

Do Fama–French common risk-factor portfolio investors herd on a daily basis? Implications for common risk-factor regressions

Chamil W. Senarathne

School of Economics, Wuhan University of Technology, Wuhan, China

Herd behavior
of common risk-
factor portfolio
investors

137

Received 1 June 2019
Revised 1 August 2019
Accepted 18 August 2019

Abstract

Purpose – The purpose of this paper is to examine whether Fama–French common risk-factor portfolio investors herd on a daily basis for five developed markets, namely, Europe, Japan, Asia Pacific ex Japan, North America and Globe.

Design/methodology/approach – To examine the herd behavior of common risk-factor portfolio investors, this paper utilizes the cross-sectional absolute deviations (CSAD) methodology, covering a daily data sampling period of July 1990 to January 2019 from Kenneth R. French-Data Library. CSAD driven by fundamental and non-fundamental information is assessed using Fama–French five-factor model.

Findings – The results do not provide evidence for herding under normal market conditions, either when reacting to fundamental information or non-fundamental information, for any region under consideration. However, Fama–French common risk-factor portfolio investors mimic the underlying risk factors in returns related to size and book-to-market value, size and operating profitability, size and investment and size and momentum of the equity stocks in European and Japanese markets during crisis period. Also, no considerable evidence is found for herding (on fundamental information) under crisis and up-market conditions except for Japan. Ancillary findings are discussed under conclusion.

Research limitations/implications – Further research on new risk factors explaining stock return variation may help improve the model performance. The performance can be improved by adding new risk factors that are free from behavioral bias but significant in explaining common stock return variation. Also, it is necessary to revisit the existing common risk factors in order to understand behavioral aspects that may affect cost of capital calculations (e.g. pricing errors) and valuation of investment portfolios.

Originality/value – This is the first paper that examines the herd behavior (fundamental and non-fundamental) of Fama–French common risk-factor investors using five-factor model.

Keywords Herd behaviour, Fundamental information, CSAD, Common risk factors, Fama–French regression, Financial crisis

Paper type Research paper

1. Introduction

The term “herding” was first rooted in zoology before it gained widespread popularity in sociology and economics. It is an act of bringing animals together and directing them to the desired destination, usually by a stockman. Herd behavior can also be observed in different markets such as labor market, where managers tend to imitate the management decisions of

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Usual disclaimer applies. The author would like to thank the Editor-in-Chief, Professor Guler Aras for giving the author the opportunity to revise the manuscript. The author is very grateful to an unknown reviewer for constructive criticisms and many useful suggestions that enormously improved the earlier version of this paper.



Journal of Capital Markets Studies
Vol. 3 No. 2, 2019
pp. 137-156
Emerald Publishing Limited
2514-4774
DOI 10.1108/JCMS-06-2019-0034

other managers, without regard to the private information that they possess (see e.g. Scharfstein and Stein, 1990). Also, investment analysts in the financial services industry have shown a tendency to base their forecasts and advisory work similar to that of the previous managers (Trueman, 1994; Graham, 1999). In economics, herding is a market phenomenon where economic agents imitate each other's actions in the market and/or base their decisions upon the actions of others. Sociological factors (e.g. social conventions) may also induce investors to imitate the actions of others, particularly when they are confronted with uncertainty in decision making (Keynes, 1937). Herding can be either rational or irrational. Rational herding occurs when a group of investors trade in the same direction, on similar information about the firm characteristics and fundamentals (Nofsinger and Sias, 1999). In the presence of rational herding, investment or trading is justified by new information pertaining to the securities and, as such, the security prices usually move toward the fundamental value of assets (Devenow and Welch, 1996). Irrational herding occurs when investors blindly imitate the actions of other investors because they have insufficient information and inadequate evaluation of securities. This form of herding leads to move the asset prices away from the fundamental value and often results in mispricing (Froot *et al.*, 1992; Hirshleifer *et al.*, 1994).

Griffin (2002) demonstrates that the performance of Fama–French country-specific factor regression is much better than global-factor model, whereas Blanco (2012) shows that its expected outcome depends upon how the stock portfolios are formed (e.g. based on characteristics relating to risk factors). Therefore, it is plausible to surmise that inefficient portfolio selection (e.g. portfolios of stocks that were subjected to herding) may significantly impact the specification and performance of Fama–French five-factor regression. This paper contributes to the literature in many ways. The standard capital asset pricing models fail to capture the common risk factors leading to variations in cross-section of average stock returns (Fama and French, 1993). The common risk-factor regressions of Fama and French (1993, 2015) are capable of explaining size, value, profitability and investment premium factors of common stocks. One of the principle assumptions of efficient market hypothesis is that the psychological factors relating to investor behavior do not impact stock market prices (Fama, 1970). However, a large literature shows that human behavior impacts common stock returns and herding is one of the key drivers of market inefficiency (see especially Froot *et al.*, 1992). Fama and French (2015) form diversified portfolios that provide different types of risk exposures to four unobserved state variables (i.e. five factors except overall market factor) of which the risk premiums cannot be captured by the market factor. If the portfolios are mean-variance efficient, there should no correlation between cross-sectional absolute deviations (CSAD) of portfolio returns and square of the market return (i.e. market factor). If the model is correctly specified under efficient conditions, the common risk-factor portfolio returns should not reflect the effect of herding on information relating to micro- and macroeconomic fundamentals[1] (i.e. herding on fundamental information). To the best of author's knowledge, there is no study that investigates herd behavior of investors in common risk-factor portfolios under different market conditions, which helps practitioners to understand economic rationale behind the model. The findings also stress scholars to revisit the five-factor model from behavioral perspective for robustness and to understand under what conditions the model can be effectively applied.

The objective of this paper is to examine whether Fama–French risk-factor portfolio investors herd toward the overall market consensus by mimicking underlying common-risk factors using cross-sectional absolute deviation (CSAD) frameworks of Chang *et al.* (2000) and Galariotis *et al.* (2015). Although the cross-sectional standard deviation (CSSD) model of Christie and Huang (1995) is also capable of detecting herd behavior of investors, many studies find that it is subject to the effect of outliers in the cross-sectional deviation (Economou *et al.*, 2011). This study, therefore, adopts CSAD model introduced by Chang *et al.* (2000).

This paper differs from Galariotis *et al.* (2015) in many ways. This paper applies their methodology to Globe and five common risk-factor portfolios across four regional markets such as Europe, Japan, Asia Pacific ex Japan and North America. In addition, this study uses Fama and French's (1995, 2015) regressions instead of Fama and French's (1995, 1996) and Carhart's (1997) frameworks used by Galariotis *et al.* (2015) for the computation of fundamental and non-fundamental CSAD. Galariotis *et al.* (2015) test for herd behavior in the UK and US markets for the period October 1989 and April 2011 but this study covers a daily sampling period of July 1990 to January 2019 for five regions, thus reflecting the current status of stock market data. Moreover, they use book-to-market value and market capitalization as the only criteria in ranking stocks for portfolio selection, whereas this paper expands the set of variables used to explain portfolio returns to four common risk factors on the basis of size and book-to-market (SBM), size and operating profitability (SOP), size and investment (SI) and size and momentum (SM). The results show that, except for common risk-factor portfolio formed on SM for Asia Pacific region, the findings do not provide evidence for herding under normal market conditions, either when reacting to fundamental information or non-fundamental information, for any region under consideration. However, the common risk-factor portfolio investors have shown a tendency to herd on fundamental information during the crisis periods in European and Japanese markets. The remainder of this paper is organized as follows. Section 2 carries an extensive review of literature. Section 3 provides the methodological framework and Section 4 provides the sources of data set. It also outlines the descriptive statistics of the sample data. Section 5 reports and discusses the findings and Section 6 concludes the paper. Section 7 provides implications for future research.

2. Literature review

Over the last two decades, a number of research papers document evidence for herd behavior in stock markets around the world. Although there have been various methods of identifying the herd behavior in financial markets (e.g. Lux, 1995; Teh and De Bondt, 1997; Avery and Zensky, 1998; Cont and Bouchaud, 2000), Chang *et al.* (2000) propose a parsimonious model of detecting herd behavior derived from a single-factor capital asset pricing model (i.e. Black, 1972). Since then, a large literature deals with detecting herd behavior in financial markets (see e.g. Peiyuan and Donghui, 2002; Demirel and Kutun, 2006; Tan *et al.*, 2008; Chiang and Zheng, 2010; Demirel *et al.*, 2010; Balcilar *et al.*, 2013; Chen, 2013). In particular, Messis and Zapranis (2014) examine the herd behavior at portfolio level using the state space model of Hwang and Salmon (2004) and find evidence for the presence of herding during high market volatility periods. Herding provides an avenue for arbitrageurs to profit from market irrationalities. Along these lines, Dang and Lin (2016) show that the herding is more pronounced in up-market periods. Their findings suggest that the arbitrageurs could profit from irrational markets than markets with correctly priced securities. Galariotis *et al.* (2016) examine the relationship between herd behavior and equity market liquidity for G5 markets which made up of five emerging economies. They document evidence for herd behavior in highly liquid stocks when liquidity of the stocks is controlled for in the model specification. As such, stock market liquidity is a critical factor affecting investor herd behavior. Humayun Kabir (2018) investigates the herd behavior in US financial services industry – paying particular attention to commercial banks, investment and insurance firms during global financial crisis periods. His findings reveal a significant herd behavior during global financial crisis period (especially in the down-market). He also finds that the tendency to herd on fundamental information is more pervasive for all financial institutions (except for insurance) during global financial crisis period.

Chiang and Zheng (2010) carry out an extensive study on the herd behavior in 18 international stock exchanges for a period of 1988–2009, and find evidence for herding in advanced stock markets (Australia, France, Germany, Hong Kong, Japan, the UK and the USA),

whereas no evidence is found for Latin American markets. They also find evidence for herding during up- and down-market conditions except for US and Latin American markets. However, US and Latin American markets were subject herding during the crisis periods. Henker *et al.* (2006) examine the intraday herd behavior in Australian equity market using the frameworks of Christie and Huang (1995) and Chang *et al.* (2000) at market level and industry level, and find no evidence for herding at either level. Similarly, Demirer and Kutan (2006) examine the herd behavior in Shanghai and Shenzhen stock exchanges using individual firm-level and sector-level data, and find no evidence for herding for the period January 1999 to December 2002 for 375 selected stocks. Lam and Qiao (2015) examine herding at market level as well as industry level under up-market, high volume and high volatility conditions in Hong Kong stock market. They find evidence for herding under all market conditions but no evidence is found for herding on systematic factors. The tendency to herd in financial markets is also determined by the knowledge and experience of investors. In particular, Venezia *et al.* (2011) investigate the herd behavior among amateur and professional investors and find that the tendency to herd is lower among the professionals. They also find that the propensity to herd depends on market risk factors such as firm's systematic risk and size – which are priced in asset pricing regression models – and the professionals are less sensitive to these factors when they trade in the market. These findings suggest that the training and experience of investors help identify the random nature of stock price changes, thus leading to a more efficient stock trading. Also, the herding phenomenon can be observed among investor groups when a group of investors follow another group of investors (e.g. foreign investors) because the later has unique skills and knowledge in trading, and possess information about the stocks being traded (see e.g. Tesar and Werner, 1995; Bohn and Tesar, 1996; Brennan and Cao, 1997). Senarathne and Jianguo (2018) examine whether the investors herd on trading strategies of foreign investors using monthly returns of individual stocks and portfolios under different market conditions, and find no evidence for herding except for bullish market condition at portfolio level. They conclude that there is no sufficient evidence to establish herding on trading strategies of foreign investors in the Colombo Stock Exchange. Herding phenomenon is closely related to volatility of the stock market and research findings show that the intensity of herding is more pronounced during high market volatility periods (e.g. Tan *et al.*, 2008; Blasco *et al.*, 2012; Venezia *et al.*, 2011) and, as such, the herd behavior may indicate the extent of future volatility of stock price changes.

On the other hand, macroeconomic variables such as inflation and interest rates may also impact investor herding. Gong and Dai (2017) examine the effect of interest rate and exchange rate on herd behavior in the stock market and find that the hike in interest rate and depreciation of Chinese currency induces herding in the market. According to Bikhchandani and Sharma (2000), herding can take the form of either “spurious” or “intentional.” Spurious herding occurs when investors trade on similar information attached to firms' fundamentals, whereas intentional herding occurs when investors simply mimic or copy others' actions in the market. Alhaj-Yaseen and Yau (2018) test for intentional and unintentional herding in 87 Chinese stocks cross-listed on the A- and B-share markets. Their sample contains daily data from 1996 to 2012 under two regimes, namely, pre- and post-liberalization (i.e. before and after 2001–2002). They find evidence for both non-fundamental and fundamental herding in A-share market over the entire sampling period and B-share market after market liberalization. B-share market, however, exhibits intentional herding prior to market liberalization. Galariotis *et al.* (2015) examine the herd behavior driven by major fundamental macroeconomic announcements toward the general market consensus in the UK and the US stock markets. They find that the US investors tend to herd during periods when major macroeconomic data are released. Stock valuation and investment decision making are very sensitive to information pertaining to micro- and macroeconomic

data (e.g. Boyd *et al.*, 2005), and scholars have shown that they impact not only stock valuation but also investor sentiments and volatility in financial markets (see e.g. Evans, 2011; Rangel, 2011).

Hwang *et al.* (2018) find a bias in cross-sectional stock returns when the stock prices of individual securities move closely, regardless of their fundamentals. They attribute this observation – which is measured by the cross-sectional variations in betas – to behavioral bias such as overconfidence or underconfidence of investors. Their findings suggest that the overconfidence leads to beta herding (i.e. individual security betas move closely with market beta) while underconfidence causes dispersion of betas away from the market beta. These findings suggest that different risk factors play a significant role in asset pricing which further motivates designing the conceptual model of this paper. Teng (2018) carries out a comparison of cross-market herding on cross-border listing stocks in the same market using high frequency daily cross-sectional dispersion of individual stocks. He uncovers interesting facts about the behavioral characteristics associated with investor herding. His study finds that the investor herding increases as the maturity level of investment portfolio decreases. Hence, the characteristics of the securities portfolios determine whether the investor sentiment co-move closely with the market perception. Similarly, these findings suggest that risk profile attached to securities portfolio is crucial for understanding the stock market efficiency as investors usually tend to label certain securities based on the characteristics of stocks in the portfolio (e.g. high or low profitability, size of firm, high or low dividend paying stocks, etc.). Hence, the return dispersions such as high minus low profitability, high minus low market-to-book value and high minus low investment stocks are usually priced in Fama–French asset pricing regressions. As such, viability of risk-factor regressions could therefore be traced by examining the herd behavior of investors of such portfolio of stocks.

3. Methodological framework

Chang *et al.* (2000) introduce a parsimonious methodology to detect herd behavior in financial markets. The model uses cross-sectional absolute deviation (CSAD) as a measure of cross-sectional return dispersion, which avoids any potential specification bias related to asset pricing. Consider the following herding specification in the sense of Chang *et al.* (2000):

$$CSAD_{ft} = \frac{1}{N} \sum_{pf=1}^N |R_{pft} - R_{mt}|, \tag{1}$$

where N is the number of portfolios formed on the basis of respective common risk-factor category (f) and $CSAD_{ft}$ is the cross-sectional absolute deviation of common risk-factor category (f) at time t . R_{pft} is the observed portfolio return of portfolio p in the common risk-factor category (f) at time t and R_{mt} is the country market return at time t . Note that a set of portfolios under a particular common risk-factor category consists of 25 portfolios. Portfolio return is computed based on weights assigned by Kenneth R. French. An alternative method would be to compute cross-sectional return dispersion using CSSD method proposed by Christie and Huang (1995). Under above variable definition, the CSSD specification can be written as follows:

$$CSSD_{ft} = \sqrt{\frac{\sum_{pf=1}^N (R_{pft} - R_{mt})^2}{(N-1)}}. \tag{2}$$

Economou *et al.* (2011) and subsequent research papers (see e.g. BenSaïda, 2017) highlight that this method is subject to cross-sectional outliers in the regression, especially under extreme market conditions. If the herd behavior is examined using CSSD under extreme

market conditions (i.e. crisis and bullish markets), the findings may be biased and provide false conclusions. In the sense of Chang *et al.* (2000) and Chiang and Zheng (2010), the following specification is used to detect the herd behavior of common risk-factor portfolio investors:

$$CSAD_{ft} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 |R_{mt}| + \Upsilon_3 R_{mt}^2 + u_t, \quad (3)$$

in which, the *CSAD* is assumed to be non-linearly dependent on the value-weighted market return and, in the presence of herding, the coefficient Υ_3 should be negative and statistically significant. The original specification of Chang *et al.* (2000) does not include a term to account for asymmetric quadratic relationship between *CSAD* and R_{mt} . As such, $|R_{mt}|$ is additionally included to reflect this asymmetry in the herding specification in the sense of Chiang and Zheng (2010). Galariotis *et al.* (2015) consider the error term from regressing *CSAD* on Fama–French overall market factor (i.e. R_{mt}) and some common risk factors such as *HML*, *SMB* and *MOM*. This study, however, considers five risk factors (note that each country has separate common risk factors) of Fama and French (2015) in ascertaining *CSAD* on non-fundamental information for each country as follows:

$$CSAD_{ft} = \phi + \psi_1 RP_{mt} + \psi_2 SMB_t + \psi_3 HML_t + \psi_4 RMW_t + \psi_5 CMA_t + \varepsilon_t, \quad (4)$$

RP_{mt} is the market risk premium of respective country and *SMB* is the return on a well-diversified portfolio of small stocks minus diversified portfolio of big shares. *HML* is the return on diversified portfolios of high *B/M* shares minus diversified portfolios of low *B/M* shares and *RMW* is the difference between the return on diversified portfolios of shares with robust profitability minus weak profitability. *CMA* is the difference between the return on diversified portfolios of conservative investment shares and aggressive investment shares. In the sense of Galariotis *et al.* (2015), let the *CSAD* based on non-fundamental information be written as follows:

$$CSAD_{ft}^{NONFUND} = \varepsilon_t, \quad (5)$$

and the *CSAD* applicable to herding on fundamental information[2] could be estimated as follows:

$$CSAD_{ft}^{FUND} = CSAD_{ft} - CSAD_{ft}^{NONFUND}. \quad (6)$$

The herding specification then becomes:

$$CSAD_{ft}^{FUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 |R_{mt}| + \Upsilon_3 R_{mt}^2 + u_t, \quad (7)$$

$$CSAD_{ft}^{NONFUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 |R_{mt}| + \Upsilon_3 R_{mt}^2 + u_t. \quad (8)$$

A number of scholars have shown that the herding is more pronounced during crisis periods (see e.g. Bove and Domuta, 2004; Bikhchandani and Sharma, 2000; Yao *et al.*, 2014; Galariotis *et al.*, 2015; Litimi *et al.*, 2016; Bekiros *et al.*, 2017) and a crisis in one market of a country may be affected by another market because the stock markets are integrated (see e.g. Theodossiou and Lee, 1993; Bagliano and Morana, 2012; Chen *et al.*, 2016; De Bruyckere *et al.*, 2013; Bekiros, 2014). As such, a dummy variable D_t^{crisis} takes the value 1 for all observations during the respective crisis periods. The major economic crises include peso crisis, Asian crisis, Russian crisis, dotcom bubble burst and subprime crisis. The regressions for both fundamental and non-fundamental become:

$$CSAD_{ft}^{FUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 |R_{mt}| + \Upsilon_3 R_{mt}^2 + \Upsilon_4 D_t^{crisis} R_{mt}^2 + u_t, \quad (9)$$

$$CSAD_{ft}^{NONFUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 |R_{mt}| + \Upsilon_3 R_{mt}^2 + \Upsilon_4 D_t^{crisis} R_{mt}^2 + u_t. \quad (10)$$

If the herding is more pronounced during crisis periods, coefficient Υ_4 should be negative and statistically significant. If investors mimic the *factors relating to crises* (not common-risk factors) during crises periods, the coefficient Υ_3 should be negative and significant when D^{crisis} is controlled for in the regressions above.

Nemours scholars have shown that the tendency to herd differs greatly between up- and down-market conditions[3] (see especially Chiang and Zheng, 2010). As such, dummy variable D^{up} takes the value 1 when the market return is positive or zero otherwise. The following regression detects the herd behavior during up-markets:

$$CSAD_{ft}^{FUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 |R_{mt}| + \Upsilon_3 R_{mt}^2 + \Upsilon_4 D^{up} R_{mt}^2 + u_t, \quad (11)$$

$$CSAD_{ft}^{NONFUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 |R_{mt}| + \Upsilon_3 R_{mt}^2 + \Upsilon_4 D^{up} R_{mt}^2 + u_t. \quad (12)$$

Similarly, if the herding is more pronounced during up-market condition, the coefficient Υ_4 should be negative and statistically significant. If investors mimic the *factors relating to bullish market* (not common-risk factors) during up market periods, the coefficient Υ_3 should be negative and significant when D^{up} is controlled for in the regressions above.

4. Data and description of sample

Data pertaining to stock returns (including market return) and common risk factors for each country are obtained covering a sampling period of July 2, 1990 to January 31, 2019 (7,349 observations) from Bloomberg database for the respective periods and Kenneth R. French-Data Library[4]. Different sizes of portfolios have been formed on SBM, SOP, SI and SM at country level. The data are available in Kenneth R. French-Data Library (available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Average portfolio return is considered from 25 portfolios (5×5) formed on the above common risk factors for each country (i.e. the average portfolio return reflects Scale 3 which is fallen between “small” and “big” classification of the Kenneth R. French-Data Library[5]). A set of 25 portfolios (5×5) each for Globe (GB), Europe (EU), Japan (JP), Asia Pacific ex Japan (AP) and North America (NA) have been formed by Kenneth R. French. The crisis periods are recognized as peso crisis from December 1, 1994 to July 31, 1995; the Asian crisis from July 1, 1997 to March 31, 1998; the Russian crisis from August 1, 1998 to March 31, 1999; the dotcom bubble burst from January 1, 2000 to June 30, 2000; and the subprime crisis from January 1, 2008 to April 30, 2011. Some descriptive statistics of the sample data are given in Table I. As Table I reports, all regression variables are stationary as ADF test statistics substantially exceed the critical value of -2.87 at 5 percent significance level. Ljung–Box Q -test for serial correlation suggests that the variables are highly serially correlated. The shape of variable distribution is given by a visual depiction of the distributions in Figure 1(a) and (b).

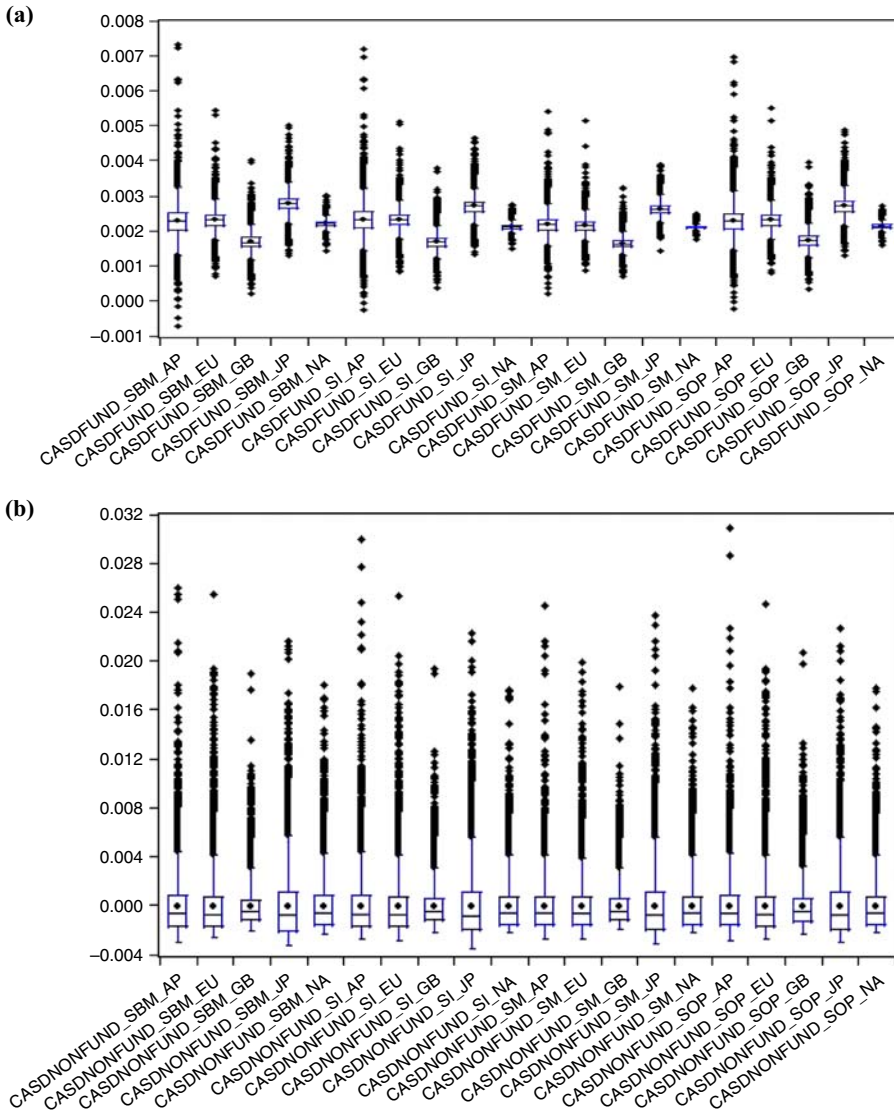
Below Box plots provide the visual depiction of the distributions of fundamental and non-fundamental CSAD. For fundamental CSAD, the median is around 0.0023 for most of the common risk factors for Japan and Globe. The median of the common risk-factor portfolio CSAD (fundamental) for Japan and Globe is around 0.0028 and 0.0018, respectively. As far as the shape of the distribution is concerned, common risk-factor portfolio CSAD for Asia pacific region is negatively skewed as most of the observations fall within the lower box, indicating non-normality of their distributions. On the other hand, the distributions of Asia pacific common risk-factor portfolio CSAD show a considerable amount of outliers, whereas North American risk-factor portfolio CSAD is distributed with minimal outliers with a median around 0.0023.

All non-fundamental CSAD distributions are positively skewed as a large proportion of observations falls within the upper box of the plot and the mean varies between -0.001 and

Variable	Description Factor	Region	Mean	Med.	Max.	Min.	ADF(35)	Q(36)
R_m	-	AP	4.1E-04	0.0006	0.1000	-0.1032	-75.77	172.65
R_m	-	EU	3.4E-04	0.0006	0.1076	-0.0898	-52.31	95.86
R_m	-	GB	3.3E-04	0.0006	0.0921	-0.0667	-59.20	259.89
R_m	-	JP	1.8E-04	0.0002	0.1301	-0.1084	-64.34	64.32
R_m	-	NA	4.3E-04	0.0005	0.1063	-0.0897	-88.22	101.46
$ R_m ^d$	-	AP	7.2E-03	0.0050	0.1032	0.0000	-10.61	10,555
$ R_m ^d$	-	EU	7.8E-03	0.0055	0.1076	0.0000	-11.97	10,407
$ R_m ^d$	-	GB	6.0E-03	0.0042	0.0921	0.0000	-9.39	12,701
$ R_m ^d$	-	JP	9.8E-03	0.0072	0.1301	0.0000	-19.52	3,527
$ R_m ^d$	-	NA	7.1E-03	0.0047	0.1063	0.0000	-9.02	14,817
D^{UP}	-	AP	5.3E-01	1.0000	1.0000	0.0000	-77.47	115.30
D^{UP}	-	EU	5.3E-01	1.0000	1.0000	0.0000	-85.68	33.65
D^{UP}	-	GB	5.4E-01	1.0000	1.0000	0.0000	-75.43	154.34
D^{UP}	-	JP	5.1E-01	1.0000	1.0000	0.0000	-87.18	25.69
D^{UP}	-	NA	5.4E-01	1.0000	1.0000	0.0000	-85.09	28.71
D^{CRISIS}	-	-	2.1E-01	0.0000	1.0000	0.0000	-3.89	226,548
$CSAD_{FUND}$	SBM	AP	2.3E-03	0.0023	0.0074	-0.0007	-78.94	121.32
$CSAD_{FUND}$	SBM	EU	2.3E-03	0.0023	0.0055	0.0007	-43.79	135.31
$CSAD_{FUND}$	SBM	GB	1.7E-03	0.0017	0.0040	0.0002	-85.19	114.52
$CSAD_{FUND}$	SBM	JP	2.8E-03	0.0028	0.0050	0.0013	-52.62	111.55
$CSAD_{FUND}$	SBM	NA	2.2E-03	0.0022	0.0030	0.0014	-82.80	86.10
$CSAD_{FUND}$	SI	AP	2.4E-03	0.0023	0.0072	-0.0002	-79.19	114.20
$CSAD_{FUND}$	SI	EU	2.3E-03	0.0023	0.0051	0.0008	-43.73	133.59
$CSAD_{FUND}$	SI	GB	1.7E-03	0.0017	0.0038	0.0004	-84.62	119.47
$CSAD_{FUND}$	SI	JP	2.7E-03	0.0027	0.0047	0.0014	-52.54	107.82
$CSAD_{FUND}$	SI	NA	2.1E-03	0.0021	0.0028	0.0015	-83.17	79.17
$CSAD_{FUND}$	SM	AP	2.2E-03	0.0022	0.0054	0.0002	-79.26	112.17
$CSAD_{FUND}$	SM	EU	2.2E-03	0.0022	0.0051	0.0009	-64.50	138.75
$CSAD_{FUND}$	SM	GB	1.7E-03	0.0017	0.0032	0.0007	-83.47	128.76
$CSAD_{FUND}$	SM	JP	2.7E-03	0.0027	0.0039	0.0015	-52.01	105.13
$CSAD_{FUND}$	SM	NA	2.1E-03	0.0021	0.0025	0.0018	-61.78	96.47
$CSAD_{FUND}$	SOP	AP	2.3E-03	0.0023	0.0070	-0.0002	-79.31	112.02
$CSAD_{FUND}$	SOP	EU	2.3E-03	0.0023	0.0055	0.0008	-64.42	132.65
$CSAD_{FUND}$	SOP	GB	1.8E-03	0.0018	0.0040	0.0004	-84.34	124.74
$CSAD_{FUND}$	SOP	JP	2.7E-03	0.0027	0.0049	0.0013	-52.72	111.53
$CSAD_{FUND}$	SOP	NA	2.2E-03	0.0022	0.0027	0.0016	-83.53	81.22
$CSAD_{NONFUND}$	SBM	AP	-1.4E-18	-0.0006	0.0260	-0.0030	-11.14	7,795
$CSAD_{NONFUND}$	SBM	EU	-1.6E-19	-0.0007	0.0255	-0.0025	-8.27	17,299
$CSAD_{NONFUND}$	SBM	GB	-1.6E-19	-0.0005	0.0190	-0.0021	-11.01	8,934
$CSAD_{NONFUND}$	SBM	JP	-1.1E-18	-0.0007	0.0217	-0.0032	-14.96	4,009
$CSAD_{NONFUND}$	SBM	NA	3.3E-19	-0.0005	0.0181	-0.0023	-9.70	6,200
$CSAD_{NONFUND}$	SI	AP	-8.6E-19	-0.0006	0.0300	-0.0026	-11.03	7,955
$CSAD_{NONFUND}$	SI	EU	-5.5E-19	-0.0007	0.0254	-0.0028	-8.14	17,862
$CSAD_{NONFUND}$	SI	GB	-9.3E-20	-0.0005	0.0194	-0.0021	-10.87	9,452
$CSAD_{NONFUND}$	SI	JP	5.4E-19	-0.0008	0.0224	-0.0035	-14.66	4,682
$CSAD_{NONFUND}$	SI	NA	6.8E-20	-0.0005	0.0177	-0.0022	-9.55	6,176
$CSAD_{NONFUND}$	SM	AP	-6.9E-19	-0.0005	0.0246	-0.0026	-11.45	5,360
$CSAD_{NONFUND}$	SM	EU	-1.7E-18	-0.0006	0.0199	-0.0027	-10.28	15,573
$CSAD_{NONFUND}$	SM	GB	1.8E-19	-0.0004	0.0180	-0.0019	-11.83	7,690
$CSAD_{NONFUND}$	SM	JP	3.5E-19	-0.0007	0.0238	-0.0031	-14.98	4,642
$CSAD_{NONFUND}$	SM	NA	-2.8E-19	-0.0005	0.0178	-0.0022	-9.68	6,382
$CSAD_{NONFUND}$	SOP	AP	-6.1E-19	-0.0006	0.0309	-0.0028	-10.61	8,496
$CSAD_{NONFUND}$	SOP	EU	-3.3E-19	-0.0007	0.0247	-0.0027	-8.25	17,334
$CSAD_{NONFUND}$	SOP	GB	8.3E-19	-0.0005	0.0208	-0.0023	-10.92	9,443
$CSAD_{NONFUND}$	SOP	JP	5.6E-19	-0.0007	0.0227	-0.0030	-17.44	4,101
$CSAD_{NONFUND}$	SOP	NA	-7.2E-19	-0.0005	0.0179	-0.0022	-9.82	5,648

Notes: ADF, augmented Dickey–Fuller test statistic for stationarity of data for maximum 35 lags. Under null hypothesis for variables having unit root, the critical value at 5 percent significance level is -2.87 . $Q(36)$ is the Ljung–Box Q -statistic for serial correlation up to 36 lags. Under the null hypothesis for no serial correlation, the critical value of $\chi^2(36)$ distribution at the 5 percent significance level is 49.80. R_m and $|R_m|^d$ are market return and absolute market return of the respective regional market. D^{UP} and D^{CRISIS} are the up-market and crisis dummy variables, respectively. $CSAD_{FUND}$ and $CSAD_{NONFUND}$ stand for the cross-sectional absolute deviation driven by fundamental and non-fundamental information, respectively

Table I.
Descriptive statistics
of regression variables



Notes: (a) Fundamental CSAD; (b) non-fundamental CSAD

Figure 1.
The visual depiction
of the distributions of
fundamental and non-
fundamental CSAD

-0.002 in the majority of cases. Heavy outliers can be observed for Asia pacific and Europe region common risk-factor CSAD.

5. Empirical findings

5.1 General herd behavior

Table II outlines regression results for herding on fundamental information. The findings suggest that there is no evidence for herding by investors of common risk-factor portfolios for all regions. Although the coefficient Υ_3 is statistically significant at 5 percent significance level, it

Equation		$CSAD_{ft}^{FUND} = \alpha + \gamma_1 R_{mt} + \gamma_2 R_{mt} + \gamma_3 R_{mt}^2 + u_t$					R^2
Risk factor	Region	γ_1	γ_2	γ_3			
SBM	AP	0.026* (23.335)	0.004* (2.406)	0.183* (3.544)		0.37	
SI	AP	0.025* (24.329)	0.003* (2.193)	0.175* (3.601)		0.38	
SM	AP	0.017* (23.873)	0.003* (2.319)	0.119* (3.483)		0.39	
SOP	AP	0.024* (24.467)	0.003* (2.162)	0.168* (3.532)		0.39	
SBM	EU	0.015* (28.172)	0.001 (0.87)	0.063* (2.724)		0.33	
SI	EU	0.014* (27.846)	0.001 (0.985)	0.059* (2.781)		0.32	
SM	EU	0.011* (29.800)	0.001 (0.998)	0.043* (2.330)		0.33	
SOP	EU	0.013* (27.873)	0.001 (0.815)	0.059* (2.628)		0.32	
SBM	GB	0.012* (19.522)	0.002* (2.424)	0.059* (2.278)		0.19	
SI	GB	0.010* (18.373)	0.002* (2.459)	0.052* (2.195)		0.17	
SM	GB	0.008* (18.209)	0.002* (2.621)	0.034** (1.876)		0.17	
SOP	GB	0.011* (17.898)	0.002* (2.421)	0.054* (2.154)		0.17	
SBM	JP	0.011* (19.82)	0.002 (1.621)	0.004 (0.097)		0.26	
SI	JP	0.009* (19.449)	0.002** (1.645)	0.004 (0.118)		0.25	
SM	JP	0.006* (17.557)	0.002** (1.813)	0.004 (0.173)		0.20	
SOP	JP	0.010* (19.529)	0.002 (1.634)	0.004 (0.096)		0.26	
SBM	NA	0.000 (1.595)	0.000 (0.968)	0.018 (1.413)		0.01	
SI	NA	0.001* (2.790)	0.000 (0.948)	0.015 (1.495)		0.01	
SM	NA	0.001* (11.621)	0.000 (0.862)	0.005 (1.045)		0.11	
SOP	NA	0.001* (4.988)	0.000 (1.031)	0.012 (1.331)		0.03	

Notes: Asymptotic *t*-statistic appears in parenthesis. The coefficients are estimated using Newey and West (1987) procedures for the estimate of regression coefficients on the robust standard errors for consistent heteroskedasticity and autocorrelation. *,**Statistically significant at the 5 and 10 percent levels, respectively

Table II.
Herding on
fundamental
information

records a nonnegative value rejecting the null hypothesis for herding. It implies that the investors have no interest for herding towards the common market consensus by mimicking (i.e. trading) the common risk-factors, based on fundamental information, under normal market condition. The R^2 -based measure of goodness of fit is poor in North American common risk-factor CSAD regressions. Herding due to common reaction to fundamental information cannot be observed for any region.

Except for the investment portfolio formed on SI factor for the Asia Pacific markets, the findings of the regression of non-fundamental herding in other markets do not provide any evidence for herding on a daily basis. Overall, there is no sufficient evidence to conclude that common risk-factor portfolio investors herd on a daily basis on fundamental and non-fundamental information in any of the markets considered. This implies that the common risk-factor portfolios are efficient as they are not common risk-factor mimicking portfolios that are subject to herding towards the common market consensus. These findings complement the findings of Chang *et al.* (2000), Henker *et al.* (2006), Demirev and Kutun (2006) and Galariontis *et al.* (2015). The form of market efficiency shown by Fama (1970) is not only based on efficiency of stock trading but also the selection of stocks to the common risk-factor portfolio categories used by Fama and French (2015) affect the efficiency of stock portfolios. Investors trading on current information pertaining to fundamentally sound portfolios may exhibit a similar trading behavior (see especially Bohlin and Rosvall, 2014) under normal market conditions (i.e. when markets are not affected by major macro- and micro-economic events). Overall findings under general CSAD regressions (i.e. fundamental and non-fundamental) suggest that the common risk-factor portfolio investments (i.e. trading) are efficient under normal market conditions. The investors' trading is therefore justified by current information pertaining to securities in the portfolios rather than the common market consensus. Hence, Fama and French (2015) common risk-factor classification provides a more prudent forecast for common stock return variation under normal market conditions (Table III).

Equation		$CSAD_{ft}^{NONFUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 R_{mt} + \Upsilon_3 R_{mt}^2 + u_t$			R^2
Risk factor	Region	Υ_1	Υ_2	Υ_3	
SBM	AP	0.003 (0.442)	0.142* (14.725)	0.119 (0.512)	0.24
SI	AP	0.004 (0.619)	0.150* (15.811)	0.268 (1.211)	0.27
SM	AP	0.003 (0.472)	0.127* (15.458)	-0.551* (-2.78)	0.15
SOP	AP	0.004 (0.672)	0.147* (16.355)	0.303 (1.333)	0.28
SBM	EU	-0.004 (-1.154)	0.128* (10.301)	0.619* (2.038)	0.27
SI	EU	-0.004 (-1.027)	0.133* (10.834)	0.621* (2.162)	0.28
SM	EU	-0.005 (-1.319)	0.121* (10.213)	-0.109 (-0.382)	0.19
SOP	EU	-0.004 (-1.123)	0.130* (10.524)	0.564** (1.924)	0.27
SBM	GB	-0.002 (-0.638)	0.080* (9.451)	1.140* (4.422)	0.20
SI	GB	-0.002 (-0.478)	0.087* (10.564)	1.309* (5.381)	0.24
SM	GB	-0.003 (-0.745)	0.080* (8.665)	0.543 (1.586)	0.15
SOP	GB	-0.002 (-0.685)	0.094* (10.627)	1.218* (4.375)	0.24
SBM	JP	-0.004 (-1.167)	0.105* (9.714)	0.275 (1.05)	0.16
SI	JP	-0.003 (-0.963)	0.107* (11.104)	0.180 (0.801)	0.16
SM	JP	-0.005 (-1.534)	0.104* (10.09)	-0.059 (-0.241)	0.13
SOP	JP	-0.004 (-1.178)	0.106* (10.058)	0.209 (0.812)	0.16
SBM	NA	0.011* (3.000)	0.089* (10.107)	-0.347 (-1.519)	0.09
SI	NA	0.012* (3.38)	0.090* (10.48)	-0.254 (-1.122)	0.11
SM	NA	0.010* (2.946)	0.095* (10.205)	-0.214 (-0.798)	0.13
SOP	NA	0.012* (3.462)	0.092* (11.471)	-0.278 (-1.377)	0.11

Notes: Asymptotic *t*-statistic appears in parenthesis. The coefficients are estimated using Newey and West (1987) procedures for the estimate of regression coefficients on the robust standard errors for consistent heteroskedasticity and autocorrelation. *,**Statistically significant at the 5 and 10 percent levels, respectively

Table III. Herding on non-fundamental information

5.2 Herd behavior in the crisis period

Table IV outlines the regression results for herd behavior in the crisis periods. To the authors' surprise, the regression results suggest that the common risk-factor portfolio investors herd on fundamental information during the crisis periods. The coefficient Υ_4 applicable to crisis dummy is negative and statistically significant for common risk-factor portfolios of European and Japanese markets. CSAD derived from risk-factor portfolio sorted on SBM for Globe is subject to herding at 10 percent significance levels. Only SM risk-factor portfolio investors herd on a daily basis in North American markets at 5 percent significance level. These findings unearth stylistic facts about changes in behavior of investors in major economic events such as economic or financial crisis. Investors may tend to herd during crisis periods due to panic selling or force-sale of shares by the lending institutions (see e.g. Hope, 2011; Huang *et al.*, 2011). A number of scholars have shown evidence for herding during major economic events (e.g. crisis, major news release, etc.) in other settings (see e.g. Bowe and Domuta, 2004; Bikhchandani and Sharma, 2000; Yao *et al.*, 2014; Galariotis *et al.*, 2015; Litimi *et al.*, 2016; Bekiros *et al.*, 2017; Humayun Kabir, 2018; Indārs *et al.*, 2019). The herd behavior of investors could be observed during economic crisis period, due to investor reaction to changes in fundamental information.

Madrigal (1996) argues that speculation on non-fundamental information (i.e. not private information on fundamental values of assets) is driven by the market consensus about certain factors pertaining to stock market environment. This research finding could be further validated, if investors of fundamentally sound stock portfolios such as Fama–French common risk-factor portfolios herd toward the market agreement. Fama–French portfolio investors mimic the underlying risk factors in returns related to SBM value, SOP, SI and SM of the equity stocks for Europe and Japan. The magnitude of herding exposure to variation in average returns is sufficient to provide strong challenges in asset pricing tests. Chiang and Zheng (2010) more specifically argue that during periods of extreme market conditions, investors tend to suppress their private information in favor of the market consensus and are

Equation		$CSAD_{ft}^{FUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 R_{mt} + \Upsilon_3 R_{mt}^2 + \Upsilon_4 D^{crisis} R_{mt}^2 + u_t$						R^2
Risk factor	Region	Υ_1	Υ_2	Υ_3	Υ_4			
SBM	AP	0.026* (23.602)	0.002 (1.203)	0.302* (3.029)	-0.108 (-1.345)	0.37		
SI	AP	0.025* (24.615)	0.002 (1.033)	0.284* (3.117)	-0.100 (-1.365)	0.38		
SM	AP	0.017* (24.145)	0.002 (1.183)	0.193* (2.977)	-0.068 (-1.291)	0.39		
SOP	AP	0.024* (24.745)	0.002 (1.038)	0.272* (3.094)	-0.095 (-1.339)	0.39		
SBM	EU	0.015* (28.795)	0.000 (0.173)	0.105* (3.475)	-0.044** (-1.838)	0.33		
SI	EU	0.014* (28.397)	0.000 (0.328)	0.096* (3.451)	-0.038** (-1.711)	0.32		
SM	EU	0.012* (30.45)	0.000 (0.363)	0.074* (3.149)	-0.032** (-1.807)	0.33		
SOP	EU	0.014* (28.517)	0.000 (0.133)	0.099* (3.391)	-0.041** (-1.836)	0.32		
SBM	GB	0.012* (19.746)	0.001 (1.312)	0.130* (2.603)	-0.067** (-1.684)	0.19		
SI	GB	0.010* (18.546)	0.001 (1.441)	0.110* (2.407)	-0.054 (-1.502)	0.17		
SM	GB	0.008* (18.307)	0.001** (1.747)	0.069* (2.015)	-0.034 (-1.221)	0.17		
SOP	GB	0.011* (18.064)	0.001 (1.425)	0.114* (2.383)	-0.056 (-1.486)	0.17		
SBM	JP	0.011* (19.796)	0.001 (0.978)	0.060** (1.758)	-0.056* (-2.06)	0.27		
SI	JP	0.009* (19.399)	0.001 (1.065)	0.053** (1.727)	-0.049* (-1.013)	0.25		
SM	JP	0.006* (17.49)	0.001 (1.303)	0.037** (1.767)	-0.033** (-1.92)	0.20		
SOP	JP	0.010* (19.487)	0.001 (1.044)	0.056** (1.686)	-0.053* (-1.997)	0.26		
SBM	NA	0.000 (1.601)	0.000 (0.556)	0.030 (1.474)	-0.010 (-0.744)	0.01		
SI	NA	0.001* (2.808)	0.000 (0.414)	0.027** (1.715)	-0.011 (-1.011)	0.01		
SM	NA	0.001* (11.866)	0.000 (-0.519)	0.022* (2.461)	-0.016* (-2.364)	0.11		
SOP	NA	0.001* (5.045)	0.000 (0.281)	0.029* (1.966)	-0.015 (-1.492)	0.03		

Table IV.
Herding in crisis periods – fundamental information

Notes: Asymptotic *t*-statistic appears in parenthesis. The coefficients are estimated using Newey and West (1987) procedures for the estimate of regression coefficients on the robust standard errors for consistent heteroskedasticity and autocorrelation. *,**Statistically significant at the 5 and 10 percent levels, respectively

more likely to mimic collective actions in investment decision making. As such, the clusters in stock returns can be observed as investors move in unison under market stress (i.e. extreme market conditions). Conversely, herding can also occur when investors lack of fundamental information due to inefficient information disclosures in the markets (Chang *et al.*, 2000). Table V reports the regression results for non-fundamental herding during the crisis periods. The regression outcome does not provide any evidence for the presence of herding on non-fundamental factors during the crisis periods. It is apparent from these findings that the common risk-factor portfolios are not subject to herding as investors do not mimic non-fundamental factors (portfolio or stock specific factors) affecting stock prices. However, when crisis dummy is controlled for in the regression, coefficient Υ_3 of all risk-factor portfolios of North American and risk-factor portfolio of SM of Asia Pacific markets become negative and statistically significant. This suggests that the investors mimic non-fundamental factors relating to market crisis (e.g. restriction on firm’s borrowing, force-selling of heavy margined stocks, and changes to capital requirements of firms, etc.) that may affect individual firms because Υ_3 becomes significant and negative when the crisis dummy D^{crisis} is controlled for in the regression.

5.3 Herd behavior in up-markets

A number of scholars have shown that herd behavior is more pronounced during up- and down-market conditions (see e.g. Chiang and Zheng, 2010; Ouarda *et al.*, 2013; Litimi *et al.*, 2016; BenSaida, 2017). In particular, Hwang and Salmon (2004) document evidence for herding in bullish and bear market conditions for the US and South Korean markets. During high bullish periods, the investors may tend to follow the trading patterns of majority of investors who possess information (e.g. fundamental information) pertaining to stock portfolios (see e.g. Tan *et al.*, 2008; Mabrouk Houda and Mohamed, 2013). The regression

Equation		$CSAD_{ft}^{NONFUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 R_{mt} + \Upsilon_3 R_{mt}^2 + \Upsilon_4 D^{crisis} R_{mt}^2 + u_t$					R^2
Risk factor	Region	Υ_1	Υ_2	Υ_3	Υ_4		
SBM	AP	0.002 (0.34)	0.150* (12.872)	-0.432 (-0.802)	0.504 (1.087)	0.24	
SI	AP	0.003 (0.54)	0.156* (12.264)	-0.201 (-0.296)	0.429 (0.749)	0.27	
SM	AP	0.003 (0.434)	0.130* (13.445)	-0.758** (-1.72)	0.189 (0.502)	0.15	
SOP	AP	0.003 (0.552)	0.156* (13.615)	-0.367 (-0.657)	0.613 (1.284)	0.28	
SBM	EU	-0.005 (-1.195)	0.130* (10.16)	0.530 (0.972)	0.092 (0.200)	0.27	
SI	EU	-0.004 (-1.026)	0.133* (10.365)	0.654 (1.16)	-0.034 (-0.071)	0.28	
SM	EU	-0.005 (-1.364)	0.122* (10.191)	-0.187 (-0.364)	0.081 (0.188)	0.19	
SOP	EU	-0.004 (-1.124)	0.129* (9.844)	0.599 (1.061)	-0.036 (-0.078)	0.27	
SBM	GB	-0.002 (-0.657)	0.083* (7.737)	0.908 (1.34)	0.220 (0.407)	0.20	
SI	GB	-0.002 (-0.486)	0.088* (7.905)	1.242** (1.691)	0.064 (0.109)	0.24	
SM	GB	-0.003 (-0.754)	0.081* (8.329)	0.476 (0.782)	0.064 (0.126)	0.15	
SOP	GB	-0.003 (-0.705)	0.096* (8.324)	1.009 (1.346)	0.198 (0.332)	0.24	
SBM	JP	-0.004 (-1.15)	0.112* (9.128)	-0.028 (-0.076)	0.305 (1.046)	0.16	
SI	JP	-0.003 (-0.934)	0.116* (9.914)	-0.268 (-0.777)	0.452 (1.574)	0.16	
SM	JP	-0.005 (-1.524)	0.109* (9.598)	-0.303 (-0.962)	0.246 (0.941)	0.13	
SOP	JP	-0.004 (-1.161)	0.111* (9.327)	-0.029 (-0.08)	0.241 (0.814)	0.17	
SBM	NA	0.011* (2.977)	0.099* (9.291)	-0.976* (-2.263)	0.574** (1.803)	0.09	
SI	NA	0.012* (3.351)	0.098* (9.861)	-0.752** (-1.936)	0.454 (1.586)	0.11	
SM	NA	0.010* (2.939)	0.107* (9.807)	-0.986* (-2.267)	0.705* (2.188)	0.13	
SOP	NA	0.012* (3.438)	0.100* (10.705)	-0.770* (-2.144)	0.449** (1.664)	0.11	

Notes: Asymptotic *t*-statistic appears in parenthesis. The coefficients are estimated using Newey and West (1987) procedures for the estimate of regression coefficients on the robust standard errors for consistent heteroskedasticity and autocorrelation. *, **Statistically significant at the 5 and 10 percent levels, respectively

Table V. Herding in crisis periods – non-fundamental

results show that only Japanese common risk-factor portfolios are subject to herding on fundamental information during up-market condition as coefficient Υ_4 is negative and statistically significant for risk-factor portfolio SI at 5 percent and others risk factors at 10 percent statistical significance level. These observations are consistent with the findings of Zhou and Lai (2009), Chiang and Zheng (2010) and Chen *et al.* (2017) who document differences in herd behavior among geographical regions. Moreover, the herd behavior of investors of global common risk-factor portfolios appears when up-market dummy is controlled for in the regression. This clearly shows that the global risk-factor portfolio investors herd on fundamental factors relating to bullish market conditions (e.g. conclusion of war, major micro- and macroeconomic announcements, etc.) (Table VI).

Table VII outlines the results of herding on non-fundamental information during up-market periods. The herding regression results do not provide any evidence for herding on non-fundamental factors under up-market condition. Again, these findings further confirm that the common risk-factor portfolio investors do not herd on non-fundamental information (i.e. mimicking non-fundamental factors) pertaining to stock trading during up-market periods. Galarotis *et al.* (2015) find similar results for UK markets while their findings on US markets support herding on non-fundamental factors by the investors. Moreover, all five common risk-factor portfolio investors of Asia Pacific and North American markets exhibit herding on non-fundamental factors relating to bullish conditions (e.g. increase in firms' cash flows due to reduction in minimum salary by governments, investments in positive NPV projects) when up-market dummy is controlled for in the regression.

6. Concluding remarks

The essence of Fama and French (1993, 2015) common risk-factor regressions is that a linear combination of observed factors of an asset pricing model could be effectively explained by

Equation		$CSAD_{ft}^{FUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 R_{mt} + \Upsilon_3 R_{mt}^2 + \Upsilon_4 D^{up} R_{mt}^2 + u_t$					R^2
Risk factor	Region	Υ_1	Υ_2	Υ_3	Υ_4		
SBM	AP	0.025* (20.668)	0.004* (2.456)	0.173* (2.157)	0.023 (0.240)	0.37	
SI	AP	0.024* (22.000)	0.003* (2.234)	0.155* (2.212)	0.045 (0.545)	0.38	
SM	AP	0.017* (40.403)	0.003* (4.003)	0.109* (6.527)	0.023 (1.014)	0.00	
SOP	AP	0.023* (22.117)	0.003* (2.209)	0.143* (2.076)	0.057 (0.708)	0.39	
SBM	EU	0.014* (21.186)	0.001 (0.946)	0.059* (2.168)	0.007 (0.161)	0.33	
SI	EU	0.014* (20.987)	0.001 (1.03)	0.060* (2.464)	-0.002 (-0.051)	0.32	
SM	EU	0.011* (21.127)	0.001 (1.18)	0.030 (1.422)	0.022 (0.667)	0.33	
SOP	EU	0.013* (20.707)	0.001 (0.91)	0.053* (2.013)	0.011 (0.264)	0.32	
SBM	GB	0.010* (12.09)	0.003* (3.000)	-0.066** (-1.759)	0.216* (4.912)	0.20	
SI	GB	0.008* (11.134)	0.003* (3.034)	-0.061** (-1.814)	0.195* (4.903)	0.18	
SM	GB	0.006* (10.478)	0.002* (3.056)	-0.058* (-2.442)	0.159* (5.190)	0.18	
SOP	GB	0.008* (10.683)	0.003* (3.029)	-0.069** (-1.938)	0.213* (5.050)	0.17	
SBM	JP	0.012* (16.093)	0.002 (0.967)	0.083 (1.137)	-0.114** (-1.787)	0.27	
SI	JP	0.011* (16.524)	0.001 (0.990)	0.078 (1.227)	-0.106** (-1.974)	0.25	
SM	JP	0.007* (14.573)	0.001 (1.143)	0.050 (1.084)	-0.067** (-1.699)	0.20	
SOP	JP	0.012* (16.583)	0.001 (0.981)	0.084 (1.221)	-0.116** (-1.955)	0.26	
SBM	NA	-0.001 (-1.449)	0.001 (1.345)	-0.017 (-1.193)	0.068* (3.097)	0.02	
SI	NA	0.000 (-0.411)	0.000 (1.292)	-0.012 (-0.992)	0.051* (2.875)	0.02	
SM	NA	0.001* (5.986)	0.000 (1.086)	-0.008 (-0.907)	0.024** (1.741)	0.11	
SOP	NA	0.000 (0.905)	0.000 (1.419)	-0.015 (-1.274)	0.052* (3.065)	0.03	

Table VI.
Herding in
up-markets –
fundamental

Notes: Asymptotic t -statistic appears in parenthesis. The coefficients are estimated using Newey and West (1987) procedures for the estimate of regression coefficients on the robust standard errors for consistent heteroskedasticity and autocorrelation. *,**Statistically significant at the 5 and 10 percent levels, respectively

Equation		$CSAD_{ft}^{NONFUND} = \alpha + \Upsilon_1 R_{mt} + \Upsilon_2 R_{mt} + \Upsilon_3 R_{mt}^2 + \Upsilon_4 D^{up} R_{mt}^2 + u_t$					R^2
Risk factor	Region	Υ_1	Υ_2	Υ_3	Υ_4		
SBM	AP	-0.037* (-6.284)	0.140* (13.931)	-1.124* (-5.048)	2.796* (5.817)	0.26	
SI	AP	-0.038* (-6.244)	0.147* (14.899)	-1.053* (-4.524)	2.971* (5.901)	0.29	
SM	AP	-0.027* (-5.218)	0.125* (14.741)	-1.468* (-7.545)	2.064* (4.573)	0.16	
SOP	AP	-0.037* (-6.206)	0.144* (14.256)	-0.985* (-3.670)	2.897* (5.711)	0.30	
SBM	EU	-0.027* (-5.156)	0.134* (11.898)	-0.315 (-1.175)	1.570* (4.298)	0.28	
SI	EU	-0.027* (-5.279)	0.139* (12.376)	-0.320 (-1.223)	1.581* (4.526)	0.29	
SM	EU	-0.024* (-4.979)	0.126* (12.207)	-0.902* (-3.631)	1.333* (4.105)	0.19	
SOP	EU	-0.027* (-5.173)	0.135* (12.124)	-0.364 (-1.362)	1.560* (4.359)	0.27	
SBM	GB	-0.023* (-4.103)	0.085* (10.242)	0.096 (0.257)	1.798* (3.291)	0.21	
SI	GB	-0.023* (-3.927)	0.092* (11.25)	0.236 (0.625)	1.847* (3.213)	0.25	
SM	GB	-0.021* (-4.269)	0.084* (10.481)	-0.378 (-0.976)	1.586* (3.355)	0.16	
SOP	GB	-0.024* (-4.169)	0.099* (11.476)	0.131 (0.319)	1.872* (3.275)	0.25	
SBM	JP	-0.001 (-0.179)	0.104* (11.177)	0.408** (1.671)	-0.193 (-0.440)	0.16	
SI	JP	-0.001 (-0.203)	0.106* (12.798)	0.273 (1.183)	-0.135 (-0.329)	0.16	
SM	JP	0.003 (0.589)	0.100* (11.333)	0.306 (1.299)	-0.531 (-1.499)	0.13	
SOP	JP	-0.003 (-0.452)	0.106* (11.843)	0.264 (1.209)	-0.080 (-0.187)	0.16	
SBM	NA	-0.006 (-1.354)	0.090* (10.65)	-0.975* (-3.814)	1.188* (3.37)	0.09	
SI	NA	-0.004 (-0.991)	0.092* (10.974)	-0.851* (-3.703)	1.129* (3.398)	0.11	
SM	NA	-0.002 (-0.505)	0.096* (9.555)	-0.646** (-1.840)	0.819* (2.538)	0.13	
SOP	NA	-0.005 (-1.255)	0.094* (11.964)	-0.927* (-3.911)	1.228* (3.986)	0.11	

Table VII.
Herding in
up-markets –
non-fundamental

Notes: Asymptotic t -statistic appears in parenthesis. The coefficients are estimated using Newey and West (1987) procedures for the estimate of regression coefficients on the robust standard errors for consistent heteroskedasticity and autocorrelation. *,**Statistically significant at the 5 and 10 percent levels, respectively

a linear combination of unobserved risk factors, if stock market efficiency is established. The validity of these models is therefore based upon how efficient the common risk-factor portfolios are traded. More importantly, Blanco (2012) show that results of Fama–French three-factor regression is based upon how the portfolios are formed (e.g. characteristics relating to risk factors). Therefore, inefficient portfolio (e.g. portfolio of stocks that were subject to herding) selection may have a significant impact on model specification and performance. The initial work of Fama and French (1993) has shown that the stock return could be explained by an overall market factor and factors relating to size and book-to-market value. Two important factors such as *RMW* and *CMA* are added to describe stock return variation in their subsequent paper (Fama and French, 2015). If the markets are integrated, asset pricing models should also explain return variations of other markets (e.g. bond). The question of whether the model is fit enough to explain the true underlying process of common stock return variation depends on how efficient the common risk-factor portfolios are selected and traded.

The regression results do not provide evidence for herding under normal market conditions, either when reacting to fundamental information or non-fundamental information, for any region under consideration. However, the common risk-factor portfolio formed on SM is subject herding at 5 percent significance level for Asia Pacific region. Although there is no tendency to herd under normal market conditions, the evidence shows that the investor behavior changes significantly in the event of a crisis. The results suggest suggests that Fama–French common risk-factor portfolio investors mimic the underlying risk factors in returns related to SBM, SOP, SI and SM of the equity stocks of Europe and Japan during the crisis periods. These changes in the behavior of investors have been largely attributed to investor panic by a number of scholars (see e.g. Hope, 2011; Huang *et al.*, 2011). No evidence for herding on non-fundamental information is found during crisis periods. However, the investors of North American market (for all risk-factor regressions) and investors of risk-factor portfolio of size and momentum of Asia Pacific markets tend to mimic non-fundamental factors relating to market crisis (e.g. restriction on firm's borrowing and changes to capital requirements of firms etc.) during crisis period. These findings unearth stylist facts about the changes in behavior of investors in major economic events such as economic or financial crisis. A number of scholars have shown that tendency to herd differs greatly between up- and down-market conditions (see especially Chiang and Zheng, 2010). The results of herding regressions with up-market dummy show that there is no sufficient evidence to conclude on investor herding during up-markets, either when reacting to fundamental or non-fundamental information. Further evidence suggests that the investors tend to mimic non-fundamental factors relating to market crisis during the crisis period in North American market for all risk-factor regressions. SM risk-factor portfolio investors tend to mimic non-fundamental factors in Asia Pacific markets. Moreover, all five common risk-factor portfolio investors of Asia Pacific and North American markets exhibit herding on non-fundamental factors relating to bullish market conditions and the global risk-factor portfolio investors herd on fundamental factors relating to bullish conditions (examples are given under discussion section).

The overall findings of the study suggest that the common risk factors recognized by Fama and French (1993, 2015) provide a more prudent basis for explaining common stock return variations under normal market conditions (i.e. except crisis market conditions). Griffin (2002) shows that country-specific Fama–French factor models effectively explain variation in portfolio returns than global-factor model. He also demonstrates that, although the five-factor model is shown to provide significant improvements compared to previous asset pricing models, its performance depends upon the efficiency of stocks selected for common risk-factor portfolios. The empirical approach followed in this paper therefore provides a behavioral interpretation for the ability of Fama–French common-risk-factor regressions to explain asset returns.

7. Implications for further research

Although the evidence suggests that Fama–French five-factor regression seems to be well specified under normal market conditions, the common risk-factor portfolio investors tend to herd on fundamental information during crisis periods. This finding sheds new light on further explaining the variation in equity returns. Further research on new risk factors explaining stock return variation may help improve the model performance. The performance can be improved by adding new risk factors that are free from behavioral bias but significant in explaining common stock return variation. Also, it is necessary to revisit the existing common risk factors in order to understand behavioral aspects that may affect cost of capital calculations (e.g. pricing errors) and valuation of investment portfolios. The model could also be improved by a careful analysis of fundamental factors – for example, large borrowing stocks, stocks subject to industry regularity concerns, bubble-stocks, etc. – affecting stock prices during extreme market conditions (i.e. market crisis situation). The five-factor model is unlikely to settle in the main asset pricing debate, unless revisited from behavioral perspective.

Notes

1. Note that herding on non-fundamental information results in efficient outcome in the trading process (see Literature review for discussion).
2. Galariotis *et al.* (2015) view this as a measure of clustering due to investors responding to fundamental information.
3. Regression for detecting herding during down-market is not considered as herding during crisis periods is examined.
4. Data are also available from the Center for Research in Security Prices (CRSP) at www.crsp.com/
5. The classification is given as small, 2, 3, 4 and big.

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About the author

Chamil W. Senarathne is PhD Student of the School of Economics, Wuhan University of Technology. He received Bachelor's Degree from the University of Sri Jayewardenepura, Sri Lanka and Master's Degree (MBA in Finance) from the University of Colombo, Sri Lanka. He is Member of the Chartered Institute of Management Accountants of UK and designated Chartered Global Management Accountant. He is also Member of the Institute of Chartered Accountants of Sri Lanka. Prior to joining Wuhan University of Technology, he has worked in the stockbroking and margin trading industry in Sri Lanka for seven years. He has spent 10 years working in the accounting and finance industry including liquidation of companies and the auditing services sector in Sri Lanka. His research interest includes financial markets, finance and financial economics. Chamil W. Senarathne can be contacted at: chamil@whut.edu.cn

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