Pacific-Basin Finance Journal 62 (2020) 101383

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

Investor-herding and risk-profiles: A State-Space model-based assessment

Harmindar B. Nath*, Robert D. Brooks

Department of Econometrics and Business Statistics, Monash University, Caulfield East 3145, Australia

ARTICLE INFO

Keywords:
Herd behaviour
Risk aversion
State-Space models
Quantile regression
Leverage effect

JEL classification:
C31
C32
G12
G14

ABSTRACT

This paper, using the Australian stock market data, examines the investor-herding and risk-profiles link that has implications for asset pricing, portfolio diversification and foreign investments. As investors may herd towards a specific factor, sector or style to combat market conditions for optimizing investment returns, examining such herding can reveal investors' risk profiles. We employ State-Space models for extracting time series of herd dynamics and the proportion of signal explained by herding (PoSEH). The possibility of a leverage effect between market returns and volatility and its implications are discussed. The change in market volatility strengthens PoSEH; its impact is maximum on high return days of stocks. Quantile regression analysis shows that herding and adverse herding can emerge during the worst and best performance days of stock returns, but extreme uncertainty can bring both herding behaviours to a near halt. The study reveals the presence of a regulated stock market environment and the change in volatility and risk-aversion as the determinants of herding behaviour.

1. Introduction

Social psychology experiments on the behaviour of individuals in group situations reveal that individuals conform to group opinion, even when they do not agree with the group or believe that the group is wrong – a phenomenon known as herd behaviour (Asch, 1952). In stock markets situations investors may adapt to herd behaviour due to lack of confidence in their own judgement or lured by successes of others and want to take advantage of opportunities availed by others or getting excited as a gambler to the thought of making quick money. Others may herd because they find it easier to dive into a risky venture in the company of others. Prechter Jr. (2001) asserts that ‘it is a lesser-known fact that the vast majority of professionals herd just like the naïve majority’. In a survey, Shiller & Pound (1989) find herding to be common among institutional investors as they place a significant weight on the advice of other professionals in making their buy/ sell decisions in volatile markets.

The existence of herd behaviour in a market challenges the validity of the efficient market hypothesis (EMH)[1] that portrays that all investors are rational and possess the same full set of information for assessing the expected stock prices (Fama, 1970). The lack of full use of available information by market participants due to herding can intensify the inefficiency of the market leading to a disequilibrium relation between risk and return. Thus, herding can be viewed as a signal of an inefficient market, and an inefficient market may be interpreted as riskier than an efficient market. Discussing the economic implications of herding in the Taiwanese market, Demirer et al. (2010) point to its likely knock-on effect on portfolio management and the need to design policies like banning the short selling to deal with its negative effect on asset pricing.

* Corresponding author.
E-mail addresses: mindi.nath@monash.edu (H.B. Nath), Robert.brooks@monash.edu (R.D. Brooks).

[1] See Lao and Singh (2011) and references therein for more details.

https://doi.org/10.1016/j.pacfin.2020.101383
Received 29 January 2020; Received in revised form 26 May 2020; Accepted 18 June 2020
Available online 25 June 2020
0927-538X/

Previous research (e.g., Chang et al. (CCK), 2000; Demirer et al., 2010; Lao and Singh, 2011; Yao et al., 2014) indicates that emerging markets that lack regulation, transparency and information efficiency are prone to herd behaviour, and that developed markets show no evidence of herding (Christie and Huang, 1995; CCK, 2000; Henker et al., 2006). In these studies, US as the developed market and China, Taiwan and South Korea as the emerging markets are the most common markets being investigated. This paper focuses on the Australian market, a developed market in the Asia and Pacific region and the only developed market to survive a recession following the Global Financial Crisis (GFC) in 2008 (Davis, 2011). This makes the Australian stock market an interesting market for examining the investor-herding and risk-profiles link. Moreover, while most of the markets around the globe recovered and surpassed their pre-GFC stock market indices well before 2017, the Australian stock market in 2017 was still struggling to break the ceiling of its pre-GFC index that grew from 3133 in March 2000 to 6873 by October 2007. A few studies (Henker et al., 2006; Chiang and Zheng, 2010; Bohl et al., 2013) that have examined herding in the Australian market use either very small sample periods or a very small sample of stocks and present conflicting evidence. This paper is the first study to combine the strengths of quantile regression and State Space modelling for understanding the investor herd behaviour.

While the concept of regular herd behaviour is easily understood and much explored via the use of the Christie and Huang (1995) and Chiang et al. (2010) models and their extensions (e.g., Chiang and Zheng, 2010; Chiang et al., 2010; Lao and Singh, 2011; Yao et al., 2014), the concept of adverse herding is relatively unexplored in the stock market settings. Effinger and Polborn (2001) explain the presence of adverse herding phenomenon via a model of competing agents facing incentives where doing things differently to the mob establishes smartness. In the context of stock markets, Hwang and Salmon (2004) argue that adverse herd behaviour is likely to emerge due to a high level of uncertainty and divergence of opinion among market participants with no clear indication of the future direction of the market. It makes a defensive stock beta (beta < 1) appear more defensive and an aggressive stock beta (beta > 1) more aggressive, inflating the cross-sectional dispersion of betas.

This paper examines the investor herding and risk-profiles link using Australian data covering the pre-, post-, and the GFC periods, and the short-selling ban period, and employing the Hwang and Salmon (2004) model. Our benchmark results apply the ordinary least squares (OLS) method for estimating betas as in Hwang and Salmon (2004) but employ the quantile regression for capturing the heterogeneous responses of stock returns to market movements and other factors. This eliminates using subjective judgement in defining the *extreme market conditions* while evaluating the changing relationship between the stock and the market returns, and/or other factors in response to the perceived risk and profit opportunities during periods of market expansions and contractions. If investors' investment strategies change due to changed conditions, they would be reflected in the quantile regression estimates of betas at the extreme quantiles and would be different from the OLS based estimates. If different, it would mean that the stocks' risk exposure to market conditions and other factors are not homogenous and that investors price their assets differently in response to the market risk situations. Thus, the time series dynamics of herding extracted using the State Space (SS) models from such varied factor sensitivities and viewed along with the market conditions would reveal investors' risk tendencies. Many studies (e.g., Lakonishok et al., 1992; Grinblatt et al., 1995) report that herding is stronger among small size stocks, however, our study focuses only on large size stocks. It also does not segregate institutional investors from the individual investors.

As investors may herd towards a specific factor, sector or style to combat market conditions and to optimize their investment returns, we investigate herding towards the market portfolio as well as herding towards book-to-market (BM) ratio[2,3]and trading volume (TR) factors. Since over and under valuations of stocks as reflected in the BM ratios are indicators of investors' risk aversion tendencies (Arnott et al., 2005), viewing the level of herding towards BM factor together with the prevalence of the market conditions would reveal investors' risk tendency in a given time period. There is much evidence that trading volume sustains stock price movements. Stickel and Verrecchia (1994) assert that "a conventional wisdom on Wall Street is that *volume is the fuel for stock prices*". Low trading volume is likely to reverse price changes more than the high trading volume. As herding can lead to significant mispricing, it would be of interest to examine herding towards the trading volume to find out what information on investor risk profile is conveyed by such herding. Our study of herding towards the BM and TR factors is different from the previous studies that explore the existence of herding towards the market portfolio by controlling the effect of volume via dummy variables, or by forming quintile portfolios on BM ratios.

We observe herding levels vary across the quantiles of the return distribution. The existence of herding and adverse herding at the extreme quantiles suggests that such behaviour can emerge during the worst and the best performance days of stock returns. The proportion of signal explained by herding (PoSEH) based on the cross-sectional standard deviations (CSSD) of average and extreme quantiles' betas of the return distribution is not the same; investors seem to value their assets differently on the low and high-performance days of stock returns compared to an average day, and adjust their herd behaviour accordingly. Like Hwang and Salmon (2004), our findings do not support the common belief reflected in past studies (e.g., Demirer et al., 2010; Chiang and Zheng, 2010; Yao et al., 2014) via the Christie and Huang (1995) and CCK (2000) models that herding occurs during market stress. We depart from Hwang and Salmon (2004) in using market returns and market volatility as a pair of explanatory variables in the same model to avoid the quadratic relationship between them and the resulting leverage effect confounding our results. Instead, we use the change in market volatility to establish the robustness of our findings. We find that the change in volatility has a significant inverse relationship

[2] Viewing the algebraic development of the BM ratio, Peterkort and Nielson, (2005) explain that the BM ratio is the product of 'financial risk' (debt divided by market equity) and 'asset risk' (the inverse of debt divided by book equity).

[3] In seeking to assign the BM ratio a 'risk-based' or a 'mispricing' connotation, Dempsey (2010) using Australian data concludes that 'BM effect cannot be divorced from underlying leverage as a risk factor'. He adds, 'the BM variable absorbs market movements as a proxy for financial risk and is seen as the price adjustment mechanism of convergence to norm from more extreme values whatever triggers such movement'.

with CSSDs of betas, but it strengthens the PoSEH in each model showing the most effect on high return days of stocks. The trading volume herding is low in general, and the market portfolio is herded the most on high return days of stocks. However, the size of the signal explained by the BM factor herding, which is consistently high across all levels of the return distribution and is not impacted by the effect of change in volatility being significant or not, suggests that BM is a highly sought-after herding factor. It can be inferred that for risk-minimising investors frequently herd towards BM ratio, a risk leverage factor. We observe investor herding/ adverse herding during tranquil/ uncertain periods, and a near halt of these two behaviours during extreme uncertainty like the GFC. Such behaviour not only implies a link between the investor herding and their risk-profiles but also endorses a risk-aversion tendency among investors. The non-significant sideways herding movements during the short-selling ban period (Nov 2008–May 2009) suggests the effectiveness of the regulatory system.

The structure of the paper is as follows. Section 2 outlines some literature on herding and the scope of the problem. Section 3 details the data and the sampling design. While Section 4 provides the methodology, Section 5 presents results and their discussion. Section 6 concludes the paper.

2. Related empirical studies on herding

The literature on empirical studies of herd behaviour documents extensive use of the return dispersion-based models of Christie and Huang (1995) and CCK (2000) and their extensions (e.g., Chiang et al., 2010; Lao and Singh, 2011; Bohl et al., 2013; Yao et al., 2014). These models are basically cross sectional in nature and are based on the notion that herding is likely to occur during extreme market stress. These methodologies explore the idiosyncratic risk behaviour of stock returns during different market conditions (Demirer et al., 2010), and as such there is no direct comparison between the results from this strand of models and the Hwang and Salmon (2004) models applying dispersions in the systematic risk. Although, the Hwang and Salmon (2004) method also uses the cross-sectional relationships, it includes a time dimension to the methodology that allows tracking finer evolutionary movements in herd behaviour. A brief outline of research that relates to the current study follows.

Hwang and Salmon (2004) argue that as the Christie and Huang (1995) methodology does not control for movements in fundamentals, it is not possible to separate investor moves being due to adjustments based on fundamentals or to herding, and whether the market is moving towards a relatively efficient or an inefficient outcome. They build their model upon the CAPM betas - the systematic risk measure of equities, which as per the literature (e.g., Fama and MacBeth, 1973; Ferson and Harvey, 1991, 1993) change over time. They contend that a time-variation effect in CAPM betas is unlikely due to fundamental shifts as capital restructuring events of firms are infrequent and are not likely to occur over short time horizons. Thus, the empirical evidence of the time effect in these betas is more likely to emerge out of behavioural anomalies like investor sentiment or herding. The method allows measuring herd movements, which may follow a different path from the market itself, separating them from asset returns movements caused by shifts in fundamentals, and thus encapsulating investors' herding as well as adverse herding tendencies. The application of their method to the US and the South Korean stock markets reveals the presence of herding towards the market portfolio during up as well as down market conditions. Contrary to the common belief put forward by earlier researchers, they observe investors exhibiting herd behaviour during calmer periods of the market and reduce their herding activity or move away from it during periods of crisis. It reappears in quieter times when investors are confident of the direction of the market.

Based on the Christie and Huang (1995) and CCK (2000) models and a partial use of the Hwang and Salmon (2004) model in the Taiwanese stock market, Demirer et al. (2010) report evidence of herding in all sectors of the market and that the herding effect is more noticeable during market downturns periods. However, their study does not provide information on the proportion of signal explained by herding or the presence of adverse herding. It is not clear if the inclusion of control variables *market volatility* and *market returns* enhances or reduces the degree of herding. A significant negative coefficient on market volatility simply suggests reduction in the cross-sectional dispersion of betas due to increase in market volatility, and as such there is no direct comparison between the outcomes of their study derived from the Christie and Huang (1995), CCK (2000) and Hwang and Salmon (2004) methods. Moreover, their results may be exposed to confounding due to Black's (1976) leverage effect between market volatility and market returns (see discussion on leverage effect in Section 4 below). Therefore, the conclusion that “herding is more likely to occur during periods of market stress, i.e., highly volatile periods” is not supported.

Applying the Christie and Huang (1995) and CCK (2000) models of herding, Henker et al. (2006) investigate intraday investor herding behaviour in the Australian Stock market for the period 2001–2002 and find no evidence of herding. Chiang and Zheng (2010) use a modified version of the CCK (2000) model to study herding in the industrial sector stocks in 18 international markets including Australia for the period May 1988–April 2009. For Australia, their study (Tables 2 and 3) exhibits the market index herding in the absence as well as in the presence of US market variables, and displays such herding (c.f., Table 5, Panel A4) during the Global Financial Crisis (GFC) period in the presence of US market variables. A positive and significant coefficient of $CSAD_{US,\ t}$ in their study simply implies a co-varying risk associated with industry sectors; a shock in a similar industry sector in US tends to get transmitted to Australia. However, their Table 4, Panel A, does not show such herding in rising or declining market conditions in the presence of US market variables.[4]

Using the CCK (2000) model, Bohl et al. (2013) examine the effect of short-selling bans imposed following the GFC on institutional investors' herding behaviour in six stock markets (US, UK, Germany, France, South Korea and Australia). They observe

[4] Using 23 countries and forming 4 regions (North America, Europe, Japan and Asia), Fama and French (2012) test whether asset prices are integrated across markets, but do not find strong support for such integration.

Australia[5] to be the only market to show a weak tendency (results significant at the 10% level) for herding. Bohl et al. (2013) document many studies that point to overvaluation of stock prices from short-selling restrictions. However, Bai et al. (2006) show that if investors are risk averse, short-selling bans may cause over or under valuations of stock prices depending on the degree of asymmetric information in a stock. Bohl et al. (2013) explain that "restricting short-sellers causes uncertainty about stock prices, which may reduce investor's trust in the market consensus resulting in adverse herding". Thus, while the over and under valuations of stocks as reflected in the BM ratios (Arnott et al., 2005) are indicators of investor risk aversion tendencies, the presence of adverse herding in a market is also a sign of risk aversion as investors resort to fundamentals.

We follow the Hwang and Salmon (2004) methodology as it allows to identify periods of herding, adverse herding or neither of the two, and the turning points in these movements. Such tendencies cannot be observed with the Christie and Huang (1995) and CCK (2000) models. The use of the Hwang and Salmon linear factor model provides additional insights into other dimensions towards which the investors may herd in addition to the market factor. It facilitates examining herding during calmer, crisis and short-selling ban periods, and thus helps infer behavioural implications of such herding in stock markets. If investors are risk averse, they are likely to stick to fundamentals during the uncertain periods of the market and an adverse herd behaviour should emerge.

3. Data description

Our sample consists of all constituent stocks in the S&P/ASX200 for the period 1st October 2000 to 31st May 2017. The S&P/ASX200 index represents approximately 89% of the total market capitalisation in the Australian market. It is most widely used as 'today's portfolio benchmark index'. The S&P/ASX200 was established in April 2000, but seemed to have teething problems at the start, so we start our sample from October 2000. The constituents of the index are reviewed every quarter by the regulatory authority making some stocks leave and new ones enter the index. However, in our sampling design we use 200 stocks in a year that were part of the ASX200 on 31st December of the previous year; the only exception is the start period where 200 stocks from the September quarter of year 2000 are included in our sample. Daily end of the day stock prices, market capitalization, trading volume, market-to-book values, as well as the S&P/ASX200 index values are downloaded from DataStream. We use the 30-day Cash rate as set by Reserve Bank of Australia Board at monthly meetings as a proxy for the daily risk-free rate of return and is also downloaded from DataStream. Excluding the non-trading days due to weekends and public holidays, our sample ends with 4216 daily observations on each variable for each stock covering a period of 200 months and approximately 200 stocks in each month.

Initially, we used the Hwang and Salmon (2004) sampling design for selecting our sample, but our sample lost too many stocks as we followed them back in time. The number of stocks per month over 17 years' period varied from 200 in 2017 to 106 in 2000. Such a sampling design would have exposed our findings to *survivorship and sample selection bias* discussed in Hwang and Salmon (2004). Moreover, we could not be sure of the robustness of our findings based on a sample comprising vast variation in its size over the study period. Nevertheless, the pattern of herding was observed to be similar based on Hwang and Salmon (2004) and our current sample design.

4. Research design and modelling framework

We follow the Hwang and Salmon (2004) methodology and set up models within the following framework. The Capital Asset Pricing Model (CAPM) in equilibrium links the expected excess returns on a risky security i and the contemporaneous expected excess returns on a market portfolio in period t as

$$E_t(r_{it}) = \beta_{imt}\, E_t(r_{mt}),\ i = 1, 2, N \tag{1}$$

where r_{it} and r_{mt} are the excess returns on security i and the market portfolio at time t, respectively, β_{imt} is the systematic risk parameter, and $E_t(\cdot)$ represents the conditional expectation at time t. The systematic risk varies over time. The existence of herding is likely to bias relationship (1) and affect $E_t(r_{it})$ and β_{imt}. Let ${\beta_{imt}}^b$ denote the biased systematic risk parameter. Hwang and Salmon (2004) introduce herding towards the market portfolio parameter h_{mt} at time t as

$$\beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1) \tag{2}$$

Relation (2) implies that when $h_{mt} = 0$, there is no herding towards the market and the equilibrium CAPM applies; when $h_{mt} = 1$, there is perfect herding towards the market portfolio, making ${\beta_{imt}}^b = 1$, and, therefore, $0 < h_{mt} < 1$ indicates some degree of herding depending on the magnitude of h_{mt}. The Hwang and Salmon (2004) measure of herding at time t is based on the cross-sectional standard deviations (CSSD) of ${\beta_{imt}}^b$ and β_{imt}, and is defined by relation

$$CSSD(\beta_{imt}^b) = CSSD(\beta_{imt})(1 - h_{mt}) \tag{3}$$

As $CSSD(\beta_{imt})$ and h_{mt} are both non-observable, Hwang and Salmon suggest building a State-Space model and use a Kalman filter for estimating h_{mt}. Taking natural logarithm of relation (3) and allowing $CSSD(\beta_{imt})$ to be stochastic, one can express the relation as

[5] A study based on 44 stocks comprising all financial stocks on the ASX200 and five other stocks that were part of the Australian Prudential Regulation Authority-regulated business. The naked short-sale ban on all stocks was imposed between 22 Sep 2008 and 18th Nov 2008, and the short-sale ban for the period 19th November 2008 and 24th May 2009.

$$\log[CSSD(\beta_{imt}^{b})] = \mu_m + \nu_{mt} + H_{mt} \tag{4}$$

where $\mu_m = E[\log[CSSD(\beta_{imt})]]$, $\nu_{mt} \sim iid(0, \sigma_{m\nu}{}^2)$, $H_{mt} = \log(1 - h_{mt})$.

Now assuming H_{mt} follows a dynamic AR(1) process with zero mean, we can express H_{mt}as

$$H_{mt} = \phi_m H_{m\,t-1} + \eta_{mt} \tag{5}$$

where $\eta_{mt} \sim iid(0, \sigma_{m\eta}{}^2)$.

Eqs. (4) and (5) represent a standard State-Space model, which can be estimated using a Kalman filter, with Eq. (4) being the measurement equation and Eq. (5) the state equation. The primary interest here is on the dynamic movements in the state variable H_{mt} captured by Eq. (5). When $\sigma_{m\eta}{}^2$ is zero, H_{mt}, and therefore, h_{mt} is also zero for all t. Thus, a significant value of $\sigma_{m\eta}{}^2$ would imply the existence of herding and a significant ϕ_m value would support the autoregressive structure assumed in this model. For herding process H_{mt} to be stationary, $|\phi_m| \leq 1$. However, in an empirical study a sample estimate of $\beta_{imt}{}^b$ will be required which will involve a sampling error and will affect the CSSD ($\beta_{imt}{}^b$). We let b_{imt} denote a sample estimate of $\beta_{imt}{}^b$ and δ_{imt} the sampling error in using this estimate, which is assumed to have a zero mean. Using b_{imt} as a sample estimate of $\beta_{imt}{}^b$, and assuming that the error in employing log [$CSSD(b_{imt})$] as an estimate of $\log[CSSD(\beta_{imt}{}^b)]$ has mean and variance as $(\mu_\delta, \sigma_{m\delta}{}^2)$, the state space model in eqs. (4) and (5) can be re-specified as

$$\log[CSSD(b_{imt})] = \mu_m^s + H_{mt} + \nu_{mt}^s \tag{6}$$

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt} \tag{7}$$

In Eq. (6), $\mu_m{}^s = E[\log[CSSD(\beta_{imt})]] + \mu_\delta$, where μ_δ is an unknown mean factor due to sampling error, and $\nu_{mt}{}^s \sim iid(0, \sigma_{m\nu}{}^2 + \sigma_{m\delta}{}^2)$. Clearly, $\mu_m{}^s \neq \mu_m$ *and Variance*$(\nu_{mt}{}^s) > $ *Variance*(ν_{mt}), and the true mean μ_m cannot be identified, but the herding state variable H_{mt} in eqs. (6) and (7) is not impacted by the estimation error. However, due to sampling error it would be harder for estimates of $\phi_m$to be significant. The estimation error impact could be minimised using a longer estimation time interval to compute beta estimates, but it would make it difficult to track rapid changes in herding. It is documented in the literature (e.g., Henker et al., 2006) that herding does not show up in very small estimation time intervals as well as in larger than one-month time frame.

Hwang and Salmon (2004) test the robustness of their herding measure by comparing its performance in models that employ CSSD of betas estimated from the market and the Fama and French (1993) three factor (FF-3) models. They extract herding movements towards the market portfolio from the CSSD of betas obtained from these models in the absence and presence of market volatility, market returns, SMB (Small minus Big), HML (High minus Low) and some microeconomic variables as controls. They report that the performance of herding variable H_{mt} is comparable, with PoSEH approximately 40% in each model (Table 3, Panel A). While the effect of market volatility and market returns in their models is significant, SMB, HML and microeconomic factors have no effect. Based on FF-3 betas, herding towards SMB (Table 3, Panel B) is not very persistent or smooth, and herding towards HML (Table 3, Panel C) is not explained well with PoSEH about 22%. It seems that the use of FF-3 betas on SMB and HML are not able to capture the finer influence of size and BM factors. In relation to using CAPM or the FF-3 model for risk adjustment, Duan et al. (2019) remark that size and value factors in FF-3 model may also be exposed to other mispricing factors. As our sample consists of large stocks only and the interest is to capture the risk adjustment effect of BM factor, we do not make use of FF-3 model for measuring herding movements towards the BM factor.

We use models (A) and (B) defined below for computing sample estimates of biased betas for each security using daily data. For each month t, we fit the model

$$r_{id} = \alpha_{it}^{b} + \beta_{imt}^{b} r_{md} + \varepsilon_{id},\ i = 1, 2, \cdots, N;\ d = 1, 2, \cdots, D \tag{A}$$

for estimating monthly betas. In Eq. (A), r_{id} is the excess returns on stock i, r_{md} the excess returns on the market portfolio on day d, $\alpha_{it}{}^b$ is the intercept term that changes over time, and ε_{id} the $iid(0, \sigma_\varepsilon{}^2)$ error term. Index N represents the number of securities trading in month t and D the number of trading days for security i in month t. To ensure the stability of the beta estimates a security must trade for at least 15 days in a month for inclusion in the sample. Model (A) is estimated using the OLS and the quantile regression methods, and for each month the CSSD of betas are calculated. Many herding studies document the presence of asymmetric herding effects under positive and negative market conditions, which should also affect the betas. If the distribution of betas at time t departs[6] from the equilibrium values asymmetrically due to the market conditions and investors' attitude to risk, the OLS based estimates of betas that capture the factor sensitivities at the average level may not serve well. Also, it is well known that the performance of the tests based on the OLS estimators that assume the errors to follow a normal distribution is compromised in the absence of normality. On the other hand, the quantile regression estimators are robust under such conditions and are not sensitive to the presence of extreme values in the response variable. Thus, we expect the use of quantile regression[7] to provide an additional dimension in understanding

[6] Hwang and Salmon (2004) state that "changes in equilibrium betas could come about if a firm changed its capital structure substantially, for example, to become highly geared or of its main business area moved from, say, manufacturing to the service sector". However, such changes are rare and are unlikely to affect a large proportion of firms in the sample within the same short time interval.

[7] The use of quantile regression is not new in empirical economics, finance and many other business areas (see e.g., Buchinsky, 1997, 1998; Barnes and Hughes, 2002; Engle and Manganelli, 2004; Nath and Brooks, 2015). Barnes and Hughs (2002) employ quantile regression for studying the contribution of the one-factor capital asset pricing model beta risk in explaining returns. Nath and Brooks (2015) use quantile regression to show that the shape of the return distribution conditioned on the same level of exposure to idiosyncratic volatility risk, a residual risk after the systematic

Table 1
Summary statistics of Market returns, Market volatility, Cross Sectional Standard Deviation (CSSD) of betas and Intercorrelations between variables.

Panel A: Summary statistics for daily and monthly excess returns on ASX200 and monthly Volatility for the period Oct 2000 to May 2017 (4216 daily observations)

	Daily excess returns on ASX200	Monthly excess returns on ASX200	Monthly volatility, V_{mt}, in ASX200	Log(V_{mt})	d(Log-V_{mt})
Mean	0.00001	0.00019	0.04071	−3.30498	−0.00161
Median	0.00005	0.00741	0.03563	−3.33444	−0.02678
Maximum	0.05614	0.06866	0.17944	−1.71792	0.94751
Minimum	−0.08721	−0.13930	0.01400	−4.26871	−0.80245
Standard dev.	0.00992	0.03776	0.02178	0.43477	0.30788
Skewness	−0.45722	−0.80551	2.59113	0.6369	0.38034
Kurtosis	8.77444	3.65920	13.43410	3.62737	3.38969
Jarque-Bera statistic (*P*-value)	6168.133 (0)	25.2494 (0.00000)	1131.052 (0)	16.801 (0.00023)	6.057 (0.04839)

Panel B: Summary statistics of CSSD of betas on ASX200 returns and their logged values

	Cross-sectional SD of betas					Log of cross-sectional SD of betas				
		Quantile					Quantile			
	OLS	0.05	0.1	0.9	0.95	OLS	0.05	0.1	0.9	0.95
Mean	0.804	2.143	1.280	1.397	2.141	−0.259	0.669	0.186	0.279	0.694
Median	0.775	1.936	1.198	1.306	1.999	−0.258	0.657	0.179	0.267	0.693
Maximum	1.895	5.902	3.673	3.418	6.038	0.639	1.775	1.301	1.229	1.798
Minimum	0.377	0.689	0.539	0.584	0.772	−0.975	−0.372	−0.617	−0.537	−0.259
Standard dev.	0.243	0.970	0.465	0.489	0.813	0.278	0.433	0.346	0.328	0.369
Skewness	1.437	1.217	1.247	1.312	1.119	0.419	0.075	0.139	0.210	0.008
Kurtosis	6.119	4.738	5.929	5.514	5.179	3.399	2.739	2.791	3.130	2.834
Jarque-Bera statistic (P-value)	149.924 (0)	74.585 (0)	123.361 (0)	110.007 (0)	81.326 (0)	7.188 (0.028)	0.754 (0.686)	1.005 (0.605)	1.610 (0.447)	0.262 (0.877)

Each month daily data are used for obtaining beta estimates on ASX200 returns using the OLS and the quantile regression methods. The CSSDs are calculated using these betas.

Panel C: Intercorrelations between variables

	log-V_{mt}	*d(log-V_{mt})*
MXRetMkt	−0.40289	−0.43876
log(CSSD_OLS-beta)	−0.55307	−0.21176
log(CSSD_Q05-beta)	−0.59061	−0.28381
log(CSSD_Q10-beta)	−0.64335	−0.26487
log(CSSD_Q90-beta)	−0.64185	−0.31931
log(CSSD_Q95-beta)	−0.67893	−0.34972

the herding pattern resulting from the likely perceived risk during periods of extreme market conditions.

Now turning to the use of log(market volatility), where log refers to the natural-log, and market return as explanatory variables in Hwang and Salmon (2004) models expressed in Eqs. (6)–(8), the simultaneous inclusion of these two variables can be problematic due to a significant negative relationship between them. Hasanhodzic and Lo (2019) state “one of the enduring empirical regularities in equity markets is the inverse relationship between stock prices and volatility”. The inverse linear relationship between the change in volatility and returns, referred to as the “leverage effect” in the literature, was first recognised by Black (1976) and, ever since, has been the topic of interest and discussion in many research papers. However, using eight different models, Hasanhodzic and Lo (2019) find that companies with no leverage show leverage effect. So, regardless of the leverage, an inverse relationship can emerge between change in volatility and returns, and it is not surprising that an inverse relationship between log(market volatility) and market return for ASX200 index exists (see Table 1(c)). Although, the variables are not perfectly correlated, the problem stems from the quadratic relationship between them. The monthly excess returns on the market index ASX200, denoted as MXRetMkt, are calculated as the sum of the daily excess returns in each month. The monthly market volatility, denoted as V_{mt}, is calculated as the square root of the sum of the squared daily excess returns on the ASX200 index in each month, and is the same definition being applied in Hwang and Salmon (2004) and in the literature. While log-V_{mt} denotes the natural log of V_{mt}, $d(log\text{-}V_{mt})$ represents the change in log of volatility. We observe that there is not only a significant quadratic relationship between log-V_{mt} and the market returns at time t, but also a significant quadratic relationship between the change in log(market volatility) at time t with respect to time (t-2) and the market

(*footnote continued*)
risk has been filtered, changes with the quantiles of the return distribution, suggesting that investors' investment strategies change with the level of exposure to risk and stakes involved.

returns at time t; the coefficient of the linear term in market return is negative and significant. The change in volatility at time t with respect to time (t-2) also has a significant negative linear relationship with the market returns at time (t-1). Thus, given the complex nature of the relationship between the time series of market volatility and returns, the simultaneous use of log(market volatility) and market return as explanatory variables in the measurement equation of a SS model can influence the estimation of the model. We also observe that using *log-*V_{mt} as the only explanatory variable in the SS model measurement equation causes a singularity problem[8] in the estimation of some models. Since volatility is an important variable in studying the investor behaviour, we use $d(log\text{-}V_{mt})$ as the explanatory variable in the SS model measurement equation, which has a linear relationship with the market returns. We note that this variable has a significant negative correlation with the market returns and each of the log of the cross-sectional standard deviations of betas (see Table 1 (c)).

Next, the movements in herd behaviour are extracted from the time series of CSSD of betas via the State Space (SS) Models (A1) and (A2), defined as

$$\begin{aligned}\log[CSSD(b_{imt})] &= \mu_m^s + H_{mt} + \nu_{mt}^s\\ H_{mt} &= \phi_m H_{mt-1} + \eta_{mt}\end{aligned} \tag{A1}$$

$$\begin{aligned}\log[CSSD(b_{imt})] &= \mu_m^s + H_{mt} + c_{m1} d(\log{-}V_{mt}) + \nu_{mt}^s\\ H_{mt} &= \phi_m H_{mt-1} + \eta_{mt}\end{aligned} \tag{A2}$$

where, ${\nu_{mt}}^s$ and η_{mt} are error terms and are assumed to have the same structure as in Eqs. (6) and (7), and $H_{mt} = \log(1\text{-} h_{mt})$.. In Model (A2), the additional variable $d(\log\text{-}V_{mt})$ represents change in the log of monthly market volatility and c_{m1} is its sensitivity parameter. While both Models (A1) and (A2) extract the herding factor from $\log[CSSD(b_{imt})]$, Model (A2) captures herd behaviour when the effect of $d(\log\text{-}V_{mt})$ is controlled for. If the herding coefficient remains significant in the presence of variable $d(\log\text{-}V_{mt})$, which reflect the state of the market, it would establish the robustness of the herd behaviour. Otherwise, the changes in $\log[CSSD(b_{imt})]$ could be due to factors other than herding.

The second model we adapt is the linear factor model discussed in Hwang and Salmon (2004). This model allows us to study herding towards the book-to-market and trading volume factors, identified as indicators of risk in Section 1, along with herding towards the market portfolio. Variable trading volume employed in this study is measured by turnover as

$$\left[Turnover = \frac{Trading\ volume \times Stock\ price}{Market\ capitalization}\right].$$

Specifically, the linear factor model considered is

$$\begin{aligned}r_{id} &= \alpha_{it}^b + \beta_{imt}^b r_{md} + \beta_{iBMt}^b BM_{id} + \beta_{iTRt}^b TR_{id} + \varepsilon_{id},\\ &i = 1, 2, \cdots, N;\ d = 1, 2, \cdots, D\end{aligned} \tag{B}$$

In Eq. (B), *BM* stands for *Book-to-Market, TR* for *Trading volume*, and coefficients ${\beta_{iBMt}}^b$ and ${\beta_{iTRt}}^b$ are the corresponding factor sensitivity parameters that may have been affected by herding at time *t*. The intercept ${\alpha_{it}}^b$ changes over time, and ε_{id} is the $iid(0, {\sigma_\varepsilon}^2)$ error term. The other terms are as explained earlier. Estimates of ${\beta_{imt}}^b$, ${\beta_{iBMt}}^b$ and ${\beta_{iTRt}}^b$ are obtained using daily data first before fitting the SS models for extracting the herd behaviour towards the market portfolio, BM and TR factors. In the following equations, we use b_{imt}, b_{iBMt} and b_{iTRt} to denote the sample estimates of ${\beta_{imt}}^b$, ${\beta_{iBMt}}^b$ and ${\beta_{iTRt}}^b$, respectively.

Model (B) is fitted using the OLS and the quantile regression estimation methods, and the herd behaviour is extracted by fitting the following SS models.

$$\begin{aligned}\log[CSSD(b_{imt})] &= \mu_m^s + H_{mt} + \nu_{mt}^s\\ H_{mt} &= \phi_m H_{mt-1} + \eta_{mt}\end{aligned} \tag{B11}$$

$$\begin{aligned}\log[CSSD(b_{imt})] &= \mu_m^s + H_{mt} + c_{m1} d(\log{-}V_{mt}) + \nu_{mt}^s\\ H_{mt} &= \phi_m H_{mt-1} + \eta_{mt}\end{aligned} \tag{B12}$$

$$\begin{aligned}\log[CSSD(b_{iBMt})] &= \mu_{BM}^s + H_{BMt} + \nu_{BMt}^s\\ H_{BMt} &= \phi_{BM} H_{BMt-1} + \eta_{BMt}\end{aligned} \tag{B21}$$

$$\begin{aligned}\log[CSSD(b_{iBMt})] &= \mu_{BM}^s + H_{BMt} + c_{m1} d(\log{-}V_{mt}) + \nu_{BMt}^s\\ H_{BMt} &= \phi_{BM} H_{BMt-1} + \eta_{BMt}\end{aligned} \tag{B22}$$

$$\begin{aligned}\log[CSSD(b_{iTRt})] &= \mu_{TR}^s + H_{TRt} + \nu_{TRt}^s\\ H_{TRt} &= \phi_{TR} H_{TRt-1} + \eta_{TRt}\end{aligned} \tag{B31}$$

[8] Such a problem may not be frequent or show up when OLS estimated betas are employed, but the use of extreme quantile-based betas would experience this situation more frequently. However, the degree and the level of the relationship between market volatility and returns can vary within individual markets, therefore, these variables should be tested for relationship before using them.

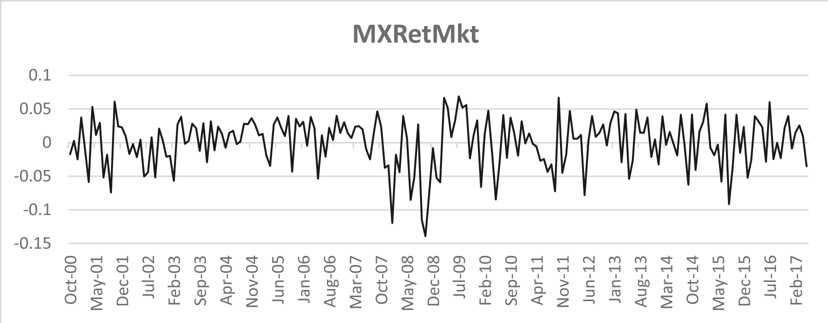


Fig. 1. Plot of monthly excess returns on ASX200 index; variable MXRetMkt.

$$\begin{aligned} \log[CSSD(b_{iTRt})] &= \mu^{s}_{TR} + H_{TRt} + c_{m1}d(\log\text{–}V_{mt}) + \nu^{s}_{TRt} \\ H_{TRt} &= \phi_{TR}H_{TRt-1} + \eta_{TRt} \end{aligned} \tag{B32}$$

5. Empirical results and discussion

5.1. Herding towards the market portfolio: models (A1) and (A2)

This section compares herding towards the market portfolio extracted from SS Models (A1) and (A2) that employ CSSD of betas estimated using the OLS and the quantile regression methods from the market model. Results from these models provide a benchmark for comparing herding movements towards the market portfolio and other factors extracted from the linear factor model in later sections. We start by describing properties of the CSSDs of betas and the explanatory variable used in SS Models (A1) and (A2).

5.1.1. Characteristics of market excess returns, market volatility and cross-sectional standard deviations of betas

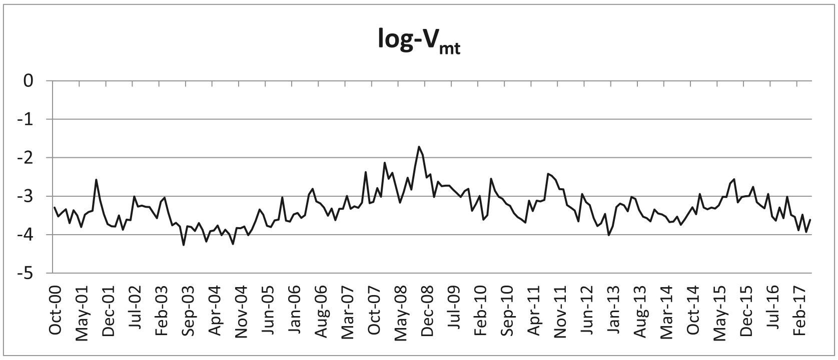
Fig. 1 graphs time series of MXRetMkt, the monthly excess returns on the ASX200 index, and Columns 2 and 3 in Table 1, Panel A, report summary statistics of daily and monthly excess returns on the ASX200 index for the period 1st October 2000– 31st May 2017. The daily excess returns for the index range between −8.7% and 5.6%, while the monthly excess returns vary between −13.9% and 6.9%. The daily and monthly mean excess returns are very close to zero, but there is considerable variation in them and both distributions are negatively skewed and leptokurtic, implying more positive returns than negative. The Jarque-Bera statistic for normality shows that daily as well as the monthly excess returns on the market index are non-Gaussian. The monthly excess returns dip sharply between Jan 2008 and Oct 2008, surrounding the GFC period.

Graphs of log-V_{mt} and $d(log\text{-}V_{mt})$ in Fig. 2 show that the volatility peaks around Oct 2008 and changes in $log\text{-}V_{mt}$ are large around this period. Columns 4, 5 and 6 in Table 1, Panel A, report properties of V_{mt}, $log\text{-}V_{mt}$ and $d(log\text{-}V_{mt})$, respectively, for the sample period. While series V_{mt} and $log\text{-}V_{mt}$ are positively skewed, leptokurtic and non-Gaussian– suggesting that extreme volatility is less common, the $d(log\text{-}V_{mt})$ series is nearly Gaussian.

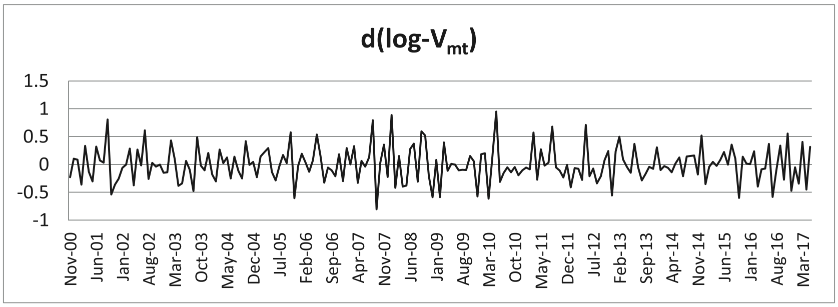
Table 1, Panel B, contains summary statistics of $CSSD(b_{imt})$ series estimated using the OLS and the quantile regression methods, and the log of these CSSDs, the $log[CSSD(b_{imt})]$. While all $CSSD(b_{imt})$ series are non-Gaussian and positively skewed, their logged values are Gaussian except the OLS based series. As the means and standard deviations of $CSSD(b_{imt})$ and $\log[CSSD(b_{imt})]$ series at the extreme quantiles are much larger than the OLS based values, we expect to find variation in herding patterns emerging from these series. Table 1, Panel C, reports Pearson's correlation of variables log-V_{mt} and $d(log\text{-}V_{mt})$ with MXRetMkt and the $log[CSSD(b_{imt})]$ series based on the OLS and quantile regression estimated betas. All correlations are significant at the 1% level of significance. Variables $log\text{-}V_{mt}$ and $d(log\text{-}V_{mt})$ both have significant negative correlation with monthly excess returns on the market index and the CSSDs of betas. Variation in negative correlation values suggest that $d(log\text{-}V_{mt})$ has a negative effect on all CSSDs but the effect varies with the quantile of the return distribution; the effect is asymmetric and more pronounced on the extreme quantiles. Fig. 3 plots monthly CSSDs of OLS and quantiles 0.05 and 0.95 estimated betas from Model (A) that are employed in Models (A1) and (A2), and Table 2 shows the estimation output for Models (A1) and (A2). Fig. 3 shows vast variations in the 5th and 95th quantiles based $CSSD(b_{imt})$ compared to the OLS based series. It suggests more uncertainty among betas from the extreme tail regions of the return distribution, and that excess market returns affect extreme returns differently to the returns on the average level.

5.1.2. Herding towards the market portfolio: evidence from ordinary least squares betas

Table 2, Column 2, reports estimation of Models (A1) and (A2) based on OLS betas. In both models, $\sigma_{m\eta}$, the standard deviation of error in the herding variable $H_{mt} = \log(1 - h_{mt})$, is significant at the 1% level of significance and suggests the existence of herding towards the market portfolio. Significant $|\phi_m| < 1$ values support the stationarity of the process and the autoregressive structure used in modelling. Sizable positive values of ϕ_m indicate persistence in the herding process. The autocorrelation function of residuals (not provided in this paper) after fitting both models showed no unexplained pattern. The Log Maximum likelihood (Log-Max. L.) and Schwarz Information Criterion (SIC) values suggest that Model (A2) fits better than Model (A1) and imply that part of the variation in



(a) Log of monthly volatility in ASX200 returns.



(b) Change in log of monthly volatility in ASX200 returns.

Fig. 2. Plot of log of monthly volatility, *log-V$_{mt}$*, and change in log of monthly volatility, *d*(*log-V$_{mt}$*), in ASX200 returns.

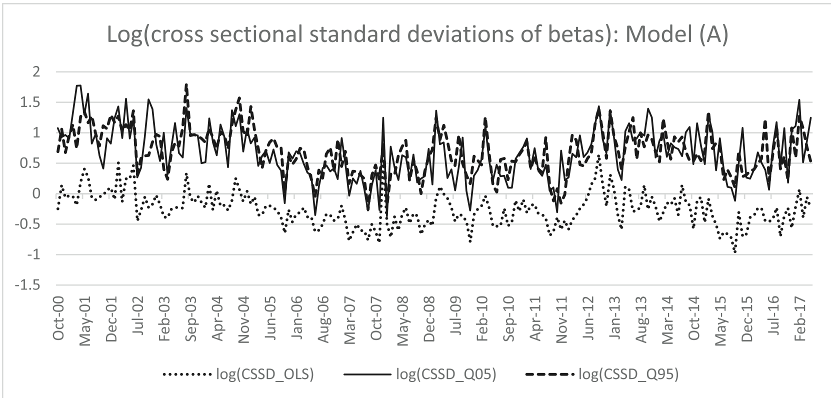


Fig. 3. Time series of log of monthly Cross-Sectional Standard Deviations (CSSD) of betas. This figure graphs the logs of CSSDs of betas obtained from fitting Model (A) using the OLS and the quantile regression estimation methods; CSSD_Q05 and CSSD_Q95 represent the 5th and the 95th quantile-based series.

log[*CSSD*(b_{imt})] is explained by *d*(*log-V$_{mt}$*). The coefficient of *d*(*log-V$_{mt}$*) for this OLS model is least negative compared to the quantile regression-based models, implying the change in log volatility causes least impact on OLS based *log*[*CSSD*(b_{imt})]. A PoSEH value of 34.1% in Model (A1) shows the amount of variation in *log*[*CSSD*(b_{imt})] due to herding and this value increases to 36.65% in Model (A2), when the effect of change in market volatility is controlled for. This indicates that volatility is perceived as an opportunity and many investors want to take advantage of change in volatility by copying other investors' behaviour.

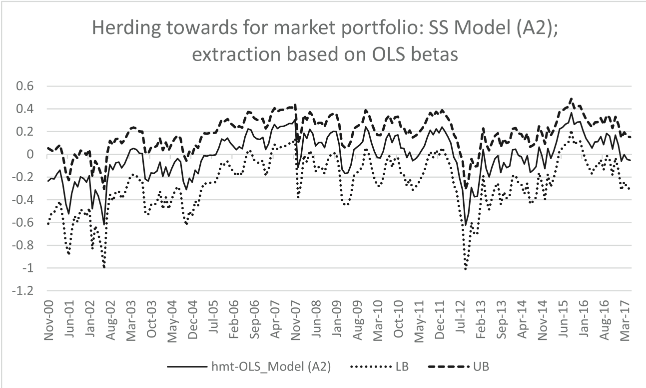
Fig. 4 (a) plots time dynamics of OLS betas-based market portfolio herding extracted from Model (A2). It displays the herding estimates, h_{mt}, along with two standard errors bounds. The graph shows many periods of herding ($0 < h_{mt} < 1$) and adverse herding ($h_{mt} < 0$) where herding estimates are highly significant. Periods January 2001–July 2002 (the Tech bubble and September 11 attacks on US period) and July 2012 - Jan 2013 (the Greek Govt. debt crisis period) display significant adverse herding, and periods Oct 2005–Dec 2007, May 2015–Dec 2015, Sep 2016–Oct 2016 show significant herding towards the market portfolio. The upward trend in herding variable extending from July 2002 to September 2007 is interesting as it shows that investors were

Table 2
Market portfolio herding: State-Space models (A1) and (A2) (standard errors are reported in parentheses).

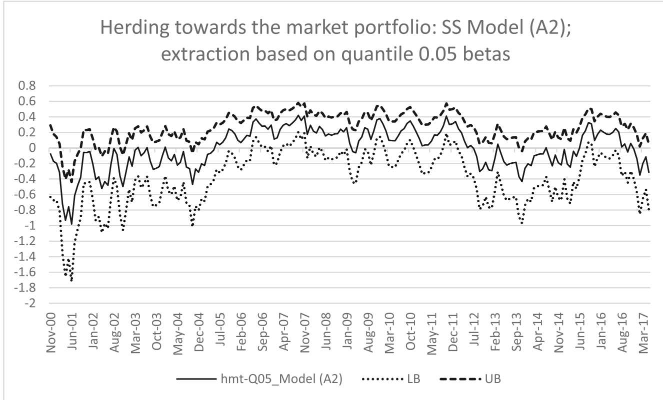
	Model (A1)					Model (A2)				
	Quantile					Quantile				
	OLS	0.05	0.1	0.9	0.95	OLS	0.05	0.1	0.9	0.95
μ_m	−0.25161	0.71259	0.21873	0.28708	0.69632	−0.24887	0.69448	0.21316	0.28926	0.69647
	(0.06394)***	(0.11752)***	(0.10150)***	(0.08279)***	(0.06807)***	(0.06157)***	(0.09955)***	(0.08894)***	(0.08061)***	(0.06175)***
φ_m	0.88722	0.94202	0.94405	0.91111	0.82752	0.87647	0.90975	0.92310	0.90080	0.77364
	(0.04706)***	(0.03419)***	(0.03138)***	(0.04228)***	(0.06729)***	(0.04942)***	(0.04587)***	(0.03691)***	(0.04571)***	(0.07600)***
$\sigma_{m\nu}$	0.18461	0.32523	0.24961	0.20715	0.23277	0.17038	0.28850	0.22340	0.17231	0.16449
	(0.01261)***	(0.02286)***	(0.01494)***	(0.01537)***	(0.02413)***	(0.06774)***	(0.02444)***	(0.01603)***	(0.01358)***	(0.03093)***
$\sigma_{m\eta}$	0.09480	0.09702	0.07916	0.10287	0.15866	0.10193	0.12425	0.09617	0.11115	0.19155
	(0.02058)***	(0.02966)***	(0.0228)***	(0.02403)***	(0.03458)***	(0.04563)***	(0.03636)***	(0.02661)***	(0.02257)***	(0.03434)***
$d(\log\text{-}V_{mt})$						−0.18302	−0.38530	−0.29032	−0.32444	−0.39955
						(0.04310)***	(0.07314)***	(0.05583)***	(0.04507)***	(0.05059)***
PoSEH	0.34081	0.22432	0.22893	0.31352	0.43047	0.36645	0.28728	0.27813	0.33875	0.51973
Log-Max. L.	10.71063	−84.66178	−33.78456	−12.19713	−49.00764	18.83047	−71.36949	−21.37848	10.45187	−23.5846
SIC	−0.00114	0.95258	0.44381	0.22794	0.59604	−0.05625	0.85028	0.34786	0.02795	0.37003

This table displays estimation of State-Space Models.
(A1): $\log[CSSD(b_{imt})] = \mu_m{}^s + H_{mt} + \nu_{mt}{}^s$ *and* $H_{mt} = \phi_m H_{mt-1} + \eta_{mt}$,
(A2): $\log[CSSD(b_{imt})] = \mu_m{}^s + H_{mt} + c_{m1} d(\log - V_{mt}) + \nu_{mt}{}^s$ *and* $H_{mt} = \phi_m H_{mt-1} + \eta_{mt}$,
and the proportion of signal explained by herding (PoSEH) based on each model, when the *Cross Sectional Standard Deviations* are obtained using the OLS and the quantile regression estimated betas. In column 1, $\sigma_{m\nu}$ and $\sigma_{m\eta}$ represent standard deviations of $\nu_{mt}{}^s$ and η_{mt}, respectively. Log-Max. L. stands for Log of maximum likelihood and SIC for Schwarz Information Criterion. Variable $d(\log\text{-}V_{mt})$ denotes the change in volatility and PoSEH = $\sigma_{m\eta}$ /Stdev(log-CSSD-Betas).

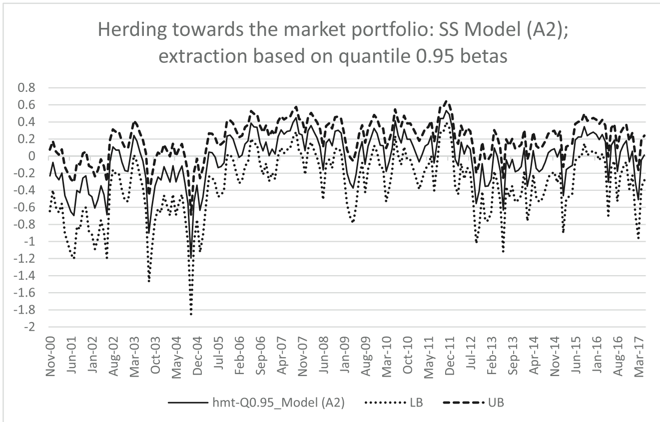
*** Significance at 1% level.



(a). Herding towards the market portfolio using OLS based CSSD(b_{imt}).



(b). Herding towards the market portfolio using CSSD(b_{imt}) based on quantile 0.05 betas.



(c). Herding towards the market portfolio using CSSD(b_{imt}) based on quantile 0.95 betas.

Fig. 4. Herding towards the market portfolio based on State Space Model (A2); LB and UB are the two standard error lower and upper bounds on the herding component h_{mt}.

becoming very confident about the performance of the market and followed the market index without any hesitation. Periods July 2008–July 2009 (the period surrounding the GFC and the short selling ban period) and Dec 2009–April 2012 neither show significant herding nor adverse herding; the movements are sideways, reflecting investors' lack of confidence in the market performance and uncertainty about the market conditions. This contradicts the Chiang and Zheng (2010) and Bohl et al. (2013) findings based on the CCK (2000) model. Thus, contrary to the common belief portrayed by previous studies (e.g., Shiller and Pound, 1989; Christie and Huang, 1995) that herd behaviour should show up during crisis periods, we observe it during calmer periods when investors are easily able to predict the market moves and become fearless in following it. This confirms that Christie and Huang (1995) and CCK (2000) models are geared towards capturing very different herding patterns compared to the Hwang and Salmon (2004) model. The sideways movements and the absence of adverse herding during the GFC and the short selling ban periods, and after the Greek Govt. debt crisis period suggests that investors were more cautious and risk-averse during these periods.

5.1.3. Herding towards the market portfolio: evidence from quantile regression betas

Table 2, Columns 3–6, reports estimation of Models (A1) and (A2) employing CSSDs of quantile regression betas. The comments made in the preceding section on herding extracted from Models (A1) and (A2) employing the OLS based $\log[CSSD(b_{imt})]$ can be extended to all model fittings based on quantile regression betas. However, we will mainly focus on quantiles 0.05 and 0.95 beta models. Clearly Model (A2) outperforms (A1). A significant negative relationship of $d(log\text{-}V_{mt})$ with $log[CSSD(b_{imt})]$ at all quantiles means that an increase in the change of market volatility reduces the $CSSD(b_{imt})$, but the impact across the quantiles is asymmetric. We observe that the PoSEH in Model (A2) increases considerably at the 5th and the 95th quantiles. While the inclusion of $d(log\text{-}V_{mt})$ has caused an increase in the PoSEH at all quantile levels and at the average level (34.1% to 36.6%), the impact is maximum at the 95th quantile (43% to 52%) and at the 5th quantile (22.4% to 28.7%). We observe that while the negative coefficients of $d(log\text{-}V_{mt})$ for the 5th and the 95th quantiles, being −0.3853 and −0.3995 respectively, are of similar magnitude, their impact on herding is unequal. A PoSEH of 28.7% on worst days and 52% on best days of stock returns suggests that herding is stronger and more common during the best performing days of stocks. This implies that investors perceive and interpret volatility and, therefore, the change in volatility, very differently on good and bad performance days of stock returns.

Table 3 exhibits correlation between $CSSD(b_{imt})$ and h_{mt} estimates extracted from Models (A1) and (A2) using the OLS and the quantile regression estimated betas. As per the literature (e.g., Hwang and Salmon, 2004), the market portfolio herding should reduce the cross-sectional variance of betas; the stronger the herding the higher the reduction in the cross-sectional variance of betas. On surface, the negative correlations in Table 3 supports this argument, but the correlations are of similar magnitude in each case. We observe in Table 2 that the level of PoSEH based on models involving these variables is quite different. For example, the similar correlation values in the OLS and the quantile 0.95 cases in Table 3 do not yield the same level of herding. Clearly, the distribution of returns is asymmetric, and the level of herding varies with its quantiles. The graphs in Fig. 4 support this argument.

Fig. 4(b) and (c) displays herd dynamics extracted from Model (A2) employing CSSDs of quantile regression estimated betas at the 5% and 95% quantiles, respectively. These graphs show many periods of herding and adverse herding; many patterns of the herd dynamics are like the OLS based herding patterns in Fig. 4(a), and the same conclusions can be replicated for the 5th and the 95th quantiles. However, the intensity of herding and adverse herding behaviour is much stronger at these quantiles; the dips due to adverse herding are much deeper. Fig. 4 (C) shows that the herding and adverse herding incidences are more frequent during the best performing days of stock returns.

The presence of herding and adverse herding at the extreme quantiles suggests that such behaviour can emerge during the worst and the best performance days of stock returns. It can be inferred from the significant adverse herding that investors move away from herding during the uncertain periods to cope with the unpredictable market movements due to risk-aversion. Additionally, the existence of nonsignificant sideways herding movements during the unseasonal shock period of the GFC implies that such turmoil periods stop the herding as well as the adverse herding activity.

5.2. Herding towards the market portfolio, book-to-market and trading volume factors: the linear factor model

This section investigates investor herding and risk profiles link using the factor sensitivities from the linear factor Model (B). We first examine the characteristics of CSSDs of betas - the factor loadings of excess market returns, Book-to-market (BM) ratios and Trading volume (TR), obtained by fitting Model (B). Table 4 displays summary statistics of CSSDs of betas estimated using the OLS and the quantile regression methods.

Table 3
Correlation between *Cross-Sectional Standard Deviations* (CSSDs) of betas and herding parameter estimates 'h_{mt}'.

	Method of beta estimation		
	OLS	Quantile 0.05	Quantile 0.95
Model (A1)	−0.859	−0.766	−0.906
Model (A2)	−0.854	−0.789	−0.898

This table reports Pearson's correlation coefficients between CSSDs of betas and herding estimates 'h_{mt}' extracted from the State-Space Models (A1) and (A2) when CSSDs are obtained using the OLS and the quantile regression estimated betas.

Table 4
Summary statistics of CSSDs of betas based on the linear factor model (B).

	Cross-sectional standard deviation of betas			Log-cross-sectional standard deviation of betas		
	XMkt-Ret	Book-to-Market	Trading volume	XMkt-Ret	Book-to-Market	Trading volume
Panel A: The OLS betas						
Mean	0.92263	1.28148	0.45315	−0.09931	0.09812	−0.79255
Median	0.88522	0.9775	0.45209	−0.12192	−0.02276	−0.79387
Maximum	2.19776	6.246	0.5077	0.78744	1.83194	−0.67787
Minimum	0.57953	0.53517	0.40473	−0.54554	−0.62517	−0.90454
Standard deviation	0.19487	0.89883	0.02041	0.18841	0.49664	0.04491
Skewness	2.20317	2.72566	0.23297	0.89425	1.23292	0.11981
Kurtosis	12.93363	11.59009	2.75178	5.3484	4.25122	2.69189
Jaque-Bera statistic (P-value)	984.106 (0)	862.555 (0)	2.323 (0.313)	72.61 (0)	63.716 (0)	1.27 (0.53)
Panel B: The quantile 0.05 betas						
Mean	1.30149	1.67199	0.0086	0.22847	0.378	−4.83219
Median	1.23708	1.34258	0.00751	0.21275	0.29459	−4.89108
Maximum	2.50815	10.91673	0.03969	0.91955	2.3903	−3.22663
Minimum	0.66392	0.67759	0.0038	−0.4096	−0.38921	−5.57301
Standard deviation	0.35636	1.18719	0.00405	0.26321	0.4683	0.36659
Skewness	0.92944	3.89038	3.19655	0.20128	1.29711	0.96698
Kurtosis	3.90644	23.94644	20.63269	2.84408	5.34713	4.41627
Jaque-Bera statistic (P-value)	35.6426 (0)	4160.779 (0)	2931.53 (0)	1.5530 (0.46)	101.9912 (0)	47.88317 (0)
Panel C: The quantile 0.95 betas						
Mean	1.33369	1.74703	0.00931	0.26177	0.41666	−4.75844
Median	1.25028	1.3507	0.0078	0.22337	0.30062	−4.85377
Maximum	2.79641	12.13479	0.03525	1.03211	2.49608	−3.34525
Minimum	0.75703	0.66341	0.00412	−0.27501	−0.41036	−5.49282
Standard deviation	0.35412	1.25613	0.00446	0.25136	0.47918	0.3806
Skewness	1.0878	4.02498	2.32437	0.34202	1.2486	1.02667
Kurtosis	4.48669	27.29473	10.13907	2.90563	4.91785	3.92027
Jaque-Bera statistic (P-value)	57.862 (0)	5458.633 (0)	604.809 (0)	3.97337 (0.137)	82.618 (0)	42.192 (0)

This table reports summary statistics of CSSDs of betas estimated from the Linear Factor Model (B) applying the OLS and the quantile regression methods at quantiles 0.05 and 0.95. XMktRet represents variable 'r_{md}', the excess returns on the market portfolio.

5.2.1. *Characteristics of cross-sectional standard deviations of betas from the linear factor model*

We start by comparing the CSSDs of OLS betas for the excess market returns obtained from Models (A) and (B). Fig. 5 graphs the time series of CSSDs of market betas ($CSSD(b_{mt})$) for Models (A) and (B). It shows that starting from about January 2006 the two series start to separate from each other; the $CSSD(b_{mt})$ values from Model (B) are generally larger than Model (A) on a monthly basis. The summary statistics of $CSSD(b_{mt})$ series for Model (A) (Table 1, Panel B, Column 2) and Model (B) (Table 4, Panel A, Column 2), reveals that Model (B) based mean, maximum and minimum values of $CSSD(b_{mt})$, when the effects of BM and TR are controlled for, are larger than the corresponding Model (A) values, but the standard deviation value of $CSSD(b_{mt})$ is lower. Larger mean, maximum and minimum values of $CSSD(b_{mt})$ imply a larger spread in market beta estimates for individual stocks on a monthly basis. This could be

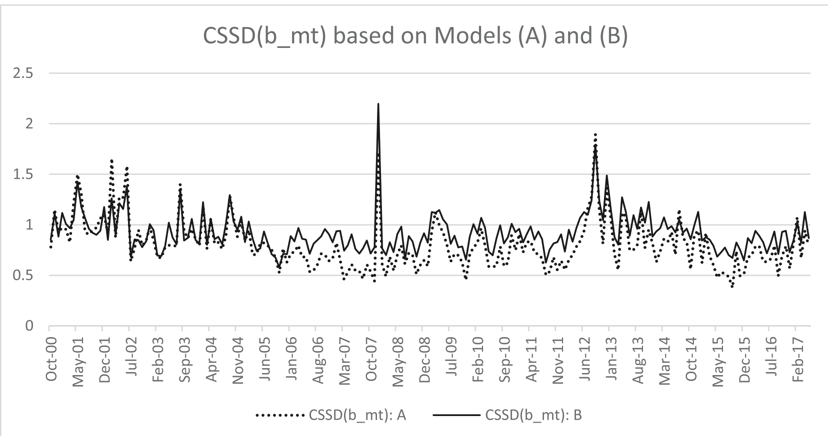


Fig. 5. Monthly Cross-Sectional Standard Deviations (CSSDs) of market betas (b_mt) from Models (A) and (B). The graph shows that the CSSDs of betas based on Models (A) and (B) are not identical due to a likely influence of other factors.

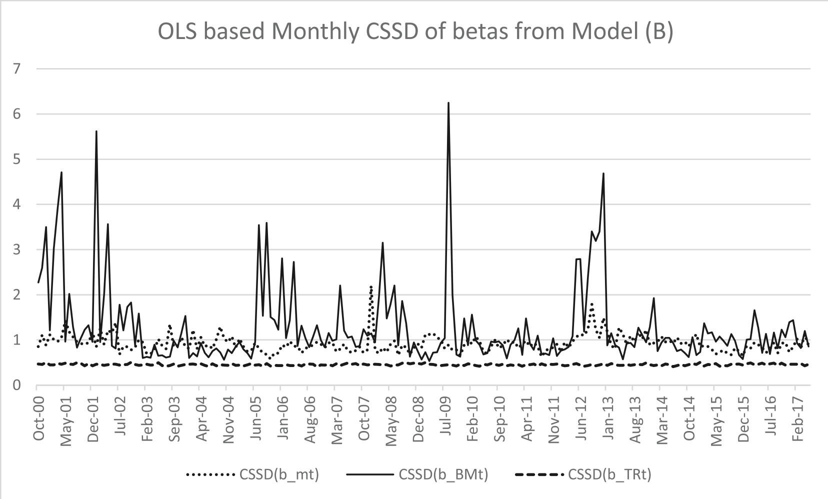


Fig. 6. Monthly Cross-Sectional Standard Deviations of Model (B) factor sensitivities. The graph shows comparison of CSSDs of betas - the sensitivities of stock returns to market portfolio, Book-to-Market and Trading volume factors in the linear factor model estimated using the OLS method.

due to the presence of information sources like BM and TR that investors resort to for their decision making in response to the varying market conditions on a daily basis, and, therefore, adding variations in individual monthly betas. Smaller standard deviation of $CSSD(b_{mt})$ values indicate similarity and stability in market betas resulting from Model (B). The usage of such betas should, therefore, extract more stable herding movement estimates from the SS models. The positive skew and kurtosis in $CSSD(b_{mt})$ series is also much larger for Model (B) compared to Model (A); the log of $CSSD(b_{mt})$ series is positively skewed, leptokurtic and non-Gaussian.

Now referring to Panel A in Table 4 we observe that OLS based CSSDs of BM betas series and its logged values are non-Gaussian; they are positively skewed and leptokurtic. However, the CSSD of TR beta series and its logged values are both Gaussian. Panel B in Table 4 reports the summary statistics of CSSDs of quantile 0.05 betas for market, BM and TR factors and Panel C for the quantile 0.95 betas. The mean, maximum, minimum and standard deviation of monthly CSSDs of quantile 0.05 market betas are larger than the corresponding OLS values. However, the skewness and kurtosis values for this series are much smaller than the OLS based values; the series is non-Gaussian, but its logged values series is Gaussian. While these comments can be replicated for mean, maximum, minimum and standard deviation of monthly CSSDs of quantile 0.05 BM betas, it is not true for skewness and kurtosis. The $CSSD(b_{BMt})$ series and its logged values are not Gaussian. The quantile 0.05 based $CSSD(b_{TRt})$ series has much smaller mean, maximum, minimum and standard deviation values than the OLS based values in Panel A, but the series is more positively skewed and leptokurtic. This series and its logged values are non-Gaussian as well. Comparing values in Panels A and C, the comments made based on quantile 0.05 can be replicated for quantile 0.95. Due to differences in CSSDs of OLS and quantile regression estimated betas, we expect the herding patterns based on these series to be different.

5.2.2. *Herding towards market portfolio, book-to-market and trading volume factors: evidence from the OLS estimated betas*

Fig. 6 displays the time series graphs of CSSDs of market, BM and TR betas obtained by OLS estimation of the linear factor Model (B). As the three series show vast variations in intensity and do not always peak in the same time period, we expect variations in the level of herding towards each factor. These variations should reveal investors' risk tendencies during the tranquil and turbulent periods.

Table 5 reports the estimation of SS models employed for extracting herd behaviour towards the market portfolio, BM, and TR factors from the log of CSSD of OLS estimated betas. Panel A in Table 5 reports the estimation of SS Models (B11), (B21) and (B31) and Panel B the estimation of Models (B12), (B22) and (B32). It follows from Panels A and B that the herding parameter φ is highly significant for all factors and in all models. However, the variance $\sigma_{,\eta}^2$ of the market portfolio and BM herding is significant in all models but for the trading volume herding, suggesting a weak tendency for TR factor herding. The Log-Max. L. and the SIC values of models in Table 5 suggest that the models representing the market portfolio and the BM factor herding perform better when variable $d(log\text{-}V_{mt})$ is included in the model, but not for TR-herding. The PoSEH towards each factor strengthens by the inclusion of $d(log\text{-}V_{mt})$ as an exogenous variable in the model, implying that change in market volatility is an important influencing variable in directing investor herding behaviour. We now discuss herding behaviour towards each factor focusing on a better fitting model.

(a) Herding towards the market portfolio: Using CSSDs of OLS estimated Model (B) betas in State-Space Models (B11) and (B12)

Columns 2 and 5 in Table 5 display estimation of Models (B11) and (B12), respectively. The Log-Max. L. and SIC values support Model (B12) as a better model. All parameters of this model are significant at 1% level of significance; change in market volatility, $d(log\text{-}V_{mt})$, has a significant inverse relationship with log[CSSD(b_{mt})] but its impact on the proportion of variation explained by market portfolio herding is positive. The PoSEH increases from 34.16% in Model (B11) to 38.55% in Model (B12). Fig. 7 plots market

Table 5
Estimates of the State-Space Models for herding towards the market portfolio, Book-to-Market & Trading Volume factors using Cross Sectional Standard Deviations of OLS based betas (parentheses display standard errors).

	Panel A			Panel B		
	Market portfolio model (B11)	Book-to-Market model (B21)	Trading volume model (B31)	Market portfolio model (B12)	Book-to-Market model (B22)	Trading volume model (B32)
μ .	−0.09788 (0.03372)***	0.10795 (0.10738)	−0.79157 (0.00533)***	−0.09678 (0.03264)***	0.10512 (0.10740)	−0.79176 (0.00527)***
φ .	0.84074 (0.07595)***	0.80123 (0.07820)***	0.91110 (0.11041)***	0.81508 (0.08207)***	0.79771 (0.08009)***	0.90815 (0.11789)***
σ. ν	0.14499 (0.00931)***	0.32587 (0.03608)***	0.04280 (0.00287)***	0.13126 (0.01166)***	0.32253 (0.03647)***	0.04280 (0.00287)***
σ. η	0.06437 (0.01931)***	0.2280 (0.05473)***	0.00550 (0.00764)	0.07263 (0.02078)***	0.22599 (0.05504)***	0.00554 (0.00819)
$d(\log\text{-}V_{mt})$				−0.15865 (0.03147)***	−0.15199 (0.09149)***	0.00908 (0.01053)
PoSEH	0.3416	0.4526	0.1226	0.38547	0.45503	0.12349
Log-Max. L.	68.7713	−115.7418	339.3896	78.71005	−114.0154	337.7098
SIC	−0.5818	1.2634	−3.2879	−0.658058	1.27888	−3.26107

Panel A in Table 5 exhibits estimation of State-Space Models (B11), (B21) and (B31), and Panel B the estimation of Models B12), (B22) and (B32), employed in extracting herding towards the Market Portfolio, Book-to-Market and Trading Volume factors, and the proportion of signal explained by herding (PoSEH) by each factor. In column 1, $\sigma._{\nu}$ and $\sigma._{\eta}$ represent standard deviations of $\nu_{.t}^{s}$ and $\eta_{.t}$, respectively; Log-Max. L. stands for Log of maximum likelihood and SIC for Schwarz Information Criterion. Variable $d(\log\text{-}V_{mt})$ denotes the change in volatility and PoSEH = σ.η / Stdev(log-CSSD-Betas).

*** Significance at 1% level.

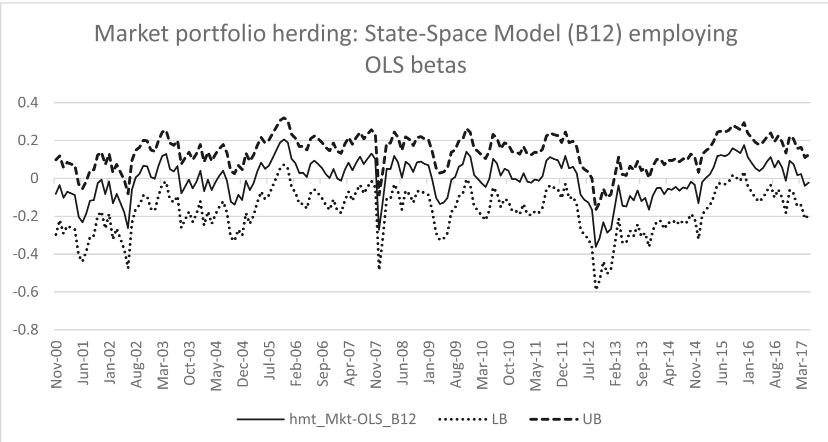


Fig. 7. Herding towards the market portfolio employing CSSDs of Linear Factor Model OLS betas in the State-Space Model (B12); LB and UB are the two standard error lower and upper bounds on h_{mt}.

portfolio herd dynamics based on Model (B12) and shows many periods of herding and adverse herding. There is a positive trend in the herding coefficient up to about December 2005, apparently the mining boom period in Australia, it plateaus and then results in adverse herding around Dec 2007. The herding movement towards the market portfolio is sideways between Jan 2008 and June 2012 that includes the GFC and short-selling ban periods in Australia and then results in adverse herding around the Greek Govt. Debt crisis period. A positive trend in the herding coefficient emerges again between Feb 2013 and Oct 2015. The pattern in Fig. 7 once again confirms that investors display herd behaviour during calmer periods of the market when investors have confidence in the future state of the market, adverse herding during periods of uncertainty, but extreme uncertainty halts herding. Thus, it can be inferred that investors in the Australian market are basically risk-wary; they follow the movements of the market portfolio only during tranquil periods.

(b) Herding towards Book-to-market factor: Using CSSDs of OLS estimated Model (B) betas in State-Space Models (B21) and (B22)

Columns 3 and 6 in Table 5 display estimation of Models (B21) and (B22). It follows that Model (B22) is a better fitting model than Model (B21). The explanatory variable $d(log\text{-}V_{mt})$ has a significant inverse relationship with $log[CSSD(b_{iBMt})]$ but causes a minimal increase in the proportion of signal explained by herding towards the BM factor. The PoSEH towards the BM factor is 45.26% in Model (B21) and 45.5% in Model (B22); the change in market volatility has negligible effect on BM herding.

Fig. 8 displays BM factor herd dynamics. There are many time periods showing incidents of herding and adverse herding. However, the adverse-herding episodes are more frequent than observed for herding towards the market portfolio, suggesting

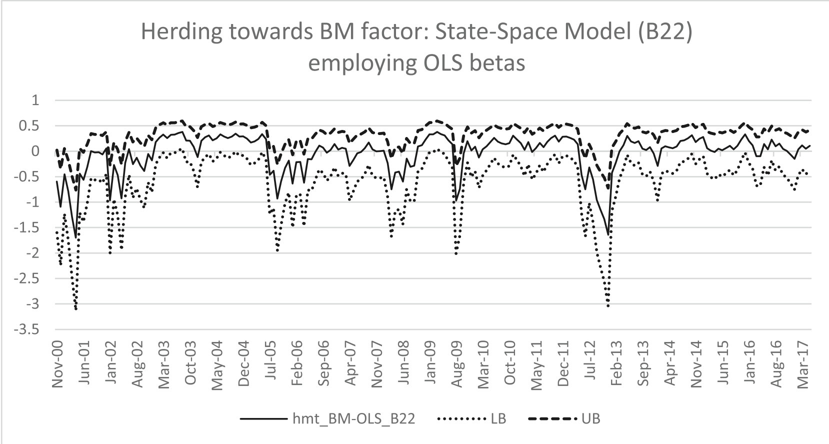


Fig. 8. Herding towards Book-to-Market factor employing CSSDs of Linear Factor Model OLS betas in the State-Space Model (B22); LB and UB are the two standard error lower and upper bounds on h_BM_t.

investors' efforts to rely on fundamentals and adjust to the changing market conditions or perceived upcoming turbulent periods and/ or bad news. There are clear adverse herding movements during the GFC, the short selling ban and the Greek Govt. Debt crisis periods. Upward trending pattern in herding coefficients is less persistent and short lived compared to the case of herding towards the market portfolio; the movements are either sideways or in adverse-herding mode that suggests a risk-aversion attitude among investors.

(c) Herding towards trading volume: using CSSDs of OLS estimated Model (B) betas in State-Space Models (B31) and (B32)

We observed in Fig. 6 that the movements in $CSSD(b_{TRt})$ series are minimal compared to $CSSD(b_{mt})$ and $CSSD(b_{BMt})$, so we expect the trading volume herding to be different from other factors. Columns 4 and 7 in Table 5 show estimation of Models (B31) and (B32). In both models the standard deviation $\sigma_{.\eta}$ of the herding variable towards the trading volume factor is very close to zero and not significant, indicating that there is no herding towards the trading volume factor. The PoSEH is just 12.26% based on Model (B31) that increases to 12.35% in Model (B32), however, the effect of change in market volatility is not significant.

Fig. 9 graphs herd dynamics based on Model (B32). This graph shows that at the average level there is no statistically significant herding towards the trading volume at any time during our study period of 17 years. There is a slight increasing trend in the herding coefficients before the GFC, but they do not achieve a statistical significance. There is inclination towards adverse herding after the GFC period, but it is not statistically significant. Bearing in mind that low and high trading volumes reflect a response due to very different market conditions, the lack of statistical significant herding towards the trading volume can be interpreted as investors being informed, rational and risk-averse, and do not get swayed easily by changes in trading volume, at least on average.

5.2.3. Herding towards Market portfolio, Book-to-Market and Trading Volume factors: evidence from the quantile-regression estimated betas

This section discusses herd behaviour based on the linear factor Model (B) when estimated using the quantile regression method focusing on quantiles 0.05 and 0.95. Panel A in Table 6 reports the estimation of SS Models (B11), (B21) and (B31) and Panel B details

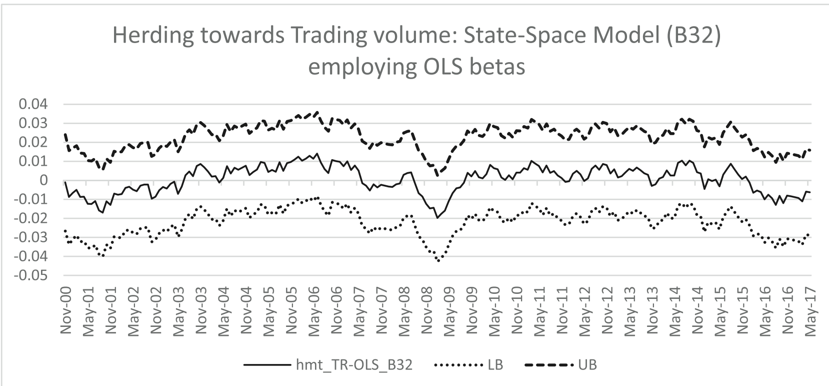


Fig. 9. Herding towards the trading volume based on the Linear Factor Model OLS betas employed in the State-Space Model (B32); LB and UB are the two standard error lower and upper bounds on $h_{\_TRt}$.

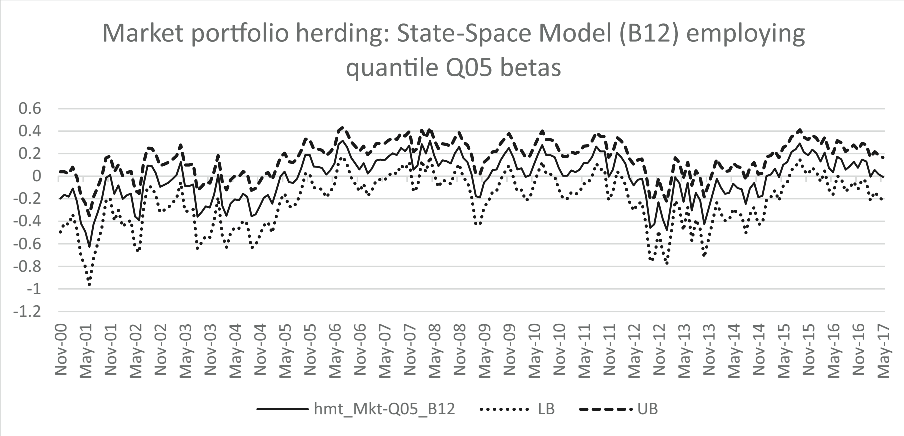
Table 6

Estimates of State-Space Models for herding towards the market portfolio, Book-to-Market and Trading Volume factors using Cross Sectional Standard Deviations of quantile regression estimated betas at quantiles 0.05 and 0.95 (parentheses display standard errors).

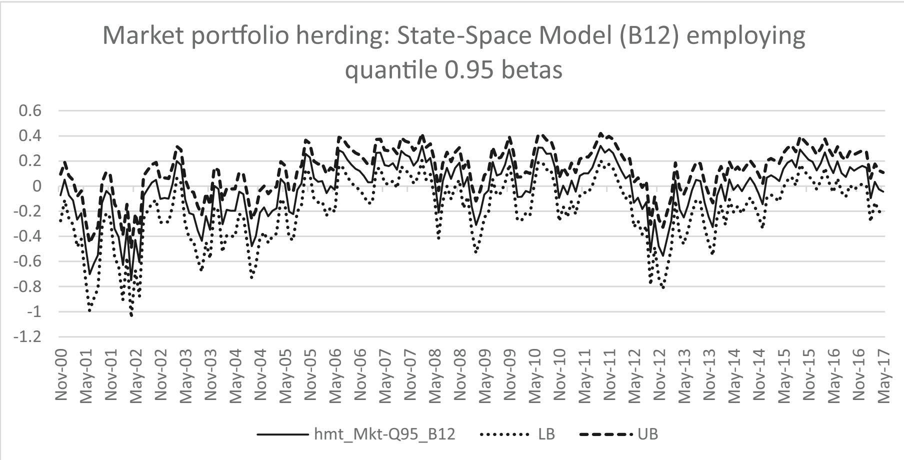
	Panel A						Panel B					
	Quantile 0.05			Quantile 0.95			Quantile 0.05			Quantile 0.95		
	Market Portfolio Model (B11)	Book-to-Market Model (B21)	Trading Volume Model (B31)	Market Portfolio Model (B11)	Book-to-Market Model (B21)	Trading Volume Model (B31)	Market Portfolio Model (B12)	Book-to-Market Model (B22)	Trading Volume Model (B32)	Market Portfolio Model (B12)	Book-to-Market Model (B22)	Trading Volume Model (B32)
μ .	0.23378	0.41245	−4.79276	0.26355	0.43341	−4.71521	0.2338	0.39084	75.2898	0.25716	0.43105	−4.72335
	(0.062)***	(0.120)***	(0.133)***	(0.055)***	(0.099)***	(0.174)***	(0.054)***	(0.102)***	(11,491.1)	(0.050)***	(0.010)***	(0.171)***
φ .	0.90603	0.88178	0.95583	0.83950	0.81466	0.96956	0.85505	0.84386	1.00005	0.80366	0.80958	0.9675
	(0.045)***	(0.044)***	(0.023)***	(0.052)***	(0.066)***	(0.020)***	(0.053)***	(0.053)***	(0.007)***	(0.057)***	(0.068)***	(0.021)***
σ. ν	0.17690	0.30277	0.20013	0.12602	0.31902	0.22295	0.13131	0.28398	‘0.20308	0.09327	0.31891	0.22234
	(0.014)***	(0.024)***	(0.014)***	(0.018)***	(0.026)***	(0.013)***	(0.015)***	(0.028)***	(0.013)***	(0.023)***	(0.026)***	(0.013)***
σ. η	0.08123	0.17873	0.09515	0.11670	0.21067	0.08552	0.10707	0.19493	0.08713	0.13166	0.21256	0.08623
	(0.021)***	(0.036)***	(0.019)***	(0.022)***	(0.039)***	(0.017)***	(0.022)***	(0.038)***	(0.015)***	(0.022)***	(0.040)***	(0.018)***
$d(\log\text{-}V_{mt})$							−0.29402	−0.22003	−0.04144	−0.21415	−0.04958	0.06064
							(0.036)***	(0.080)***	(0.056)	(0.030)***	(0.103)	(0.054)
PoSEH	0.30862	0.38166	0.25955	0.46427	0.43965	0.22470	0.40677	0.41625	0.23768	0.52377	0.44360	0.22656
Log-Max. L.	23.47828	−95.59491	−6.44682	49.11612	−109.2438	−20.01019	50.53877	−89.702	−15.57779	66.11943	−108.9787	−19.61018
SIC	−0.12882	1.06192	0.17044	−0.3852	1.1984	0.30607	−0.37493	1.03453	0.28956	−0.53152	1.22826	0.33009

Panel A in Table 6 exhibits estimation of State-Space Models (B11), (B21) and (B31), and Panel B the estimation of Models (B12), (B22) and (B32), employed in extracting herding towards the Market Portfolio, Book-to-Market and Trading Volume factors, and the proportion of signal explained by herding (PoSEH) by each factor. In column 1, $\sigma._{\nu}$ and $\sigma._{\eta}$ represent standard deviations of $\nu._t^s$ and $\eta._t$, respectively; Log-Max. L. stands for Log of max likelihood and SIC for Schwarz Information Criterion. Variable $d(\log\text{-}V_{mt})$ denotes the change in volatility and PoSEH = σ.η / Stdev(log-CSSD-Betas).

*** Significance at 1% level.



(a). Herding towards the Market Portfolio using the quantile 0.05 betas.



(b). Herding towards the Market Portfolio using the quantile 0.95 betas.

Fig. 10. Herding towards the Market Portfolio using cross sectional standard deviations from the Linear Factor Model betas in State-Space Model (B12); LB and UB are the two standard error lower and upper bounds on the herding component $h_{mt_}$Mkt.

SS Models (B12), (B22) and (B32) employed in extracting herd behaviour towards the Market portfolio, Book-to-Market and Trading volume factors. Figs. 10(a)–12(b) show herd dynamics based on a better fitting models for each factor. An inspection of models in Panels A and B reveals that the herding parameter φ and the herding standard deviation, $\sigma_{.\eta}$, are highly significant in each model. Generally, models (B12), B(22) and B(32) perform better than Models (B11), B(21) and (B31). Table 7 lists the PoSEH based on better fitting models towards each factor employing CSSDs of the OLS and the quantiles 0.05 and 0.95 betas. We now discuss the herding pattern for each factor separately.

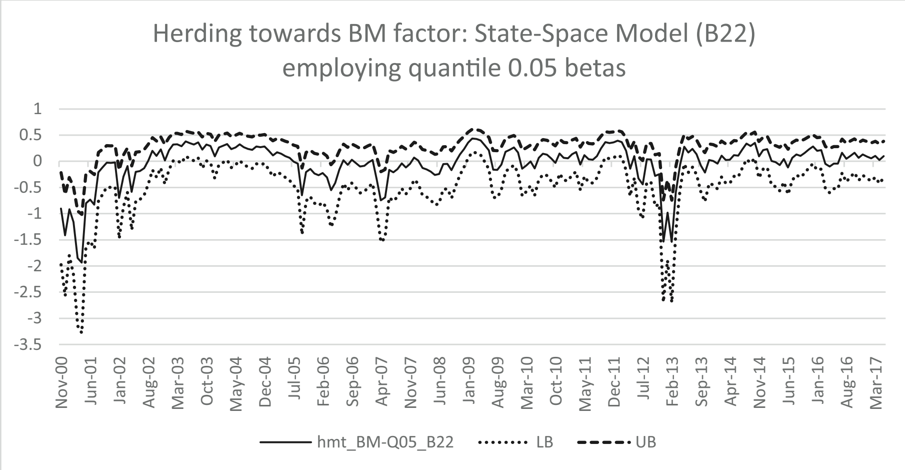
(a) Herding towards the market portfolio: Using CSSDs of Quantile regression estimated Model (B) betas at quantiles 0.05 and 0.95 in State-Space Models (B11) and (B12)

It was pointed out above that Model (B12) is a better fitting than Model (B11) for quantiles 0.05 and 0.95. In Model (B12) market

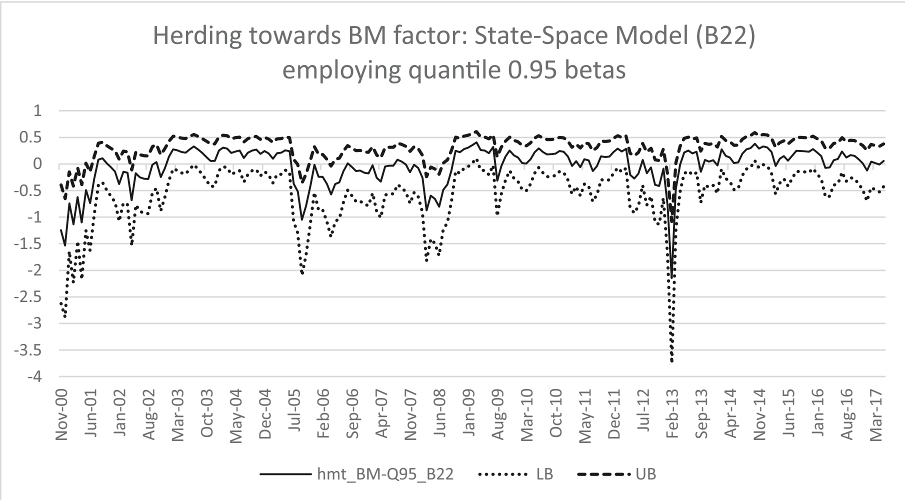
Table 7
Proportion of signal explained by herding based on the Linear Factor Model betas.

Beta estimation method	Market portfolio	Book-to-Market	Trading volume
OLS	38.55%	45.56%	12.35%
Quantile 0.05	40.68%	41.63%	25.95%
Quantile 0.95	52.38%	44.36%	22.66%

The values reported in Table 7 are extracted from Tables 5 and 6 for easy comparison of values.



(a). Book-to-Market factor herding using the quantile 0.05 betas.



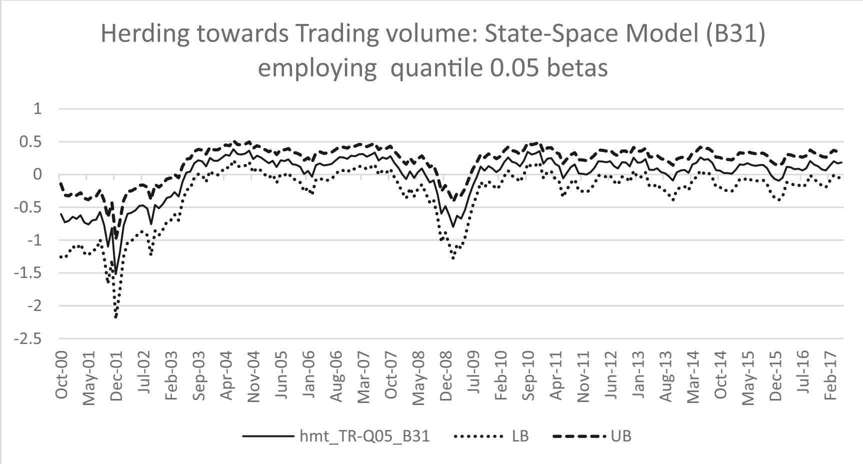
(b). Book-to-Market factor herding using the quantile 0.95 betas.

Fig. 11. Herding towards the Book-to-Market factor using cross sectional standard deviations from the Linear Factor Model betas in the State-Space Model (B22); LB and UB are the two standard error lower and upper bounds on the herding component hmt_BM.$h_{mt_}$BM.

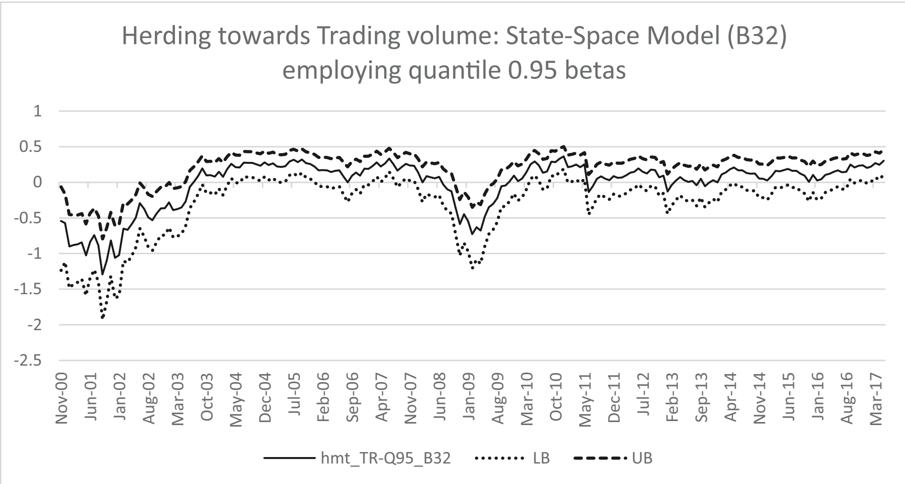
portfolio herding explains 40.68% of the variation in quantile 0.05 based log[$CSSD(b_{Mt})$], while 52.38% for quantile 0.95. Both these percentages are higher than 38.55% for the OLS based better fitting Model (B12) in Table 5. Comparing herd dynamics in Figs. 7, 10(a) and (b), it follows that there is a lot more persistence in herding as well as incidences of adverse herding towards the market portfolio at quantile 0.95 compared to quantile 0.05 and at the average level. It can be inferred from this pattern that during the high-performance days of stocks, investors are very watchful of the market, quick to respond to the market movements and are frequently adjusting their investment strategies to optimize returns on their investments.

(b) Herding towards the Book-to-Market factor: Using CSSDs of Quantile regression estimated Model (B) betas at quantiles 0.05 and 0.95 in State-Space Models B21 and B22

We noted earlier from Table 6 that Model (B22) performs better than Model (B21) for quantiles 0.05 and 0.95. State Space Model (B22) shows that BM factor herding explains 41.63% of the variation in quantile 0.05 based log[CSSD(b_{BMT})] and 44.36% for quantile 0.95 compared to 45.5% for the average level (Table 7). The inverse relationship of $d(log\text{-}V_{mt})$ with log[CSSD(b_{BMt})] is not significant for quantile 0.95, and the Log(Max. L.) and SIC values are barely improved by its inclusion. From Figs. 8, 11(a) and (b), we observe that the OLS and quantile 0.95 betas-based analysis for the BM factor shows adverse herding around the GFC period, but the quantile 0.05 based analysis reveals non-significant sideways movements. Viewing Figs. 8, 11(a) and (b), and comparing the BM factor herding with the market portfolio herding, we notice that the sideways movements in the BM factor herding are for longer periods compared to market portfolio. While there are incidences of adverse herding during 2000–2002, between June 2005 and April 2007 and around 2013 based on CSSDs of quantile 0.05 betas, the incidences of adverse herding based on CSSDs of quantile 0.95 betas are



(a). Herding towards Trading volume using the quantile 0.05 betas.



(b). Herding towards Trading volume using the quantile 0.95 betas.

Fig. 12. Herding towards Trading volume using cross sectional standard deviations from the Linear Factor Model betas in the State-Space Model (B32); LB and UB are the two standard error lower and upper bounds on the herding component $h_{mt_}$TR.

more frequent and intense and include the GFC period along with many other periods. Referring to the assertion in Footnote 2 from Dempsey (2010) that 'the BM variable absorbs market movements as a proxy for financial risk', it can be inferred that the BM factor herding suggests a risk-aversion tendency of investors in the Australian market. There is no significant adverse herding towards the BM factor during the short-selling ban period; the movements are generally sideways and reflect the effectiveness of the regulation. Since the BM herding is stronger at all levels of the return distribution and is not impacted by the effect of change in volatility being significant or not, it can be inferred that BM herding is followed more intently.

(c) Herding towards the trading volume factor: Using CSSDs of Quantile regression estimated Model (B) betas at quantiles 0.05 and 0.95 in State-Space Models (B31) and (B32)

It follows from Table 6 that State-Space Model (B31) performs better than Model (B32) for trading volume herding when quantiles 0.05 betas are used; the situation reverses for the 0.95 betas. Table 7 shows that the trading volume herding explains 25.96% of the variation in quantile 0.05 betas-based $log[CSSD(b_{TRt})]$ and 22.66% from quantile 0.95 betas compared to 12.35% from OLS betas. Comparing trading volume herd dynamics in Figs. 9(a), 12(a) and (b), it follows that there is not much significant herding towards the TR on an average day, but investors do observe the movements of trading volume on the low as well as on the high-performance days of stock returns. These findings on trading volume tie closely with the findings of Gebka and Wohar (2013). Based on OLS estimation they report that there is no causal link between trading volume and returns; the volume-return causality is non-persistent in nature and is of limited use for return forecasting, and therefore, there is support for the efficient market hypothesis. However, their results show trading volume-return causality in quantiles. Inspecting Fig. 12(a) and (b), we observe a few incidences of herding towards the trading volume during calmer periods. There is a significant adverse herding around the Tech bubble, the Sep 11 attack and the GFC periods. The effect of $d(log\text{-}V_{mt})$ on log[CSSD(b_{TRt})] is not significant on good or bad performance days of stock returns. Thus, it can be concluded that herding towards the trading volume may be endorsing the presence of information rich investors as argued by Stickel and Verrecchia (1994), who would be savvy enough to be risk-averse during the calmer as well as the turbulent periods.

6. Conclusion

This paper examines investor-herding and risk-profiles link for understanding the implied risk in a stock market that carries implications for portfolio diversification and asset pricing. Employing Australian data, we use an in-depth time series approach to evaluate herd dynamics towards the market portfolio, Book-to-Market ratio and trading volume factors and to find the proportion of signal explained by herding (PoSEH) in each case. Specifically, State-Space models are used for extracting the latent herding component from the cross-sectional standard deviations (CSSD) of factor sensitivities estimated using the quantile regression and the OLS methods that capture the effect of various factors at the extreme quantiles and at the average level of the return distribution. To avoid the quadratic relationship between market returns and volatility and the resulting leverage effect confounding our results, change in volatility is used to establish the robustness of findings.

We observe many periods of herding and adverse herding towards the market portfolio; the frequency and intensity of both events is much greater when extreme quantile betas are employed compared to the use of average betas. The existence of herding and adverse herding at the extreme quantiles indicates that such behaviour can emerge during the worst and the best performance days of stock returns. The PoSEH using the OLS and the 5th and 95th quantile betas are 36.65%, 28.73% and 52% (Table 2), respectively. This suggests that the level of herding is not homogenous across the return distribution; investors value their assets differently on low- and high-performance days of stock returns compared to an average day and adjust their herding behaviour accordingly. We observe investor herding/ adverse herding during tranquil/ uncertain periods, and a near halt of these two behaviours during extreme uncertaint periods like the GFC. Thus, it can be concluded that investors in the Australian market are risk averse.

Change in market volatility has a significant inverse relationship with CSSD of betas at all levels of the return distribution, but it strengthens the PoSEH in each model; its impact being maximum on high-performance days of stock returns. It can be inferred that volatility is an important influencing variable in directing investor behaviour; it is perceived as an opportunity and many investors want to take advantage of change in volatility by copying other investors' behaviour.

The PoSEH based on the linear factor model shows that the trading volume is herded the least, and the market portfolio herding is maximum (52.38%) during the best return days of stocks. However, the PoSEH towards the BM factor is high (41.63% to 45.56%; Table 7) at all levels of the return distribution, which is not impacted by the effect of change in volatility being significant or not, suggests that BM is a highly sought-after herding factor. Keeping in view the assertion 'the BM variable absorbs market movements as a proxy for financial risk' from Dempsey (2010), it can be inferred that the BM factor herding in the Australian market endorses risk-aversion tendencies of investors. The non-significant sideways herding movements during the short-selling ban period (Nov 2008–May 2009) imply the presence of a regulated stock market environment.

Acknowledgements

We thank an anonymous reviewer for bringing to our attention the possibility of a leverage effect between the market returns and the volatility variables confounding our results in an earlier version of the paper.

References

Arnott, R.D., Hsu, J., Moore, P., 2005. Fundamental indexation. Fin. Anal. J. 61, 83–99.
Asch, E., 1952. Social Psychology. Englewood Cliffs, N. J., Prentice Hall.
Bai, Y., Chang, E.C., Wang, J., 2006. Asset Prices Under Short-sale Constraints. (Working paper, 'web.mit.edu/wangj/www/pap/BCW_061112.pdf').
Barnes, M., Hughes, A., 2002. A quantile regression analysis of the cross section of stock market returns. Federal Reserve Bank of Boston, pp. 1–34 working paper. 02-2002.
Black, F., 1976. Studies of Stock Price Volatility Changes. Proceedings of the Meeting of Business and Economic Statistics Section. American Statistical Association, pp. 177–181.
Bohl, M.T., Klein, A.C., Siklos, P.L., 2013. Short-selling Bans and Institutional Investor's Herding Behaviour: Evidence From the Global Financial Crisis. CIGI Papers, No. 18. https://www.cigionline.org.
Buchinsky, M., 1997. The dynamics of changes in the female wage distribution in the USA: a quantile regression approach. J. Appl. Econ. 13, 1–30.
Buchinsky, M., 1998. Recent advances in quantile regression models: a practical guideline for empirical research. J. Hum. Resour. 33, 88–126.
Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behaviour in equity markets: an international perspective. J. Bank. Financ. 24, 1651–1679.
Chiang, T.C., Zheng, D., 2010. An empirical analysis of herd behaviour in global stock markets. J. Bank. Financ. 34, 1911–1921.
Chiang, T.C., Li, J., Tan, L., 2010. Empirical investigation of herding behaviour in Chinese stock markets: evidence from quantile regression analysis. Glob. Financ. J. 21, 111–124.
Christie, W.G., Huang, R.D., 1995. Following the Pied Piper: do individual returns herd around the market? Fin. Anal. J. 51, 31–37.
Davis, K., 2011. The Australian Financial System in the 2000s: Dodging the Bullet. Proceedings of the Reserve Bank of Australia Conference: The Australian Economy in the 2000s. pp. 301–348.
Demirer, R., Kutan, A., Chen, C., 2010. Do investors herd in emerging markets? Evidence from the Taiwanese market. J. Econ. Behav. Organ. 76, 283–295.
Dempsey, M., 2010. The book-to-market equity ratio as a proxy for risk: evidence from Australian market. Aust. J. Manag. 35, 7–21.
Duan, X., Guo, L., Li, F.W., Tu, J., 2019. Sentiment, limited attention and mispricing. In: European Financial Management Association Conference-2019. University of Azores, S. Maguel, Portugal.
Effinger, M.R., Polborn, M.K., 2001. Herding and anti-herding: a model of reputational differentiation. Eur. Econ. Rev. 45 (3), 385–403.
Engle, R.F., Manganelli, S., 2004. CAViaR: conditional value at risk by regression quantile. J. Bus. Econ. Stat. 22, 367–381.

Fama, E., 1970. Efficient capital market: A review of theory and empirical work. The Journal of Finance. 25, 383–417.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 3, 3–56.
Fama, E.F., French, K.R., 2012. Size, value and momentum in international stock returns. J. Financ. Econ. 105, 457–472.
Fama, E., MacBeth, J., 1973. Risk, return and equilibrium: empirical tests. J. Polit. Econ. 81, 607–636.
Ferson, W.E., Harvey, C.R., 1991. The variation of economic risk premiums. J. Polit. Econ. 99, 285–315.
Ferson, W.E., Harvey, C.R., 1993. The risk and predictability of international equity returns. Rev. Financ. Stud. 6, 527–566.
Gebka, B., Wohar, M.E., 2013. Causality between trading volume and returns: evidence from quantile regressions. Int. Rev. Econ. Financ. 27, 144–159.
Grinblatt, M., Titman, S., Wermers, R., 1995. Momentum investment strategies, portfolio performance, and herding: a study of mutual fund behaviour. Am. Econ. Rev. 85 (5), 1088–1105.
Hasanhodzic, J., Lo, A.W., 2019. On Black's leverage effect in firms with no leverage. J. Portf. Manag. 46 (1), 106–122. https://doi.org/10.3905/jpm.2019.46.1.106.
Henker, J., Henker, T., Mitsios, A., 2006. Do investors herd intraday in Australian equities? Int. J. Manag. Financ. 2 (3), 196–219.
Hwang, S., Salmon, M., 2004. Market stress and herding. J. Empir. Financ. 11, 585–616.
Lakonishok, J., Shleifer, A., Vishny, R.W., 1992. The impact of institutional trading on stock prices. J. Fin. Econ. 32, 23–44.
Lao, P., Singh, H., 2011. Herding behaviour in the Chinese and Indian stocks market. J. Asian Econ. 22, 495–506.
Nath, H.B., Brooks, R.D., 2015. Assessing the idiosyncratic risk and stock returns relation in heteroskedasticity corrected predictive models using quantile regression. Int. Rev. Econ. Financ. 38, 94–111.
Peterkort, R.F., Nielson, J.F., 2005. Is the book-to-market ratio a measure of risk? J. Financ. Res. 28, 487–502.
Prechter Jr., R.R., 2001. Unconscious herding behaviour as the psychological basis of financial market trends and patterns. J. Psychol. Fin. Market. 2 (3), 120–125.
Shiller, R.J., Pound, J., 1989. Survey evidence of diffusing interest among institutional investors. Journal of Economic Behaviour and Organization. 12, 47–66.
Stickel, S.E., Verrecchia, R.E., 1994. Evidence that trading volume sustains stock price changes. Financ. Anal. J. 50, 57–67.
Yao, J., Ma, C., He, W.P., 2014. Investor herding behaviour of Chinese stock market. Int. Rev. Econ. Financ. 29, 12–29.