Herding and Returns in Taiwan's Stock Market

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In this paper, we systematically examine the market herding behavior in Taiwan with monthly observations of all common stocks from January 1991 to August 2016. Several interesting empirical results emerge. First, Taiwan's stock market herding is time-varying and negatively correlated with the market sentiment. Secondly, irrespective of the factor model used in estimation, the degree of herding is higher in the pre-2000 and the post-2008 periods. Thirdly, our quantile regression results indicate that during market downturns, a higher degree of market herding can aggravate the panic of the market, which causes the market return to drop even further.

INTRODUCTION

Herding arises when investors decide to imitate observed decisions of others or movements on the market rather than follow their own beliefs and information. Empirical analysis of herding behavior on international markets has received considerable attention in recent finance literature. In contrast, herding behavior in Taiwan's stock market has not been thoroughly investigated, and there has been relatively little empirical investigation of such a behavior, and its impact on the market. Compared to stock markets of other economies, Taiwan's stock market is typically dominated by noise-traders. It is therefore interesting to conduct a systematic examination of the overall herding behavior of Taiwan's stock market. In the literature, there are at least three popular measures of herding behavior: the herding measure of individual trading activity (Lakonishok, Shleifer, and Vishny, 1992; Wermers, 1999), the market herding measure based on simple cross-sectional variability of returns (Christie and Huang, 1995; Chang, Cheng, and Khorana, 2000), and another market herding measure based on the cross-sectional variability of betas from their equilibrium values (Hwang and Salmon, 2004 and 2009), and hence the name of *beta herding*. By examining the cross-sectional variability of betas, instead of cross-sectional variability of returns, Hwang and Salmon' last measure controls for the systematic risk, and therefore is better suited for studying market herding behavior. Hence, in this paper, we follow their approach in constructing the beta herding measure for Taiwan's stock market.

Since the level of herding generally depends on market conditions (Chiang, Li, and Tan, 2010; Chiang and Zheng, 2010; Lao and Singh, 2011), it can have different impacts on the market under various market states. In light of this stylized fact, we investigate how market returns may be affected by investors' herding behavior with the quantile regression analysis. In spirit, this approach is similar to the one in Chiang et al. (2010), they find supporting evidence of herding behavior in both A-share and B-share investors in China in the lower quantile region of the herding measure. A notable difference between their approach and ours is that the dependent variable in their study is the herding measure instead of market return. Since one of the objectives of this paper is to examine how market returns may be affected by market herding behavior at different market states, we choose market return as the dependent variable and investigate the relation therein with the quantile regression analysis.

Our empirical investigation demonstrates a time-varying beta herding behavior in Taiwan's stock market. The estimated herding measure is also positively correlated with the implied volatility index (often used to gauge the amount of negative sentiment investors have), which supports the fact that the beta herding measure exhibits a negative relation with market sentiment. Interestingly, the standard error of the estimated beta herding measure is significantly affected by additional asset pricing factors such as the size factor (SMB) and the value factor (HML). Since asset pricing factors control for systematic risk on the market, estimating the herding behavior with cross-sectional variability of betas is justified. Moreover, irrespective of the factor model used in estimating beta herding measures, the degree of herding is higher in the pre-2000 period (with the Asian financial crisis and the Dot-com bubble), and the post-2008 period (the Great Recession). The pattern is more pronounced when the beta herding measures are estimated with the Fama-French three-factor model and the Carhart four-factor models. This is different from the evidence found in Hwang and Salmon (2009) which states that herding does not occur when financial markets are in stress (or in crisis) for the U.S. market. Presumably, this is because Taiwan's stock market is more dominated by noise-traders. In addition, our quantile regression results indicate that a higher beta herding measure (smaller degree of market herding) can significantly and positively affect market returns in their left tail distribution (below the 20^{th} quantile of market return distribution.) In other words, during market downturns, a higher degree of market herding can aggravate the panic in the market, which then causes the market return to drop even further.

In the next section, we review related literature to motivate our research questions. In the third section, we outline our methodology. In the fourth section, we examine the empirical properties of the beta herding behavior in Taiwan's stock market, and their relation with the market sentiment. The fifth section examines how asset returns are affected by the beta herding measure in a quantile regression framework. In the last section, we conclude this paper.

REVIEW OF RELATED LITERATURE

Herding Measures

In recent finance literature, empirical analysis of herding behavior has received considerable attention, see Lakonishok et al. (1992); Christie and Huang (1995); Graham (1999); Nofsinger and Sias (1999); Wermers (1999); Chang et al. (2000); Hirshleifer and Teo (2003); Gleason, Mathur, and Peterson (2004); Hwang and Salmon (2004, 2009); and Sias (2004), to name a few. Among these, there are at least three popular measures of herding behavior. The herding measures of individual trading activities proposed by Lakonishok et al. (1992) and Wermers (1999) require detailed records of individual trading activity, which may not be readily available. Another popular measure is based on simple cross-sectional variability of returns (Christie and Huang, 1995; Chang et al., 2000), which is not necessarily indicative of irrational pricing on the market, as it may just reflect fundamental changes in common pricing factors. Hwang and Salmon (2004) propose a new *beta herding* measure of market herding behavior based on cross-sectional variability of betas. Among the above measures, the beta herding measure proposed by Hwang and Salmon (2004) can more sensibly capture irrational pricing, while the other measures may not be able to differentiate irrational pricing from a rational reaction to changes in fundamentals.

Hwang and Salmon (2009) introduce a more flexible approach in estimating the beta herding measure. This new measure assumes no particular parametric dynamic process for herding behavior. In addition, it incorporates market-wide sentiment as a source of herding. Specifically, the new herding measure proposed by Hwang and Salmon (2009) is driven by two forces: one from cross-sectional herding towards the market portfolio, and the other one from market-wide sentiment that evolves over time and drives the market as a whole. This is interesting, as an increase in herding from increased market-wide sentiment is more likely to occur during bull markets rather than bear markets (Brown and Cliff, 2004), while an increase in herding from increased cross-sectional herding is possible at any time.

In contrast, there has been relatively little empirical investigation of herding behavior in Taiwan's stock market. Studies have been conducted on mutual fund managers (Lee, Shen, and Yen, 2010; Lee and Wu, 2009), institutional investors (Li and Laih, 2005; Shyu and Sun, 2010), and market participants (Chang et al., 2000; Lo and Li, 2009; Yeh and Li, 2012). Lee et al. (2010) study the fund investors' disposition effect vis-a-vis herding redemption and non-herding redemption. Lee and Wu (2009) examine herding behavior among fund managers who buy and sell stocks with technical analysis. Li and Laih (2005) investigate the total market herding behavior and its effect on stock market returns in Taiwan during extreme movements, and among domestic institutional investors. Shyu and Sun (2010) employ daily trading data to examine the herding behavior of institutional investors in Taiwan's stock market. These studies examine herding behavior of individual mutual fund managers and individual institutional investors. For market herding behavior, the targeted topic of this paper, Chang et al. (2000) construct a measure based on the cross-sectional absolute deviation (CSAD) of return dispersion from the market return. They find evidence of herding in emerging markets, such as Taiwan, and no evidence of herding in developed markets. Similar to the measure proposed by Christie and Huang (1995), evidence obtained from the CSAD is not necessarily indicative of irrational pricing. Lo and Li (2009), and Yeh and Li (2012) both follow Hwang and Salmon (2004) in measuring herding behavior of market participants, and discover a higher degree of herding in periods with extreme movement in Taiwan's stock market. However, the Kalman filter approach embedded in Hwang and Salmon (2004) assumes a particular parametric dynamic process for herding, and does not easily facilitate statistical inferences. Furthermore, results in Lo and Li (2009), and Yeh and Li (2012) are conditioned on the ten deciles of market return/volatility, instead of the entire distribution. This may potentially lead to inefficient deduction of the relation between market return and herding behavior.

Among the various aforementioned measures, the beta herding proposed by Hwang and Salmon (2009) appears to be more suitable for studying herding behavior and its impact on the efficiency of the stock market as a whole. Therefore, in this paper, we follow Hwang and Salmon (2009) in constructing the herding measure for Taiwan's stock market and examine its impact in Taiwan's stock market in a quantile regression framework. The quantile regression and its application in studying Taiwan's stock market is briefly reviewed in the next subsection.

Quantile Regression

Quantile regression is a method for estimating functional relations between variables for all portions of a probability distribution (Koenker and Bassett, 1978; Koenker, 2005). A low-quantile (high-quantile) regression estimator could be heuristically interpreted as the regression slope for the left-tail (right-tail) distribution of the dependent variable, although all observations on the distribution are utilized for the quantile regression estimation. Therefore, quantile regressions can be used in various distributions, and hence can be more efficient and appropriate especially when extreme values are present. This is especially true for stock return distributions that exhibit fat tails and/or skewed distributions. Unlike the ordinary least squares regression, quantile regressions help to alleviate some of the statistical problems with fat tails or outliers.

For Taiwan's stock market, it has been applied to study the return-volume relation on the Taiwan stock exchange (Chuang and Kuan, 2005), and to study the fund investors' herding redemption and non-herding redemption (Lee et al., 2010).

Unlike the decile approach adopted in Lo and Li (2009), and Yeh and Li (2012), the quantile regression analysis also allows us to investigate market return/herding relation efficiently. Therefore, we investigate market herding behavior in Taiwan with the quantile regression analysis in this paper.

METHODOLOGY

Herding- and Sentiment-Biased Beta of Hwang and Salmon (2009)

A novelty in Hwang and Salmon (2009) lies in their proposal that both cross-sectional herding and sentiment can have impact on betas, although the justifications behind these two forces are different. The cross-sectional herding arises from investors' relative valuation of the market regardless of systematic risk, while impact of sentiment comes from investors' biased expectation on future returns. These two behavioral biases have a common effect on betas.

To show this, Hwang and Salmon (2009) offer the following heuristic model-based explanation. Simply put, they first define sentiment with reference to its effect on the mean of quasi-rational investors' subjective returns. If sentiment is relatively high (low), an optimistic (pessimistic) sentiment exists. Then, with s_{mt} and s_{it} denoting sentiment of the market portfolio, *m*, and sentiment of an individual asset *i*, Hwang and Salmon (2009) decompose s_{it} into three components: a common market-wide sentiment that evolves over time; a cross-sectional herding; and a zero-mean idiosyncratic sentiment as follows,

$$s_{it} = s_{mt} - h_{mt}\left(\beta_{imt} - 1\right) + \omega_{it}, \tag{1}$$

where β_{imt} is the unbiased beta of asset *i* with respect to the market portfolio *m* at time *t*, and h_{mt} is the degree of herding on individual asset *i*. Such a decomposition ensures that the cross-sectional expectation of s_{it} is equal to s_{mt}. Then a herding- and sentiment-biased beta is derived as follows,

$$\beta_{imt}^{s} = 1 + \frac{1}{1+s_{mt}}\left[\left(1-h_{mt}\right)\left(\beta_{imt}-1\right)+\omega_{it}\right]. \tag{2}$$

Based on equation (2), several important and interesting predictions follow. First, when there is neither herding nor sentiment, $\beta_{imt}^{s} = \beta_{imt}$. Second, for a given s_{mt}, a positive h_{mt} (herding) generally makes β_{imt}^{s} move towards 1, and a negative h_{mt} (adverse herding) makes β_{imt}^{s} move away from 1. Third, for a given h_{mt}, β_{imt}^{s} moves toward 1 as s_{mt} increases, and vice versa. Furthermore, when β_{imt} is independent of ω_{it},

$$Var_c\left(\beta_{imt}^{s}\right) = \frac{1}{\left(1+s_{mt}\right)^2}\left[\left(1-h_{mt}\right)^2 Var_c\left(\beta_{imt}\right) + Var_c\left(\omega_{it}\right)\right]. \tag{3}$$

Assuming that neither $Var_c\left(\beta_{imt}\right)$ nor $Var_c\left(\omega_{it}\right)$ changes significantly over time, the dynamics of the cross-sectional variance of the biased betas, $Var_c\left(\beta_{imt}^{s}\right)$, reflect changes in sentiment (s_{mt}) or cross-sectional herding (h_{mt}). More specifically, $Var_c\left(\beta_{imt}^{s}\right)$ decreases whenever there is cross-sectional herding and/or positive market-wide sentiment.

The above heuristic model offers a theoretical explanation on how market herding may be affected by cross-sectional herding and market-wide sentiment. Empirically, the degree of herding towards the market may be computed as follows,

$$H_{mt} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\beta_{imt}^{s} - 1\right)^2, \tag{4}$$

where N_t is the number of stocks at time *t*. Beta herding towards the market increases as H_{mt} gets smaller. Since β_{imt}^{s} is unknown, it needs to be replaced by an estimated one as follows,

$$H_{mt}^{O} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\hat{\beta}_{imt}^{s} - 1\right)^2. \tag{5}$$

However, since H_{mt}^{O} could be affected by insignificant estimates of β_{imt}^{s}, Hwang and Salmon (2009) suggest an alternative standardized beta herding measure defined as follows,

$$H_{mt}^{*} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\frac{\hat{\beta}_{imt}^{s} - 1}{\sigma_{\hat{\beta}_{imt}^{s}}}\right)^2, \tag{6}$$

where $\sigma_{\hat{\beta}_{imt}^{s}}$ is the robust standard error of β_{imt}^{s}. Hwang and Salmon (2009) prove that this new measure of herding is distributed as $1/N_t$ multiplied by the sum of a non-central χ^2 distribution and a constant, c^*, as follows,

$$H_{mt}^{*} \sim \frac{1}{N_t}\left[\chi^2\left(R;\delta_m^{*R}\right) + c^*\right], \tag{7}$$

where R is the rank of the covariance matrix; V_{mt}^{*}; $B_{imt}^{*} \equiv \left(\hat{\beta}\%_{imt}^{s} - 1\right)/\sigma_{\hat{\beta}_{imt}^{s}}$; $B_{mt}^{*} \equiv \left(B_{1mt}^{*}, B_{2mt}^{*}, \cdots, B_{N_t mt}^{*}\right)$ is the vector of B_{imt}^{*}; $\delta_m^{*R} = \sum_{j=1}^{R}\left(\delta_j^{A*}\right)^2/\lambda_j^{*}$; $c^* = \sum_{j=R+1}^{N}\left(\delta_j^{A*}\right)^2$; δ_j^{A*}; δ_j^{A*} is the j^{th} element of the vector $C_{mt}^{*'}B_{mt}^{*}$; C_{mt}^{*} is the ($N_t \times N_t$) matrix of eigenvectors of V_{mt}^{*}; and λ_j^{*}s are the corresponding eigenvalues. Therefore, the variance of H_{mt}^{*} can be computed as follows,

$$Var\left(H_{mt}^{*}\right) = \frac{2}{N_t^2}\left[R + 2\delta_m^{*R}\right], \tag{8}$$

which could be used to draw statistical inferences on H_{mt}^{*}.

In our later empirical investigation, we will focus on the standardized beta herding, H_{mt}^{*}, defined in equation (6) and its variance, $Var\left(H_{mt}^{*}\right)$, defined in equation (8) to conduct hypotheses testing and statistical inferences on the market herding behavior in Taiwan.

Quantile Regression Analysis of Asset Returns and Herding

In general, a linear conditional quantile function can be stated as

$$Q_{y_t}(\tau \mid X = x) = x_t'\gamma, \tag{9}$$

where y_t is a dependent variable, x_t is a vector of independent variables, τ is a real number between 0 and 1, and γ is a vector of coefficients. By minimizing weighted deviations from the conditional quantile, we obtain the quantile estimators as

$$\hat{\gamma}_\tau = \min_\gamma \left\{ \sum_{t:\, y_t \geq x_t'\gamma} \tau \left| y_t - x_t'\gamma \right| + \sum_{t:\, y_t < x_t'\gamma} (1-\tau) \left| y_t - x_t'\gamma \right| \right\} \tag{10}$$

$$= \min_\gamma \rho_\tau \left(y_t - x_t'\gamma \right)$$

$$= \min_\gamma \left(\tau - 1_{\left(y_t < x_t'\gamma\right)} \right) \left(y_t - x_t'\gamma \right)$$

where $1_{\left(y_t < x_t'\gamma\right)}$ is an indicator function which equals 1 if $y_t < x_t'\gamma$, and 0 otherwise. In other words, the quantile regression estimators can be derived by minimizing an asymmetrically weighted sum of the absolute errors, where the weights are dependent on the quantile values. A low-quantile (high-quantile) regression estimator could be heuristically interpreted as the regression slope for the left-tail (right-tail) distribution of the dependent variable, although all observations on the distribution are utilized for the estimation. In short, the quantile regression allows us to estimate the interrelation between a dependent variable and its explanatory variables at any specific quantile of the dependent variable.

Applying the quantile regression in estimating the relation between market return and the standardized beta herding measure conditional on other explanatory variables, the τ quantiles are characterized as

$$Q_{r_{mt}}(\tau \mid X = x) = \gamma_{0\tau} + \gamma_{1\tau} SMB_t + \gamma_{2\tau} HML_t + \gamma_{3\tau} H^*_{mt} + \varepsilon_{\tau t}, \tag{11}$$

where r_{mt} is the market return; SMB_t (Small Minus Big) is the return on the mimicking portfolio for the size factor; HML_t (High Minus Low) is the return on the mimicking portfolio for the value-growth factor. Unlike Hwang and Salmon (2009), we do not include the market sentiment as one of the explanatory variables. This is because, by construction, the beta herding measure, H^*_{mt}, is negatively correlated with market sentiment, and hence can create some collinearity in the regression. Note that we omit excess market return from the right-hand side since the dependent variable is the market excess return. In this fashion, we can examine how herding behavior affect market returns at different market states (high or low market return according to different return quantiles) with greater flexibility and higher precision.

EMPIRICAL BETA HERDING

In this section, we describe how beta herding in Taiwan's stock market are constructed, and examine their sampling statistical properties. The relation between beta herding and sentiment follows subsequently.

Estimation of Beta and Data

To construct the beta herding measure, betas for each individual stock must first be estimated. In addition to the capital asset pricing model (CAPM), we estimate betas with two other popular multi-factor models, namely the Fama-French three-factor model (Fama and French, 1993) and the Carhart four-factor model (Carhart, 1997). These asset pricing models account for well-known pricing factors, which include the size factor (*SMB*), the value-growth factor (*HML*) and the momentum factor (*MOM*).

We use rolling windows of 60 monthly observations, and update the herding measure as in equation (6) and its variance as in equation (8). Specifically, we use the initial 60 observations to acquire the OLS estimates of betas and their *t* statistics obtained with Newey-West heterskedasticity consistent standard errors for each individual stock, and then calculate the herding measure and its variance. We then add one observation at the end of the sample and drop the first, and thus use the next 60 observations to calculate the herding measure, and so on. Therefore, we only include individual stocks whose past 60 monthly observations are available. Following Hwang and Salmon (2009), the top and bottom 1% of the standardized beta estimates are also omitted in our estimation, as these outliers might affect herding measure significantly even if the majority of estimates do not change in a meaningful way.

Our sample period consists of 308 monthly observations of all common stocks traded on the Taiwan stock exchange, with financial firms excluded, from January 1991 to August 2016. The number of stocks employed in this study starts from 128 at January 1991 and increases to 808 at August 2016. For computing excess returns, the average one-month time deposit rate from five main Taiwanese commercial banks is used to proxy the risk-free rate. All of the required data for our analysis are retrieved from the Taiwan Economic Journal (TEJ), which is a local data vendor in Taiwan.

Empirical Properties of Beta Herding Measures

Table **1** reports some of the basic statistical properties of standardized herding measures estimated with the CAPM model, the Fama-French three-factor model (FF3), and the Carhart four-factor model (Carhart4). The FF3 and the Carhart4 herding measures are highly non-normal. Due to this non-normality, rank correlations are calculated to investigate the relation between the three measures, and are reported in the last row of Table **1**. The correlation coefficient between the CAPM and the FF3 is 0.606, the correlation coefficient between the CAPM and the Carhart4 is 0.535, while the correlation coefficient between the FF3 and the Carhart4 is 0.964. These indicate that the standard errors of the estimated bates are significantly affected by additional asset pricing factors, such as the *SMB*, the *HML* and the *MOM*.

TABLE 1
PROPERTIES OF BETA HERD MEASURE ON TAIWAN'S EQUITY MARKET

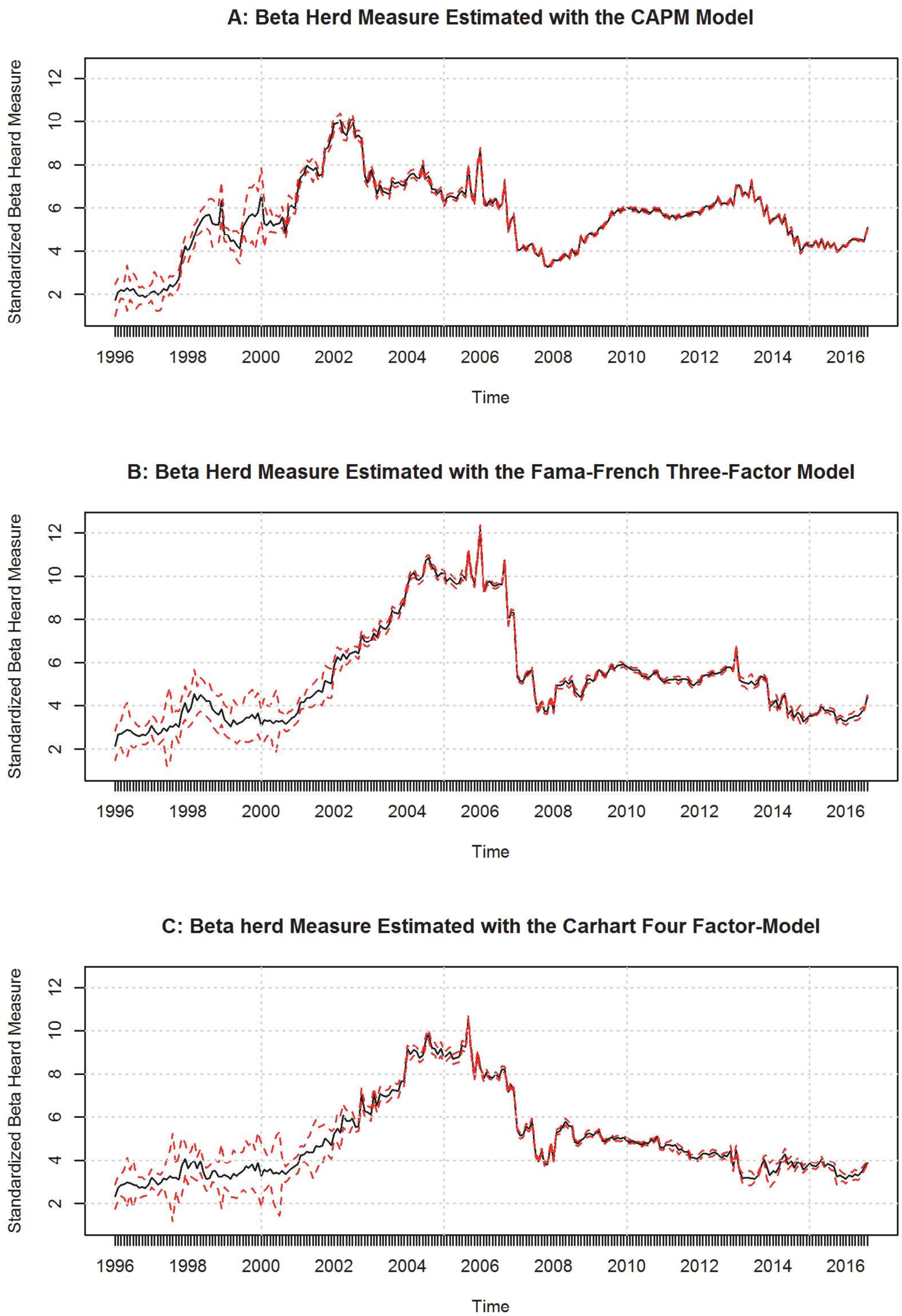
The beta-based herd measure is calculated with the cross-sectional variance of *t* statistics of betas which are calculated with the Newey-West heteroskedastic adjusted standard errors. We use 60 past monthly returns to estimate betas with the CAPM, the Fama-French three-factor model, and the Carhart four-factor model. Using 308 monthly observations from January 1991 to August 2016 and rolling windows of 60 months, we obtain 248 monthly herd measures from January 1996 to August 2016. * represents significance at the 1% level.

	CAPM	Fama-French (FF3) three-factor model	Carhart four-factor model
Mean	5.549	5.395	4.920
Standard Deviation	1.747	2.264	1.864
Skewness	0.072	1.039	1.124
Excess Kurtosis	0.156	0.119	0.211
Jarque-Bera Statistics	0.558	45.35*	53.44*
Spearman Rank	CAPM and FF	CAPM and Carhart	FF and Carhart
Correlations	0.606*	0.535*	0.964*

Figure 1 shows the evolution of market herding (estimated with all three asset pricing models) over time in Taiwan's stock market with the 95% confidence interval represented by the dashed lines. With hundreds of stocks, the confidence level calculated by equation (8) is so small that we observe many significant but small changes in herding activity. It is interesting to note that the market herding estimated from each model follows similar trend; and, irrespective of the factor model used in estimating these herding measures, the degree of herding is higher (with smaller beta herding values) in the pre-2000 period (with the Asian financial crisis and the Dot-com bubble) and the post-2008 period (the Great Recession). The pattern is more pronounced when beta herding measures are estimated with the FF3 and the Carhart4 factor models. This is different from evidence found in Hwang and Salmon (2009), which states that beta herding does not occur when financial markets are in stress (or in crisis) for the U.S. market. Presumably, this is because Taiwan's stock market is more dominated by noise-traders.

Although both the FF3 and the Carhart4 models dominates the CAPM model, and perform equally well around crisis periods, the Carhart4 model is estimated with larger errors during the pre-2000 period. Therefore, from this point onwards, we will stick to the standardized market herding measure estimated with the Fama-French three-factor model for the rest of our empirical analysis.

FIGURE 1
EVOLUTION OF HERDING OVER TIME IN TAIWAN'S STOCK MARKET



The Relation between Market Sentiment and Beta Herding

As described in equation (3), the variance of sentiment-biased beta decreases whenever there is positive market-wide sentiment. This implies that the beta herding measure, H^*_{mt}, should also decrease with market-wide sentiment, ceteris paribus. It is thus interesting to examine whether such a construct gains any empirical support in Taiwan's stock market.

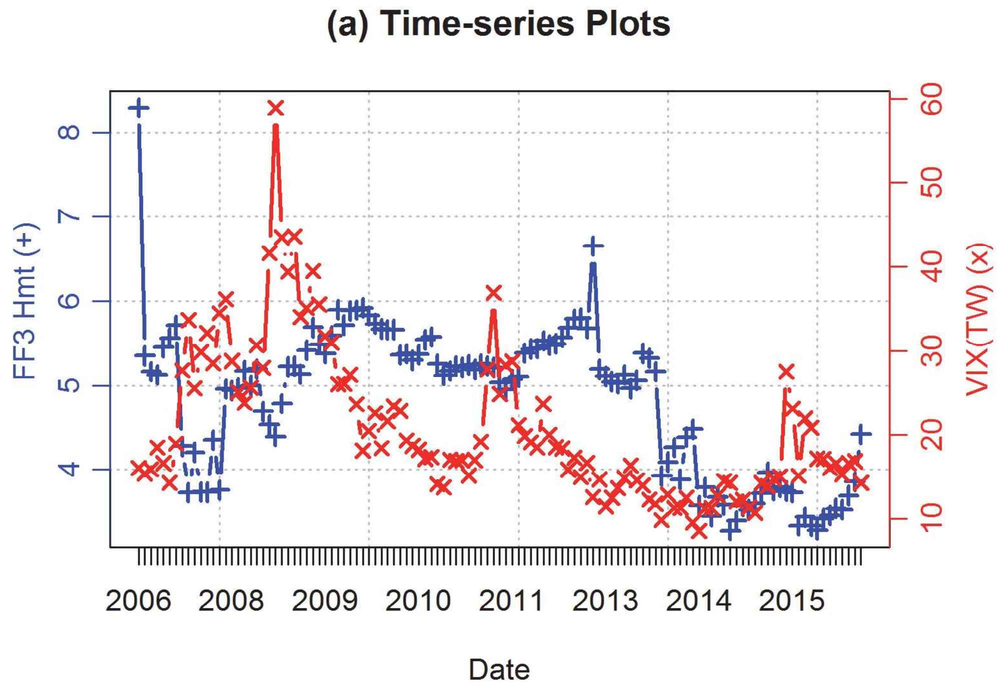
For measuring market sentiment, there is currently no aggregate market sentiment index existing in Taiwan. A viable proxy for measuring market sentiment is the volatility index (VIX), which is a measure of implied volatility obtained from options markets. It represents a market consensus estimate of future stock market volatility, and is often referred to as the *fear gauge* because it is thought to gauge the amount of *negative sentiment* investors have. Whaley (2000) and Baker and Wurgler (2007) suggest the volatility index (VIX) as an alternative market sentiment measure. In Taiwan's market, the volatility index was also introduced by the Taiwan Futures Exchange (TAIFEX), and is calculated using the VIX formula developed by the Chicago Board Options Exchange since December, 2006. Hence, we choose the VIX index in Taiwan as the proxy for negative market sentiment.

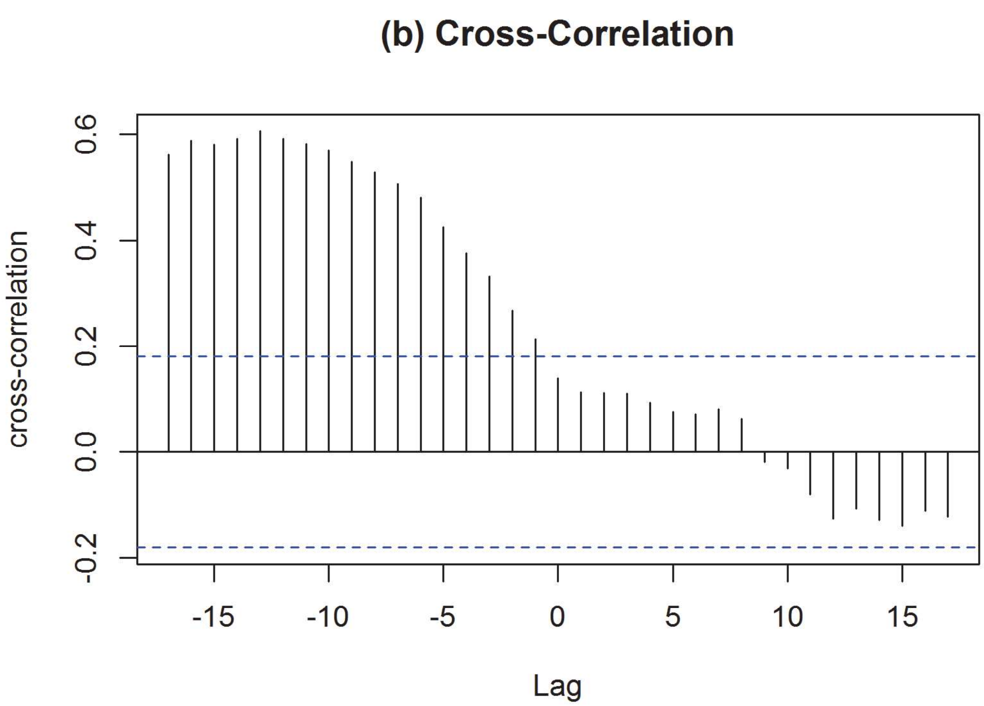
We plot the relation between the beta herding and the VIX index in Taiwan's stock market in Figure 2(a). The VIX index and our estimated beta herding measure appear to follow the same trend, although they are insignificantly correlated (with a Spearman rank correlation of 0.139, and a p-value of 0.134). Despite the lack of significant contemporaneous correlation, we plot the sample cross-correlation function between the beta herding measure and the VIX index for $h = 0, \pm 1, \pm 2, \pm 3$ (plotted along the horizontal axis) in Figure 2(b). It is interesting to note that the cross-correlations are significantly positive for all negative h, while insignificant for all positive h. This indicates that the volatility index series positively leads the beta herding series. However, since cross-correlations do not necessarily imply causality, one has to be more careful in interpreting the information contained in Figure 2(b). Compared to our estimated market herding, we have too short a VIX series to facilitate any reliable analysis of the relation between these two time series. Nonetheless, we have discovered positive contemporaneous- and cross-correlations between the beta herding and the volatility index, which justifies the application of Hwang and Salmon's heuristic model in studying herding behavior in Taiwan's stock market.

ASSET RETURNS AND BETA HERDING

From empirical results reported in the previous section, we discover some variations in beta herding behavior in Taiwan's stock market over time. In this section, we examine whether a time-varying beta herding behavior results in a different degree of impact on the stock market at various market states. One way to investigate this issue is to sort the entire sample into sub-groups according to market returns, as what is done in Lo and Li (2009), and Yeh and Li (2012). However, conditional on sub-groups, instead of the entire distribution, may potentially lead to inefficient deduction of the relation between the market return and the beta herding behavior. Alternatively, the quantile regression analysis enables us to cover a full range of conditional quantile functions, and consequently produce more robust and efficient estimates. In addition, as in equation (11), our quantile regression model is not restrictive at the mean level and therefore provides a broader picture of the relation between market return and the beta herding measure at different market return quantiles.

FIGURE 2
BETA HERDING MEASURE (FF3) VS. VOLATILITY INDEX





The estimation results are presented in Figure **3** and Table **2**. While Table **2** offers detailed estimates and *t*-values at 9 different deciles of the market return, Figure **3** is more convenient for illustration purposes. Specifically, the solid line and the two dashed horizontal lines in Figure **3** represent the OLS coefficient estimates for each explanatory variable, and their corresponding 95% confidence interval, while the black dash-dot lines and the associated grey areas represent the quantile regression counterparts. It is interesting to note that, while the OLS estimate indicates that the beta herding measure does not significantly affect market return for the entire return distribution (as 0 is always contained within the 95% confidence interval), the quantile regression results indicate that a higher (lower) beta herding measure, smaller (higher) degree of market herding, can significantly and positively (negatively) affect market returns at their left-tail distribution (below the 20^{th} quantile of the market return distribution.) In other words, during market downturns, a higher degree of market herding can aggravate the panic of market participants, which then causes the market return to drop even further.

To sum up, our quantile regression analysis provides a much more complete picture of the return-herding relation. In particular, we are able to spot that herding behavior can significantly affect market returns at the lower quantile of the return distribution.

CONCLUSIONS

The importance of investigating herding behavior and its impact on the market stems from the fact that it could potentially divert stock prices away from their fundamental values, and therefore offers arbitrage opportunities. A long-run consequence of herding behavior may lead to greater inefficiency if the market fails to make its price converge to the fundamental value. Compared to stock markets of other economies, Taiwan's stock market is typically dominated by noise-traders, and hence deserves a systematic examination of herding behavior therein and its possible impact on market returns.

In this paper, we apply the beta herding measure of Hwang and Salmon (2009) to examine empirical properties of herding in Taiwan's stock market, and its relation with market sentiment and returns. We find time-varying beta herding behavior in Taiwan's stock market, and the standard errors of the estimated beta herding measures are significantly affected by the additional asset pricing factors, such as SMB and HML. Interestingly, irrespective of the factor models used in estimating these herding measures, the degree of herding is higher in the pre-2000 period (with the Asian financial crisis and the Dot-com bubble), and the post-2008 period (the Great Recession). This pattern is more pronounced when the beta herding measures are estimated with the Fama-French three-factor model, and the Carhart four-factor model. This is different from the evidence found in Hwang and Salmon (2009) which states that herding does not occur when financial markets are in stress (or in crisis) for the U.S. market. Presumably, this is because Taiwan's stock market is more dominated by noise-traders.

We have also discovered positive contemporaneous- and cross-correlations between the market herding and the volatility index, which justifies the application of Hwang and Salmon's heuristic model in studying the herding behavior in Taiwan's stock market. However, data availability of the volatility index in Taiwan prohibits us from pursuing further causal analysis between time series of these two important stock market variables. We shall leave this for future research endeavor.

Our quantile regression results indicate that a higher beta herding measure can significantly and positively affect market returns in their left tail distribution (below the 20^{th} quantile of the market return distribution.) In other words, during market downturns, a higher degree of market herding can aggravate the panic of market participants, which then causes the market return to drop even further.

Overall, apart from a systematic investigation of the herding behavior in Taiwan's stock market, this study also contributes to related literature by providing some insights into herding-return relation with the quantile regression analysis.

FIGURE 3
ASSET RETURNS AND BETA HERDING WITH QUANTILE REGRESSION

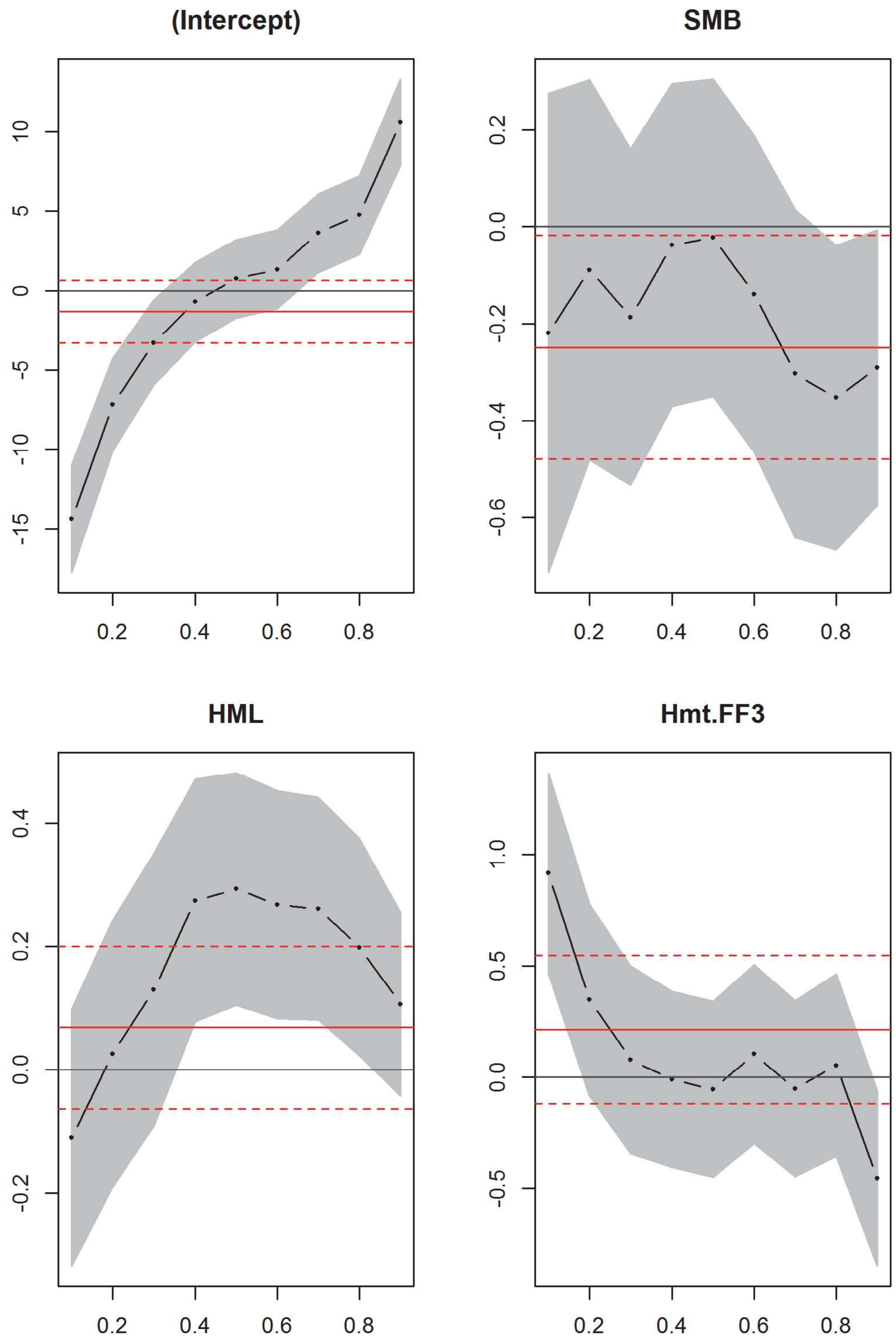


TABLE 2
QUANTILE REGRESSION ANALYSIS OF RETURNS AND HERDING ON TAIWAN'S STOCK MARKET

This table reports estimates of the following quantile regression:

$$Q_{r_{mt}(\tau|X=x)} = \gamma_{0\tau} + \gamma_{1\tau}SMB_t + \gamma_{2\tau}HML_t + \gamma_{3\tau}H^*_{mt} + \varepsilon_{\tau t},$$

where r_{mt} is the market return; SMB_t is the return on the mimicking portfolio for the size factor; HML_t is the return on the mimicking portfolio for the value-growth factor; and H^*_{mt} is the beta herding measure. The sample period is from January 1999 to August 2016. Numbers in parentheses are t-statistics. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	γ_0	γ_1	γ_2	γ_3
Quantile (τ = 0.1)	-14.37	-0.22	-0.11	0.92
	(-7.00)***	(-0.73)	(-0.87)	(3.34)***
Quantile (τ = 0.2)	-7.17	-0.09	0.03	0.35
	(-4.06)* ***	(-0.37)	(0.20)	(1.33)
Quantile (τ = 0.3)	-3.28	-0.19	0.13	0.08
	(-2.02)**	(-0.89)	(0.96)	(0.31)
Quantile (τ = 0.4)	-0.72	-0.04	0.27	-0.01
	(-0.47)	(-0.19)	(2.30)**	(-0.04)
Quantile (τ = 0.5)	0.74	-0.02	0.29	-0.05
	(0.50)	(-0.11)	(2.56)**	(-0.23)
Quantile (τ = 0.6)	1.33	-0.14	0.27	0.1
	(0.88)	(-0.70)	(2.38)**	(0.42)
Quantile (τ = 0.7)	3.62	-0.3	0.26	-0.05
	(2.42)**	(-1.47)	(2.38)**	(-0.22)
Quantile (τ = 0.8)	4.76	-0.35	0.2	0.05
	(3.15)***	(-1.85)*	(1.85)*	(0.21)
Quantile (τ = 0.9)	10.6	-0.29	0.11	-0.46
	(6.42)***	(-1.68)*	(1.18)	(-1.90)*

REFERENCES

Baker, M., & Wurgler, J. (2007). Investor Sentiment in the Stock Market. *Journal of Economic Perspectives, 21*, 129-152.

Brown, G. W., & Cliff, M. T. (2004). Investor Sentiment and the near term Stock Market. *Journal of Empirical Finance, 11*, 1-27.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance, 52*, 57-82.

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An Examination of Herd behavior in Equity Markets: An International Perspective. *Journal of Banking and Finance, 24*, 1651-1679.

Chiang, T. C., Li, J., & Tan, L. (2010). Empirical investigation of herding behavior in Chinese stock markets: Evidence from quantile regression analysis. *Global Finance Journal, 21*, 111-124.

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance, 34*, 1911-1921.

Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd Around the Market? *Financial Analysts Journal, 51*, 31-37.

Chuang, C.-C., & Kuan, C.-M. (2005). A quantile regression analysis of return-volume relation: Evidence from the Taiwan and U.S. stock exchanges. *Academia Economic Papers, 33*, 379-404.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3-56.

Gleason, K. C., Mathur, I., & Peterson, M. A. (2004). Analysis of intraday herding behavior among the sector ETFs. *Journal of Empirical Finance, 11*, 681-694.

Graham, J. R. (1999). Herding among investment newsletters: theory and evidence. *Journal of Finance, 54*, 237-268.

Hirshleifer, D., & Teo, S. H. (2003). Herd Behavior and Cascading in Capital Markets: A Review and Synthesis. *European Financial Management, 19*, 25-66.

Hwang, S., & Salmon, M. (2004). Market Stress and Herding. *Journal of Empirical Finance, 11*, 585-616.

Hwang, S., & Salmon, M. (2009). Sentiment and Beta Herding.

Koenker, R. W. (2005). *Quantile Regression*: Cambridge University Press.

Koenker, R. W., & Bassett, G. (1978). Regression quantile. *Econometrica, 46*, 33-50.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The Impact of Institutional Trading on Stock Prices. *Journal of Financial Economics, 32*, 23-43.

Lao, P., & Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian Economics, 22*, 495-506.

Lee, H.-Y., & Wu, H.-C. (2009). The Impact of Information in Technical Analysis on Herd Behavior of Mutual Fund. *NTU Management Review, 20*, 227-260.

Lee, J.-S., Shen, C.-H., & Yen, P.-H. (2010). Fund Investors' Disposition Effect vis-a-vis Herding Redemption and Non-Herding Redemption Using Quantile Regression Least Square Dummy Variable Estimator. *Journal of Management & Systems, 17*, 1-26.

Li, C.-A., & Laih, Y.-W. (2005). Taiwan stock market and domestic institutional investors herding behaviors during acutely market volatility periods. *Taiwan Academy of Management Journal, 5*, 231-268.

Li, C.-A., Luo, J.-S., & Su, Y.-Y. (2006). Momentum Returns, Investor Sentiments and Business Cycle. *Journal of Financial Studies, 14*, 73-109.

Lo, C.-S., & Li, C.-A. (2009). The Impact of Herding and Non-herding on Market Returns. *Management Review, 28*, 21-41.

Nofsinger, J., & Sias, R. W. (1999). Herding and Feedback Trading by Institutional and Individual Investors. *Journal of Finance, 54*, 2263-2295.

Shyu, J., & Sun, H. M. (2010). Do Institutional Investors Herd in Emerging Markets? Evidence from Taiwan's Stock Markets. *Asian Journal of Finance & Accounting, 2*, 1-20.

Sias, R. (2004). Institutional Herding. *Review of Financial Studies, 17*, 165-206.

Wermers, R. (1999). Mutual Fund Herding and the Impact on Stock Prices. *Journal of Finance, 54*, 581-622.
Whaley, R. E. (2000). The Investor Fear Gauge. *The Journal of Portfolio Management, 26*, 12-17.
Yeh, C.-C., & Li, C.-A. (2012). The Relationship Among Investor Sentiment, Herding and Non-herding. *Review of Securities and Futures Markets, 24*, 141-182.