns from those of the US market. High levels of  $h_{mt}$  can be found in August 1993 and from 1995 to early 1997. These are coincident with the introduction of the real-name financial transaction system in August 1993 and the Asian Crisis of 1997, respectively, both of which had significant impact on the South Korean economy. Interestingly, the South Korean market shows significant adverse herd behaviour since 1999, especially in 2002. This suggests that when the market went down in late 2002, stocks with large betas (larger than one) went down further than their long run average levels would suggest, while stocks with small betas (smaller than one) went down less than their long-run average levels suggest.

Panels B and C of Table 4 report the results on SMB and HML. Herding towards SMB in the South Korean market is quite different from that in the US market;  $H_{St}$  for the South Korean case is highly persistent and smooth, while  $H_{St}$  in the US is less persistent with a large signal to noise ratio. However, all the standard deviations for  $\eta_{mt}$  are significant at the 10% level, suggesting significant herd behaviour towards SMB and we can see high  $h_{St}$  during January 1995, late 1996, and early 1999. We can also see that the SMB index began to increase from September 1994 and that herding towards SMB followed. A second herding phase began simultaneously with the increase in the SMB index from early 1996. However, again just before the SMB index approached its highest point in late 1997, herd



Table 4

Herding measures calculated with Fama–French three factor model in the South Korean market

## (A) Herding measure towards the market portfolio

Exogenous variables	Cross-sectional variance of betas in the market model		Cross-sectional variance of betas in the Fama–French three factor model
	No exogenous variables (Model 1)	No exogenous variables (Model 1)	Excess market return and volatility (Model 2)
$\mu$	– 0.618 (0.035)*	– 0.362 (0.055)*	– 0.355 (0.243)
$\phi_m$	0.777 (0.143)*	0.742 (0.114)*	0.994 (0.056)*
$\sigma_{mv}$	0.142 (0.021)*	0.175 (0.034)*	0.149 (0.034)*
$\sigma_{m\eta}$	0.086 (0.035)*	0.159 (0.042)*	0.093 (0.052)*
log-Vm	–	–	– 0.532 (0.076)*
$r_m$	–	–	0.006 (0.002)*
Proportion of signal ( $\sigma_\eta$ ) to S.D.(log-CXB)	0.436	0.646	0.378
Maximum likelihood values	35.560	– 6.114	21.884
Schwarz information criteria	– 52.004	31.344	– 15.093

## (B) Herding measure towards the size factor (SMB)

Exogenous variables	No exogenous variables (Model 1)	Excess market return and volatility (Model 1)	Excess market return, volatility, SMB and HML (Model 3)
$\mu$	0.013 (0.099)	– 0.008 (0.393)	– 0.022 (0.375)
$\phi_S$	0.942 (0.090)*	0.995 (0.127)*	0.995 (0.126)*
$\sigma_{sv}$	0.171 (0.020)*	0.162 (0.024)*	0.161 (0.023)*
$\sigma_{s\eta}$	0.082 (0.028)*	0.076 (0.043)*	0.076 (0.042)*
log-Vm	–	– 0.182 (0.063)*	– 0.166 (0.070)*
$r_m$	–	0.003 (0.002)	0.003 (0.002)
SMB	–	–	0.002 (0.002)
HML	–	–	0.001 (0.003)
Proportion of signal ( $\sigma_\eta$ ) to S.D.(log-CXB)	0.366	0.338	0.341
Maximum likelihood values	15.851	20.668	21.085
Schwarz information criteria	– 12.585	– 12.662	– 3.938

## (C) Herding measure towards the value/growth factor (HML)

Exogenous variables	No exogenous variables (Model 1)	Excess market return and volatility (Model 1)	Excess market return, volatility, SMB and HML (Model 3)
$\mu$	0.207 (0.051)*	0.322 (0.049)*	0.347 (0.052)*
$\phi_H$	0.830 (0.124)*	0.697 (0.203)*	0.688 (0.177)*
$\sigma_{Hv}$	0.172 (0.029)*	0.153 (0.040)*	0.142 (0.037)*
$\sigma_{H\eta}$	0.099 (0.041)*	0.118 (0.054)*	0.125 (0.047)*
log-Vm	–	– 0.206 (0.054)*	– 0.235 (0.056)*
$r_m$	–	– 0.001 (0.002)	– 0.002 (0.002)
SMB	–	–	– 0.004 (0.002)*
HML	–	–	– 0.005 (0.003)
Proportion of signal ( $\sigma_\eta$ ) to S.D.(log-CXB)	0.402	0.480	0.507
Maximum likelihood values	13.326	19.245	21.987
Schwarz information criteria	– 7.536	– 9.816	– 5.741

See notes in Table 3 for explanation.

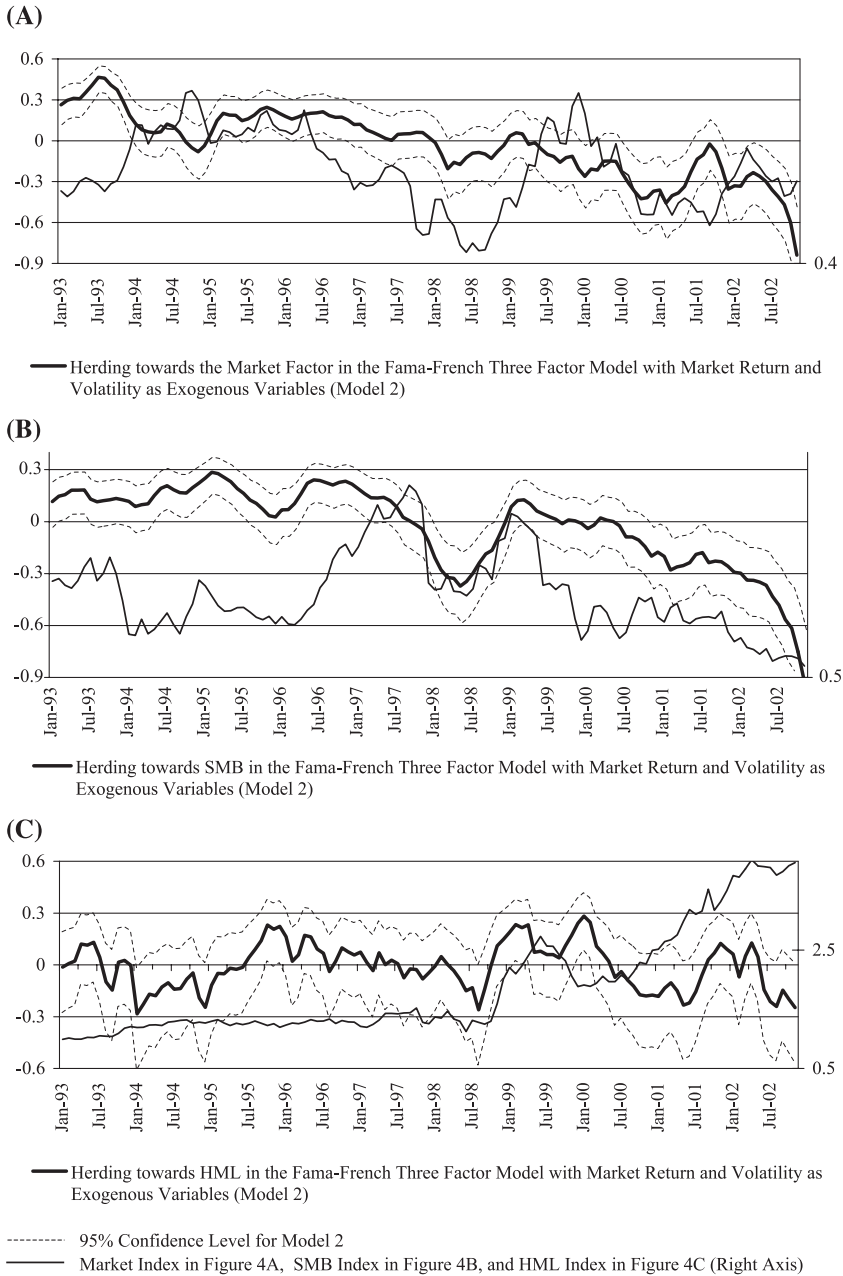


Fig. 4. (A) Herding towards the market portfolio in the Fama–French three factor model in the South Korean market. (B) Herding Towards the SMB factor in the Fama–French three factor model in the South Korean market. (C) Herding towards the HML factor in the Fama–French three factor model in the South Korean market.

activity began to decrease and finally with the Asian crisis adverse herding towards SMB took over in 1998. The final wave of herding started from the summer of 1998, after the Russian crisis, and the SMB index began to increase. One interesting trend is that since early 2000, herding towards SMB continuously declines. This means that the betas on the SMB factor are more cross-sectionally dispersed and thus opinions in the market become more divided regarding the size factor; one group showing a positive reaction to size and the other a negative reaction.

Herding towards HML is also evident in the South Korea market; all standard deviations on  $\eta_{Ht}$  are highly significant, and persistence levels are around 0.7. Estimates of Models 2 and 3 show that log-market volatility and market returns do not explain the cross-sectional standard deviation of the betas on HML. We also find some evidence that SMB explains  $\text{Std}_c(\beta_{iHt}^b)$ . Fig. 4C shows that the South Korean HML index goes through a sudden large increase from late 1998 to June 1999. This is the period when investors began to regain confidence in the South Korean economy and thus high book-to-market value (BM) stocks performed better than low BM stocks. Note that at the same time  $h_{St}$  increased during this period. Interestingly in 1995 we observe a significant increase in herd behaviour, when there is no movement in the HML index itself. This is another example where herding arises without any apparent underlying factor movements in the market. The highest herding level can be found in early 2000, but this is herding towards the declining HML index. We can see another big movement in herd behaviour during late 2001, which is a delayed response to the increasing HML index because of market uncertainty in 2000 and early 2001.

#### 4.5. Relationship between different herding activity and different countries

Given the results above, we can see some evidence of correlation in herding patterns towards market portfolio and the different factors such as SMB and HML. We can also

Table 5  
Relationship between herding in the different markets and between the different factors

(A) Correlation between the different herding factors						
	US			South Korea		
	Herding towards market portfolio	Herding towards SMB	Herding towards HML	Herding towards market portfolio	Herding towards SMB	Herding towards HML
Herding towards market portfolio	1.000	0.133	0.286*	1.000	0.812*	0.349*
Herding towards SMB		1.000	-0.098		1.000	0.338*
Herding towards HML			1.000			1.000

(B) Correlation in herding between the US and South Korean markets			
Herding objectives	Herding towards market portfolio	Herding towards SMB	Herding towards HML
Correlation coefficients	0.110	0.088	-0.127

The correlation coefficients are calculated with the herd measures we calculated from the state-space model without exogenous variables and the cross-sectional standard deviation of betas from the Fama–French three factor model.

\* represents significance at 5% level.

consider if common movements in herding exist between the two markets. To investigate these relationships, we report the correlation matrices in [Table 5](#).

We can see that  $h_{mt}$  is correlated to some degree with both  $h_{St}$  and  $h_{Ht}$ . Panel A of [Table 5](#) shows that in the South Korean market the estimated correlation coefficients are both significant and positive at the 5% level. On the other hand, only  $h_{mt}$  and  $h_{Ht}$  are correlated in the US market. These results suggest that herding towards the market portfolio is likely to be accompanied by either herding towards SMB or herding towards HML. The second panel in [Table 5](#) reports correlations for the same type of herd behaviour between the two markets. We find little or no significant correlation between US and South Korea. The form of herd behaviour we are measuring is thus more likely to be a domestic event rather than reflect international investor sentiment.

#### 4.6. Robustness of the herding measures

The results reported above support the view that there were significant relative movements in herd behaviour in both the US and South Korean market over the sample period. Since the constituents included in our indices are as defined on 19 December 2002, we need to consider the effects of survivorship bias on our herding measures and hence the robustness of our conclusions. Since our herding measure only depends on the cross-sectional standard deviation of the individual betas in the market, we would expect it to be robust against survivorship bias unless the constituents of the index were removed in some systematic manner as opposed to randomly.<sup>19</sup> In addition, since our sample is a subgroup in each country, our results may also be exposed to selection bias. In order to evaluate these issues, we estimated the model on a series of subsamples of the available data. This exercise does not directly evaluate the effects of the survivorship bias on the herd measures but by showing how the herd measures change with the different subsamples we can indirectly examine the robustness of our results.

For the US market, we calculated the three herd measures for different subsets of equities using the FF model and Model 2. The total number of equities available to use for the entire sample period is 413. Using average returns for the whole sample, we construct four subsets; high performance stocks (top 80%), low performance stocks (bottom 80%), stocks that performed in the middle (middle 80%), and stocks that performed high and low excepting the middle 20% (except middle 20%). We also use the estimated betas to rank the stocks and make four subgroups; high beta stocks (top 80%), low beta stocks (bottom 80%), middle beta stocks (middle 80%) and high–low beta stocks (except middle 20%). Then for each of these subsamples, we apply the same analysis outlined above. We do not report the estimates of the state-space models or the results on herding towards the two factors, since the results are similar to those discussed above. To summarise our results though, we plot  $h_{mt}$  for the entire sample and for the eight subgroups in [Fig. 5](#) which shows that the differences between the herding measures for the different subgroups are essentially trivial. This suggests that our results are robust to survivorship bias as well as selection bias.

<sup>19</sup> The discussion on the effects of survivorship bias on the construction of SMB and HML can be found in Appendix A.

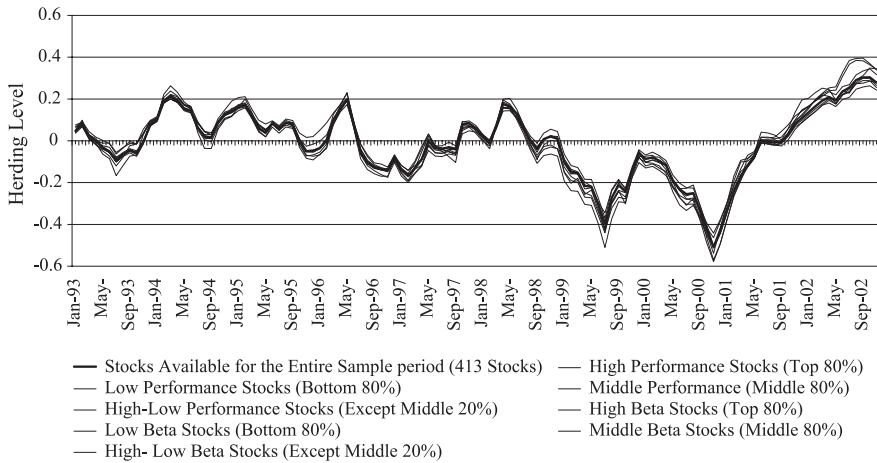


Fig. 5. Robustness of the herding measure towards the market portfolio in the Fama–French three factor model in the presence of market volatility and returns (Model 2) for various subsets of stocks in the US market.

Another question that could be raised regarding our results is how robust are they given a value-weighted cross-sectional expectation. Our results may be dictated for instance by herding in small stocks while large stocks do not show herd behaviour. So in order to investigate if herding is a market-wide activity including large stocks we calculated the following value-weighted cross-sectional standard deviation;

$$\text{Std}_c^v(\hat{\beta}_{imt}^b) = \sqrt{\sum_{i=1}^{N_t} w_{it} (\hat{\beta}_{imt}^b - \overline{\hat{\beta}_{imt}^b}^v)^2}, \tag{16}$$

where  $\overline{\hat{\beta}_{imt}^b}^v = \sum_{i=1}^{N_t} w_{it} \hat{\beta}_{imt}^b$ ,  $N_t$  is the number of equities in month  $t$ , and  $w_{it}$  is the relative size of the stock  $i$  to the market at time  $t$ .

The last column of panel A of Table 3 shows the corresponding estimates of  $H_{mt}$  in the US market calculated with the value-weighted cross-sectional standard deviation. The results are little different from those shown without using market weights in the first column; herding towards the market portfolio is still significant, highly persistent with a similar signal-to-noise ratio. The plot of the herd measure calculated using the value-weighted cross-sectional standard deviation is only marginally different from what we report in Fig. 1 and hence not included.

### 5. Conclusions

Herding is widely believed to be an important element of behaviour in financial markets and particularly when the market is in stress, such as during the Asian and Russian Crises of 1997 and 1998. In this paper, we have proposed a new approach to measuring and testing herding. We argue that our measure has better empirical and theoretical

properties than previous measures in the sense that the new measure conditions automatically on fundamentals and can also measure herding towards other factors. The new measure also accounts automatically for the influence of time series volatility.

We have applied our approach to the US and South Korean stock markets and found that herding towards the market shows significant movements and persistence independently from and given market conditions as expressed in return volatility and the level of the mean return. Macro factors do not explain the herd behaviour. We have also found evidence of herding towards the market portfolio both when the market is rising and when it is falling. The Asian Crisis and in particular the Russian Crisis are clearly identified as turning points in herding behaviour. These results suggest that periods of market crisis or stress help return markets to equilibrium, implying that efficient pricing may be helped by market stress. We have found a number of cases where herding behaviour turned before the market itself turned.

These results provide us with a more detailed explanation of the dynamics of herding around market crises and why [Christie and Huang \(1995\)](#) fail to find herding during market crises given that herding has often turned down before a crisis comes about and represents a flight to fundamentals. Perhaps more importantly, given that herding can lead to significant mispricing, it is interesting to note that in the US market there were five periods in the sample when herding was a major concern and statistically significant.

We have also examined herding towards size and value factors and found a range of results including evidence of significant periods of herding towards value at different times in the sample within the US market but particularly since January 2001. We can also see that the cycle of herding and adverse herding over time suggests why investment strategies using factors taking long and short positions for the styles may work well sometimes and not in others. The herding relationships across the two markets and herding objectives show some common patterns but far from perfect co-movements with a correlation of only 0.110 in market wide herding between the US and the South Korean market. This implies that market sentiment may not always transfer internationally.

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## **Appendix A. Survivorship bias and the size and book-to-market factors**

Because of the potential for survivorship bias in our data, the SMB and HML series calculated using the equities could also be biased. In order to evaluate the effects of the survivorship bias on these two factors, we apply the same procedure for the constituents of

the S&P500 index in the US market and then compare these factors with Fama and French's series. If survivorship bias is a serious problem then the difference between our factors and Fama and French's factors should be much larger during the earlier sample period. We first calculate correlation coefficients between Fama and French's factors and our SMB and HML. The correlation coefficients for SMB and HML before the end of 1996 are 0.62 and 0.78, respectively, while after 1996 they are 0.50 and 0.74, respectively. For the two subperiods, the correlation coefficients on HML change little whereas those on SMB dropped significantly. The big drop in the correlation of SMB after the end of 1996 comes from equities that were not included in the S&P500 index but significantly affected SMB through large price changes (or market values) during the late 1990s. These results suggest that the effects of the survivorship bias on the construction of factors during the early part of our sample period may not be particularly serious. However, we find that the average values of our SMB and HML are different from those of Fama and French. On average, our SMB is larger than Fama and French's SMB, whereas our HML is smaller than Fama and French's HML series over the full sample period. The difference in average returns is however less important in our study, since we are concerned with the relationship between factors and individual asset returns rather than performance. Finally, we calculated the herding measures using both Fama and French's and our own factors for the US market and found that the differences were in fact marginal.

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