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Option-implied information and stock herding

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Abstract

In this paper, we examine if herding behaviour in the equity market can be explained by option-implied information. Our empirical results confirm the commonly reported absence of herding as a general tendency in the U.S. equity market. However, we find evidence of significant herding behaviour during periods when option-implied information reflects a pessimistic view about the future prospects of the equity market. More specifically, we find that individual stock returns tend to cluster more closely around the market consensus during days of high implied index volatility, more pronounced negative implied skewness, and higher trading volume in index puts.

KEYWORDS

cross-sectional dispersion, herding, market stress, options

JEL CLASSIFICATION

G14; G11

1 | INTRODUCTION

The behavioural finance literature has been paying increasing attention to the way in which investors form beliefs about the future evolution of asset prices and, ultimately, how they trade based on these beliefs. One stream of the literature, in particular, has focused on the potential tendency of investors to follow some type of aggregate consensus, a behaviour typically referred to as *herding*. For instance, investors could exhibit herding behaviour when trading a particular stock by following the actions of other investors who trade the same stock. Alternatively, investors might use the aggregate market return as a consensus around which to herd when they price individual stocks.

From a psychological point of view, suppressing one's prior beliefs in order to follow the actions of others could reflect an irrational behaviour (Devenow & Welch, 1996). However, herding could also represent a rational strategy for a less sophisticated investor who faces high costs of information (Chiang & Zheng, 2010). In this case, mimicking the actions of more sophisticated investors or following the overall market consensus could be more efficient compared to collecting and analysing information in order to form independent views about asset prices. Importantly, suppressing individual beliefs in favour of following the prevailing consensus has significant implications. Pricing assets by following the market consensus is likely to lead asset prices to deviate considerably from their true fundamental values, whereas herding also mechanistically increases correlations among assets, thereby reducing diversification benefits.

Currently, there is a substantial literature that examines the topic of herding in equity markets (see Spyrou, 2013, for a comprehensive review of the literature).[1] Generally, the

[1]In addition to the substantial literature on herding in the equity market (see Andrikopoulos, Kallinterakis, Ferreira, & Verousis, 2017 and Frijns & Huynh, 2018 for two recent studies), other empirical studies have examined herding effects in other markets, such as mutual funds (Grinblatt, Titman, & Wermers, 1995; Jiang & Verardo, 2018), Exchange Traded Funds (Gleason, Mathur, & Peterson, 2004), corporate bonds (Cai, Han, Li, & Li, 2019), commodities (Demirer, Lee, & Lien, 2015), and options (Bernales, Verousis, & Voukelatos, 2016).

extent to which investors herd when trading in stocks varies across different equity markets, with most studies finding very little, if any, evidence of significant herding in the U.S. equity market. In this paper, we focus on a more targeted research question. Instead of examining unconditional herding, where investors might consistently cluster around the market consensus, we investigate whether herding is more likely during specific states of the market. More specifically, we use information extracted from the options market as a proxy for investors' expectation of the future state of the equity market, and we explore if this information can explain herding behaviour in stocks.

This paper contributes to the literature by bridging the gap between herding behaviour in the equity market and information extracted from the respective options market. To the best of our knowledge, this is the first time that this issue has been addressed in the literature. Previous studies have tended to examine herding predominantly as a general tendency that might unconditionally characterize investor behaviour, whereas a smaller number of empirical papers have explored if herding effects are related to other variables that are contemporaneously observed in equity markets. In contrast, our paper focuses on the relationship between the equity market and the options market, as we attempt to understand if information extracted from the latter can explain investors' tendency to herd when trading in the former. Our empirical results are indeed consistent with the notion that option-implied information can explain herding in stocks.

Our focus on information from the options market in the context of herding is motivated by the forward-looking nature of options. Investors' propensity to herd is likely to be related to the way in which they form expectations about future stock prices. Options, in particular, have been shown to contain information about the future distribution of stock returns that is incremental to information that is contemporaneously available in the underlying equity market. For instance, previous studies have shown that stock returns can, to some extent, be forecasted using option-implied volatility (Govindaraj, Jin, Livnat, & Zhao, 2014; Lin & Lu, 2015), option-implied skewness (Conrad, Dittmar, & Ghysels, 2013; Fu, Arisoy, Shackleton, & Umutlu, 2016; Jin, Livnat, & Zhang, 2012; Liu, Pong, Shackleton, & Zhang, 2014), and measures related to options trading volume (Blau & Wade, 2013; Pan & Poteshman, 2006; Roll, Schwartz, & Subrahmanyam, 2010). In this spirit, our emphasis throughout this paper is to understand if measures extracted from the options market (which could reflect investors' expectations about future stock returns) can explain why investors might choose to follow the consensus during certain periods, even if they do not necessarily herd as a general strategy.

A large part of the herding literature focuses on the cross-sectional dispersion of stock returns as a measure of the extent to which the returns of individual stocks tend to cluster around the market consensus. Using this approach, a number of studies have found no significant evidence of herding in the U.S. equity market (Chang, Cheng, & Khorana, 2000; Chiang & Zheng, 2010; Christie & Huang, 1995), although investors in emerging markets have been documented to herd around the domestic market return (Chang, Cheng, & Khorana, 2000) or around the performance of the U.S. market index (Chiang & Zheng, 2010). We follow this stream of the literature in terms of using stock returns' cross-sectional dispersion when examining herding effects, with our paper being more closely related to Galariotis, Rong, and Spyrou (2015) who explore if herding in stocks is more pronounced during certain periods. Specifically, Galariotis, Rong, and Spyrou (2015) find that investors in the U.S. equity market do no exhibit herding behaviour unconditionally, but they tend to herd on days of macroeconomic announcements and during crisis periods.

Our results are consistent with previous empirical findings that highlight the absence of herding as a general investment behaviour in the U.S. equity market. This rejection of unconditional herding is based on the fact that the cross-sectional dispersion of stock returns is found to be increasing with the magnitude of market returns, consistent with the theoretical predictions developed in Chang, Cheng, and Khorana (2000). However, we find strong support for the hypothesis that information extracted from the options market can explain herding in stocks under certain market conditions. More specifically, we find that stock return dispersion is significantly lower during days with higher index implied volatility. In other words, when investors anticipate a higher level of future volatility at the market level, they tend to price individual stocks in a way that produces a closer cluster around the market consensus, to an extent that cannot be explained by the theoretical relationship between dispersion and the market return. Similarly, we find that stock returns cluster significantly closer to the market return during days of greater negative implied index skewness. Intuitively, investors' tendency to herd appears to depend on the extent to which they hold a pessimistic view about future market returns, with herding being more likely during days when the probability of large market drops is higher. Furthermore, we find that dispersion is significantly negatively related to the put-to-call trading volume ratio and to the trading volume of out-of-the-money (OTM) index puts in particular. Given that trading in index puts can be thought of as indicative of a negative view about the future performance at the aggregate market level, we interpret this finding as investors being substantially more inclined to follow the consensus when they are relatively more pessimistic about the equity market.

Overall, our empirical findings support the notion that investors' expectations about the future performance of the equity market, as these are reflected by forward-looking information extracted from the options market, are strongly related to their propensity to herd when trading individual stocks. In this sense, herding behaviour seems to prevail during periods of market stress rather reflecting a general tendency. Moreover, our findings are robust to alternative proxies for implied volatility and implied skewness, and they also hold after accounting for additional factors that have been previously shown to be related to herding behaviour, such as stock trading volume, crisis periods, and macroeconomic announcements.

In addition to these findings on conditional herding, we also report some evidence of strong herding during extreme market conditions. When we focus on subsamples of days when the option-related variables take extreme values (in the 1% tail of their distribution), we find that dispersion is no longer positively related to market returns, in contrast to theoretical predictions as well as to our findings in the full sample. Theoretically, in the absence of herding, larger absolute market returns are expected to be associated with higher dispersion of individual stock returns. However, we find that on days with extremely high implied volatility, extremely negative implied skewness or extremely high trading volume in index puts (and particularly OTM puts), larger market movements are actually associated with lower dispersion, that is, with stock returns clustering more closely around the market consensus.

The remaining of the paper is organized as follows. Section 2 discusses the methodology used to detect herding in individual stocks and the different definitions of herding that we examine. Section 3 presents the data used in the empirical analysis, whereas Section 4 discusses the empirical results. Finally, Section 5 concludes.

2 | FRAMEWORK FOR DETECTING HERDING

Our examination of herding in the equity market is based on the cross-sectional dispersion of stock returns around the market return. In this sense, our methodology is similar to the standard framework for examining herding in stocks that has been employed by, among others, Christie and Huang (1995), Chang, Cheng, and Khorana (2000), Chiang and Zheng (2010), and Galariotis, Rong, and Spyrou (2015). We measure the dispersion of stock returns as the cross-sectional absolute deviation (*CSAD*) of the returns of individual stocks from the overall market return

$$CSAD_t = \frac{\sum_{i=1}^{N} |r_{i,t} - r_{mkt,t}|}{N-1}, \tag{1}$$

where $r_{i,t}$ is the return of stock i at time t, $r_{mkt,t}$ is the market return at t, and N is the number of stocks included in the cross-section at t. This dispersion measure quantifies the average proximity of stock returns from the market consensus and, intuitively, it reflects heterogeneity at the aggregate level. The unconditional level of cross-sectional dispersion is not a measure of herding in the equity market, because *CSAD* is expected to be time-varying even in the absence of any herding effects. However, the magnitude of *CSAD* should be directly related to the magnitude of contemporaneous market returns, as formally shown by Chang, Cheng, and Khorana (2000). Therefore, our measure of herding is based on the relationship between cross-sectional dispersion and market returns.

More specifically, Chang, Cheng, and Khorana (2000) show that, under the moderate assumptions of the Capital Asset Pricing Model (CAPM), the cross-sectional dispersion of stock returns must be positively related to the market return. Under the CAPM, the expected stock return can be expressed as

$$E\left[r_{i,t}\right] = r_{f,t} + \beta_i \times E\left[r_{mkt,t} - r_{f,t}\right], \tag{2}$$

where β_i is the stock's time-invariant market beta and $r_{f,t}$ is the risk-free rate (the return of a zero-beta asset) at t. Let β_{mkt} denote the systematic risk of an equally weighted market portfolio, so that $\beta_{mkt} = {}^{1}\!/\!_{N}\sum_{i=1}^{N}\beta_i$. Then, the absolute deviation of stock return i from the average portfolio return can be written as

$$\left|r_{i,t} - r_{mkt,t}\right| = |\beta_i - \beta_{mkt}| E\left[r_{mkt,t} - r_{f,t}\right]. \tag{3}$$

Hence, the expected cross-sectional absolute deviation of stock returns (*ECSAD*) at t can be expressed as

$$ECSAD_t = \frac{1}{N}\sum_{i=1}^{N} |\beta_i - \beta_{mkt}| E\left[r_{mkt,t} - r_{f,t}\right]. \tag{4}$$

Importantly, from Equation (4), it can be easily shown that

$$\frac{\partial ECSAD_t}{\partial E\left[R_{mkt,t}\right]} = \frac{1}{N}\sum_{i=1}^{N} |\beta_i - \beta_{mkt}| > 0, \tag{5}$$

$$\frac{\partial^2 ECSAD_t}{\partial E\left[R_{mkt,t}\right]^2} = 0. \tag{6}$$

Similar to the previous literature, we test for herding effects in the equity market based on the relationships in (5) and (6), using *CSAD* and $R_{mkt,t}$ as a proxy for the unobservable *ECSAD* and $E[R_{mkt,t}]$, respectively. The positive linear relationship between $CSAD_t$ and $R_{mkt,t}$ means that we expect dispersion to be higher on days of higher market returns (in absolute terms). Equally, we expect dispersion to be systematically lower when the absolute market return is lower, and this would not necessarily constitute evidence of herding. Our methodology would classify as herding the case where larger price movements at the market level are associated with a decrease in the dispersion of individual stocks around the market consensus.

We test for the presence of herding behaviour in the equity market by regressing the cross-sectional dispersion of stock returns against market returns and a set of exogenous variables X_t, as given in (7):

$$CSAD_t = \alpha + \beta_1(1-D_t)r_{mkt,t} + \beta_2 D_t r_{mkt,t} + \beta_3(1-D_t) r^2_{mkt,t} + \beta_4 D_t r^2_{mkt,t} + \beta_5 D_{LOW,t} + \beta_6 D_{UP,t} + B_{HERD} X_t + \varepsilon_t, \quad (7)$$

where D_t is a dummy variable that takes the value of one when the market return $r_{mkt,t}$ is negative and the value of zero otherwise, $D_{LOW,t}$ is a dummy that takes the value of one when the market return is located in the lower 5% tail of its distribution, and $D_{UP,t}$ is a dummy that takes the value of one when the market return is located in the upper 5% tail of its distribution.[2] The dummy variable D_t allows for potentially asymmetric herding effects in up and down markets, whereas the use of squared market returns allows for herding potentially being driven by a non-linear relationship between dispersion and market returns. The tail dummy variables $D_{LOW,t}$ and $D_{UP,t}$ allow for the possibility of herding in extreme market conditions. The variables included in X_t are exogenous, and they are computed at the aggregate market level.

Under the null hypothesis of no herding, the cross-sectional dispersion of stock returns should be driven only by the magnitude of market returns. In other words, *CSAD* should be positively related to positive market returns and negatively related to negative market returns ($\beta_1 > 0$ and $\beta_2 < 0$). Moreover, this relationship should be linear, so the coefficients of any non-linear terms should be equal to zero ($\beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$). Finally, assuming that investors use the CAPM to price stocks, all the exogenous variables in X_t should not have an impact on dispersion, so the coefficients in B_{HERD} should be statistically indistinguishable from zero.

Overall, we define herding as violations of the above nulls, and we examine several different types of herding. First, we define *strong herding* as the case where *CSAD* decreases with the magnitude of market returns. Under strong herding, large price swings at the market level would cause investors to herd more closely around the market consensus when pricing individual stocks, thereby resulting in a significantly lower cross-sectional dispersion of stock returns. This alternative hypothesis of strong herding would translate into the linear coefficients of market returns taking the wrong signs (i.e., $\beta_1 < 0$ and/or $\beta_2 > 0$), meaning that dispersion decreases with the magnitude of market returns.

We define *moderate herding* as the case where dispersion increases with market returns but at a decreasing rate. Under moderate herding, *CSAD* could still be expected to be higher during large price swings, but it would be consistently lower than what would be expected given the actual magnitude of market returns. This hypothesis would translate to the coefficients of squared returns being significantly negative (i.e., $\beta_3 < 0$ and/or $\beta_4 < 0$).

We define *herding under extreme market conditions* the case where dispersion is significantly lower than would have been expected during extreme market movements. Under the null of no herding, very large market returns are expected to be associated with higher dispersion of individual stock returns. On the other hand, if extreme market conditions tend to cause investors to herd more closely around the market consensus, then dispersion would be significantly lower on days of large price swings. The hypothesis of herding under extreme market conditions translates to significantly negative coefficients for the two tail dummies (i.e., $\beta_5 < 0$ and/or $\beta_6 < 0$).

Finally, we define *conditional herding* as the case where stock return dispersion is significantly lower (compared with what the market return would suggest) when some exogenous variable takes certain values. Under the CAPM, dispersion should be driven only by market returns, and the variables in X_t should not have an incremental impact on *CSAD*. Alternatively, if conditional herding takes place, stock returns would cluster around the market consensus more closely than what would have been expected given the market return during specific states of the market, rejecting the hypothesis of no herding. Significant coefficients in B_{HERD} would constitute evidence for conditional herding.[3]

3 | DATA

We examine herding in the U.S. equity market, for a sample period of January 1996 to December 2015. We use data on stocks from CRSP, with the dataset including closing daily prices, adjusted returns and trading volume, among other fields. The dates of U.S. macroeconomic announcements have been obtained from Bloomberg and checked against the minutes of the Federal Open Market Committee and the U.S. Bureau of Labour Statistics. We use data on options

[2]We have also replicated the empirical analysis at the alternative 2.5% and 1% tails for D_{LOW} and D_{UP}. The results (unreported for brevity) are similar to the ones we obtain when using the 5% cut-off point.

[3]Our definitions of *strong* and *moderate* herding are similar to those used in Chang, Cheng, and Khorana (2000). Our definition of *herding under extreme market conditions* is similar to the one proposed by Christie and Huang (1995), whereas our definition of *conditional* herding is similar to the one introduced in Bernales, Verousis, and Voukelatos (2016).

written on the S&P 500 index from OptionMetrics. The options dataset includes, among other fields, daily best bid and best ask quotes, trading volume, open interest, Black and Scholes implied volatilities, and option Greeks. We apply several filters on the options dataset. First, we exclude all option observations with prices that violate standard no-arbitrage bounds. Second, we drop all options with fewer than five trading days to maturity. Third, we exclude option observations with fewer than five traded contracts on a given day, to avoid illiquidity concerns.

On each day of the sample period, we compute the cross-sectional dispersion of daily stock returns using Equation (1). In Table 1, we present summary statistics for CSAD. Statistics are reported for the full sample as well as for precrisis, during crisis, and post-crisis periods separately. Mean dispersion is relatively higher at the start of the sample. Across subsamples and for the whole sample, CSAD is also positively skewed and leptokurtic.

As can be seen from Figure 1, *CSAD* is substantially time-varying, ranging from a minimum of 0.21% to a maximum of 1.87% during the financial crisis. However, as was discussed in the previous section, the unconditional level of dispersion does not reflect whether investors tend to herd or not when pricing individual stocks. In other words, low *CSAD* levels are not necessarily indicative of a greater propensity to follow the market consensus, whereas high *CSAD* levels do not necessarily suggest that investors tend to price individual stocks independently of the market consensus.

In order to get a first idea about the presence of herding in the U.S. market, Figure 2 plots *CSAD* against the equally weighted market return for the period January 1996 to December 2015. The relationship indeed appears to be

TABLE 1 Descriptive statistics of CSAD

	Full sample	January 1996–March 2000	March 2000–August 2002	August 2002–September 2007	September 2007–March 2009	March 2009–August 2015
Mean	0.0055	0.0083	0.0083	0.0040	0.0064	0.0036
Median	0.0045	0.0079	0.0080	0.0037	0.0055	0.0034
St.dev	0.0026	0.0014	0.0020	0.0012	0.0026	0.0010
Skewness	0.9442	1.9633	1.2435	2.1800	1.4750	2.9449
Kurtosis	3.5798	9.4016	5.3751	9.5071	5.5478	21.0004
Minimum	0.0021	0.0060	0.0052	0.0024	0.0030	0.0021
Maximum	0.0187	0.0175	0.0181	0.0117	0.0187	0.0161
No. of obs	4,935	1,050	626	1,254	394	1,611

Note. The sample runs from January 1996 to December 2015. The dot-com and the financial crisis periods refer to March 2000 to August 2002 and September 2007 to March 2009, respectively.

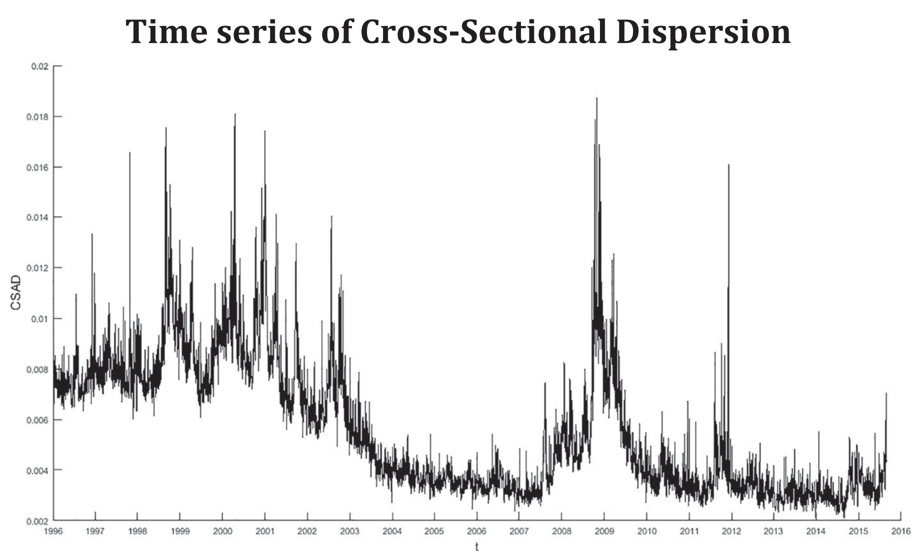
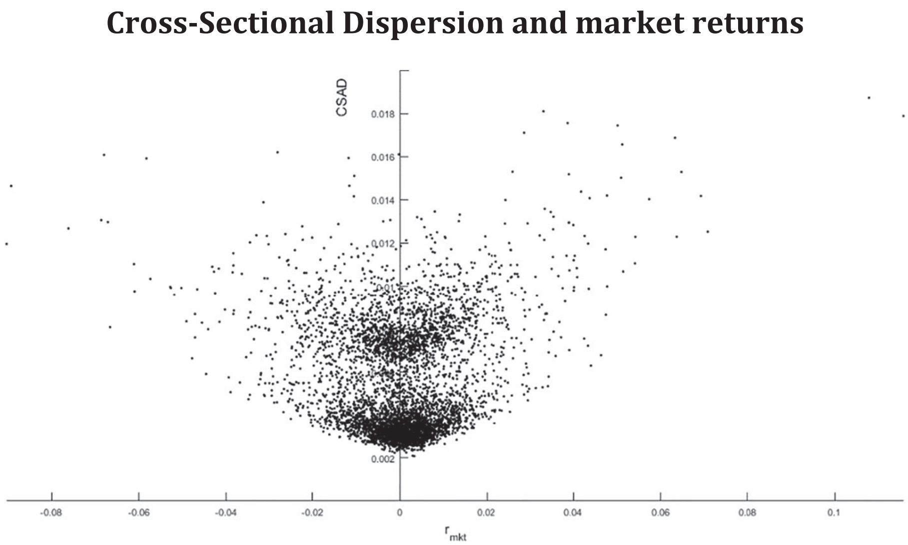


FIGURE 1 Time series of cross-sectional dispersion

Notes: This figure plots the cross-sectional dispersion of daily stock returns. The sample runs from January 1996 to December 2015.



Notes: Figure 2 plots CSAD against the equally-weighted market return for the period January 1996 to December 2015.

FIGURE 2 Cross-sectional dispersion and market returns

positive, and potentially linear, with larger (absolute) market returns being associated with higher levels of dispersion. The herding hypothesis is examined in a comprehensive way in the next section.

4 | EMPIRICAL RESULTS

4.1 | Basic specification

We begin the empirical analysis by estimating a "basic" herding specification, where *CSAD* is regressed only against market returns, without including any additional exogenous variables. Statistical significance is established using Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors. In terms of the general herding specification in (7), the basic version refers to an empty X_t. As stated earlier, the null hypothesis of no herding would be confirmed if *CSAD* increases linearly with the magnitude of market returns. The results reported in Table 2 indeed provide some initial support for the null hypothesis of no herding.

More specifically, as can be seen from the first column of Table 2, cross-sectional dispersion is positively related to positive market returns and negatively related to negative market returns. This result is consistent with the asset pricing predictions discussed in Section 2 and, importantly, these relationships are statistically significant at the 1% level. Hence, we find no support for the alternative hypothesis of *strong herding*. Furthermore, we find that the rate at which dispersion increases with the magnitude of the market return is higher in up markets compared to down markets ($|\beta_1| > |\beta_2|$), consistent with the findings of McQueen, Pinegar, and Thorley (1996) and Chang, Cheng, and Khorana (2000).

However, the positive relationship between *CSAD* and market returns does not appear to be linear, as evidenced by the coefficients of squared market returns. The significantly positive β_3 coefficient of squared positive market returns suggests that cross-sectional dispersion increases at an increasing rate when the market return is positive and,

TABLE 2 Basic herding specification

Constant	I	II
	0.0044***	0.0044***
$(1-D_t)r_{mkt,t}$	0.2637***	
$D_t r_{mkt,t}$	−0.1299***	
$(1-D_t)r^2_{mkt,t}$	0.3807**	
$D_t r^2_{mkt,t}$	−0.3603*	
$D_{LOW,t}$	0.0000	
$D_{UP,t}$	0.0004*	
$r_{mkt,t}$		0.0124***
$\lvert r_{mkt,t}\rvert$		0.1363****
$r^2_{mkt,t}$		−0.1461
Adj. R^2	0.21	0.21

Note. Column I reports the results of the basic herding specification given by $\mathrm{CSAD_t} = \alpha + \beta_1(1-\mathrm{D_t})\mathrm{r_{mkt,t}} + \beta_2 \mathrm{D_t r_{mkt,t}} + \beta_3(1-\mathrm{D_t})\mathrm{r^2_{mkt,t}} + \beta_4 \mathrm{D_t r^2_{mkt,t}} + \beta_5 \mathrm{D_{LOW,t}} + \beta_6 \mathrm{D_{UP,t}} + \varepsilon_t$, where CSAD is the cross-sectional absolute dispersion at time *t*, $\mathrm{D_t}$ is a dummy variable that takes the value of one when the market return $\mathrm{r_{mkt,t}}$ is negative and the value of zero otherwise, $\mathrm{D_{LOW,t}}$ is a dummy that takes the value of one when the market return is located in the lower 5% tail of its distribution, and $\mathrm{D_{UP,t}}$ is a dummy that takes the value of one when the market return is located in the upper 5% tail of its distribution. Column II reports the results of an alternative herding specification. The sample runs from January 1996 to December 2015.

*Significance at 10%.

**Significance at 5%,

***Significance at 1%,

whereas in contrast to theoretical predictions, this finding does not suggest the presence of herding behaviour either. Nevertheless, the significantly negative coefficient β_4 supports the alternative hypothesis of *moderate herding* during down markets. When the market return is negative, *CSAD* seems to be increasing at a decreasing rate, with its overall level being lower than what the magnitude of the market return would suggest in the absence of herding.

Finally, we find very limited evidence of *herding under extreme market conditions.* The coefficients of the tail dummies are positive, suggesting that cross-sectional dispersion tends to be larger on days of extreme market returns. However, the β_5 coefficient of the lower tail dummy is statistically indistinguishable from zero at any meaningful significance level, whereas the β_6 coefficient of the upper tail dummy is significant only at the 10% significance level. Interestingly, and somewhat surprisingly, our results seem to suggest that investors are more likely to herd around the consensus during extreme upwards market movements compared with downward movements. Nevertheless, this relationship is found to be relatively weak compared with the empirical findings of Christie and Huang (1995).

In the interest of comparability with the previous literature, we also examine the relationship between cross-sectional dispersion and market returns using a slightly different specification. Following Chiang and Zheng (2010), we regress cross-sectional dispersion against market returns, absolute market returns, and squared market returns, as given in (8). The term $\gamma_1+\gamma_2$ captures the impact of market returns on dispersion when $r_{mkt,t} > 0$, whereas $\gamma_2+\gamma_1$ captures the same impact when $r_{mkt,t} < 0$.

$$CSAD_t = \alpha + \gamma_1 r_{mkt,t} + \gamma_2 \left| r_{mkt,t} \right| + \gamma_3 r^2_{mkt,t} + \varepsilon_t. \qquad (8)$$

As can be seen from Column II of Table 2, we find no evidence of strong or moderate herding in the U.S. equity market (similarly to Chiang & Zheng, 2010). The cross-sectional dispersion is found to be positively related to the magnitude of market returns, for both down and up markets, rejecting the hypothesis of strong herding. In addition, the coefficient of squared market terms is statistically insignificant, rejecting the hypothesis of moderate herding.

4.2 | Implied volatility

We begin the empirical analysis of the explanatory power of the options market on herding in the underlying equity market by focusing on the implied volatility of the market index.[4] We consider index implied volatility as an indicator of market stress, given that given that implied volatility is often considered as a proxy for investor sentiment regarding the future state of the market. Furthermore, the forecasting ability of implied volatility over future stock returns (Govindaraj, Jin, Livnat, & Zhao, 2014; Lin & Lu, 2015) highlights a strong relationship between implied volatility and the way in which investors form expectations about the future which could, in turn, affect their decision on whether to follow the market consensus when trading stocks.

We follow the Britten-Jones and Neuberger (2000) methodology to construct model-free estimates of future market volatility using options written on the S&P 500 index.[5] The results from including index implied volatility IV_t as an additional regressor in the herding specification are presented in the first column of Table 3.

The results from the extended specification highlight a significant impact of index implied volatility on the relationship between cross-sectional dispersion and market returns in the equity market. The coefficient of IV_t is negative and highly statistically significant, suggesting that *CSAD* is significantly lower on days of high implied volatility at the market level, even after accounting for the magnitude of market returns. This result supports the alternative hypothesis of *conditional herding*, and it indicates that investors tend to herd more closely around the market consensus when implied volatility is higher.

The negative relationship between index implied volatility and cross-sectional dispersion is consistent with the empirical findings of Bernales, Verousis, and Voukelatos (2016) on herding in the options market. Given that implied volatility is computed under the risk-neutral measure, higher levels of IV_t could mean that investors are expecting a higher level of future realized volatility or that they exhibit a higher risk-aversion to future realized volatility or, most likely, both. The previous empirical finding suggests that, during these periods of market stress, investors seem to be paying very close attention to market returns when they price individual stocks, to an extent that is not compatible with theoretical predictions.

4.3 | Implied skewness

In addition to information about the second moment contained in IV_t, we proceed to extract information from index

[4]The variables studied in this and subsequent subsections (IV, IV skew, IV spread, put-call ratio, and OTM put volume) are free from any multicollinearity problems. The correlation table is available upon request.

[5]More specifically, we follow the Jiang and Tian (2005) discretization approach on the Britten-Jones and Neuberger (2000) methodology for obtaining model-free implied volatilities from options at finite strike prices. On each day, we compute the market's implied volatility at a standardized 30-day maturity using all available index option contracts (after filtering). This approach is similar but not identical to the one adopted by the CBOE to compute the VIX index. For robustness, we also replicate the analysis using the VIX directly, obtaining similar results (omitted to save space but available upon request).

TABLE 3 Herding and information from options

	I	II	III
Constant	**0.0017*****	**0.0016*****	**0.0097*****
$(1 - D_t)r_{mkt,t}$	0.1422***	0.1477***	0.1867***
$D_t r_{mkt,t}$	−0.0527***	−0.0577***	−0.1303***
$(1-D_t)r^2_{mkt,t}$	0.4205**	0.5151***	1.6728***
$D_t r^2_{mkt,t}$	−0.6273***	−0.7100***	−1.2548***
$D_{LOW,t}$	0.0000	0.0000	0.0000
$D_{UP,t}$	0.0004*	0.0004*	0.0004*
IV	−0.0155***	−0.0184***	−0.0165***
IV skew		−0.0282***	−0.0067*
IV spread		−0.0124***	−0.0113***
put-call ratio			−0.0003***
OTM put volume			−0.0009***
Adj. R^2	0.39	0.40	0.56

Note. This table reports the results of herding specification given by $\mathrm{CSAD_t} = \alpha+\beta_1(1-\mathrm{D_t})\mathrm{r_{mkt,t}}+\beta_2\mathrm{D_t r_{mkt,t}}+\beta_3(1-\mathrm{D_t})\mathrm{r^2_{mkt,t}}+\beta_4\mathrm{D_t r^2_{mkt,t}}+\beta_5\mathrm{D_{LOW,t}}+\beta_6\mathrm{D_{UP,t}}++B_{\mathrm{HERD}}\mathrm{X_t}+\varepsilon_t$, where CSAD is the cross-sectional absolute dispersion at time t, $\mathrm{D_t}$ is a dummy variable that takes the value of one when the market return $\mathrm{r_{mkt,t}}$ is negative and the value of zero otherwise, $\mathrm{D_{LOW,t}}$ is a dummy that takes the value of one when the market return is located in the lower 5% tail of its distribution, and $\mathrm{D_{UP,t}}$ is a dummy that takes the value of one when the market return is located in the upper 5% tail of its distribution. $\mathrm{X_t}$ refers to the following variables: Implied Volatility (IV), Implied Skewness (IV Skew), IV spread, Put-Call ratio and Out-of-the-market put option volume (OTM put volume). The sample runs from January 1996 to December 2015.

*Significance at 10%.

**Significance at 5%,

***Significance at 1%,

options about the future skewness of market returns. More specifically, we construct a measure of the index's implied volatility skew as the difference of the implied volatility of an OTM index put minus the implied volatility of an at-the-money (ATM) index call (see also Xing, Zhang, & Zhao, 2010). On each day, we identify an OTM put as the option contract with a Black and Scholes delta of −0.25 and an ATM call as the contract with a delta of 0.50. We then compute a measure of risk neutral skewness as the difference in terms of Black and Scholes implied volatilities between the two options.

This difference in implied volatility between an OTM put and an ATM call reflects investors' expectations about large downward movements of the underlying market index. Following a demand-based argument (Garleanu, Pedersen, & Poteshman, 2009), if investors attach a higher probability on large falls of the market index, they would buy OTM index puts in order to hedge against (or to speculate on) these market drops. The price and, by extension, the implied volatility of OTM puts would increase as a result of this demand pressure and the implied volatility skew would become larger. In general, higher values of the implied volatility skew reflect more pessimistic views about the future performance of the market index, in terms of the probability and/or magnitude of negative index returns.

We follow Cremers and Weinbaum (2010) and Lin and Lu (2015), and we use the IV spread as another option-based measure of investors' expectations of bad news at the market level. On each day, we identify the pairs of puts and calls with identical strike prices and expiration dates. Then, we compute the IV spread as the open-interest weighted average of the differences between the implied volatilities of puts minus the implied volatilities of matched calls. The rationale for using the IV spread is very similar to that for using the IV skew. More specifically, if investors expect large downward movements of the marker index, they would be likely to bid up the prices of puts relative to calls. This would lead to higher put IVs relative to call IVs, increasing the IV spread.

The results from adding the IV skew and the IV spread in an extended herding specification are reported in the second column of Table 3. Consistent with the hypothesis of *conditional herding*, we find that both measures are significantly negatively related to cross-sectional dispersion, after accounting for the magnitude of market returns. The coefficients for both variables are negative and statistically significant at the 1% level, suggesting that stock returns cluster more closely around the market return on days that are characterized by a more pronounced negative skewness implied by option prices. In other words, when investors expect bad news at the aggregate market level, they seem to be more likely to herd around the market consensus when pricing individual stocks.

4.4 | Options trading volume

We proceed to examine if trading volume in the options market is associated with herding behaviour in the underlying equity market. Generally, trading volume is expected to be related to information flows. In options market, in particular, trading activity in specific types of option contracts is likely to reflect investors' expectations about specific types of movements of the underlying market index.

In order to understand the potential informational content of trading volume with respect to herding, we focus on the put-call ratio and the trading volume of OTM puts. On each trading day, the put-call ratio is computed simply as the dollar trading volume of all index puts divided by the dollar trading volume of all index calls that were traded on that day. Given that index puts (calls) offer positive returns when the market falls (rises), the put-call ratio is typically considered as a proxy for investor sentiment. High values of the put-call ratio can be thought of as indicative of a pessimistic view at the aggregate market level, with more trading activity focusing on the downward protection of puts relative to the upward exposure of calls. In the same spirit, the total trading volume of OTM puts also reflects investor sentiment. If investors anticipate a downward market movement, then trading in OTM puts would be expected to increase given the insurance-type properties and the high leverage of these contracts. In this sense, higher values of OTM index put trading volume could also indicate a more pessimistic view about the market in terms of the probability and/or magnitude of negative returns of the market index. Hence, we include the logarithm of the total trading volume of all puts with deltas below −0.50 as an additional regressor in the extended herding specification.

As can be seen from the third column of Table 3, both option trading volume variables are negatively related to cross-sectional dispersion in the equity market and the respective coefficients are highly statistically significant. This finding provides further support for the alternative hypothesis of *conditional herding*, suggesting that investors tend to herd more closely around the market consensus during periods when trading activity in the options market indicates a relatively pessimistic view. Our results suggest that when the expectation of bad news at the market level shifts trading activity in the options market towards puts relative to calls (and, especially, towards OTM puts), then the returns of individual stocks tend to cluster more closely around the market return. This significantly denser clustering in the cross-section of stock returns cannot be simply explained by the magnitude of the market return, as theory would predict.

Interestingly, the trading volume variables seem to subsume some of the explanatory power of implied skewness that was previously reported. More specifically, when the put-call ratio and the OTM put trading volume are added as additional regressors, the coefficients of IV skew and IV spread decrease substantially, suggesting a smaller incremental impact on *CSAD* after accounting for information contained in trading volume. Nevertheless, the coefficients of IV skew and IV spread remain statistically significant at the 10% and 1% levels, respectively.

4.5 | Alternative proxies of volatility and skewness risk

We check the robustness of our results by using tradeable option strategies as alternative proxies for volatility and skewness risk. First, we proxy market volatility risk by the daily returns of a short-maturity straddle written on the S&P 500 index. On each day, we create a straddle by buying an ATM index put and an ATM index call, with absolute deltas of 0.50 for both options. This straddle represents a very common volatility trading strategy that tends to offer positive returns when the underlying index's volatility increases, thus acting as a natural choice for a volatility risk proxy (Coval & Shumway, 2001; Santa-Clara & Saretto, 2009).

Second, we proxy market skewness risk by the returns of a risk reversal on the S&P 500 index. On each day, we identify a deep OTM index put and a deep OTM index call (with absolute deltas of 0.125). Then, we create a risk reversal by buying the more expensive of the two options and simultaneously selling the cheaper one. Given that the returns of risk reversals are driven by changes in the tails of the implied volatility smirk (and, by extension, by changes in investors' expectations about the tails of the index's distribution), these strategies are often used as proxies for skewness risk (Bakshi et al., 2008; Bernales, Verousis, & Voukelatos, 2016).

Table 4 reports the results from estimating the extended herding specification where straddle returns have replaced the index's IV and risk reversal returns have replaced the IV skew and the IV spread. The magnitude of the estimated coefficients of volatility risk and skewness risk is somewhat different, and the adjusted R-square of the regressions is lower compared with those reported in Table 3. More

TABLE 4 Alternative proxies for volatility and skewness risk

Constant	I	II	III
	0.0043^{***}	0.0048^{***}	0.0126^{***}
$(1-D_t)r_{mkt,t}$	0.2879^{***}	0.2377^{***}	0.2740^{***}
$D_t r_{mkt,t}$	-0.1643^{***}	-0.1335^{***}	-0.1996^{***}
$(1-D_t)r^2_{mkt,t}$	0.1918*	0.2756*	0.4769*
$D_t r^2_{mkt,t}$	-0.3459^{**}	−0.4048*	−0.1067*
$D_{LOW,t}$	0.0000	0.0000	0.0000
$D_{UP,t}$	0.0003	0.0002	0.0002
straddle	-0.0443^{***}	-0.0423^{***}	-0.0573^{***}
risk reversal		-0.0256^{***}	-0.0279^{***}
put-call ratio			-0.0004^{***}
OTM put volume			-0.0009^{***}
Adj. R^2	0.22	0.27	0.44

Note. This table reports the results of herding specification for alternative proxies for volatility and skewness risk as given by $\mathrm{CSAD_t} = \alpha + \beta_1(1-\mathrm{D_t})\mathrm{r_{mkt,t}} + \beta_2\mathrm{D_t r_{mkt,t}} + \beta_3(1-\mathrm{D_t})\mathrm{r^2_{mkt,t}} + \beta_4\mathrm{D_t r^2_{mkt,t}} + \beta_5\mathrm{D_{LOW,t}} + \beta_6\mathrm{D_{UP,t}} + + B_{\mathrm{HERD}}\mathrm{X_t} + \varepsilon_t$, where CSAD is the cross-sectional absolute dispersion at time t, $\mathrm{D_t}$ is a dummy variable that takes the value of one when the market return $\mathrm{r_{mkt,t}}$ is negative and the value of zero otherwise, $\mathrm{D_{LOW,t}}$ is a dummy that takes the value of one when the market return is located in the lower 5% tail of its distribution, and $\mathrm{D_{UP,t}}$ is a dummy that takes the value of one when the market return is located in the upper 5% tail of its distribution. $\mathrm{X_t}$ refers to the following variables: Straddle, Risk reversal, Put-Call ratio and Out-of-the-market put option volume (OTM put volume). The sample runs from January 1996 to December 2015.

*Significance at 10%.

**Significance at 5%,

***Significance at 1%,

importantly, though, the results in Table 4 remain unchanged in terms of the coefficients' sign and statistical significance. In other words, our previous findings of conditional herding in the equity market during periods of high volatility risk and skewness risk seem to be robust to alternative ways of calculating these market risks. The coefficient of straddle returns is significantly negative, confirming our earlier finding of individual stock returns clustering more closely around the market return when the options market reflects an increase in volatility risk. Similarly, the coefficient of risk reversal returns is significantly negative, consistent with individual stock returns following the market consensus more closely when investors anticipate large downward movements of the market index.

4.6 | Controlling for other factors

We further explore the robustness of our results by extending the herding specification with a set of additional variables that are not based on the options market but could potentially be related to herding in stocks. The first variable that we consider is the total dollar trading volume in the equity market. The rationale for including the trading volume in stocks is similar to the one discussed earlier for the case of the options trading volume variables. More specifically, it would be reasonable to expect that trading volume in the equity market reflects information flows which are likely, in turn, to be associated with the way in which investors form expectations about future stock returns.

Second, we explore whether investors are more likely to herd during crisis periods by adding two crisis dummies to the herding specification. Previous studies have documented a more pronounced tendency for herding during crises (Bernales, Verousis, & Voukelatos, 2016; Chiang & Zheng, 2010), suggesting that investors tend to focus on the market consensus substantially more during turbulent times. In order to examine this effect, we create one dummy variable for the dot-com bubble burst (March 2000 to August 2002) and another dummy variable for the recent financial crisis (September 2007 to March 2009).[1006,7]

Third, we examine if the timing of U.S. macroeconomic announcements has an impact on the cross-sectional dispersion of stock returns, potentially by subsuming the informational content of the option-related variables. The motivation for focusing on scheduled macroeconomic announcements stems from previous empirical findings of trading activity being significantly impacted by these events (Boyd, Hu, & Jagannathan, 2005; Savor & Wilson, 2013). More importantly, macroeconomic announcements have been previously shown to be related to herding effects in stocks (Galariotis, Rong, & Spyrou, 2015) and options (Bernales, Verousis, & Voukelatos, 2016). Therefore, we extend the herding specification with a dummy variable that takes the value of one on days of Federal Open Market Committee or Bureau of Labour Statistics announcements, and the value of zero otherwise.[8]

Table 5 reports the results from estimating this extended herding specification. The first thing to notice is the significantly negative coefficient of total stock trading volume. This finding is somewhat surprising because it would seem to suggest that investors are more likely to herd around the market consensus during periods of higher trading activity in the equity market. From an information-flows argument, we might have expected that higher trading volume would reflect a higher level of information in the stock market thereby making investors more likely to price individual stocks without having to refer to the market return for information. This argument would, then, predict a positive coefficient for total stock trading volume. Nevertheless, our empirical results do not confirm this prediction as they support the alternative hypothesis of conditional herding during high trading activity in stocks.

Another potentially counterintuitive finding is the positive coefficients of the two crisis dummies. This result means that the cross-sectional dispersion of stock returns tends to be higher during particularly turbulent periods, with this relationship being highly significant for the dotcom bubble collapse but only marginally significant for the recent financial crisis. Finally, the coefficient of the macroeconomic announcements dummy is negative, suggesting that investors tend to follow the market consensus more closely on days when important macroeconomic news is released. However, this effect is not particularly strong, as evidenced by the fact that the coefficient is statistically insignificant.

More importantly, the coefficients of the option variables remain largely unchanged after accounting for these additional factors. When stock trading volume, crisis periods and macroeconomic announcement dates are included as additional regressors in the herding specification, the cross-sectional dispersion of stock returns is still found to be significantly related to the index's implied volatility and implied skewness, as well as to trading activity in the options market.

[6]Given the substantial difficulty in accurately defining the exact time period of a crisis, we adopt two relatively common windows for the dot-com bubble collapse and the 2000 financial crisis. We have also replicated the empirical analysis using shorter and longer crisis periods, obtaining similar results (not reported for brevity).

[7]As a robustness test, we have also split the sample to precrisis, post-crisis, and during crisis periods and estimated the original regressions for each subsample. The results remain qualitatively similar with the full sample results and are consistent across subsamples (available upon request).

[8]The Federal Open Market Committee normally meets eight times a year, on prescheduled dates, and their meetings are released to the public shortly afterwards. The Bureau of Labour Statistics announces the unemployment rate and other related data once a month.

TABLE 5 Additional factors

	I	II	III
Constant	**0.0354*****	**0.0343*****	**0.0343*****
$(1 - D_t)r_{mkt,t}$	0.1599***	0.1408***	0.1407***
$D_t r_{mkt,t}$	−0.0813***	−0.0653***	−0.0634***
$(1-D_t)r^2_{mkt,t}$	0.7794***	0.04964**	0.4943**
$D_t r^2_{mkt,t}$	−0.5300***	−0.2476	−0.2457
$D_{LOW,t}$	0.0000	0.0000	0.0000
$D_{UP,t}$	0.0000	0.0000	0.0000
IV	−0.0161***	−0.0145***	−0.0145***
IV skew	−0.0025*	−0.0018*	−0.0018*
IV spread	−0.0010***	−0.0016***	−0.0016***
put-call ratio	−0.0002***	−0.0001***	−0.0001***
OTM put volume	−0.0003**	−0.0002**	−0.0002**
stock volume	−0.0014***	−0.0014***	−0.0014***
dot-com crisis		0.0014***	0.0014***
financial crisis		0.0003*	0.0003*
macro announcements			−0.0001
Adj. R^2	0.72	0.72	0.75

Note. This table reports the results of herding specification given by $CSAD_t = \alpha + \beta_1(1-D_t)r_{mkt,t} + \beta_2 D_t r_{mkt,t} + \beta_3(1-D_t)r^2_{mkt,t} + \beta_4 D_t r^2_{mkt,t} + \beta_5 D_{LOW,t} + \beta_6 D_{UP,t} + +B_{HERD} X_t + \varepsilon_t$, where CSAD is the cross-sectional absolute dispersion at time t, D_t is a dummy variable that takes the value of one when the market return $r_{mkt,t}$ is negative and the value of zero otherwise, $D_{LOW,t}$ is a dummy that takes the value of one when the market return is located in the lower 5% tail of its distribution, and $D_{UP,t}$ is a dummy that takes the value of one when the market return is located in the upper 5% tail of its distribution. X_t refers to the following variables: Implied Volatility (IV), Implied Skewness (IV Skew), IV spread, Put-Call ratio, and Out-of-the-market put option volume (OTM put volume). Stock volume refers to stock trading volume. The dot-com dummy takes the value of one for the period March 2000 to August 2002 and the financial crisis dummy takes the value of one for the period September 2007 to March 2009. We extend the herding specification with a dummy variable that takes the value of one on days of Federal Open Market Committee or Bureau of Labour Statistics announcements, and the value of zero otherwise. The sample runs from January 1996 to December 2015.
*Significance at 10%.
**Significance at 5%,
***Significance at 1%,

In particular, *CSAD* is still found to decrease when index implied volatility increases and when index implied skewness becomes more negative. Dispersion is also lower on days when puts are trading at relatively larger volumes, and this is especially pronounced with respect to OTM puts. These relationships are statistically significant, and they suggest that information extracted from the options market can explain the conditional herding behaviour in the underlying stock market, to an extent that is not subsumed by other macroeconomic or equity-related factors.

4.7 | Herding during market stress

Our empirical results so far support the existence of *conditional herding* in the equity market. In this context, conditional herding refers to the fact that, during certain periods, the cross-sectional dispersion of stock returns is systematically lower than what would have been expected given the magnitude of the market return. These periods of conditional herding, when investors are significantly more likely to cluster around the market consensus as they price individual stocks, are characterized by higher implied volatility, more negative implied skewness, and higher trading activity in puts, particularly OTM contracts. However, the fundamental relationship between cross-sectional dispersion and the market return does not seem to change when we account for these option-related variables. In other words, even when we control for the effect of option variables in the herding specification, *CSAD* is still found to be positively related to the magnitude of index returns, as theory would suggest, rejecting the hypothesis of strong herding.

We further explore the possibility of *strong herding* in the equity market by focusing on periods when the option variables take extreme values. To this end, we estimate the basic herding specification separately for subsamples of days when each of the option variables takes values that fall in the lower or upper 1% of its distribution. The empirical results presented in Table 6 cast some doubt on the universality of the strictly positive relationship between *CSAD* and market returns that is predicted by theory.

For instance, when the basic herding specification is estimated for the subsample of days with very low index implied volatility, *CSAD* is found to be positively related to positive market returns and negatively related to negative ones. In other words, dispersion is found to be increasing with the magnitude of the market consensus. However, even though the signs of the coefficients of market returns are consistent with theoretical predictions, the coefficients are now statistically insignificant, in sharp contrast to our results when the basic specification was estimated in the full sample where the coefficients were very highly significant. At the other end of the spectrum, when we estimate the herding regression on days with very high levels of VIX, the coefficient of negative returns is positive, suggesting that *CSAD* decreases with the magnitude of market drops. Although this coefficient is also statistically insignificant, its negative sign provides some support for the alternative hypothesis of strong herding during periods of particularly high levels of implied volatility. Intuitively, periods of market stress, as reflected by exceptionally high market volatility and negative market returns, seem to cause investors to follow the market consensus very closely when they price individual stocks. The more negative the market return is, the more closely individual

TABLE 6 Herding under market stress

	VIX		IV skew		IV spread		Put-call ratio		OTM puts volume	
	Low 1%	High 1%	Low 1%	High 1%	Low 1%	High 1%	Low 1%	High 1%	Low 1%	High 1%
constant	0.0028***	0.0095***	0.0076***	0.0079***	0.0079***	0.0080***	0.0082***	0.0043***	0.0072***	0.0050
$(1-D_t)r_{mkt,t}$	0.3793	0.0406	0.1875***	0.0726	−0.0352	0.1604*	0.0127	0.8776***	0.7352	−6.3249
$D_t r_{mkt,t}$	−0.0933	0.0161	−0.0639	−0.0265	0.0497	−0.0617	0.1630	−0.3371***	−0.6793	0.0263
$(1-D_t)r^2_{mkt,t}$	−33.7972	−0.4177	0.0410	0.1282	−2.6073	0.0700	−17.9101***	−27.7378	102.9768	5.0063
$D_t r^2_{mkt,t}$	1.2850	0.6411**	−0.1961	0.3301	3.7237*	−0.1746	11.6233**	−8.1480***	−101.4344	1.3902
Adj. R^2	0.01	0.64	0.57	0.03	0.29	0.26	0.20	0.10	0.10	0.08

Note. This table reports the results of herding specification for various subsamples given by $CSAD_t = \alpha + \beta_1(1-D_t)r_{mkt,t} + \beta_2 D_t r_{mkt,t} + \beta_3(1-D_t)r^2_{mkt,t} + \beta_4 D_t r^2_{mkt,t} + \epsilon_t$, where CSAD is the cross-sectional absolute dispersion at time t, D_t is a dummy variable that takes the value of one when the market return $r_{mkt,t}$ is negative and the value of zero otherwise. The subsamples include the VIX index, Implied Skewness (IV Skew), IV spread, Put-Call ratio and Out-of-the-market put option volume (OTM put volume). The sample runs from January 1996 to December 2015.

*Significance at 10%.

**Significance at 5%,

***Significance at 1%,

stocks returns are likely to cluster around it on days of greater market stress.

The results from conditioning on index implied skewness further confirm the presence of strong herding during periods of market stress. When we estimate the herding specification separately for days of very low and days of very high IV skew, the coefficients of market returns are of the correct sign but, in contrast to the full sample results, statistically insignificant. More importantly, when we estimate the basic herding specification in the subsample of very low IV spread, we find that positive (negative) market returns are negatively (positively) related to cross-sectional dispersion, although these coefficients are statistically insignificant. Based on the coefficients' sign, it seems that, when investors anticipate extreme negative skewness in future market returns, the relationship between dispersion and market returns reverses compared with what theory would predict. On these days of extreme negative implied skewness, higher absolute market returns are associated with investors herding more closely around the market consensus when pricing individual stocks.

Our results from conditioning on the trading activity in OTM puts are also consistent with strong herding effects during periods of extremely pessimistic views about future market returns. When we estimate the basic herding specification in the subsamples of days with exceptionally high (1% upper tail) trading volume in OTM puts, we find that dispersion is negatively related to market returns. This negative relationship is observed for positive and negative market returns, although the coefficients in both cases are statistically insignificant. Similar to the previous findings about the effect of implied skewness, larger market movements seem to cause investors to herd more closely around the consensus during periods of particularly pessimistic views about the aggregate market, as reflected in exceptionally high trading volume in OTM put options.

As a robustness test, we estimate a set of regressions reexamining the role of market stress on the relationship between CSAD and market returns. In particular, in Table 7, we re-estimate the basic herding specification in (7) separately for days when the option-related variable is above its 20-day mean. Conditioning on any of the option-related variable, CSAD is positively related to positive market returns and negatively related to negative market returns. However, the relationship for negative returns remains insignificant across all subsamples. In line with the findings for the basic specification, β_3 remains positive and significant for four of five regressions. Moderate herding is detected when the put-call ratio is above its 20-day mean.

Overall, these results support a mixture of the strong and conditional herding hypotheses as a potential explanation of how investors price individual stocks during periods of

TABLE 7 Herding regressions during market stress

	IV	IV skew	IV spread	put-call ratio	OTM put volume
Constant	0.0047***	0.0044***	0.0044***	0.0043***	0.0044***
$(1 - D_t)r_{mkt,t}$	0.2147***	0.2848***	0.2762***	0.2855***	0.2789***
$D_t r_{mkt,t}$	−0.2339	−0.2279	−0.1605	−0.2518	−0.0175
$(1-D_t)r^2_{mkt,t}$	0.0851***	0.1242***	0.1129***	−0.1398***	0.1152***
$D_t r^2_{mkt,t}$	−0.1620	−0.0743	−0.2539	−0.3922	−0.1522
$D_{LOW,t}$	0.0004	−0.0002	0.0000	−0.0002	0.0001
$D_{UP,t}$	0.0009*	0.0003	0.0004	0.0007	0.0005
Adj. R^2	0.22	0.22	0.21	0.22	0.21

Note. This table reports the results of herding specification for various subsamples given by $CSAD_t = \alpha + \beta_1(1-D_t)r_{mkt,t} + \beta_2 D_t r_{mkt,t} + \beta_3(1-D_t)r^2_{mkt,t} + \beta_4 D_t r^2_{mkt,t} + \varepsilon_t$, where CSAD is the cross-sectional absolute dispersion at time t, Dt is a dummy variable that takes the value of one when the market return rmkt,t is negative and the value of zero otherwise. The sample runs from January 1996 to December 2015. Each regression is estimated only for days when the respective option-related variable (IV, IV skew, IV spread, put-call ratio, OTM put volume) exceeds its 20-day moving average.
*Significance at 10%.
**Significance at 5%,
***Significance at 1%,

market stress. On the one hand, the positive relationship between dispersion and absolute market returns suggests that the equity market does not exhibit strong herding during “normal” times. On the other hand, the negative relationship between dispersion and absolute market returns on days with extremely high implied volatility, negative skewness, and trading volume in OTM puts indicates strong herding during periods of market stress. The latter is further supported when we examine herding in periods of high put-call ratios.

5 | CONCLUSION

This paper examines herding behaviour in the U.S. equity market, with a particular emphasis on whether information extracted from the corresponding options market can explain herding effects when trading stocks. Our empirical results confirm that option-based measures are indeed significantly related to how closely individual stock returns cluster around the market consensus, highlighting a strong relationship between trading activity in options and herding in stocks.

Consistent with the previous literature, we find no evidence of herding as a general tendency of investors in the U. S. equity market. Importantly, though, our results highlight significant herding effects during days when activity in the options market is indicative of market stress. More specifically, investors' tendency to herd is substantially more pronounced when the options market is characterized by a higher level of implied volatility, more negative implied skewness and increased trading of put options, particularly OTM contracts. In other words, investors seem to be more inclined to follow the market consensus when they hold relatively more pessimistic views about the future performance of the aggregate equity market.

These findings challenge the commonly held view about the absence of herding in the U.S. equity market, in favour of the alternative hypothesis of conditional herding during periods of market stress. This type of behaviour has important implications for asset allocation, with asset prices deviating from their fundamental values during more turbulent periods when investors tend to hold more pessimistic views. In terms of portfolio diversification, this closer clustering of individual stocks around the consensus during periods of market stress reduces diversification benefits precisely when they would be needed the most.

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