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Did Investors Herd during the Financial Crisis? Evidence from the US Financial Industry

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ABSTRACT

We examine the herding behavior of investors in the US financial industry, especially commercial banks, S&Ls, investment and insurance firms during global financial crisis of 2008 towards own sub-sector and market consensus using augmented cross sectional absolute deviation of returns (CSAD) model. After distinguishing between fundamental and non-fundamental information, we find a greater influence of global financial crisis on spurious herding for commercial and investment banks, and such herding increases in the down market and with conditional volatility of returns, but adverse herding is prevalent among investors during normal period in response to fundamental information. We also find that herding intensity on fundamental information is relatively high with market consensus for all financial institutions except insurance firms in high volatility regime, and intentional herding is only significant and limited to S&Ls and investment banks in high volatility regime. Our findings suggest limited spillover effects of herding when investors face non-fundamental information.

JEL Codes: G11; G12; G21; G29

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I. INTRODUCTION

Herding behavior emerges when individuals ignore or suppress their own belief or private signal and follow the actions of other individuals or investors. Early studies focus on rational herding showing that such behavior may be optimal as individuals, who are followed by others may possess important information (Bikhchandani et al. 1992), and managers or analysts want to protect reputation (Scharfstein and Stein 1990; Trueman 1994; Graham 1999) or insure against underperformance with peers (Rajan 2006). However, Froot et al. (1992) show that naïve investors may herd in short investment horizon to exploit the informed investors. Other studies depart from investors' rationality and put more emphasis on the presence of irrational and psychological or sentiment that affect trading behavior leading to herd phenomena (Shleifer and Summers 1990; DeLong et al. 1991; Cipriani and Guarino 2005). If the correlated behavior of investors due to suppression of private information leads to the situation when the market price fails to reflect fundamental information, herding can result in extreme effects in mispricing and inefficiency in the asset market. Studies based on trading data by institutional investors find mixed evidence of herding (Lakonishok et al. 1992; Grinblatt et al. 1995; Nofsinger and Sias 1999; Sias 2004; Choi and Sias 2009; Brown et al. 2013; Holmes et al. 2013).[1] Methodologically different from such studies, Gleason et al. (2004), Tan et al. (2008), Zhou and Lai (2009), Chiang and Zheng (2010), Gębka and Wohar (2013), and Chiang et al. (2013) use aggregate market data to detect herd behavior by investors across markets or sectors following Chang et al. (2000).

The purpose of the present study is to examine the herding behavior of investors in the US financial industry, especially commercial banks, savings and loan institutions (S&L), investment and insurance firms during global financial crisis of 2008 following the methodology of Chang et al. (2000). The epicenter of the 2007–2008 financial crisis was the banks and other financial institutions. The crisis was triggered by the revelation of losses faced by major financial institutions from subprime mortgages. Later, subsequent losses due to counterparty exposures resulted in systemic risk with collapse and near-failure of major banks. Beltrattia and Stulz (2012) find that the buy-and-hold dollar return of larger banks worldwide was −51.84% with standard dev iation of 27.74% during the period of 2007–2008 crisis, which is extremely high. The interconnectedness and the complexity of financial structure and institutions have contributed to such systemic failure. For example, although insurance industry did not have direct exposure to the financial crisis, American International Group (AIG), the world's largest insurance company, was on the verge of collapse. The fact is that AIG was a complex financial group, consisting of 70 US-based insurance companies and another more than 170 other financial service companies. The complexity of such interconnections created through credit default swaps and securities lending resulted in AIG to be an important counterparty to other systemically important banks. The losses and systemic risk during 2007–2008 reached to such an extent that Fed and Treasury had to come up with the plan to rescue banks, and prevent disorderly winding of exposed financial institutions.[2] Treasury established several programs under TARP to stabilize banking institutions, restart credit markets, and avoid foreclosures.[3]

1 More discussion is presented in literature review in section II.

2 A comprehensive financial crisis timeline and policy actions have been documented by Federal Reserve Bank of St Louis, and available online: https://www.stlouisfed.org/financial-crisis/full-timeline

3 Congress initially authorized $700 billion for TARP in October 2008, which was reduced to $475 billion by the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act). Approximately $250 billion of that amount was committed in programs to stabilize banking institutions, $27 billion was committed through programs to restart credit markets, $70 billion was committed to stabilize American International Group (AIG), and Treasury purchased $20 billion in preferred stock from two institutions, Citigroup Inc. and Bank of America. Treasury also provided capital to 707 financial institutions in 48 states, including more than 450 small and community banks and 22 certified community development financial institutions (CDFIs). The largest investment was $25 billion and the smallest was $301,000.

Given the extent and depth of the crisis, it is worthwhile to examine how investors buying and selling financial stocks behave in the market when financial institutions were facing hurdles as their interdependence through different channels exerting systemic risks. Did the investors participate based on their own belief or swayed away by other investors when defaults on mortgages spread to investment banks and commercial banks via an elaborate network of derivatives? Did the ripple effects of the demise of some financial institutions as well as the evaporation of liquidity through the interaction of market liquidity and funding liquidity result in nervousness in investors' psyche generating market transactions following each other? Previous studies concentrate examining mostly herding in national markets leaving sector-level herding, especially in the financial sector which was vital during the financial crisis of 2007–2008.[4]

Diamond and Dybvig (1983), Swary (1986), and Lang and Stulz (1992) have shown how a bank-specific event or bank-specific trouble can create shock to other banks and affects the whole financial sector. Similarly, investors' expectations, beliefs, and memories of past crises (Masson 1998 and Mullainathan 1998), and information asymmetry between the informed and uninformed investors (Clavo 1999) can generate contagious effects in response to a crisis. James (1991) suggests that the direct costs of bank failures are larger than that of bankruptcy of non-financial firms. Acharya and Yorulmazer (2008) develop a model to explore various aspects of systemic risk analyzing the *ex-ante* effects of bank failures and losses, and likelihood of information contagion that induce profit maximizing bank owners to herd with other banks.

Herding behavior is manifested in an increased similarity of returns across stocks resulting in a lower cross-sectional variability of returns. Chang et al. (2000) propose a measure of cross-sectional variability of returns, CSAD, cross-sectional absolute standard deviation with respect to the average return of all stock returns. Chiang et al. (2013) find that herding is time-varying and depends on prevailing market returns and conditional volatility. Motivated by Chiang et al. (2013), we augment the base CSAD model to explore the possibility of herding towards own sub-sector as well as the market (for example, commercial banks herding towards the consensus or equally weighted returns of all commercial banks, and equally weighted returns of CRSP firms). However, Gębka and Wohar (2013) argue that there might be an increased dispersion in returns across assets leading to adverse herding when investors overemphasize their own view or focus on views dominant among subset of actors excessively ignoring market information. We also explore such possibility, which might be due to localized herding (Gębka and Wohar 2013), excessive "flight to quality" during market stress (Favero and Giavazzi 2002; Kaminsky et al. 2004; Baur and

4 Gębka and Wohar (2013) find no evidence of herding using DataStream sectoral indices in a global scale. They also find that some sector-specific indices like basic materials, consumer services, and oil and gas reveal traders' irrationality, which could be due to overconfidence, or excessive flight to quality.

Lucey 2009; Berger and Turtle 2011; Davis and Madura 2012), and overconfidence (Goodfellow et al. 2009).

Second, Bikhchandani and Sharma (2001) differentiate spurious or unintentional herding driven by fundamental information from intentional herding, which is driven by non-fundamentals. Holmes et al. (2013) note that while informational cascades may lead to intentional herding, the characteristic trading (momentum, contrarian, value versus growth, small versus big) may result in unintentional or spurious herding. If herding is unintentional, then it is expected that investors' behavior should not be affected by market returns and volatility. In contrast, if herding is intentional, then the extent of any such behavior should show some relation between market returns and volatility. Following Galariotis et al. (2015), we decompose cross-sectional return deviations to deviations due to reaction to fundamental information and deviations due to non-fundamentals using common risk factors like Small Minus Big return, High Minus Low return (Fama and French 1995, 1996), and Momentum factors (Carhart 1997). Such methodology helps us to isolate and identify the relation between intentional or spurious herding and market return, and volatility.

Third, methodologically, this paper differs from other previous studies as we apply Seemingly Unrelated Regression (SUR) method in all CSAD regressions rather than simple OLS. This is because the returns of the sample firms of the same industry measured over a common time-period are contemporaneously correlated, the residuals are not independently and identically distributed. Moreover, the SUR method assumes that the variances of disturbances differ across equations (Cornett and Tehranian 1990; Kabir and Hassan 2005).

Fourth, following the methodology proposed by Teräsvirta (1994), we use nonlinear method of the smooth transition regression (STR) model to examine whether volatility exhibits substantial nonlinearity with regimes switches, and how herding behavior is evolved in high and low volatility regimes. Finally, we explore the spillover effects among financial institutions in the framework of STR model.

The remainder of this paper is organized as follows. Section II presents a brief review of literature followed by the empirical design in section III. Section IV describes the data and summary statistics. Sections V and VI report empirical evidence of herding behavior using different models. Section VII concludes.

II. A BRIEF REVIEW OF LITERATURE

Methodologies aiming at herding by institutional investors use trading data and find mixed results. Evidence on US pension and mutual fund managers (Lakonishok et al. 1992; Grinblatt et al. 1995) is not strong enough to support the presence of herd behavior. On the other hand, Nofsinger and Sias (1999), Sias (2004), Choi and Sias (2009), Choi and Sias (2009), and Walter and Weber (2006) find significant herding effects generated by institutional investors who follow positive feedback trading strategies. Wermers (1999) finds higher level of herding among growth-oriented funds than among income funds as the growth funds possess less precise information about future earnings. Welch (2000) finds that herding towards consensus among financial analysts is less likely to be caused by fundamental information, and herding is stronger in times when recent returns are positive and consensus is optimistic. In a recent study, Brown et al. (2013) show that mutual fund managers have a greater tendency to herd on negative stock information, given the greater reputational and litigation risk of holding losing stocks, and herding effect is stronger with analyst downgrades. Holmes et al. (2013) also identify reputational concern among fund managers who are likely to know one another and know the relative strengths of each manager by examining herding within a concentrated market. Dasgupta et al. (2011) devise a model showing that the presence of institutional herding among career-concerned money managers, which is positively correlated with short-term returns, but negatively correlated long-term returns. Thus, herding has a stabilizing effect in the short term and a destabilizing effect in the long term. On the other hand, Hsieh (2013) examines herding among institutional and individual investors using high frequency data from Taiwan, and finds that stronger herding effects in trading of institutional investors. Villatoro (2009) devises a model to show that intermediaries with poor reputation tend to imitate others who have high reputation and prone to invest in information.

Methodologically different than the above-mentioned papers, other studies use aggregate market data to examine herding towards the consensus or market following Christie and Huang (1995), and Chang et al. (2000). While the former study employs the cross-sectional standard deviation of returns (CSSD) to detect herding and find no evidence of herding, the later one finds significant evidence of herding for South Korea and Taiwan, Japan but no evidence for the US and Hong Kong using cross-sectional absolute standard deviation (CSAD).[5] Gleason et al. (2004) use data on US Exchange Traded Funds and find no herding during periods of extreme market moves. Boyer et al. (2006), and Chiang et al. (2007) show that the herding activity deepens market crises following the spread of contagion effects across markets. While Demirer and Kutan (2006) find no evidence of herding in the Chinese A and B share market, Tan et al. (2008) report herding in both rising and falling market conditions. However, Zhou and Lai (2009) report significant herding behavior in falling markets than rising markets in Hong Kong equity market. Chiang and Zheng (2010) find evidence of herd behavior in many advanced stock markets and Asian markets, but no evidence of herding for the US and the Latin American markets among 18 markets. Klein (2013) examines whether

5 Chang et al. (2000) find the CSSD measure tends to be sensitive to outliers. Hwang and Salmon (2004) follow different approach using cross-sectional dispersion of betas and find evidence consistent with herding for the US and South Korean equity markets irrespective of the condition of the market. However, the Asian and Russian financial crises reduce rather than increase herding.

herding is time varying using Markov regime switching model and find evidence consistent with herding during periods of turmoil and high volatility. However, using DataStream national and sectoral indices in a global scale, Gębka and Wohar (2013) find no evidence of herding, and some sector-specific indices like basic materials, consumer services, and oil and gas reveal traders' irrationality, which could be due to overconfidence, or excessive flight to quality.

Chiang et al. (2013) identify limitations of constant coefficient model and use a time-varying model for a number of Pacific-Basin equity markets, and find that herding is positively related to state of market return, but negatively related to market volatility. Moreover, herding coefficients are positively correlated across markets implying interdependence of herding behavior in the region. Galariotis et al. (2015) examine herding towards the market consensus for US and UK stocks with major macroeconomic announcements, and find that US investors tend to herd during days when important macro data are released, but such herding during the recent Subprime crisis can be attributed to non-fundamental information. For the UK market herding is driven by only fundamentals during the Dotcom bubble burst. They also find herding spillovers effects from the US to the UK during the Asian crisis and the Dotcom bubble burst.[6] In a recent study, Babalosa and Stavroyiannisb (2015) examine the existence of herding behavior in metal commodities futures, and find a time-varying anti-herding behavior before the global financial crisis and the absence of herding or anti-herding behavior during the crisis. By the using the dynamic conditional correlations via the DCC-GARCH family multivariate modeling the paper document a shift in the correlations and covariance of the commodity futures especially during the crisis.

III. EMPIRICAL DESIGN

In order to detect herding behavior towards the market, Christie and Huang (1995) propose a measure of cross-sectional variability of return, CSSD, the cross-sectional standard deviation of stock returns with respect to average return of all stock returns. Herding behavior is manifested in an increased similarity of returns across stocks resulting a lower cross-sectional variability of returns and a more synchronized movement in stock prices. Such behavior is intensified during market stress when investors suppress their own belief and make investment decisions based on collective actions in the market. However, CSSD

6 There are numerous studies examining herd behavior in different national and asset markets like Caparrelli et al. (2004), Economou et al. (2011), Pierdzioch and Rulke (2012), Pierdzioch et al. (2013), Philippas et al. (2013).

tends to be sensitive to outliers. As a result, Chang et al. (2000) propose an alternative measure, CSAD, cross-sectional absolute deviation of returns[7]:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \quad (1)$$

where $R_{m,t}$ is the equally weighted returns of $R_{i,t}$'s 's or market return at time t. The regression equation can be written as:

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \quad (2)$$

The presence of herding with reference to market or industry is detected if γ_3 is significantly negative, i.e. $\gamma_2 < 0$. On the other hand, if γ_3 turns out to be significantly positive, i.e. $\gamma_2 > 0$, we observe the presence of adverse herding.

Gębka and Wohar (2013) argue that when investors overemphasize their own view or focus on views dominant among subset of actors (who may herd jointly moving in and out of positions) excessively ignoring market information, it results in increased dispersion in returns across assets leading to adverse herding. As the possible explanation of adverse herding, Gębka and Wohar (2013) identify localized herding, excessive "flight to quality" during market stress (Favero and Giavazzi 2002; Kaminsky et al. 2004; Baur and Lucey 2009; Berger and Turtle 2011; Davis and Madura 2012), and overconfidence (Goodfellow et al. 2009). When a subset of investors synchronously move into (move out of) a subset of assets, the resulting increase (decrease) of prices lead to excessive dispersion in return across assets creating localized herding. Second, during highly volatile or turmoil period investors may shift their capital more from risk positions to more secure ones due to irrational fears, which can lead to very high CSAD values above the rational levels. Third, high return dispersion might be a result of investors' overconfidence during high market returns due to their perceived ability of stock-picking or timing skill rather than the market conditions.

We attempt to examine whether the herding takes place towards (1) the whole financial sector, (2) the own sub-sector (commercial banks, S&Ls, investment firms, or insurance firms), and (3) the whole market. As a result, when calculating CSAD using equation (1) we use different measures of $R_{m,t}$. For herding towards the whole financial sector, we calculate $R_{m,t}$ as the equally weighted returns of all firms in the sample. For herding towards the own sub-sector, we calculate $R_{m,t}$ as the equally weighed returns for commercial banks, S&Ls, investment firms, or insurance firms separately using all firms from the respective sector. Finally, the

7 Papers those study herding behavior using institutional holdings use different methodology to measure herding. For example, Lakonishok et al. (1992) measure herding, $H(i)$ as $H(i) = |B(i)/(B(i) + S(i)) - p(t)| - AF(i)$where $B(i)$ is the number of money managers who increase their holdings in the stock in the quarter (net buyers), $S(i)$ is the number of money managers who decrease their holdings (net sellers), $p(t)$ is the expected proportion of money managers buying relative to the number active aggregated across all stocks, and $AF(i)$ is an adjustment factor which is the expected value of $|B/(B + S)\text{-}p|$ under the null hypothesis of no herding.

CRSP equally weighted NYSE/AMEX/NASDAQ portfolio returns is calculated as the proxy for market return.

We use Seemingly Unrelated Regression method to estimate the parameters of the equations following Cornett and Tehranian (1990), and Kabir and Hassan (2005). Since the returns of the sample firms of the same industry measured over a common time-period are contemporaneously correlated, the residuals are not independently and identically distributed. As a result, simple OLS gives us biased estimates of parameter. The system of Seemingly Unrelated Regressions takes into account heteroskedasticity across equations and contemporaneous correlation between disturbances. Moreover it assumes that the variances of disturbances differ across equations.

IV. DATA AND SUMMARY STATISTICS

A. Data and sample

We use daily returns rather than weekly or monthly since Christie and Huang (1995) argue that herd behavior is a very short-lived phenomenon. The sample period starts on January 01, 2003 and ends on December 31, 2012. We collect daily returns of commercial banks, savings and loan institutions (S&L), investment, and insurance firms based on SIC codes from CRSP.[8] We have 1163 firms in total for the sample years. The number of financial institutions is highest for commercial banks (46%) followed by S&Ls (24%). The sample also consists of 112 investment firms (10%), and 238 insurance firms (20%). We identify the crisis period from August 1, 2007 to December 31, 2008. The daily 30-day maturity T-bill rate and trade-weighted daily foreign exchange rate of major countries have been collected from the St. Louis Fed's FRED database. The Small Minus Big (SMB), High Minus Low (HML), and Momentum (MOM) factors are downloaded from Fama–French data library.[9]

B. Summary statistics

Table 1 provides a summary statistics of CSAD of stock returns by sectors of financial institutions. In panel A, we subtract daily return of each firm in a sector from the equally weighted returns of portfolio of all firms in that sector in calculating CSAD except for "all firms" in the first row where we subtract daily return of each firm from the equally weighted returns of portfolio of all firms in the sample. In panel B, we use the CRSP equally weighted NYSE/AMEX/NASDAQ portfolio return to calculate the CSAD.

8 The firms are selected based on the following SIC codes: commercial banks—6021, 6022, 6029; S&Ls—6035, 6036; investment banks—6210, 6211, 6280, 6282; insurance firms—6310, 6311, 6330, 6331, 6350, 6351.

9 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 1 Descriptive statistics of the cross-sectional absolute deviation (CSAD)

	No. of firms (%)	Mean	Median	Max	Min	Std. dev.	Skewness	Kurtosis
Panel A: CSAD with respect to respective sector portfolio returns								
All firms	1163	0.023	0.018	0.127	0.007	0.016	2.346	10.570
Commercial banks	531 (46)	0.020	0.017	0.101	0.007	0.012	1.919	7.944
S&Ls	282 (24)	0.020	0.016	0.086	0.006	0.012	1.588	6.160
Investment firms	112 (10)	0.019	0.016	0.092	0.008	0.010	2.821	13.838
Insurance firms	238 (20)	0.016	0.013	0.084	0.007	0.009	2.890	13.681
Panel B: CSAD with respect to CRSP equally weighted portfolio returns								
All firms	1163	0.024	0.019	0.138	0.008	0.015	2.271	10.139
Commercial banks	531 (46)	0.021	0.017	0.103	0.008	0.013	1.950	8.175
S&Ls	282 (24)	0.021	0.017	0.088	0.007	0.012	1.652	6.507
Investment firms	112 (10)	0.019	0.016	0.096	0.008	0.010	2.814	13.503
Insurance firms	238 (20)	0.016	0.013	0.084	0.007	0.009	2.812	12.915

Note: This table presents the cross-sectional absolute deviation ($CSAD_{i,t}$) of daily stock returns with respect to portfolio returns for each group or sector of financial institutions where, $CSAD_{i,t}=\frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t}-R_{m,t}\right|$, where $CSAD_{i,t}$ stands for the cross-sectional absolute deviation of daily stock returns with respect to portfolio returns, $R_{m,t}$ for the *i*th sector of financial institutions except for "all firms" where we subtract daily return of each firm from the equally weighted returns of portfolio of all firms in the sample. In panel B, $R_{m,t}$ is the CRSP equally weighted NYSE/NASDAQ/AMEX portfolio daily returns, respectively.The sample period covers period from January 01, 2003 to December 31, 2012.

We find similarity in distribution of CSAD irrespective of measurements with respect to reference portfolios. The commercial banks and S&Ls have relatively higher mean (0.020) and median (0.017 and 0.016) compared to investment and insurance firms in Panel A. The mean CSAD for commercial banks and S&Ls is in the range of 0.024–0.021 while the median is 0.017 in Panel B. Both mean and median CSAD are the lowest for insurance firms in both panels. We find similar pattern in the standard deviations of CSAD across the financial institutions.

V. RESULT ANALYSIS

A. Base model results

Table 2 presents the seemingly unrelated regression estimates of base model of equation (2). In panel A, we report the results with reference to the equally

Table 2 Estimates of herding behavior from basic model

	γ_0	$\gamma_1 \lvert R_{m,t} \rvert$	$\gamma_2 R^2_{m,t}$	Adj. R^2 (%)
Panel A: When $\mathbf{R_{m,t}}$ is the sample sub-sector portfolio returns				
All firms	1.146***	1.433***	−0.016***	78
	(43.831)	(40.977)	(−2.501)	
Commercial banks	1.167***	1.034***	−0.028***	56
	(39.262)	(27.234)	(−4.022)	
S&Ls	1.229***	1.309***	−0.044***	49
	(40.041)	(22.447)	(−2.754)	
Investment firms	1.364***	0.353***	0.016***	54
	(58.638)	(22.447)	(5.742)	
Insurance firms	1.035***	0.512***	0.002	58
	(53.439)	(25.292)	(0.849)	
Panel B: When $\mathbf{R_{m,t}}$ is the CRSP equally weighted portfolio returns				
All firms	1.227***	1.334***	−0.002	70
	(38.257)	(33.539)	(−0.203)	
Commercial banks	1.326***	0.865***	−0.004	43
	(40.474)	(19.088)	(−0.438)	
S&Ls	1.321***	0.888***	−0.011	45
	(41.170)	(21.152)	(−1.427)	
Investment firms	1.350***	0.665***	0.016***	48
	(49.435)	(18.613)	(2.418)	
Insurance firms	1.116***	0.528***	0.025***	47
	(46.092)	(16.686)	(4.141)	

Note: This table reports the estimated coefficients of the model: $CSAD_t = \gamma_0 + \gamma_1 \lvert R_{m,t} \rvert + \gamma_2 R^2_{m,t} + \varepsilon_t$, where $CSAD_{i,t}$ stands for the cross-sectional absolute deviation of daily stock returns with respect to portfolio returns, $R_{m,t}$ for the ith sector of financial institutions except for "all firms" where we subtract daily return of each firm from the equally weighted returns of portfolio of all firms in the sample. In panel B, $R_{m,t}$ is the CRSP equally weighted NYSE/NASDAQ/AMEX portfolio daily returns, respectively. The sample period is January 01, 2003 – December 31, 2012. The estimates are based on seemingly unrelated regressions. t-statistics are given in the parentheses. "***", "**", and "*" represent statistical significance at 1, 5, and 10% levels, respectively.

weighted return of portfolio of all firms in specific sub-sector. In panel B, the CRSP equally weighted NYSE/AMEX/NASDAQ portfolio returns are used as the reference portfolio. We find investors, as a whole, herd towards sectoral portfolio returns as the coefficient of squared return of portfolio, γ_2, is −0.016 with significance at 1% level in Panel A. Similarly, γ_2 is −0.028 and −0.044 for commercial banks and S&Ls, respectively, and both the coefficients are significant at 1% level suggesting the existence of herding in both types of financial institutions. However, the herding intensity of S&Ls stocks is stronger than that of commercial bank stocks as the absolute value of the coefficient is higher for S&Ls. We do not find significant herding behavior with the CRSP NYSE/NASDAQ/AMEX market portfolio for any sector though the coefficient, γ_2 is negative for commercial banks and S&Ls in Panel B. It is rather that γ_2 is significantly positive for both investment and insurance firms in panel B when using market returns, squared as a measure of market movements, implying adverse herding. In Panel A, we also find similar results for investment firms, but not for insurance firms. In other words, investors in these two sectors do not suppress their own views, rather overemphasize their own views or focus on views dominant among subset of actors (who may herd jointly moving in and out of positions) excessively ignoring market information. As a result, cross-sectional dispersion in returns across assets increases substantially (Gębka and Wohar 2013). This might be caused by localized herding, excessive "flight to quality" during market stress, and overconfidence by investors.

B. Augmented model results

Chiang et al. (2013) in a recent paper argue that herding behavior is sensitive to the prevailing market returns and conditional return volatility. DeLong et al. (1991) suggest that the positive (negative) feedback traders buy (sell) stocks in a rising market and sell (buy) stocks in a falling market. The effect of such trading can be positive or negative based on the type of feedback strategy investors follow. Moreover, rational arbitrageurs are reluctant to bet against the mispricing because the timing of price adjustment is unpredictable. Prices become volatile due to lack of arbitrage activities against the noise traders. On the other hand, cross-market correlations rise when volatility is too high (Forbes and Rigobon 2002; Corsetti et al. 2005). As a result, $R^2_{m,t}$ alone cannot adequately capture the dynamics of nonlinearity. Chiang et al. (2013) introduce additional variables in the regression. The first one is $R^3_{m,t}$, which is the product of $R^2_{m,t}$ and $R_{m,t}$ representing the interaction of herding behavior with the market. The other one is $\hat{\sigma}^2_t R^2_{m,t}$, which is the interaction of herding with conditional variance of the market return. The conditional variance of returns, $\hat{\sigma}^2_t$, are calculated using threshold GARCH (1,1) or GJR-GARCH(1,1) model. The statistical significance of both interactive variables signifies the additional information related to state of the market inducing herding towards the market. Chiang et al. (2013) find the coefficient on the $R^2_{m,t}$ is more negative in the new specification than in equation (2), suggesting the presence of herding that otherwise could not be detected using specification in equation (2). Chiang et al. (2013) use chi-square test of equality of two herding coefficients from standard model (2) and augmented model (4), and they find that the coefficient on the squared market return is more negative in the augmented model than in the standard one rejecting the hypothesis. In other words, the augmented specification may be better in detecting the presence of herding. We incorporate these two variables in the new regression equation[10]:

10 The regression equation (4) can be written as $CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \left(\gamma_2 + \gamma_3 R_{m,t} + \gamma_4 \hat{\sigma}^2_t\right) R^2_{m,t} + \varepsilon_t$, where $\left(\gamma_2 + \gamma_3 R_{m,t} + \gamma_4 \hat{\sigma}^2_t\right)$ is the measure of herding. While the coefficients of γ_3 and γ_4 capture the nonlinearity of herding with market return and conditional volatility respectively, a significant negative value of coefficient of γ_2 still important for herding to exist. Similarly, a significant positive value of γ_2 identifies the presence of adverse herding.

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \gamma_4 \hat{\sigma}_t^2 R_{m,t}^2 + \varepsilon_t \quad (3)$$

A positive (negative) and significant coefficient of $R_{m,t}^3$ implies that the herding increases in a downward (upward) market. Similarly, if the coefficient of the interaction variable of $R_{m,t}^2$ and $\hat{\sigma}_t^2$ is positive and significant, herding is said to decrease (increase) as the volatility increases (decreases). We use both equally weighted return of portfolio of all firms in specific sub-sector and the CRSP equally weighted NYSE/NASDAQ/AMEX daily portfolio returns[11] as proxy for $R_{m,t}$.

Table 3 presents the results of equation (3) where $R_{m,t}^3$ and the interaction between conditional volatility, $\hat{\sigma}_t^2$ and squared portfolio or market returns, $R_{m,t}^2$ are included in the regression following Chiang et al. (2013). We find that the explanatory power of the regressions has increased marginally with the inclusion of additional variables. However, most importantly, results from all types of financial institutions now show significant levels of herding intensities as the coefficients of $R_{m,t}^2$ are significantly negative at around 1% level. For S&Ls, γ_2 is -0.241 followed by commercial banks, for which γ_2 is -0.144 in Panel A. The same coefficient is -0.023 and -0.033 for investment and insurance firms, respectively. On the other hand, the coefficient is uniformly around -0.10 for all types of financial institutions in Panel B implying similarity in herding behavior towards the market. Moreover, our findings suggest that herding behavior is sensitive to market condition and conditional volatility.

All coefficients of $R_{m,t}^3$ are positive and significant except for commercial banks and insurance firms in Panel A and for only insurance firms in Panel B implying that herding generally increases in a downward market. Such increase in herding effect could result from selling securities due to significant redemption requests from investors during market crisis (Chiang et al. 2013), or increase in contemporaneous betas of small stock resulting in increased pairwise stock correlation (McQueen et al. 1996). Similarly, we find the coefficients of the interaction variable of $R_{m,t}^2$ and $\hat{\sigma}_t^2$ are all positive and highly significant at 1% level. This implies that herding effect decreases (increases) as the volatility increases (decreases). This is consistent with the finding of Chiang et al. (2014) —during high market uncertainty "investors who lack clear signals and fundamentals are prone to act independently".

C. Herding during financial crisis

In order to capture the effect of herding during 2008 financial crisis we use multiplicative dummy variable in the following regression equation:

11 In fact we have used value-weighted as well, but the findings are not significantly different. Second, we did not find any size effect by forming size-based portfolios of each subsector.

Table 3 Estimates of herding behavior from augmented model

	γ_0	$\gamma_1\lvert R_{m,t}\rvert$	$\gamma_2 R^2_{m,t}$	$\gamma_3 R^3_{m,t}$	$\gamma_4\hat{\sigma}^2_t R^2_{m,t}$	Adj. R^2 (%)
Panel A: When $\mathbf{R_{m,t}}$ *is the sample sub-sector portfolio returns*						
All firms	1.109***	1.561***	−0.092***	0.001**	0.006***	80
	(42. 521)	(41.713)	(−8.593)	(2.534)	(8.492)	
Commercial banks	1.119***	1.206***	−0.144***	0.000	0.014***	60
	(38.442)	(30.014)	(−12.303)	(0.537)	(11.731)	
S&Ls	1.178***	1.547***	−0.241***	0.004**	0.033***	51
	(38.301)	(24.306)	(−8.541)	(2.474)	(7.796)	
Investment firms	1.313***	0.467***	−0.023***	0.001***	0.001***	58
	(57.301)	(20.344)	(−5.312)	(5.012)	(10.954)	
Insurance firms	0.994***	0.611***	−0.033***	0.000	0.001***	60
	(49.654)	(24.580)	(−5.418)	(0.606)	(6.145)	
Panel B: When $\mathbf{R_{m,t}}$ *is the CRSP equally weighted portfolio returns*						
All firms	1.203***	1.399***	−0.029**	0.001**	0.001**	71
	(42.497)	(32.944)	(−2.156)	(2.413)	(2.043)	
Commercial banks	1.218***	1.104***	−0.104***	0.002***	0.007***	57
	(44.360)	(27.884)	(−8.988)	(3.556)	(10.076)	
S&Ls	1.247***	1.084***	−0.102***	0.001**	0.010***	55
	(45.365)	(27.377)	(−8.817)	(2.371)	(8.593)	
Investment firms	1.281***	0.868***	−0.096***	0.001*	0.011***	60
	(46.575)	(21.925)	(−8.314)	(1.808)	(11.829)	
Insurance firms	1.040***	0.757***	−0.101***	0.000	0.009***	59
	(37.934)	(19.272)	(−8.773)	(0.803)	(12.274)	

Note: This table reports the estimated coefficients of the model: $CSAD_t = \gamma_0 + \gamma_1 \lvert R_{m,t}\rvert + \gamma_2 R^2_{m,t} + \gamma_3 R^3_{m,t} + \gamma_4 \hat{\sigma}^2_t R^2_{m,t} + \varepsilon_t$, where $CSAD_{i,t}$ stands for the cross-sectional absolute deviation of daily stock returns with respect to portfolio returns, $R_{m,t}$ for the *i*th sector of financial institutions except for "all firms" where we subtract daily return of each firm from the equally weighted returns of portfolio of all firms in the sample. In panel B, $R_{m,t}$ is the CRSP equally weighted NYSE/NASDAQ/AMEX portfolio daily returns, respectively. $R^3_{m,t}$ is the product of $R^2_{m,t}$ and $R_{m,t}$ representing the interaction of herding behavior with the market, and $\hat{\sigma}^2_t R^2_{m,t}$ is the interaction of herding with conditional variance of the market return. The conditional variance of returns, $\hat{\sigma}^2_t$, are calculated using threshold GARCH (1,1) or GJR-GARCH(1,1) model. The sample period is January 01, 2003 – December 31, 2012. The estimates are based on seemingly unrelated regressions. *t*-statistics are given in the parentheses. "***", "**", and "*" represent statistical significance at 1, 5, and 10% levels, respectively.

$$CSAD_t = \gamma_0 + \gamma_1 \lvert R_{m,t}\rvert + \gamma_2 R^2_{m,t} + \gamma_3 D R^2_{m,t} + \gamma_4 R^3_{m,t} + \gamma_5 \hat{\sigma}^2_t R^2_{m,t} + \varepsilon_t \tag{4}$$

where dummy variable D takes the value of 1 for the crisis period from August 1, 2007 to December 31, 2008, zero otherwise. The crisis has started in the second half of 2007 with turmoil in the subprime mortgage market, and most of events took place in 2008. Banks perform poorly during the first quarter of 2009; but such poor performance can be attributed to "uncertainty about resolution mechanisms and the possibility of nationalization" (Beltrattia and Stulz 2012). As a result, following Beltrattia and Stulz (2012) we identify the crisis period from the August of 2007 to December of 2008. The negative significant value of the coefficient γ_3 indicates the incremental effect in cross sectional variation of returns implying the presence of herding during crisis period.

Table 4 presents the estimates of the equation (4). In panel A, we report the results with reference to the equally weighted return of portfolio of all firms in specific sub-sector. We find that the coefficients of $R^2_{m,t}$ are significantly negative in all cases in Panel A. However, the coefficients of $DR^2_{m,t}$ are significantly positive for commercial banks; but insignificantly negative for S&Ls, investment and insurance firms. Such results imply that the presence of herding by investors for all financial stocks in general; but the global financial crisis do not have any

Table 4 Estimates of herding behavior during financial crisis

	γ_0	$\gamma_1\lvert R_{m,t}\rvert$	$\gamma_2 R^2_{m,t}$	$\gamma_3 DR^2_{m,t}$	$\gamma_4 R^3_{m,t}$	$\gamma_5\hat{\sigma}^2_t R^2_{m,t}$	Adj. R^2
Panel A: When $R_{m,t}$ is the sample sub-sector portfolio return							
All firms	1.108***	1.566***	−0.092***	−0.008	0.001**	0.006***	80
	(42.422)	(41.724)	(−8.565)	(−1.525)	(2.406)	(8.608)	
Commercial banks	1.129***	1.191***	−0.151***	0.025**	0.001	0.010***	60
	(38.797)	(29.646)	(−12.827)	(2.129)	(0.488)	(12.004)	
S&Ls	1.179***	1.539***	−0.233***	−0.016	0.001**	0.033***	51
	(38.315)	(24.071)	(−8.000)	(−1.143)	(2.390)	(7.851)	
Investment firms	1.131***	0.467***	−0.024***	−0.006	0.001***	0.001***	57
	(57.368)	(20.333)	(−5.458)	(1.133)	(5.022)	(8.881)	
Insurance firms	0.990***	0.618***	−0.035***	−0.011	0.000	0.001***	61
	(9.511)	(24.965)	(−5.741)	(1.282)	(0.885)	(4.363)	
Panel B: When $R_{m,t}$ is the CRSP equally weighted portfolio returns							
All firms	1.203***	1.405***	−0.031**	−0.032***	0.001**	0.003***	71
	(8.246)	(29.745)	(−2.075)	(−3.586)	(2.570)	(3.459)	
Commercial banks	1.214***	1.123***	−0.111***	−0.015**	0.002***	0.008***	57
	(39.873)	(25.292)	(−8.482)	(−2.396)	(3.095)	(9.131)	
S&Ls	1.243***	1.097***	−0.116***	−0.010*	0.001**	0.007***	55
	(42.024)	(25.412)	(−8.377)	(−1.651)	(2.124)	(7.791)	
Investment firms	1.286***	0.851***	−0.089***	−0.014	0.001**	0.008***	60
	(53.226)	(24.131)	(−8.546)	(1.003)	(2.205)	(10.390)	
Insurance firms	1.049***	0.729***	−0.089***	−0.013	0.001	0.008***	59
	(48.539)	(23.138)	(−9.575)	(1.298)	(1.082)	(12.202)	

Note: This table reports the estimated coefficients of the model: $CSAD_t = \gamma_0 + \gamma_1\lvert R_{m,t}\rvert + \gamma_2 R^2_{m,t} + \gamma_3 DR^2_{m,t} + \gamma_4 R^3_{m,t} + \gamma_5\hat{\sigma}^2_t R^2_{m,t} + \varepsilon_t$, where $CSAD_{i,t}$ stands for the cross-sectional absolute deviation of daily stock returns with respect to portfolio returns, $R_{m,t}$ for the *i*th sector of financial institutions except for "all firms" where we subtract daily return of each firm from the equally weighted returns of portfolio of all firms in the sample. In panel B, $R_{m,t}$ is the CRSP equally weighted NYSE/NASDAQ/AMEX portfolio daily returns, respectively. $R^3_{m,t}$ is the product of $R^2_{m,t}$ and $R_{m,t}$ representing the interaction of herding behavior with the market, and $\hat{\sigma}^2_t R^2_{m,t}$ is the interaction of herding with conditional variance of the market return. The conditional variance of returns, $\hat{\sigma}^2_t$, are calculated using threshold GARCH (1,1) or GJR-GARCH(1,1) model. D is the indicator variable that takes the value of 1 for the financial crisis period August 1, 2007 – December 31, 2008. The sample period is January 01, 2003 – December 31, 2012. The estimates are based on seemingly unrelated regressions. *t*-statistics are given in the parentheses. "***", "**", and "*" represent statistical significance at 1, 5, and 10% levels, respectively.

incremental effect on herding. We still find γ_5 to be positive and highly significant in all cases suggesting inverse relation between herding and volatility. Thus, the lack of evidence of significant herding during crisis may be explained by the presence of localized herding as investors overemphasize their own view or focus on views dominant among subset of actors excessively ignoring market information (Gębka and Wohar 2013) and/or the excessive "flight to quality" (which is due to irrational fears) when volatility is high.

Panel B reports the herding results towards the overall market. In all cases the estimated coefficient values of $R^2_{m,t}$ are significantly negative. On the other hand, we find negative values of γ_3 for commercial banks (−0.015) and S&Ls (−0.010) significant at 5 and 10% levels, respectively. Thus, investors' herding increases for commercial banks and S&Ls towards market consensus during crisis period. The investment firms and insurance firms show no incremental role of herding during crisis period as the coefficients are negative and insignificant.

D. Is herding spurious or intentional?

Bikhchandani and Sharma (2001) differentiate between spurious or unintentional herding driven by fundamental information and intentional herding, which is driven by non-fundamentals. While spurious herding emerges as investors react independently in a similar manner to common news, intentional herding emerges as the investors follow each other with intent. Holmes et al. (2013), in a recent paper, note that while informational cascades and reputational reasons may lead to intentional herding, the relative homogeneity of investment professionals and the characteristic trading (momentum, contrarian, value versus growth, small versus big) may result in unintentional or spurious herding. Hirshleifer and Teoh (2003) argue that when herding is driven by agency considerations, it is expected that any price effect of herding will be driven by institutional investors.

Since we are using aggregate market data rather than trading data of institutional investors, we cannot directly test the reputational factors and the relative homogeneity of investment professionals. However, Holmes et al. (2013) demonstrate that if herding is unintentional then it is expected that investors' behavior should not be affected by market returns and volatility. In contrast, if herding is intentional then the extent of such behavior should show some relation between market returns and volatility. Galariotis et al. (2015) also distinguish between fundamental or "spurious" and intentional herding following Campbell and Kyle (1993) who also suggest that excessive volatility of stock prices do not attribute to fundamentals. Hwang and Salmon (2004) note that stock returns and herding are likely to be affected by both market-level and firm-level fundamentals. They use variables such as the dividend-price ratio, the Treasury bill rate, the term spread, and the default spread in their analysis of herding. Similarly, Tan et al. (2008) use demand deposit rate and firms' earnings yield as fundamental variables to the herding regression. As the macroeconomic and firm fundamentals are not available on daily basis we use a specification that controls for fundamental information set or common risk factors like Small Minus Big return (SMB), High Minus Low return (HML), and Momentum (MOM) return affect stock valuation in addition to market return (Fama and French 1995, 1996 and Carhart 1997) following Galariotis et al. (2015). Since our sample consists of financial stocks, which are sensitive to interest rate and exchange rate movements due to the nature of business and financial operation, we also include returns on exchange rate (E_t), and returns on 30-day maturity daily US T-bill rate, (I_t) in the regression equation following Kabir and Hassan (2005, 2009). We first run the following regression:

$$CSAD_t = \gamma_0 + \gamma_1 \left(R_{m,t} - R_{f,t}\right) + \gamma_2 SMB_t + \gamma_3 HML_t + \gamma_4 MOM_t + \gamma_5 E_t + \gamma_6 I_t + \varepsilon_t \quad (5)$$

where HML is the High Minus Low return factor, SMB is the Small Minus Big return factor, and MOM is the Momentum factor. The residuals form the above regression equation reflects the cross-sectional deviation of returns due to non-fundamental factors. We define the residuals as $CSAD_{nonfund,t}$. And cross-sectional deviation due to fundamental factors can be defined as $CSAD_{fund,t} = CSAD_t - CSAD_{nonfund,t}$. As a result, we can write two more regression equations as follows:

$$CSAD_{fund,t} = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 DR_{m,t}^2 + \gamma_4 R_{m,t}^3 + \gamma_5 \hat{\sigma}_t^2 R_{m,t}^2 + \varepsilon_{i,t} \quad (6)$$

$$CSAD_{nonfund,t} = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 DR_{m,t}^2 + \gamma_4 R_{m,t}^3 + \gamma_5 \hat{\sigma}_t^2 R_{m,t}^2 + \varepsilon_t \quad (7)$$

Galariotis et al. (2015) find that the market participants in the US trade in the same direction for various periods as a reaction to the arrival of fundamental economic information, and during the Asian and the Russian crises US investors herd due to common reaction to fundamental information while during the Subprime crisis herding is due to non-fundamental information. In the UK there is little herding, and when so it is only on fundamentals.

Using equation (5), we calculate two series $CSAD_{fund,t}$ and $CSAD_{nonfund,t}$, and then estimate equation (6) and (7). The results are presented in Panel A for fundamental ($CSAD_{fund,t}$) and Panel B for non-fundamental ($CSAD_{nonfund,t}$) in Table 5. In Panel A, we find the estimates of coefficient of return squared, γ_2 are positive and significant irrespective whether we use own sector portfolio return or CRSP portfolio returns as the benchmark. In other words, investors' behavior indicates the presence of adverse herding in tranquil market in response to fundamentals. The coefficient of γ_3 is only significantly negative for commercial banks and investment firms. The absolute values of coefficients are relatively higher (−0.022 and −0.071 for commercial banks and investment firms, respectively) when CRSP equally weighted portfolio return used as the market consensus. In other words, we find some incremental herding effects in the wake

Table 5 Estimates of herding towards fundamental and non-fundamental across FIs

	γ_0	$\gamma_1\lvert R_{m,t}\rvert$	$\gamma_2 R^2_{m,t}$	$\gamma_3 DR^2_{m,t}$	$\gamma_4 R^3_{m,t}$	$\gamma_5 \hat{\sigma}^2_t R^2_{m,t}$	Adj. R^2
Panel A: Herding towards fundamental							
Sub-panel A1: When $R_{m,t}$ is the sample sub-sector portfolio return							
All firms	2.346***	0.094***	0.051***	0.009***	0.001***	−0.001***	15
	(70.841)	(4.568)	(9.263)	(2.927)	(6.457)	(−4.335)	
Commercial banks	2.018***	0.055***	0.038***	−0.011***	0.001***	−0.002***	18
	(78.439)	(4.156)	(10.074)	(−5.228)	(9.520)	(−6.256)	
S&Ls	1.976***	−0.029	0.004***	0.000	0.004***	0.003**	12
	(77.005)	(−0.938)	(4.788)	(0.098)	(9.272)	(2.250)	
Investment firms	1.876***	0.031***	0.011***	−0.051***	0.001***	−0.000**	19
	(49.785)	(3.842)	(7.072)	(−3.616)	(14.416)	(−2.043)	
Insurance firms	1.557***	−0.023***	0.015***	−0.003	0.001***	−0.000***	11
	(54.875)	(−2.848)	(7.696)	(−1.803)	(8.673)	(−6.224)	
Sub-panel A2: When $R_{m,t}$ is the CRSP equally weighted portfolio returns							
All firms	1.147***	1.403***	0.058***	0.010	−0.001**	−0.002**	65
	(34.820)	(28.382)	(3.377)	(1.045)	(−2.522)	(−2.501)	
Commercial banks	0.760***	−0.964***	0.071***	−0.022**	−0.001	−0.003***	39
	(21.213)	(−17.942)	(4.228)	(−2.209)	(−1.439)	(−3.689)	
S&Ls	0.758***	−0.954***	0.061***	0.010	−0.001	0.002**	42
	(22.693)	(19.061)	(3.914)	(1.006)	(−1.553)	(2.296)	
Investment firms	0.645***	0.829***	0.082***	−0.071***	0.000	−0.006***	45
	(22.995)	(−19.707)	(6.241)	(−3.800)	(0.484)	(−7.614)	
Insurance firms	0.545***	−0.695***	0.070***	−0.020	0.000	−0.005***	44
	(21.838)	(−18.588)	(6.030)	(−1.133)	(0.228)	(−8.284)	
Panel B: Herding towards non-fundamental							
Sub-panel B1: When $R_{m,t}$ is the sample sub-sector portfolio return							
All firms	1.231***	1.638***	−0.139***	−0.016*	−0.001	0.007***	74
	(43.244)	(40.418)	(−12.097)	(−1.656)	(−0.672)	(9.727)	
Commercial banks	0.887***	1.234***	−0.167***	−0.018	−0.001**	0.011***	55
	(29.936)	(30.517)	(−14.427)	(−1.117)	(−2.521)	(13.124)	
S&Ls	0.795***	1.549***	−0.267***	−0.016	0.001	0.035***	47
	(25.507)	(24.067)	(−9.436)	(−1.113)	(0.281)	(8.302)	

Table 5 (*continued*)

	γ_0	$\gamma_1 \vert R_{m,t} \vert$	$\gamma_2 R^2_{m,t}$	$\gamma_3 DR^2_{m,t}$	$\gamma_4 R^3_{m,t}$	$\gamma_5 \hat{\sigma}^2_t R^2_{m,t}$	Adj. R^2
Investment firms	0.560***	0.495***	−0.034***	0.009***	0.000	0.001***	51
	(23.716)	(20.998)	(−7.480)	(3.235)	(0.436)	(11.193)	
Insurance firms	0.559***	0.628***	−0.046***	0.014***	0.001*	0.001***	55
	(27.225)	(24.855)	(−7.546)	(4.504)	(1.960)	(7.822)	
Sub-panel B2: When $R_{m,t}$ is the CRSP equally weighted portfolio returns							
All firms	1.136***	1.417***	−0.058***	−0.010	0.001*	0.002**	65
	(34.158)	(28.418)	(−3.758)	(−1.074)	(1.647)	(2.513)	
Commercial banks	0.747***	0.974***	−0.071***	−0.002	0.001	0.003***	39
	(20.656)	(17.951)	(−4.218)	(−0.230)	(1.448)	(3.683)	
S&Ls	0.745***	0.964***	−0.061***	−0.010	0.001	0.002***	42
	(22.094)	(19.070)	(−3.903)	(−1.023)	(1.505)	(2.691)	
Investment firms	0.633***	0.837***	−0.082***	−0.030	−0.000	0.006***	45
	(22.324)	(19.719)	(−6.233)	(1.077)	(−0.466)	(7.613)	
Insurance firms	0.534***	0.702***	−0.071***	−0.022	0.000	0.005***	44
	(21.211)	(18.598)	(−6.021)	(1.112)	(0.218)	(8.284)	

Note: This table reports the estimated coefficients of the model: $CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 DR^2_{m,t} + \gamma_4 R^3_{m,t} + \gamma_5 \hat{\sigma}^2_t R^2_{m,t} + \varepsilon_t$, where $CSAD_{i,t}$ is $CSAD_{fund,t}$ in Panel A, and $CSAD_{nonfund,t}$ in Panel B. In panel A1 and B1, $R_{m,t}$ is the equally weighted daily portfolio returns of sector based financial institutions except for "all firms" where we subtract daily return of each firm from the equally weighted returns of portfolio of all firms in the sample. In panel A2 and B2, $R_{m,t}$ is the CRSP equally weighted portfolio daily returns, respectively. $CSAD_{fund,t} = CSAD_{i,t} - CSAD_{nonfund,t}$, where the residuals from the following regression is defined as $CSAD_{nonfund,i,t}$: $CSAD_t = \gamma_0 + \gamma_1(R_{m,t} - R_{f,t}) + \gamma_2 SMB_t + \gamma_3 HML_t + \gamma_4 MOM_t + \gamma_5 E_t + \gamma_6 I_t + \varepsilon_t$, where, HML is the High Minus Low return factor, SMB is the Small Minus Big return factor, MOM is the Momentum factor, E_t is the returns on exchange rate, and I_t is the returns on interest rate. The sample period is January 01, 2003 – December 31, 2012. The estimates are based on seemingly unrelated regressions. *t*-statistics are given in the parentheses. "***", "**", and "*" represent statistical significance at 1, 5, and 10% levels, respectively.

of global financial crisis, but such incremental effects are limited to commercial banks and investment firms in response to fundamental factors.

The coefficients of $R^3_{m,t}$ are only significantly positive in sub-panel A1 implying that herding with their own sub-sector in case of commercial banks and investment firms happens in down market; but the market return does not play any role in case of herding with overall market consensus as values of γ_4 are not significant in sub-panel A2. In contrast to the results in Tables 3 and 4, the coefficients of the interaction variable of $R^2_{m,t}$ and $\hat{\sigma}^2_t$ are negative and highly significant in most of the cases implying that return clustering increases as the volatility increases in response to fundamental factors. In other words, the increase in herding during financial crisis when volatility increases may be attributed to fundamental information. Thus, our results stand in contrast to the hypotheses forwarded by Holmes et al. (2013) that unintentional or spurious herding by investors should not be affected by market returns and volatility. Moreover, given that the coefficients of squared return squared are positive in all cases indicating the presence of adverse herding during tranquil periods, the positive coefficients of $R^3_{m,t}$ and negatively significant coefficients of interaction variable of $R^2_{m,t}$ and $\hat{\sigma}^2_t$ indicate localized herding as investors overemphasize their own view or focus on views dominant among subset of actors excessively ignoring market information (Gębka and Wohar 2013) rather than excessive "flight to quality" arising from irrational fears when volatility is high.

Panel B presents the results for non-fundamental CSAD. In contrast to Panel A, the coefficients of return squared, γ_2 are negative and significant irrespective of whether we use own sector portfolio return or CRSP portfolio returns as the benchmark. The coefficient values are −0.267 and −0.167 for S&Ls and commercial banks, respectively, in sub-panel B1. The estimated values of γ_2 are relatively higher for investment and insurance firms in sub-panel B2 (−0.082 and −0.071 compared to −0.034 and −0.046 in sub-panel B1). In other words, investors herd in response to non-fundamental factors in general for all financial institutions, and herding effect is higher for commercial banks and S&Ls with their own sectoral consensus. On the other hand, investors herd more significantly towards overall market in case of investment and insurance firms, but there is some uniformity in herding towards the market consensus as the values of coefficients are in the range between −0.061 and −0.082 in Panel B. The coefficients of γ_3 are negative for in all cases, but not significant. This implies that the financial crisis do not exert any significant influence on return clustering with market. In contrast to the results in Panel A, the coefficients of γ_5 are positive and highly significant in all cases implying that herding behavior decreases as the volatility increases in response to non-fundamental factors. In other words, financial institutions do not show an increase in herding during crisis, and the presence of herding is intentional in response to non-fundamental information.

The distinction between fundamental and non-fundamental CSAD reveals a greater influence of global financial crisis on herding by commercial and investment banks in response to fundamental factors, but not non-fundamental ones, which has not been picked up by the results reported in Table 4. In addition, herding decreases as volatility increases in response to non-fundamental factors explaining the absence of any herding by investors during the financial crisis period. On the other hand, the incremental effect on herding with increase in volatility in response to fundamental factors is essentially spurious or unintentional.

VI. HERDING AND VOLATILITY REGIMES: SMOOTH TRANSITION REGRESSION MODEL APPROACH

The methodology followed by Chiang et al. (2013) is based on liner regression. While Chiang et al. (2013) model is reasonably good in identifying herding behavior by taking into account market state and conditional volatility in the regression analysis, it cannot directly disentangle the role of volatility if volatility exhibits substantial nonlinearity with regimes switches, and explain how herding behavior is evolved in high and low volatility regimes. In order to do so, we need to move away from linear regression to nonlinear method. Klein (2013) uses Markov switching model to examine such nonlinearity. However, the Markov switching model is characterized by unobservable transition variable. We rather propose the STR model, which uses observable transitional variable. As we want to examine herding behavior in high and low volatility regimes, our transitional variable is the conditional volatility measure in the STR model. The STR model is given as

$$CSAD_t = \alpha_0 + \beta_0 |R_{m,t}| + \gamma_0 R_{m,t}^2 + \left[\alpha_1 + \beta_1 |R_{m,t}| + \gamma_1 R_{m,t}^2\right] F(\vartheta; \delta, c) + \varepsilon_t \tag{8}$$

where ε_t is $iid\left(0, \sigma_\varepsilon^2\right)$, $F(\vartheta; \delta, c)$ is the transition function bounded by zero and unity, ϑ is the transition variable, and c is the threshold parameter. In our case, this transition variable is the conditional volatility. The slope parameter, $\delta > 0$ determines the speed and smoothness of the transition from one regime to the other at c. Regimes are defined as linear or low volatility and nonlinear or high volatility, and the smoothness of transition implies the existence of a continuum of states between extreme regimes. Two transition functions are commonly used in literature:

$$\text{Logistics STR model: (LSTR)}: F(\vartheta; \delta, c) = (1 + \exp(-\delta(\vartheta - c)))^{-1} \tag{9}$$

$$\text{Exponential STR model (ESTR)}: F(\vartheta; \delta, c) = 1 - \exp\left(-\delta(\vartheta - c)^2\right) \tag{10}$$

The logistic model is monotonically increasing in ϑ, with $F(\vartheta; \delta, c) \to 0$ as $(\vartheta - c) \to -\infty$, and $F(\vartheta; \delta, c) \to 1$ as $(\vartheta - c) \to +\infty$. Thus, the logistic transition seems to be the most adequate to capture cyclical asymmetries in two regimes. When the slope parameter, ϑ, in both models goes to zero, the STR reduces to linear model. On the other hand, when ϑ tends to infinity, the LSTR model becomes a step function and the transition between the regimes is abrupt. For the ESTR model, when the slope parameter, $\delta \rightarrow \infty$, then $F(\vartheta; \delta, c) \rightarrow 1$ except a narrow range of values around the threshold. The choice between LSTR and ESTR can hardly be justified based on economic theory due to enough *a priori* information to distinguish between them. We follow the methodology proposed by Teräsvirta (1994).

The first step is to test the nonlinearity. The null hypothesis of linearity can be expressed as either H_0: $\delta = 0$, or H_0: $\alpha_1 = \beta_1 = \gamma_1 = 0$. Van Dijk et al. (2002) suggest an approximation of the transition function by third-order Taylor approximation that corresponds to Lagrange multiplier (LM) test for linearity introduced by Luukkonen et al. (1988):

$$\begin{aligned} CSAD_t = \theta_0 + \theta_1 |R_{m,t}| + \theta_2 R_{m,t}^2 + \left[\theta_3 |R_{m,t}| + \theta_4 R_{m,t}^2\right] \vartheta_t + \left[\theta_5 |R_{m,t}| + \theta_6 R_{m,t}^2\right] \vartheta_t^2 + \\ + \left[\theta_7 |R_{m,t}| + \theta_8 R_{m,t}^2\right] \vartheta_t^3 + u_{,t} \end{aligned} \tag{11}$$

The null hypothesis is H_0: $\theta_i = 0$ with $i = 3,\ldots..,8$ against alternative that at least one $\theta_i \neq 0$. The test statistics has χ^2 distribution with six degrees of freedom. Once the linearity null is rejected we can use the above equation to test the specification between LSTR and ESTR by using following hypotheses successively:

$$\begin{aligned} &H_3 : \theta_7 = \theta_8 = 0 \\ &H_2 : \theta_5 = \theta_6 = 0 | \theta_7 = \theta_8 \\ &H_1 : \theta_3 = \theta_4 = 0 | \theta_7 = \theta_8 = \theta_7 = \theta_8 = 0 \end{aligned} \tag{12}$$

Following Teräsvirta (1994), the rejection of H_3 leads to the choice of LSTR model. If H_3 is accepted and H_2 is rejected, the ESTR model is selected. Finally, if both H_3 and H_2 are accepted and $H_1$is rejected, the LSTR specification is chosen.[12]

Table 6 shows the test statistics of the LM tests for nonlinearity and model selection (LSTR or ESTR) with associated *p*-values in parentheses. The null hypothesis of linearity is rejected in all cases at 1% level. In specification tests, the null hypothesis of H_3 stated in (12) is rejected for both commercial banks and investment firms, which leads to the choice of LSTR model. For S&Ls and investment firms, both H_3 and H_2 are accepted and H_1 is rejected significantly leading to the selection of LSTR model.

12 We do not find significant nonlinearity in market return to use it as the transition variable in the STR model.

Table 6 Nonlinearity and specification tests for STR model

	Nonlinearity test	Model specification test		
	H_0: $\theta_i = 0$	H_3	H_2	H_1
All firms	62.12***	2.33	2.64	36.45***
	(0.00)	(0.26)	(0.24)	(0.00)
Commercial banks	90.70***	1.35	2.71	45.62***
	(0.00)	(0.44)	(0.21)	(0.00)
S&Ls	93.71***	35.02***	1.40	2.30
	(0.00)	(0.00)	(0.42)	(0.26)
Investment firms	96.33***	0.35	2.34	12.52***
	(0.00)	(0.88)	(0.27)	(0.00)
Insurance firms	53.11***	29.11***	1.00	3.01
	(0.00)	(0.00)	(0.60)	(0.18)

Note: The table reports the test statistics of the LM test for nonlinearity, and model selection (LSTR or ESTR) with *p*-values in parentheses. The test statistics is distributed as with six degrees of freedom for nonlinearity test, and one degree of freedom for model selection. "***", "**", and "*" represent the rejection of null hypothesis at 1, 5, and 10% significance level, respectively.

The parameter estimates of herding based (8), (9) and (10) are presented in Table 7 for both low volatility (linear) and high volatility (nonlinear) regimes. Panel A presents the results of LSTR models when own sector portfolio return is used as the consensus.[13] We find that the estimates of γ_0 are negative and significant for only commercial banks (−0.038) and investment firms (−0.011) in sub-panel A1 while that of γ_1 are negative and significant in all cases except for commercial banks and insurance firms implying that S&Ls and investment firms tend to herd to their own sectoral consensus during high volatility or nonlinear regime as a whole. However, investment firms herd both low and high volatility regimes. When compared with the results in sub-panel B1, the coefficient estimates are higher in absolute values in both regimes implying that return clustering towards the market consensus is higher than sectoral consensus.

Sub-panels A2 and A3 report the results for fundament and non-fundamental CSAD. We find that none of the linear coefficients are negative, and the coefficients of $\gamma_1$are significantly negative for all except insurance firms in response to fundamental factors in sub-panel A2. The herding coefficient is as high as −0.324 for commercial banks followed by −0.044 and −0.037 for S&Ls and investment banks, respectively, in high volatility regime. In sub-panel B2, the coefficient of $\gamma_1$is −0.411 for commercial banks followed by −0.136 and −0.052 for S&Ls and investment banks, respectively. This implies that herding effects on fundamental is relatively high with overall market for these three types of financial institutions in high volatility regime. We can compare such findings with the results reported in Table 5. In panel A of Table 5, we find that investors herd incrementally only in commercial banks' and investment firms' returns in

13 We report only herding coefficients for both linear and nonlinear parts along with t-statistics for brevity.

Table 7 Estimates of herding using smooth transition regression (STR) model

	Model	Linear coefficient		Non-linear coefficient		Transition parameter		
		$\gamma_0 R^2_{m,i,t}$	*t*-stat	$\gamma_1 R^2_{m,i,t}$	*t*-stat	δ	C	R^2
Panel A: When $R_{m,t}$ is the sample sub-sector portfolio return								
Panel A1: Overall herding								
All firms	LSTR	0.075***	(14.177)	−0.116**	(−3.747)	10.00	13.61	94
Commercial banks	LSTR	−0.038***	(−8.451)	0.038***	(8.876)	10.00	14.49	90
S&Ls	LSTR	0.072***	(4.684)	−0.052***	(−7.413)	1.56	16.07	91
Investment firms	LSTR	−0.011***	(−6.135)	−0.013***	(8.915)	0.93	15.03	82
Insurance firms	LSTR	0.015***	(5.069)	0.053***	(2.817)	2.89	17.42	86
Panel A2: Herding towards fundamental								
All firms	LSTR	0.167***	(3.372)	−0.170***	(−3.641)	3.95	13.82	87
Commercial banks	LSTR	0.057**	(2.221)	−0.324***	(−6.335)	0.50	15.27	84
S&Ls	LSTR	0.099	(1.522)	−0.044**	(−2.121)	0.50	15.24	75
Investment firms	LSTR	0.105	(0.932)	−0.037**	(−2.201)	0.50	16.64	86
Insurance firms	LSTR	0.061***	(3.649)	0.071	(1.211)	0.55	20.06	82
Panel A3: Herding towards non-fundamental								
All firms	LSTR	−0.037***	(−3.248)	0.284	(0.742)	0.93	14.59	88
Commercial banks	LSTR	−0.054***	(−3.129)	0.244***	(3.156)	0.50	15.28	84
S&Ls	LSTR	−0.035*	(−1.710)	0.048	(1.032)	0.50	16.65	86
Investment firms	LSTR	−0.061***	(−5.199)	−0.098**	(−2.247)	0.68	15.96	78
Insurance firms	LSTR	−0.079***	(−6.188)	−0.038	(−1.142)	0.50	17.32	81
Panel B: When $R_{m,t}$ is the CRSP equally weighted portfolio return								
Panel B1:Overall herding								
All firms	LSTR	0.086***	(7.112)	−0.142**	(−3.552)	10.00	14.55	95
Commercial banks	LSTR	−0.041***	(−5.613)	0.025***	(7.469)	10.00	14.46	93
S&Ls	LSTR	0.079***	(4.009)	−0.063***	(−5.562)	2.90	15.37	92
Investment firms	LSTR	−0.022***	(−8.331)	−0.025***	(9.537)	2.85	14.66	85
Insurance firms	LSTR	0.011***	(4.167)	0.052***	(2.937)	2.80	15.64	87
Panel B2: Herding towards fundamental								
All firms	LSTR	0.150***	(4.171)	−0.205***	(−4.221)	5.95	12.44	90
Commercial banks	LSTR	0.049**	(2.521)	−0.411***	(−8.556)	1.70	15.43	86

Table 7 (*continued*)

	Model	Linear coefficient		Non-linear coefficient		Transition parameter		
		$\gamma_0 R^2_{m,i,t}$	t-stat	$\gamma_1 R^2_{m,i,t}$	t-stat	δ	C	R^2
S&Ls	LSTR	0.089**	(2.637)	−0.136***	(−3.489)	1.70	12.33	80
Investment firms	LSTR	0.108	(1.239)	−0.052***	(−2.963)	1.60	17.56	85
Insurance firms	LSTR	0.062***	(4.002)	0.133	(1.750)	1.65	23.35	80
Panel B3: Herding towards non-fundamental								
All firms	LSTR	−0.133***	(−4.445)	0.213	(0.742)	1.85	15.70	88
Commercial banks	LSTR	−0.102***	(−2.995)	0.284***	(3.252)	1.30	14.35	85
S&Ls	LSTR	−0.126**	(−2.490)	−0.020**	(2.010)	1.20	15.48	83
Investment firms	LSTR	−0.090***	(−5.322)	−0.182***	(−3.527)	1.35	16.71	80
Insurance firms	LSTR	−0.100***	(−5.552)	−0.078	(1.452)	1.70	18.23	82

Note: This table reports the result from the STR model: $CSAD_t = \alpha_0 + \beta_0|R_{m,t}| + \gamma_0 R^2_{m,t} + \left[\alpha_1 + \beta_1|R_{m,t}| + \gamma_1 R^2_{m,t}\right] F(\vartheta;\delta,c) + \varepsilon_t$, where $F(\vartheta;\delta,c) = (1+\exp(-\delta(\vartheta - c)))^{-1}$, and ϑ is the transition variable – conditional volatility, and c is the threshold parameter, and δ is the slope parameter determining the speed and smoothness of the transition from one regime to the other at c. The sample period is January 01, 2003 – December 31, 2012. "***", "**", and "*" represent statistical significance at 1, 5, and 10 levels, respectively. We report only estimates of herding coefficients in two volatility regimes in the table for brevity.

response to fundamental information during the financial crisis when volatility increases substantially. The STR model results, in contrast, show S&Ls in addition to commercial banks and insurance firms exhibit increased herding during high volatility regime explaining nonlinearity with regimes switches.

In sub-panels A3 and B3 we report the estimates due to reaction to non-fundamental factors. All the values of γ_0 are negative and significant irrespective of the type of financial institutions implying that intentional herding is prevalent in low volatility regime. This finding is in contrast to herding due to fundamentals. The herding coefficient is as high as −0.079 for insurance firms with own sector and −0.126 for S&Ls with market. We also find that it is only for the investment firms that the investors herd significantly with own sector in the high volatility regime. On the other hand, herding with market is observed for both S&Ls and investment firms in the high volatility regime. However, the herding towards the market almost twice as much high as the herding towards own sector for investment firms as the coefficient of $\gamma_1$is −0.182 in sub-panel B3 compared to −0.098 in sub-panel A3. Note that the sum of γ_0 and γ_1, which represents the total effect of intentional herding, is only significantly negative at 1% level for investment firms (−0.159 in sub-panel A3, and −0.272 in sub-panel B3) with Wald χ^2 statistics being 7.42 and 8.62, respectively, and for S&Ls (−0.159 in sub-panel B3) with Wald χ^2 statistics being 6.20. These findings stand in contrast to the results reported in panel B of Table 5 where we try to capture nonlinearity associated with $R^2_{m,t}$ by adding additional variables in multiplicative form. In panel B of Table 5, we do not find any significant herding by investors during financial crisis in response to non-fundamental information. We rather find significant levels of adverse herding by investment banks and insurance firms only towards their sectoral consensus, and a decreasing herding tendency with increases in volatility. In contrast, the STR results reported in Table 7 reveal a strong presence of herding by investors in S&Ls and investment banks with reference to market consensus and insurance firms with reference to sectoral consensus in the high volatility regime in addition to low volatility regime.

Thus, while our results confirm the presence of herding in high volatility regime, such herding is spurious as they occur in response to fundamental factors. Intentional herding is only limited to S&Ls and investment firms in high volatility regime. Herding is observed for all financial institutions in response to non-fundamental information even when volatility is low.

VII. EVIDENCE OF CROSS-HERDING DURING FINANCIAL CRISIS

Previous studies (Ng 2000; Marais and Bates 2006; Chiang et al. 2007; Diebold and Yilmaz 2009), find interdependence and spillovers from stock return volatility across markets during crises. Demirer and Kutan (2006), Tan et al. (2008), Chiang and Zheng (2010), Economou et al. (2011), Galariotis et al. (2015) use squared market return of country *j* in addition to squared market

Table 8 Estimates of cross herding across FIs using smooth transition regression (STR) model

i	Commercial bank (COM)			S&L (S&L)			Investment firms (INV)			Insurance firms (INS)		
j	S&L	INV	INS	COM	INV	INS	COM	S&L	INS	COM	S&L	INV
Panel A: Herding towards fundamental												
Linear coefficient												
$\gamma_0 R^2_{m,i,t}$	0.059***	0.119***	0.021***	0.080***	0.573***	0.094***	0.013***	0.012***	0.020***	0.004***	0.023***	0.218
	(8.391)	(7.797)	(7.005)	(5.695)	(9.138)	(7.909)	(5.003)	(5.841)	(6.174)	(3.771)	(5.219)	(1.212)
$\pi_0 R^2_{m,j,t}$	−0.045***	−0.009**	−0.024***	0.074***	0.079***	0.012***	0.035***	0.026***	0.024***	0.037***	0.021**	−0.398**
	(3.109)	(−2.154)	(−4.987)	(11.592)	(7.669)	(3.126)	(9.488)	(2.919)	(5.875)	(3.201)	(2.279)	(−2.165)
δ	10.00	9.00	9.50	10.00	5.50	5.50	10.00	4.50	8.50	5.00	10.00	9.00
C	14.22	15.20	13.15	12.87	13.44	16.23	13.11	14.34	16.20	14.34	17.21	18.22
R^2	89	88	79	88	77	78	74	92	90	88	87	84
Non-linear coefficient												
$\gamma_1 R^2_{m,i,t}$	−0.036**	−0.034***	0.011	−0.046**	−0.135***	−0.078***	−0.050*	−0.014**	−0.015***	−0.004	−0.025***	−0.202**
	(−2.577)	(−6.644)	(1.547)	(−2.280)	(−9.841)	(−4.321)	(−1.921)	(2.203)	(−2.512)	(−0.374)	(−8.972)	(−2.110)
$\pi_1 R^2_{m,j,t}$	−0.033***	0.0162***	0.020**	−0.079***	−0.079***	−0.012**	−0.054**	−0.082**	−0.032***	−0.020	−0.027	0.483**
	(−4.236)	(4.318)	(−2.074)	(−4.771)	(−8.114)	(−2.113)	(−2.184)	(−2.221)	(−3.424)	(−0.778)	(−1.088)	(2.174)
δ	10.00	9.50	10.00	10.00	5.60	5.50	10.00	4.50	9.00	6.60	10.00	10.00
C	16.00	14.33	14.90	12.77	14.40	18.89	13.12	13.33	17.55	15.88	16.12	17.99
R^2	91	77	88	86	90	79	92	79	77	87	88	88
Panel B: Herding towards non-fundamental												
Linear coefficient												
$\gamma_0 R^2_{m,i,t}$	−0.025**	−0.013**	−0.010*	−0.127***	0.069*	−0.512**	0.122**	0.085	0.110*	0.138	0.124	0.030***
	(−2.531)	(−2.554)	(−1.711)	(−5.281)	(1.776)	(−2.110)	(2.041)	(0.397)	(1.791)	(0.991)	(1.221)	(3.656)
$\pi_0 R^2_{m,j,t}$	0.073**	0.027***	0.005	−0.039**	−0.013	0.054	−0.245	−0.093	−0.039	0.004	0.052	0.011*
	(2.127)	(6.267)	(0.996)	(−1.982)	(−1.001)	(0.359)	(−1.143)	(−1.022)	(−1.210)	(1.310)	(0.892)	(1.823)
δ	10.50	9.50	9.50	10.00	5.00	6.50	9.50	4.50	7.50	5.50	12.00	9.50
C	14.70	14.12	13.67	14.91	15.00	17.11	15.23	13.41	16.21	14.40	15.82	17.92
R^2	88	82	89	78	77	91	79	87	83	83	86	87
Non-linear coefficient												
$\gamma_1 R^2_{m,i,t}$	0.041***	0.010	0.047***	0.052***	0.032	0.262*	−0.169***	−0.080*	−0.141**	−0.077	−0.112	−0.030**
	(2.669)	(0.690)	(3.020)	(4.172)	(1.090)	(1.740)	(−5.364)	(−1.772)	(−2.101)	(−1.234)	(−1.151)	(−1.92)
$\pi_1 R^2_{m,j,t}$	−0.117***	−0.047***	−0.011	0.146*	0.055	−0.054***	0.325**	0.192	0.062	−0.023	−0.017	−0.104***
	(−2.636)	(−6.221)	(−1.358)	(1.694)	(1.252)	(−2.899)	(2.101)	(0.992)	(1.443)	(−1.291)	(−1.544)	(−3.189)

Table 8 *(continued)*

i	Commercial bank (COM)			S&L (S&L)			Investment firms (INV)			Insurance firms (INS)		
j	S&L	INV	INS	COM	INV	INS	COM	S&L	INS	COM	S&L	INV
δ	10.00	9.50	7.00	10.50	5.50	6.00	8.50	7.50	7.00	10.50	10.00	10.50
$C.$	15.77	14.65	15.70	10.62	12.10	17.43	13.09	12.00	14.99	11.22	17.62	18.20
$R^2.$	87	84	92	94	91	79	78	84	81	79	90	89

Note: This table reports cross herding estimates of the STR model: $CSAD_{i,t} = \alpha_0 + \beta_0 |R_{m,i,t}| + \gamma_0 R^2_{m,i,t} + \pi_0 R^2_{m,j,t} + \left[\alpha_1 + \beta_1 |R_{m,i,t}| + \gamma_1 R^2_{m,i,t} + \pi_1 R^2_{m,j,t}\right] F(\vartheta; \delta, c) + \varepsilon_t$, where $i \neq j$, and $F(\vartheta; \delta, c) = (1 + \exp(-\delta(\vartheta - c)))_{-1}$, and ϑ is the transition variable – conditional volatility, and c is the threshold parameter, and δ is the slope parameter determining the speed and smoothness of the transition from one regime to the other at c.. The sample period is January 01, 2003 – December 31, 2012. t-statistics are given in the parentheses. "***", "**", and "*" represent statistical significance at 1, 5, and 10% levels, respectively. We report only estimates of herding coefficients in two volatility regimes in the table for brevity.

return of country *i* on the right hand side of the regression equation (3) or (5) to capture the spillover effects of herding. We use STR model as follows:

$$
\begin{aligned}
CSAD_{i,t} &= \alpha_0 + \beta_0 |R_{m,i,t}| + \gamma_0 R^2_{m,i,t} + \pi_0 R^2_{m,j,t} \\
&\quad + \left[\alpha_1 + \beta_1 |R_{mi,t}| + \gamma_1 R^2_{m,i,t} + \pi_1 R^2_{m,j,t}\right] F(\vartheta;\delta,c) + \varepsilon_{i,t}
\end{aligned}
\tag{13}
$$

where $i \neq j$, and $CSAD_{i,t}$ stands for the cross-sectional absolute deviation of daily stock returns with respect to equally weighted daily portfolio returns, $R_{m,i,t}$ for the *i*th sector of financial institutions, and $R^2_{m,j,t}$ is the herding variable for the *j*th sector. Thus the estimates of π_0 and π_1 capture the cross herding by *i*th sector with *j*th sector or the spillover effects from *j*th sector to *i*th sector in low and high volatility regimes, respectively.[14]

The results of the cross herding is presented in Table 8. In Panel A, we find that the investors in commercial banks herd with all three other financial institutions in low volatility regime, and with only S&Ls in high volatility regime due to fundamental factors as the coefficients of π_0 and $\pi_1$are highly significant at 1% level. On the other hand, investors in S&Ls and investment firms herd with others in the high volatility regimes. Investors in insurance firms herd with only investment bank in a significant way in low volatility periods as the coefficient of π_0 is -0.398 with significance level at 5% level. We do not find any significant herding in response to non-fundamental information in low volatility regime in Panel B. During high volatility period, we find spillover effects of herding from S&Ls and investment banks to commercial banks as the coefficients of $\pi_1$are -0.117 and -0.047 with statistical significance at 1% level. Similarly, we find spillover effects of herding from S&Ls and investment banks to insurance firms as the coefficient of $\pi_1$is around -0.10. S&Ls only herd with insurance firms in high volatility regime. Our findings show less frequent intentional cross herding compared to spurious herding among financial institutions during high volatility regime implying that there is limited spillover effect of herding when investors face non-fundamental information.

VIII. CONCLUSION

We examine the herding behavior of investors in the US financial industry, especially commercial banks, S&Ls, investment and insurance firms during global financial crisis of 2008 towards their own sub-sector and the market using CSAD and augmented CSAD models. We also distinguish between herding in response to fundamental and non-fundamental information, and find a greater influence of global financial crisis on herding towards their sectoral consensus by commercial and investment banks in response to fundamental factors, which

14 The transitional variable is the conditional volatility. We find the selection of LSTR models in all regressions as well.

implies that such herding is spurious. We also find that the spurious herding increases with conditional volatility of returns. We also use STR approach with conditional volatility as the transition variable to examine how herding behavior is evolved in high and low volatility regimes when volatility exhibits substantial nonlinearity with regime switches. Our findings suggest that investors do not herd in low volatility regime in response to fundamental information, and herding effects on such fundamentals is relatively high with market consensus for all financial institutions except insurance firms. On the other hand, investors herd in response to non-fundamental information in low volatility regimes, and such intentional herding is only significant and limited to S&Ls and investment banks in high volatility regime. We also find less frequent intentional herding compared to spurious herding among investors in high volatility regimes implying that there is limited spillover effects of herding when investors face non-fundamental information.

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