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Do Investors Follow the Herd in Option Markets?

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Abstract

We investigate the previously unexplored herding behaviour of investors in option markets, by examining equity option contracts traded in the US between 1996 and 2012. We document strong herding effects in option trading activity that are conditional on a set of systematic factors related to periods of market stress. More specifically, we find that option investors tend to herd during periods of high market volatility risk, on dates of macroeconomic announcements, during the financial crisis of 2008, when a large number of market option positions is either opened or closed, and during periods of a large average dispersion of analysts' forecasts.

Keywords: Herding; Cross-Sectional Dispersion; Options

JEL Classifications: G14; G11

1 Introduction

Financial economic models based on a strong form of the Efficient Market Hypothesis (EMH) rely on the assumption that individual market participants make investment decisions by processing their own information sets. However, in line with behavioural explanations, a number of recent studies have examined the tendency of investors to suppress their own beliefs in favour of the market consensus

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when trading in individual assets (see Galariotis et al., 2014 and Holmes et al., 2013). Such behaviour is typically referred to as “herding” and carries significant implications in terms of reducing diversification benefits and, in general, causing asset prices to deviate from their fundamental values.¹

Currently, there is a considerable empirical literature on detecting a potential herding behaviour, but it is mainly focused on stock markets (see, for instance, Christie and Huang, 1995, Chang et al., 2000, Chiang and Zheng, 2010, and Galariotis et al., 2014, among others). Nevertheless, the issue of a similar behaviour among investors who trade options has remained under-researched. The objective of this paper is to bridge this gap by studying the previously unexplored herding mechanism in option trading activity. We use data from the US equity options market between 1996 and 2012 to investigate potential herding attitudes reflected in option transactions. More specifically, we examine whether, and under what circumstances, the returns of individual option contracts tend to cluster around the market consensus more closely than would have been expected.

The study of herding among option investors is of particular importance for several reasons. First, option trading represents a considerable segment of global financial markets and has experienced a constant and rapid growth. For instance, between 1973 and 2012 in the US, the equity options volume and the number of stocks with options written on them have grown on average by 33% and 24% per annum, respectively.² Moreover, empirical evidence suggests that option trading improves the market’s informational efficiency as a whole by increasing the quality of information flows (Chern et al., 2008; De Jong et al., 2006; Kumar et al., 1998). In this context, a potential herding behaviour in options, where investors may suppress their own beliefs in favour of mimicking the actions of the majority, would decrease potential benefits in market quality stemming from option trading. Furthermore, given the use of options for hedging purposes, herding is also likely to affect the risk exposure of portfolios that use option contracts as a risk management tool.

One stream of the related literature has investigated the presence of herding by analysing the correlation dynamics among stocks in a particular market or, from an international perspective, between different markets (Bekaert et al., 2012; Boyer et al., 2006; Chiang et al., 2007). A second stream of the literature proposes the cross-sectional dispersion of asset returns around the market consensus as an economically meaningful measure of herding. However, these studies do not find, in general, evidence to support the hypothesis of herding in the US equity market. For instance, Christie and Huang (1995) and Chang et al. (2000) examine whether

¹See, Devenow and Welch (1996) and Spyrou (2013) for a literature review in relation to herding behaviour.

²Option Clearing Corporation, [http:// www.optionsclearing.com](http://www.optionsclearing.com).

cross-sectional dispersion tends to be significantly lower during extreme negative and positive market returns, which would imply that investors herd, and find no evidence to support this hypothesis. However, Chiang and Zheng (2010) and Galariotis et al. (2014) represent the exception. Chiang and Zheng (2010) detect the presence of moderate herding in the equity market during the 2008 financial crisis, while Galariotis et al. (2014) find evidence of herding around fundamental macroeconomic announcements and stress periods in the US and the UK.³

Our paper contributes to the empirical literature on herding in a number of ways. First, we extend the investigation of herding behaviour into a new asset class, namely equity options. To this end, we perform tests to detect herding across groups of option contracts with different characteristics (i.e., leverage and contract type). Second, we expand the set of factors that may drive herding effects; in particular factors associated with periods of uncertainty. Previous studies have examined the impact of factors related to firm size, exchange price limits and crises on herding behaviour. We investigate the role of different systematic factors associated with periods of market stress such as volatility risk, skewness risk, index options' open interest, macroeconomic announcements and the mean dispersion of analysts' forecasts.

We follow the methodology used by Christie and Huang (1995), Chang et al. (2000), Chiang and Zheng (2010) and Galariotis et al. (2014), in which herding is proxied by the cross-sectional dispersion of asset returns (differentiated by contract features) around the market consensus. The intuition behind this measure is that investors make their trading decisions for different assets by solving a multi-dimensional problem which is particular to each agent. For example, trading decisions are based on the way each investor analyses and interprets information about different securities, the individual's prior beliefs, the investor's particular reasons for trading (e.g., some investors trade to make profits through the trading activity per se, while others trade for hedging purposes or tax reductions), among other reasons that are intrinsic to each investor and to each asset. Therefore, prices and returns should reflect heterogeneities in the decision processes followed by different agents and for different financial instruments; hence a considerable cross-sectional dispersion of individual asset returns is expected. Moreover, the cross-sectional dispersion of individual asset returns should be even higher in "ex-

³Despite the lack of strong evidence of herding behaviour in the US equity market, herding effects have been documented in other international equity markets, such as European and Latin American markets, Australia, and most Asian markets (Chang et al., 2000; Economou et al., 2011; Galariotis et al., 2014; Mobarek et al., 2014; Chiang and Zheng, 2010; Chiang et al., 2013). Stocks in most of these countries have been shown to herd around the return of the domestic market, as well as to those of neighbouring equity markets. Other studies have also detected herding behaviour in mutual funds (Grinblatt et al., 1995), corporate bonds (Cai et al., 2012) and commodity futures (Demirer et al., 2013).

treme market conditions” such as periods of high volatility, during crises, or around days of new information releases (e.g., macro announcements). In contrast, the herding hypothesis suggests that market participants are more likely to suppress their own private views during “periods of market stress”, in favour of following the market consensus, thus the cross-sectional dispersion is expected to decrease in scenarios surrounded by a significant degree of uncertainty.

We find evidence in support of the herding hypothesis in the option market, conditional on a set of systematic factors related to periods of market stress. Thus, our study is particularly related to Chiang and Zheng (2010) and Galariotis et al. (2014) who report herding attitudes around macro announcements and during crises, albeit using data from equity markets. First, we show that herding in options is associated with market volatility risk, suggesting that investors tend to follow the market consensus during periods of high market uncertainty. We report strong herding effects when macroeconomic information is released, as well as during the financial crisis of 2008. We show that herding tendencies are more pronounced when an extremely high number of market option positions is either opened or closed, as reflected in changes in the open interest of index options. Moreover, we find that the mean analysts’ forecast dispersion in the aggregate equity market is also related to herding effects.⁴

The remaining of the paper is organized as follows. Section 2 presents the methodology used to compute the cross-sectional dispersion of option returns and to test for the presence of herding effects in option markets. Section 3 provides a brief description of the data used in the empirical analysis. Section 4 discusses the main empirical findings, and Section 5 concludes.

2 Measuring Herding in Options

We apply a modified version of the methodology used by Christie and Huang (1995), Chang et al. (2000), Chiang and Zheng (2010) and Galariotis et al. (2014) for herding in stock markets. In these studies, herding behaviour is explored by examining the cross-sectional dispersion of individual stock returns around the market consensus, where the market consensus is usually proxied by the returns of

⁴In addition, in unreported analyses, we also study whether idiosyncratic characteristics of option contracts (e.g. option trading volume, implied volatility and open interest of each option contract group) and features of underlying assets (e.g. stock trading volume, stock CAPM betas, historical volatility, number of analysts and forecasts dispersions per each underlying stock) are related to option herding behaviours. However, we do not find any evidence of herding effects in relation to specific characteristics of individual options or features of underlying assets. We discuss further about these analyses in Section 4.

market indices (e.g., S&P 500 or Dow Jones).⁵ The rationale behind this measure is related to the heterogeneity which characterizes trading decisions followed by different investors and for different assets.

Our use of options in detecting herding attitudes has two significant methodological implications given that the cross-section of options on individual stocks constitutes a group of assets that is far from homogeneous. For instance, consider the realized return $R_{mkt,t}$ of the equity market at time t . When examining the underlying equity market, the extreme hypothetical case of “perfect” herding would be represented by all stocks offering exactly the same return as the equity market, i.e. $R_{i,t} = R_{mkt,t}, \forall i \in N$. This is an appealing and intuitive property for the dispersion measure, but it is not applicable when the entire cross-section of options is considered. More specifically, let $R_{i,t}^{cp,m,M}$ denote the return at time t of an option contract written on the underlying asset i , where cp is the option type (either c for call or p for put), m refers to the option’s moneyness, and M is the time-to-maturity. The first derivative of the expected option return with respect to the underlying expected return is positive for calls ($\frac{\partial E[R_{i,t}^{c,m,M}]}{\partial E[R_{i,t}]} > 0$) and negative for puts ($\frac{\partial E[R_{i,t}^{p,m,M}]}{\partial E[R_{i,t}]} < 0$). Therefore, including both calls and puts in the same dispersion measure would be highly problematic since their prices would move in different directions by default, artificially increasing cross-sectional dispersion.

In addition, the first derivative of expected option returns with respect to the strike price K is positive for both calls and puts, i.e. $\frac{\partial E[R_{i,t}^{c,m,M}]}{\partial K} > 0$ and $\frac{\partial E[R_{i,t}^{p,m,M}]}{\partial K} > 0$ (propositions 1 and 2 in Coval and Shumway, 2001), with options offering expected returns that are higher in absolute terms than the underlying asset and, more importantly, the magnitude of expected option returns increases with their inherent leverage. Furthermore, empirical evidence suggests that options across different maturities tend to offer significantly different returns, mainly because of the different horizons associated with the underlying distributions used to price them and the differences in the options’ relative time-value (see, e.g., Constantinides et al., 2013).

Consequently, the first change to the original methodology of the cross-sectional dispersion of asset returns (used in equity markets by Christie and Huang, 1995, Chang et al., 2000, Chiang and Zheng, 2010, Galariotis et al., 2014) is that measures of cross-sectional dispersion of option returns have to refer to contracts with similar characteristics in terms of option type (calls versus puts), moneyness and

⁵Chang et al. (2000) propose the Cross-Sectional Absolute Deviation (*CSAD*) measure while Christie and Huang (1995) and Chiang and Zheng (2010) suggest an alternative measure of dispersion, based on the Cross-Sectional Standard Deviation (*CSSD*). Both measures of cross-sectional dispersion are fairly similar, with Chang et al. (2000) motivating their use of absolute deviations by a lower sensitivity to outliers compared to *CSSD*.

maturity. To this end, we focus only on short-term options on individual stocks, which tend to be more liquid than longer-term contracts, and group them according to their moneyness, separately for calls and puts. In addition, with the objective of selecting the appropriate proxy for the market consensus, we use the returns of the respective index options for each particular option group (same type, short-term, and same moneyness).

Overall, our methodology is based on examining herding separately across two option types (calls and puts) and three levels of moneyness for a total of six option groups. First, on each trading day, we select the nearest-to-maturity index option contracts, as long as they have at least one week to expiration. We then identify one index option contract for each of three target levels of moneyness, namely OTM (with absolute deltas equal to 0.25), At-The-Money (ATM, absolute deltas equal to 0.50) and In-The-Money (ITM, absolute deltas equal to 0.75), separately for calls and puts. For each of the six target index options, we calculate the respective individual equity option returns by identifying, for each individual underlying asset, the short-term option contract with the same option-type and moneyness.⁶ We subsequently explore herding in equity options by computing the cross-sectional absolute deviation (*CSAD*) for each group as

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

where $R_{mkt,t}^{cp,m,M}$ is the daily arithmetic return at time t of an index option of type cp , moneyness m , and maturity M . The length N of the cross-section of individual options varies both across groups and across time within the same group (subscripts have been suppressed for notational convenience).

Similarly to previous studies that focused on the equity market (Chang et al., 2000; Chiang and Zheng, 2010; Galariotis et al., 2014), our measure of herding is given by the relationship between *CSAD* and index option returns, and not by the unconditional level of *CSAD*. Chang et al. (2000) show that, under the moderate assumption of expected stock returns being determined by the Capital Asset Pricing Model (CAPM), *CSAD* in stock returns is positively linearly related to the absolute spot index return. We follow a similar approach to show that, under the additional assumption of expected option returns being determined by the Black and Scholes (1973) model, *CSAD* in option returns is positively linearly related to the absolute index option return (see the Appendix).

⁶Regarding options leverage in particular, we select individual options with the same moneyness (by using the option delta) as that of the target index option in that group, as long as they are within 7.25% in either direction from the target delta of the index option. If a particular stock does not have an option with a delta close enough to that of the index option, then it does not enter the cross-section of option returns on that day.

We test for the presence of herding effects by regressing the cross-sectional dispersion against index option returns and a set of variables $HerdVariables_t$ that characterize periods of market stress, as given in (2).

$$\begin{aligned}
CSAD_t^{cp,m,M} = & \alpha + \beta_1(1 - D_t)R_{mkt,t}^{cp,m,M} + \beta_2D_tR_{mkt,t}^{cp,m,M} \\
& + \beta_3(1 - D_t)(R_{mkt,t}^{cp,m,M})^2 + \beta_4D_t(R_{mkt,t}^{cp,m,M})^2 + \beta_5D_t^L + \beta_6D_t^U \quad (2) \\
& + B^{Herd}HerdVariables_t + \epsilon_t
\end{aligned}$$

where D_t is a dummy variable that takes the value of one if the index option return $R_{mkt,t}^{cp,m,M}$ is negative and the value of zero otherwise, in order to allow for asymmetric effects in up and down (option) markets. Also, D_t^L (D_t^U) is a dummy variable that takes the value of one if the index option return on a given day is located in the 5% lower (upper) tail of the distribution, and zero otherwise.⁷ The herd variables are computed at the aggregate market level and they consist of volatility risk, skewness risk, trading volume, open interest, macroeconomic announcements, crisis periods, dispersion of analysts' earnings forecasts, the spot index return and the cross-sectional dispersion observed in the underlying equity market. Option-specific subscripts have been suppressed in all dummy variables, as well as in the random error term, for notational convenience.

Under the null hypothesis of no herding, $CSAD$ should be positively related to positive index option returns and negatively related to negative ones ($\beta_1 > 0$ and $\beta_2 < 0$). Furthermore, given the strictly linear relationship between dispersion and index option returns, the null of no herding predicts that the coefficients of the non-linear returns terms should be equal to zero ($\beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$). Finally, if investors price individual stocks using the CAPM and individual stock options using the Black and Scholes (1973) model, then the herd variables should not have an impact on $CSAD$ so, under the null of no herding, the vector B^{Herd} should consist of coefficients that are not different from zero. Moreover, even if the CAPM and the Black and Scholes (1973) model are not the actual models used to price assets, the coefficients in B^{Herd} would still be expected to be zero under the null of no herding as long as the herd variables do not constitute systematic factors that are priced in the cross-section of expected returns (to the best of our knowledge, none of these factors has been previously found to be a priced state variable).

⁷The two additional dummies for extreme down and up market movements were first proposed by Christie and Huang (1995). All subsequent empirical tests have also been run at the alternative 2.5% and 1% tails for the D_t^L and D_t^U dummy variables. The (unreported) results of these analyses are quantitatively and qualitatively similar to the results presented here, and also consistent with the empirical literature.

We define violations of the above nulls as evidence of herding. Similarly to Chang et al. (2000), we define strong herding as the case where $CSAD$ decreases with the magnitude of index option returns ($\beta_1 < 0$ and/or $\beta_2 > 0$) and moderate herding as the case where $CSAD$ increases with absolute index option returns but at a decreasing rate ($\beta_3 < 0$ and/or $\beta_4 < 0$). Similarly to Christie and Huang (1995), we define herding in extreme market conditions as the case where $CSAD$ is significantly lower when the returns of the index option are in the tails of their distribution ($\beta_5 < 0$ and/or $\beta_6 < 0$). Finally, we define as conditional herding the case where $CSAD$ is significantly lower (than what would have been expected given the index option return) during periods when our herd variables take particular values (i.e. coefficients in B^{Herd} being significant). Overall, a lower conditional expectation of $CSAD$ in periods of market stress would imply that individual option returns tend to cluster around the market consensus more closely than what the index option return would suggest during specific states of the market.

3 Data

We use the OptionMetrics database, which covers the entire US equity options market, from January 1996 to December 2012. The dataset contains daily prices of option contracts written both on individual stocks and on the S&P 500 index. The options data includes, among other fields, daily best bid and best ask quotes, implied volatilities (IV), trading volume, open interest and option Greeks. Option prices are computed as the midpoint of the best bid and the best ask quote. The data on the underlying stocks are from CRSP, and they include closing daily prices, adjusted returns and trading volume, among other fields. Analysts' earnings forecasts data are from the Thomson I/B/E/S database. The dates of US macroeconomic announcements were obtained from Bloomberg and checked against the minutes of the Federal Open Market Committee (FOMC) and the US Bureau of Labour Statistics (BLS), available on their respective websites.

We apply several filters. First, we exclude all option contracts with zero bids or asks, non-positive bid-ask spreads, and prices that violate standard no-arbitrage bounds. Second, options with less than one week (five trading days) to maturity are dropped from the dataset. Finally, options with a trading volume of less than five contracts on a given day are filtered out to avoid liquidity issues. We use daily returns to calculate our proxy for herding behaviour, i.e. the return dispersion measure $CSAD$ as given in Equation (1). It is important to mention that despite the fact that a considerable part of the literature that examines option returns has focused on monthly returns of options held to maturity (e.g., Goyal and Saretto, 2009), and to a lesser extent on weekly returns (e.g., Coval and Shumway, 2001), we use daily returns when computing dispersion measures. The use of option

returns computed at a higher frequency is dictated by our research question, since herding effects are typically considered to be short-lived and unlikely to persist for an entire week or a month. This rationale is also evident from the fact that the literature on herding uses asset returns computed predominantly at a daily, or even intra-daily, frequency.⁸

On each day of the sample period, we identify the set of index options as well as all available options written on individual stocks. We only keep the nearest-to-maturity options, which are more liquid than longer-term contracts, and compute their daily option returns across the six option groups discussed in the previous section. Thus, we calculate the dispersion measure on each trading day and for each option group. The relatively few days when an index option of particular target moneyness is not available are treated as missing observations for that option group. As a result, the number of days for which dispersion can be computed varies somewhat across the six option groups. Moreover, since it is not always possible to find individual options with moneyness, measured by the option delta, exactly equal to the target delta of each group, we keep only contracts with deltas that do not deviate from the target delta by more than 0.0725 in either direction. Whenever a particular individual option contract is not traded for two consecutive days, we do not take into account the return of this option contract.

Figure 1 plots the time-series of daily index option returns across the six groups. Figure 2 shows the resulting time-series of *CSAD* and Table 1 provides some descriptive statistics.⁹

[Figure 1 around here]

[Figure 2 around here]

[Table 1 around here]

Table 1, Figure 1 and Figure 2 confirm the need to test for the presence of herding effects separately for different option groups. Figure 1 shows that the returns of index options vary significantly across different moneyness levels, with OTM contracts offering the highest (absolute) returns and their ITM counterparts offering the lowest, consistent with the Coval and Shumway (2001) results. Furthermore, Table 1 and Figure 2 suggest that the cross-sectional dispersion also varies across option groups, with *CSAD* increasing as we move from ITM to OTM

⁸For a more comprehensive discussion on alternative frequencies for computing option returns see Broadie et al. (2009).

⁹All subsequent empirical tests are performed using Cross-Sectional Absolute Deviations and Cross-Sectional Standard Deviations. However, we only report results for the *CSAD* measure, because absolute deviations are less sensitive to outliers. Furthermore, results for *CSSD* are virtually identical.

contracts, mainly as a result of absolute index option returns also increasing in the same direction.

4 Empirical Results

4.1 Volatility Risk and Skewness Risk

We begin the empirical analysis by exploring whether *CSAD* is driven by factors associated with periods of high uncertainty. The first two variables that we consider are the volatility risk and skewness risk of the market. Volatility risk at the market level is proxied by the daily returns of short-maturity Crash-Neutral Straddles (*CNS*) written on the S&P 500 index. More specifically, on each sample day we construct a *CNS* by buying an ATM index call and an ATM index put, while going short in a deep OTM index put (with a delta of -0.125). The long position in ATM index options (straddle) is a very common volatility strategy with returns being positively related to the underlying index’s future volatility, and it represents a natural candidate to proxy for volatility risk (Coval and Shumway, 2001; Santa-Clara and Saretto, 2009). The short position in the deep OTM put protects the straddle against large market crashes and it is intended to “orthogonalize”, to the extent possible, the two risk factors by reducing the *CNS*’s exposure to skewness risk (Driessen and Maenhout, 2013).

We proxy skewness risk by the daily returns of Risk Reversals (*RR*). On each trading day, we identify a deep OTM index call and a deep OTM index put (with absolute deltas of 0.125). A *RR* is then constructed by buying the “more expensive” option while selling the “cheaper” one. Any divergence between the prices of these two options reflects the difference between the implied volatilities extracted from the tails of the underlying’s distribution, thus the returns of the index *RR* provide a natural proxy for market skewness risk (Bakshi et al., 2008). For our sample in particular, deep OTM index puts predominantly trade at a higher price than equally OTM index calls, implying a negatively skewed risk-neutral distribution.

We examine the relationship between cross-sectional dispersion of option returns and the volatility risk and skewness risk of the market (reflected in daily returns of *CNS* and *RR*, respectively) by estimating Equation (3), with the results presented in Table 2. Statistical significance is established using Newey and West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors.

$$\begin{aligned}
CSAD_t^{cp,m,M} &= \alpha + \beta_1(1 - D_t)R_{mkt,t}^{cp,m,M} + \beta_2D_tR_{mkt,t}^{cp,m,M} \\
&+ \beta_3(1 - D_t)(R_{mkt,t}^{cp,m,M})^2 + \beta_4D_t(R_{mkt,t}^{cp,m,M})^2 + \beta_5D_t^L + \beta_6D_t^U \\
&+ \beta_7CNS_t + \beta_8RR_t + \epsilon_t
\end{aligned} \tag{3}$$

[Table 2 around here]

Table 2 shows that the coefficient β_1 (β_2) of the linear term in up (down) markets is consistently positive (negative) and statistically significant. This indicates that *CSAD* tends to increase with the absolute level of index option returns, consistent with the theoretical predictions discussed in Section 2 and rejecting the hypothesis of strong herding. The coefficients of signed squared returns (β_3 and β_4) are significantly positive, suggesting that the *CSAD* of option returns is non-linearly related to the level of index option returns. In addition, the coefficients β_5 and β_6 for index option returns on a given day falling in the lower and upper tails of its distribution are positive, although not always significant. The latter findings of a non-linear relationship between *CSAD* and index option returns stand in contrast to the theoretical strictly linear relationship described in Section 2. However, this result does not support the alternative hypothesis of herding either, since the coefficients of the non-linear terms are positive, suggesting that investors actually tend to diverge more strongly from the market consensus at a rate that is increasing in that consensus' magnitude, and significantly more so when that consensus takes extreme values.¹⁰

The results are also consistent with the stylized fact of equity returns exhibiting markedly different behaviour during down and up markets (Bekaert and Wu, 2000; Bollerslev et al., 2006). This asymmetric effect is evident from the fact that the rate of *CSAD* increases, with respect to the magnitude of market returns, is substantially higher during up markets (β_1) compared to down markets (β_2), with the difference in (absolute) coefficients being statistically significant across all option groups. However, the asymmetry in the non-linear term is in the opposite direction, since the down market coefficients (β_4) are consistently and significantly higher than those associated with up markets (β_3). A final dimension of asymmetry in the herding regression results refers to the fact that, while extreme negative

¹⁰As a robustness check, we also address the potential issue of diminished comparability of option returns by computing the returns of leverage-adjusted option portfolios (following the methodology of Constantinides et al., 2013). Thus, all empirical tests for herding effects presented in this study have also been performed on leverage-adjusted option portfolio returns, for which comparability concerns are substantially mitigated. The results are similar to those obtained using conventional daily returns and are, thus, not reported for brevity but they are available upon request.

index option returns are not always significantly associated with high levels of *CSAD*, extreme positive index option returns appear to result in a significantly higher cross-sectional dispersion.

Overall, the extent to which investors in the options market diverge from the consensus increases as the magnitude of index option returns increases. This finding is consistent with theoretical predictions and it stands in contrast to the hypothesis of herding. However, the positive relationship between returns' dispersion and the index option returns magnitude seems to be somewhat weaker during down markets. In other words, investors seem to be paying relatively more attention to negative returns of index options, as opposed to positive ones, when pricing individual stock options, although they are still found not to herd in either case.

In relation to variables associated with periods of market stress, Table 2 reports evidence that there is a negative relationship between *CSAD* and our proxy for market volatility risk. The coefficient β_7 of daily *CNS* returns is negative and statistically significant across all six option groups. The negative *CNS* coefficient can be interpreted as an increase in the investors' tendency to follow the market consensus during periods of high volatility risk, and it represents the first set of evidence of a potential herding behaviour in the option market.

Regarding skewness risk, results from estimating a specification of Equation (2) where *RR* is the only risk factor added to the "basic" model (unreported), suggest that *CSAD* is significantly negatively related to skewness risk (or "downward jump" risk) across all option groups. On the face of it, such a finding would translate to investors following the market instead of trading on their private information sets during periods characterized by high expected negative skewness or increased risk aversion to skewness risk or, most likely, both. However, as can be seen from Table 2, when both *CNS* and *RR* returns are included in the specification described in Equation (3), the impact of skewness risk on *CSAD* is found to be statistically insignificant (with the exception of OTM puts). This is somewhat surprising since, as was previously mentioned, the crash-neutral element of straddles should have "orthogonalized" them to skewness risk. Furthermore, the two factors are only weakly correlated (the correlation coefficient is -0.08). Nevertheless, based on these results we proceed to include only volatility risk, proxied by *CNS* returns, as an additional explanatory variable in the extended specification henceforth, since it appears to subsume information contained in the skewness risk factor.

It is important to mention, before continuing with our analysis of systematic factors related to periods of market stress, that we also examine (in unreported results) whether idiosyncratic characteristics of option contracts (e.g., option trading volume, implied volatility and open interest of each option contract group) and features of underlying assets (e.g., stock trading volume, stock CAPM betas, his-

torical volatility, number of analysts, and forecast dispersions for each underlying stock) are related to option herding behaviour. In particular, we examine whether specific features of option contracts or their underlying assets are associated with herding effects by sorting option contracts into portfolios, based on each particular characteristic. For instance, we repeat the same analysis reported in Table 2, but performed individually for five portfolios sorted by the implied volatility level of the contracts used in each group. We repeat the same procedure with all characteristics of individual option contracts and features of the underlying asset. Nevertheless, we do not find any evidence that characteristics of each individual option contract and each underlying asset affect the tendency of investors to herd (or not) in option markets (these results are available from the authors upon request).

4.2 Index Option Trading Volume and Open Interest

It would be reasonable to assume that the open interest and trading volume of index options may be related to investors' tendency to follow the market. For instance, trading activity should be related to liquidity shocks and informational events, while open interest has been used in empirical studies as a proxy for divergences of opinion (Bessembinder et al., 1996; and Girma and Mougou, 2002), information flows (Chuang-Chang et al., 2009), information processing (Donders et al., 2000) and informed trading (Bessembinder and Seguin, 1992). Thus, as a first step, we adopt various approaches to test whether trading volume and open interest in index options can explain a potential tendency of investors to follow the consensus instead of their own beliefs.

The first test involves splitting the full sample (across each moneyness group) into two subsamples according to whether the trading volume of the corresponding index options is below or above its 20-day moving average and then estimating the model in Equation (3), separately for each subsample. We also perform an extended full-sample regression which includes *CNS* returns and index options' trading volume as additional explanatory variables in the "basic" model. The results suggest that cross-sectional dispersion is not significantly linearly related to the level of the market's trading volume, nor to whether this trading volume at t is higher or lower than its moving average.

Despite the above inability of trading volume to explain *CSAD*, we find that extreme levels of trading in index options are in fact strongly related to investors' attitudes with respect to following (or deviating from) the market consensus. More specifically, we extend the specification in (3) by adding two dummy variables, namely $D_t^{vol,L}$ and $D_t^{vol,U}$, which take the value of 1 if the trading volume in the corresponding index options at t is located in the lower and upper 5% tails of the distribution respectively, and the value of zero otherwise. We find that the

coefficients of $D_t^{vol,L}$ are negative and highly significant for all three put groups, as well as for OTM calls. The fact that $CSAD$ tends to be significantly lower during periods of extremely low market trading volume, after accounting for the magnitude of market returns, is consistent with a herding effect whereby investors follow the market consensus more closely when the level of trading (in periods of high illiquidity problems) is substantially low. At the other end of the spectrum, cross-sectional dispersion tends to be significantly higher during periods of extremely high trading volume, as evidenced by the significantly positive coefficients of the upper-tail dummy variable $D_t^{vol,U}$. This finding is consistent across all moneyness levels, for both calls and puts, suggesting that investors tend to diverge (instead of herding) from the market consensus when the level of trading volume (presumably with elevated information flows) is particularly high in the market.

It should be noted that endogeneity is a potential issue in our analysis of the relationship between $CSAD$ and index options' trading volume. We interpret the above findings as investors being more likely to herd when information flows through trading volume at the market level are substantially decreased. However, it is conceivable that causality might be running in the opposite direction. For instance, it could be argued that larger divergence of beliefs (and, hence, larger $CSAD$) could be the reason for (rather than the result of) increased trading volume.

Overall, the level of trading volume is not related to herding effects, but the coefficients of the volume tail dummies indicate a strong herding behaviour during extremely low trading volumes, especially in the case of puts. However, we find that this impact of trading volume actually seems to be subsumed by the informational content of open interest, as our next results suggest. When the daily changes in open interest of index options is incorporated as an additional regressor, the coefficients of both trading volume dummies become statistically indistinguishable from zero. Moreover, the coefficients of the new variable OI are positive and statistically significant for calls and puts, across all moneyness bins.

A possible explanation for this finding probably lies in the different informational contents of trading volume and open interest. On the one hand, trading volume reflects the level of investors' activity in buying and selling options, without distinguishing between an exchange of existing contracts and the creation of new ones. On the other hand, changes in open interest directly refer to investors' willingness to open new positions in the options market, which is more directly associated with information flows. With this distinction in mind, our empirical results suggest that herding is significantly more pronounced when open interest decreases, i.e. when investors tend to close their positions in index options as opposed to opening new ones. Such behaviour is independent of the level of trading volume, which could either increase or decrease in this case, and it seems to subsume the explanatory power of extreme movements in the level of option trading

activity.

Furthermore, we explore whether the relationship between cross-sectional dispersion and changes in index options' open interest has a non-linear element. Thus, we extend the analysis by constructing two dummy variables to capture extremely low (large negative) or high (large positive) changes of open interest in index options, with $D_t^{OI,L}$ ($D_t^{OI,U}$) taking the value of 1 if changes in the open interest at t falls in the distribution's lower (upper) 5% tail, and the value of zero otherwise. This extended specification is given in Equation (4), and the results are presented in Table 3.

$$\begin{aligned}
CSAD_t^{cp,m,M} = & \alpha + \beta_1(1 - D_t)R_{mkt,t}^{cp,m,M} + \beta_2D_tR_{mkt,t}^{cp,m,M} \\
& + \beta_3(1 - D_t)(R_{mkt,t}^{cp,m,M})^2 + \beta_4D_t(R_{mkt,t}^{cp,m,M})^2 + \beta_5D_t^L + \beta_6D_t^U \quad (4) \\
& + \beta_7CNS_t + \beta_8OI_t + \beta_9D_t^{OI,L} + \beta_{10}D_t^{OI,U} + \epsilon_t
\end{aligned}$$

After including $D_t^{OI,L}$ and $D_t^{OI,U}$ in the extended specification, the coefficient of open interest remains positive and statistically significant. In addition, the coefficients of both dummies are significantly negative across all option groups, with herding being significantly more likely when changes in index options' open interest are extremely low or high. This finding can be interpreted as investors tending to suppress their own views in favour of the market consensus during periods when new positions in index options are opened, or existing positions are closed, at particularly large quantities. Finally, this herding effect is more pronounced for OTM options compared to their ATM and ITM counterparts.

[Table 3 around here]

4.3 Macroeconomic Announcements and Crises

A number of previous studies have documented important changes in the trading activity around news releases due to the uncertainty that may be generated by such events (see for instance Boyd et al., 2005, and Savor and Wilson, 2013). Thus, we examine whether the timing of US macroeconomic announcements can explain investors' herding behaviour, in excess of the impact of the previously discussed factors.

We consider the scheduled monthly announcements from the Federal Open Market Committee's (FOMC) meetings and the Bureau of Labour Statistics (BLS) as our news release events. The FOMC normally meets on pre-scheduled dates eight times a year, and these meetings' minutes are made available to the public

shortly afterwards.¹¹ We use the dates of the minutes' publication as the relevant macroeconomic announcement dates. In addition, once a month (normally on a Friday) the BLS publishes the US unemployment rate along with other related data, such as the total number of employed and its regional distribution.

In order to test for the presence of herding effects during macroeconomic announcement dates, we estimate an extended specification which includes a dummy variable D_t^{macro} that takes the value of 1 on announcement dates (FOMC or BLS), and the value of zero otherwise. The coefficients of the dummy variable for macroeconomic announcement dates are consistently negative and statistically significant for both calls and puts, indicating that herding is more likely on these dates. For instance, $CSAD$ in OTM puts is on average lower by 0.17% during macroeconomic announcement dates, as given by the estimated β_{11} , suggesting that investors tend to herd around the market consensus on future downward movements of the underlying index more closely when FOMC and BLS release macroeconomic data. Overall, our results are consistent with a significant herding effect during dates of US macroeconomic announcements, with investors being more inclined to follow the market consensus and, as a result, cross-sectional dispersion of option returns being lower than would have been otherwise expected.

Other sources of market stress periods that may induce herding effects are economic crises. For example, Chiang and Zheng (2010) examine the impact of a number of crises (1994 Mexican crisis, 1997 Asian crisis, 1999 Argentinean crisis and 2008 US financial crisis) on investors' tendency to herd, finding that turbulent periods are associated with moderate herding in the country of origin as well as in neighbouring markets. In the same vein, we explore whether investors in the US options market tended to follow the market's lead more closely than expected during the dot-com bubble collapse at the beginning of the past decade and the 2008 financial crisis, by extending the specification with two crisis dummies. The first dummy variable $D_t^{cr.dotcom}$ takes the value of 1 during the dot-com bubble collapse, i.e. from March 2000 to August 2002, and the value of zero otherwise. Similarly, the dummy variable $D_t^{cr.subprime}$ takes the value of 1 during the recent financial crisis, i.e. from September 2007 to March 2009, and the value of zero otherwise.¹² The new specification, extended for macroeconomic announcements

¹¹The FOMC reviews economic and financial conditions, determines the appropriate stance of monetary policy, and assesses the risks to its long-run goals of price stability and sustainable economic growth. The FOMC consists of twelve members: the seven members of the Board of Governors of the Federal Reserve System, the president of the Federal Reserve Bank of New York, and four of the remaining eleven Reserve Bank presidents, who serve one-year terms on a rotating basis.

¹²Given that defining the exact period of a particular crisis represents a notoriously difficult task, we have adopted two commonly used windows for the dot-com bubble burst and the financial crisis of 2008. The subsequent analysis has also been performed under narrower and wider windows, obtaining similar results which are not reported for brevity. Furthermore, despite the

and crisis periods, is given in (5) and the results are reported in Table 4.

$$\begin{aligned}
CSAD_t^{cp,m,M} = & \alpha + \beta_1(1 - D_t)R_{mkt,t}^{cp,m,M} + \beta_2D_tR_{mkt,t}^{cp,m,M} \\
& + \beta_3(1 - D_t)(R_{mkt,t}^{cp,m,M})^2 + \beta_4D_t(R_{mkt,t}^{cp,m,M})^2 + \beta_5D_t^L + \beta_6D_t^U \\
& + \beta_7CNS_t + \beta_8OI_t + \beta_9D_t^{OI,L} + \beta_{10}D_t^{OI,U} \\
& + \beta_{11}D_t^{macro} + \beta_{12}D_t^{cr.dotcom} + \beta_{13}D_t^{cr.subprime} + \epsilon_t
\end{aligned} \tag{5}$$

Somewhat surprisingly, the coefficients of $D_t^{cr.dotcom}$ are positive across all option groups, implying that cross-sectional dispersion was in fact higher than expected and herding was less pronounced during the dot-com bubble collapse. However, these coefficients are significant only for ATM options. On the other hand, the coefficients of $D_t^{cr.subprime}$ are negative and statistically significant across all groups, suggesting that $CSAD$ was significantly lower than expected and, thus, herding was more likely during the financial crisis of 2008, after accounting for the impact of the previously discussed systematic factors. This finding is consistent with the moderate herding effect observed during the same period in the US equity market reported by Chiang and Zheng (2010). A potential explanation for the different results regarding the two crisis periods is that herding effects may be triggered depending on the magnitude and nature of the crisis. The dot-com bubble burst represented a crisis that was more industry-focused and less systematic, while the 2008 crisis was essentially a global one with an impact across most sectors and countries.

[Table 4 around here]

4.4 Dispersion of Analysts' Forecasts

The next systematic factor that we consider represents a more direct proxy for the level of uncertainty about the future performance of the underlying assets at the aggregate market level. On each trading day, we collect the dispersion of analysts' forecasts for each stock in the entire US equity market. Each stock-specific observation of the dispersion of analysts' forecasts is normalized by the

reasonable consensus on the origins of the dot-com bubble collapse, the financial crisis of 2008 refers to a series of market events rather than a single one. More specifically, this (essentially global) crisis originated in the collapse of the US subprime mortgage market which was then followed by a credit crunch in the US financial market and then spread to financial markets around the globe. Note that the subscript "subprime" of the respective dummy variable reflects more the starting point of this crisis rather than its nature as a whole.

respective stock's mean forecast, in order to adjust for "level" differences, and thus to have comparable observations. We then calculate the cross-sectional average of all the stocks' adjusted forecast dispersions (FD) at t as a proxy for investors' uncertainty around the future performance of the aggregate equity market. We include FD as an additional explanatory variable in our regression analysis:

$$\begin{aligned}
CSAD_t^{cp,m,M} = & \alpha + \beta_1(1 - D_t)R_{mkt,t}^{cp,m,M} + \beta_2D_tR_{mkt,t}^{cp,m,M} \\
& + \beta_3(1 - D_t)(R_{mkt,t}^{cp,m,M})^2 + \beta_4D_t(R_{mkt,t}^{cp,m,M})^2 + \beta_5D_t^L + \beta_6D_t^U \\
& + \beta_7CNS_t + \beta_8OI_t + \beta_9D_t^{OI,L} + \beta_{10}D_t^{OI,U} \\
& + \beta_{11}D_t^{macro} + \beta_{12}D_t^{cr.dotcom} + \beta_{13}D_t^{cr.subprime} + \beta_{14}FD_t + \epsilon_t
\end{aligned} \tag{6}$$

As can be seen from Table 5, the coefficients of FD are negative for all options, and statistically significant in 4 out of the 6 option bins. Given that $CSAD$ is significantly lower when analysts' forecast market dispersion is larger, investors seem to herd more closely to the market consensus during periods of higher uncertainty around the future prospects of the aggregate underlying market. Considering that investors incorporate analysts' forecasts in their information sets (presumably affording them considerable weight) when making investment decisions, high levels of FD are likely to be interpreted as indicative of less confidence about the accuracy of the forecasted performance of the average stock. As a result, investors could place a higher weight on the market consensus when making their investment decisions under conditions of high uncertainty.

[Table 5 around here]

4.5 Dispersion of Returns in the Underlying Market

A number of previous studies have examined whether herding in a particular market is affected by events in other markets (see, for instance, Chiang and Zheng, 2010; Klein, 2013; Galariotis et al., 2014). In a similar spirit, we proceed to explore whether herding in the options market might be related to herding behavior in the underlying stock market. To this end, we include in our regression analysis the cross-sectional dispersion in the spot market $CSAD_t^S$:

$$\begin{aligned}
CSAD_t^{cp,m,M} = & \alpha + \beta_1(1 - D_t)R_{mkt,t}^{cp,m,M} + \beta_2D_tR_{mkt,t}^{cp,m,M} \\
& + \beta_3(1 - D_t)(R_{mkt,t}^{cp,m,M})^2 + \beta_4D_t(R_{mkt,t}^{cp,m,M})^2 + \beta_5D_t^L + \beta_6D_t^U \\
& + \beta_7CNS_t + \beta_8OI_t + \beta_9D_t^{OI,L} + \beta_{10}D_t^{OI,U} + \beta_{11}D_t^{macro} + \beta_{12}D_t^{cr.dotcom} \\
& + \beta_{13}D_t^{cr.subprime} + \beta_{14}FD_t + \beta_{15}CSAD_t^S + \beta_{16}(R_{mkt,t}^S)^2 + \epsilon_t
\end{aligned} \tag{7}$$

Here, $CSAD_t^S$ is the cross-sectional absolute deviation calculated with returns of the underlying stock market, where the market consensus is proxied by the returns of the S&P 500 index, $R_{mkt,t}^S$. Following Chiang and Zheng (2010), we also incorporate the squared spot index return as an additional regressor to avoid ‘level’ problems and to capture non-linear relationships with the option market. Table 6 reports the results from estimating Equation (7).

[Table 6 around here]

The first point to notice is that including the cross-sectional dispersion and the index return from the spot market in the herding specification does not change the magnitude, sign and statistical significance of the other coefficients (β_7 to β_{14}). In other words, activity in the spot equity market does not subsume the informational content of the other systematic factors, which are still found to be associated with significant herding effects in option returns.

It is interesting to observe that the coefficients of cross-sectional dispersion in the spot market are found to be consistently negative across all groups, while statistically significant for all put groups and OTM calls. This negative relationship stands in contrast to previous studies that have reported significant spillover effects in terms of herding between different markets at an inter-country level (see, for instance, Chiang and Zheng, 2010; Mobarek et al., 2014). Instead of clustering around the market consensus at the same times, the returns of individual options in fact appear to be more clustered when the returns of stocks are more dispersed (and vice versa).

The negative relationship between cross-sectional dispersions in the option market and the underlying stock market can be explained through divergences of investors’ opinions that may induce herding effects in the option market. As described in the introduction, Christie and Huang (1995) and Chang et al. (2000) do not find evidence of herding in the US equity market; therefore cross-sectional dispersions in stocks, $CSAD_t^S$, can be interpreted as a measure of divergence of opinion amongst investors in relation to stocks’ performance, rather than herding tendencies in the underlying equity market. Hence, when there is a high value of $CSAD_t^S$, indicating discrepancies in investors’ beliefs, option investors seem to be more likely to follow the market consensus, thus reducing the level of $CSAD_t^{cp,m,M}$.

4.6 Robustness Checks

As a robustness check, we estimate a modified version of the previous specification, where all systematic factors are used in return form. Similarly to Galariotis et al. (2014) and Mobarek et al. (2014), we use dummy variables multiplied with the

index option's squared return, replacing the factors that were previously expressed as levels. More specifically, we create a dummy variable $D_t^{OI < MA}$ that takes the value of 1 when the index options' open interest is lower than its 20-day moving average, and the value of zero otherwise. We also use the dummy variable $D_t^{FD > MA}$ which takes the value of 1 when the cross-sectional average of forecast dispersions is greater than its 20-day moving average, and the value of zero otherwise. These variables are used to replace the OI_t and FD_t factors, respectively, from the specification in Equation (7). In addition, the dummy variables $D_t^{OI,L}$, $D_t^{OI,U}$, D_t^{macro} , $D_t^{cr.dotcom}$ and $D_t^{cr.subprime}$ are still incorporated in the modified specification in (8), but now they are multiplied with the squared option market return. Lastly, the variables CNS_t , $CSAD_t^S$ and $(R_{mkt,t}^S)^2$ are included in the same way as before, since they are already expressed in terms of returns.

$$\begin{aligned}
CSAD_t^{cp,m,M} = & \alpha + \beta_1(1 - D_t)R_{mkt,t}^{cp,m,M} + \beta_2D_tR_{mkt,t}^{cp,m,M} + \beta_3(1 - D_t)(R_{mkt,t}^{cp,m,M})^2 \\
& + \beta_4D_t(R_{mkt,t}^{cp,m,M})^2 + \beta_5D_t^L + \beta_6D_t^U + \beta_7CNS_t + \beta_8D_t^{OI < MA}(R_{mkt,t}^{cp,m,M})^2 \\
& + \beta_9D_t^{OI,L}(R_{mkt,t}^{cp,m,M})^2 + \beta_{10}D_t^{OI,U}(R_{mkt,t}^{cp,m,M})^2 + \beta_{11}D_t^{macro}(R_{mkt,t}^{cp,m,M})^2 \\
& + \beta_{12}D_t^{cr.dotcom}(R_{mkt,t}^{cp,m,M})^2 + \beta_{13}D_t^{cr.subprime}(R_{mkt,t}^{cp,m,M})^2 \\
& + \beta_{14}D_t^{FD > MA}(R_{mkt,t}^{cp,m,M})^2 + \beta_{15}CSAD_t^S + \beta_{16}(R_{mkt,t}^S)^2 + \epsilon_t
\end{aligned} \tag{8}$$

Table 7 reports the results from estimating Equation (8). The intuition behind the estimated coefficients of the systematic factors is slightly different compared to those in the previous specification. On the one hand, significantly negative coefficients for the systematic factors in Equation (7) are interpreted as evidence that $CSAD_t^{cp,m,M}$ is lower than expected when these factors take high values (for level variables) or during specific periods (for dummy variables), supporting the hypothesis of herding in periods of market stress. On the other hand, significantly negative coefficients for the systematic factors in the modified Equation (8) would imply that $CSAD_t^{cp,m,M}$ is not only lower, but that it also decreases as the (absolute) index option return increases during specific states of the market. In this setting, herding in option markets must be reflected in a low dispersion of individual option returns during periods of market stress (as given by the systematic factors), which should not be the case when the magnitude of index option return increases (due to level issues, explained in Section 2).

[Table 7 around here]

The results support the hypothesis of herding for all of the systematic factors related to periods of market uncertainty. Cross-sectional dispersion is lower when changes in index options' open interest fall below its 20-day moving average, with an additional impact when an extremely large number of option positions are

closed, and these decreases in $CSAD_t^{cp,m,M}$ are larger when coinciding with large absolute index option returns. However, a similar effect is not evident for days of extremely high open interest when, although $CSAD_t^{cp,m,M}$ tends to be lower than expected, it is not consistently decreasing with the magnitude of the market consensus. The significantly negative β_{11} coefficients further suggest that the option return dispersion is lower when macroeconomic information is released, with individual option returns clustering more closely when large market movements are observed on those days. A similar relationship is found to characterize the subprime crisis period (but not the dot-com bubble burst) as well as the periods when analysts' forecasts tend to be more dispersed. Overall, our findings support the hypothesis of investors in the US options market herding under certain market conditions, with the returns of individual options clustering around the market consensus more closely than expected during these periods, and this clustering being even stronger when index option returns are larger.

5 Conclusions

Cross-sectional dispersion quantifies the average proximity of individual assets' returns to the market consensus. As such, it provides a useful measure of investors' tendency to follow the market's lead when trading in individual assets, a tendency that is typically referred to as herding. We report significant herding effects in option returns, using their cross-sectional dispersion, conditional on a set of systematic factors related to periods of market stress.

In particular, herding appears to be driven primarily by market uncertainty and periods of high information flows. Investors tend to herd more closely when they face high volatility risk. Herding effects are also more pronounced during periods when an extremely high number of option positions is closed or opened. Finally, investors tend to follow the market consensus more closely than expected on dates when significant information about the US economy is released, during the financial crisis of 2008, as well as during periods when analysts' forecasts about the equity market's future performance are more divergent.

This tendency to herd might be motivated by behavioural biases, but it could also represent a rational element of the investment decision-making process, for instance within the context of high costs of information and the fear for the loss of reputation. Irrespective of the potential explanations, the presence of herding effects carries significant implications for asset pricing and portfolio management. When investors tend to trade in individual assets in the same direction as that of the market, asset prices are bound to deviate from their fundamental values and a larger number of securities are required in order to achieve the same diversification benefits. In the case of options, herding has the additional implication of limiting

the ability of market participants to hedge the risks associated with their positions in the underlying equities, as well as to engage in leveraged speculation on these assets.

Other interesting issues remain to be addressed. For instance, the study of herding behaviour in other option markets, a similar analysis using other derivative securities, and the design of a theoretical model of herding in option pricing are left for future research.

Appendix: The relationship between *CSAD* and index option returns

The Cross-Sectional Absolute Deviation (*CSAD*) of individual option returns (that are comparable in terms of type, leverage and time-to-maturity) is expected to increase linearly with the respective absolute index option return, i.e. the magnitude of the market consensus. This relationship must hold under the relatively mild assumption of asset prices following geometric Brownian motions. The first derivative of *CSAD* with respect to the index option return can then be computed using the continuous-time Capital Asset Pricing Model (CAPM) of Merton (1971) and the Black and Scholes (1973) option pricing framework.

Proposition. The Cross-Sectional Absolute Deviation of expected individual European option returns (comparable in terms of type, leverage and time-to-maturity) against the expected return of the respective index option is a positive linear function of the expected index option return.

Proof. Let $R_{i,t}^s$ denote the return at t of the individual stock i , while $R_{mkt,t}^s$ refers to the market index return at t . Furthermore, let $R_{i,t}^{cp,m,M}$ denote the return at t of a European option of type cp , (c for call or p for put), moneyness m and time-to-maturity M , written on the individual stock i ($R_{mkt,t}^{cp,m,M}$ in the case of an index option). We begin by making the following assumption

Assumption. *Expected asset returns vary linearly with their respective market betas. In the case of options, expected returns must satisfy the CAPM equation*

$$E[R_{i,t}^{cp,m,M}] = \beta_i^{cp,m,M} (E[R_{mkt,t}^s] - R_{f,t}) + R_{f,t} \quad (\text{A1})$$

where $\beta_i^{cp,m,M}$ is the option's beta and $R_{f,t}$ is the risk-free rate at t .

Option betas are a linear function of the underlying asset's beta (Black and Scholes, 1973; Jarrow and Rudd, 1983), given by

$$\beta_i^{cp,m,M} = \omega_{i,t}^{cp,m,M} \beta_i^s \quad (\text{A2})$$

where β_i^s is the market beta of the underlying asset i . The leverage inherent in a particular option contract is given by the option's Black and Scholes (BS) elasticity $\omega_{i,t}^{cp,m,M} = \frac{\partial E[R_{i,t}^{cp,m,M}]}{\partial E[R_{i,t}^s]}$, which is simply equal to the option's delta divided by the option-to-stock price ratio. Note that all options in the cross-section, as well as the index option, are assumed to have the same BS elasticity, i.e.

$\omega_{i,t}^{cp,m,M} = \omega_{j,t}^{cp,m,M} = \omega_{mkt,t}^{cp,m,M} = \omega_t^{cp,m,M}$, $\forall i, j \in N$. Given that $\beta_{mkt}^s = 1$ by default, combining (A1) and (A2) allows us to express the expected return of an individual option as

$$\begin{aligned}
E[R_{i,t}^{cp,m,M}] &= \omega_t^{cp,m,M} \beta_i^s (E[R_{mkt,t}^s] - R_{f,t}) + R_{f,t} \\
&= \omega_t^{cp,m,M} \beta_{mkt}^s (E[R_{mkt,t}^s] - R_{f,t}) \beta_i^s + R_{f,t} \\
&= \beta_{mkt}^{cp,m,M} (E[R_{mkt,t}^s] - R_{f,t}) \beta_i^s + R_{f,t} \\
&= [\beta_{mkt}^{cp,m,M} (E[R_{mkt,t}^s] - R_{f,t}) + R_{f,t}] \beta_i^s - \beta_i^s R_{f,t} + R_{f,t} \\
&= E[R_{mkt,t}^{cp,m,M}] \beta_i^s - \beta_i^s R_{f,t} + R_{f,t}
\end{aligned} \tag{A3}$$

Now, consider a cross-section at time t of the expected returns of options (same type, leverage, and time-to-maturity) written on N individual assets. The respective expected index option return represents the market consensus. We follow the related herding literature and denote the cross-sectional absolute deviation of expected option returns by *EC SAD* (first introduced for stocks by Chang et al., 2000). This measure of cross-sectional dispersion at the level of expected returns can be written as

$$\begin{aligned}
EC SAD_t^{cp,m,M} &= \frac{1}{N-1} \sum_{i=1}^N |E[R_{i,t}^{cp,m,M}] - E[R_{mkt,t}^{cp,m,M}]| \\
&= \frac{1}{N-1} \sum_{i=1}^N |E[R_{mkt,t}^{cp,m,M}] \beta_i^s - \beta_i^s R_{f,t} + R_{f,t} - E[R_{mkt,t}^{cp,m,M}]| \\
&= \frac{1}{N-1} \sum_{i=1}^N |(\beta_i^s - 1)(E[R_{mkt,t}^{cp,m,M}] - R_{f,t})| \\
&= \frac{\sum_{i=1}^N |\beta_i^s - 1|}{N-1} \times |E[R_{mkt,t}^{cp,m,M}] - R_{f,t}|
\end{aligned} \tag{A4}$$

The first derivative of *EC SAD* with respect to the expected index option return can be easily computed by distinguishing between positive and negative excess returns of index options.

Case 1. $E[R_{mkt,t}^{cp,m,M}] - R_{f,t} > 0$

In the case of positive expected excess returns of index options, the term inside

the absolute bars in (A4) is positive, and the first derivative of $ECSAD$ can be computed as

$$\begin{aligned}\frac{\partial ECSAD_t^{cp,m,M}}{\partial E[R_{mkt,t}^{cp,m,M}]} &= \frac{\sum_{i=1}^N |\beta_i^s - 1|}{N - 1} \times \frac{\partial(E[R_{mkt,t}^{cp,m,M}] - R_{f,t})}{\partial E[R_{mkt,t}^{cp,m,M}]} \\ &= \frac{\sum_{i=1}^N |\beta_i^s - 1|}{N - 1} > 0\end{aligned}\tag{A5}$$

Case 2. $E[R_{mkt,t}^{cp,m,M}] - R_{f,t} < 0$

In the case of negative expected excess returns of index options, the term inside the absolute bars in (A4) is negative, and the first derivative of $ECSAD$ can be computed as

$$\begin{aligned}\frac{\partial ECSAD_t^{cp,m,M}}{\partial E[R_{mkt,t}^{cp,m,M}]} &= \frac{\sum_{i=1}^N |\beta_i^s - 1|}{N - 1} \times \frac{\partial(R_{f,t} - E[R_{mkt,t}^{cp,m,M}])}{\partial E[R_{mkt,t}^{cp,m,M}]} \\ &= -\frac{\sum_{i=1}^N |\beta_i^s - 1|}{N - 1} < 0\end{aligned}\tag{A6}$$

Summing up, for both calls and puts, the first derivative of $ECSAD$ with respect to index option returns is positive (negative) when the index option return is positive (negative). Equivalently, $ECSAD$ is expected to increase with the absolute magnitude of index option returns.

$$\frac{\partial ECSAD_t^{cp,m,M}}{\partial E[R_{mkt,t}^{cp,m,M}]} \begin{cases} > 0 & \text{if } E[R_{mkt,t}^{cp,m,M}] - R_{f,t} > 0 \\ < 0 & \text{if } E[R_{mkt,t}^{cp,m,M}] - R_{f,t} < 0 \end{cases}$$

Finally, it is straightforward to see that the second derivative is equal to zero

$$\frac{\partial^2 ECSAD_t^{cp,m,M}}{\partial E[R_{mkt,t}^{cp,m,M}]^2} = 0$$

for both calls and puts, and irrespective of the index option return's sign, so the above relationship between $ECSAD_t^{cp,m,M}$ and $E[R_{mkt,t}^{cp,m,M}]$ is linear.

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Table 1: Descriptive Statistics of Cross-Sectional Dispersion (*CSAD*)

moneyness	Calls			Puts		
	OTM	ATM	ITM	OTM	ATM	ITM
Mean	0.18	0.12	0.08	0.16	0.12	0.10
Median	0.13	0.09	0.06	0.12	0.09	0.07
St.Dev	0.17	0.1	0.06	0.18	0.11	0.09
Skewness	5.17	3.65	2.93	14.57	3.23	6.64
Min	0.03	0.02	0.01	0.02	0.01	0.01
Max	2.86	1.60	0.83	6.57	1.22	2.39
Obs	3,691	3,675	3,692	3,752	3,667	3,575

Notes: This Table reports descriptive statistics of the daily time-series of Cross-Sectional Dispersion (*CSAD*) measures, which are computed as

$$CSAD_t^{cp,m,M} = \frac{\sum_{i=1}^N |R_{i,t}^{cp,m,M} - R_{mkt,t}^{cp,m,M}|}{N-1}$$

where $R_{i,t}^{cp,m,M}$ ($R_{mkt,t}^{cp,m,M}$) is the daily arithmetic return at time t of an option written on the individual stock i (on the market index) with type cp , moneyness m , and maturity M , while N is the number of individual stocks for which option returns are available at t . Statistics are tabulated separately for calls and puts, across three different moneyness levels, namely OTM, ATM and ITM (with absolute deltas of 0.25, 0.50 and 0.75, respectively). The sample period runs from January 1996 to December 2012.

Table 2: Herding Regressions - Volatility Risk and Skewness Risk

moneyness	Calls			Puts		
	OTM	ATM	ITM	OTM	ATM	ITM
constant	0.0469*	0.0273*	0.0232*	0.0362*	0.0226*	0.0172*
$(1 - D_t)R_{mkt,t}^{cp,m,M}$	0.2916*	0.2872*	0.2598*	0.2835*	0.2817*	0.2819*
$D_t R_{mkt,t}^{cp,m,M}$	-0.1678*	-0.2098*	-0.1971*	-0.1889*	-0.2139*	-0.2309*
$(1 - D_t)(R_{mkt,t}^{cp,m,M})^2$	0.0123*	0.0139*	0.0349*	0.0057*	0.0182*	0.0166*
$D_t(R_{mkt,t}^{cp,m,M})^2$	0.1377*	0.1194*	0.1342*	0.1308*	0.1287*	0.1078*
D_t^L	0.0163*	0.0012	0.0011	0.0119*	0.0016	0.0104*
D_t^U	0.0341*	0.0345*	0.0218*	0.0480*	0.0301*	0.0270*
CNS_t	-0.0933*	-0.0438*	-0.0269*	-0.0644*	-0.0486*	-0.0415*
RR_t	0.0027	-0.0022	-0.0013	-0.0030*	-0.0024	-0.0001
$AdjR^2$	0.94	0.94	0.93	0.96	0.94	0.95

Notes: This Table reports the results of regressing the Cross-Sectional Dispersion $CSAD$ against a set of exogenous variables. The return of the respective option written on the market index with type cp , moneyness m and maturity M is denoted by $R_{mkt,t}^{cp,m,M}$. The dummy variable D_t takes the value of 1 if the index option return at t is negative and the value of zero otherwise. The dummy variables D_t^L and D_t^U take the value of 1 if the respective index option return at t is located in the 5% lower and upper tail, respectively, of the distribution, and the value of zero otherwise. The CNS_t and RR_t factor-mimicking portfolios proxy for volatility risk and skewness risk, respectively. The regression results are presented separately for calls and puts, across three different moneyness levels, namely OTM, ATM and ITM (with absolute deltas of 0.25, 0.50 and 0.75, respectively). The Table reports the estimated coefficients, their statistical significance, and the Adjusted R^2 . Statistical significance at the 5% level is denoted by *, and it is based on Newey and West (1987) HAC standard errors. The sample runs from January 1996 to December 2012.

Table 3: Herding Regressions - Index Options' Trading Volume and Open Interest

moneyness	Calls			Puts		
	OTM	ATM	ITM	OTM	ATM	ITM
constant	0.0264*	0.0147*	0.0154*	0.0198*	0.0098*	0.0069*
$(1 - D_t)R_{mkt,t}^{cp,m,M}$	0.2750*	0.2758*	0.2500*	0.2757*	0.2709*	0.2784*
$D_t R_{mkt,t}^{cp,m,M}$	-0.1739*	-0.2141*	-0.1969*	-0.1800*	-0.2121*	-0.2268*
$(1 - D_t)(R_{mkt,t}^{cp,m,M})^2$	0.0132*	0.0154*	0.0371*	0.0057*	0.0185*	0.0163*
$D_t(R_{mkt,t}^{cp,m,M})^2$	0.1092*	0.0799*	0.1008*	0.1145*	0.1007*	0.0898*
D_t^L	0.0098*	0.0039	0.0032	0.0069	0.0006	0.0062*
D_t^U	0.0288*	0.0264*	0.0180*	0.0371*	0.0262*	0.0227*
CNS_t	-0.0422*	-0.0097*	-0.0076*	-0.0275*	-0.0152*	-0.0193*
OI_t	0.0056*	0.0036*	0.0022*	0.0046*	0.0037*	0.0027*
$D_t^{OI,L}$	-0.0326*	-0.0232*	-0.0154*	-0.0247*	-0.0223*	-0.0165*
$D_t^{OI,U}$	-0.0183*	-0.0135*	-0.0079*	-0.0173*	-0.0148*	-0.0112*
$AdjR^2$	0.97	0.97	0.96	0.97	0.97	0.97

Notes: This Table reports the results of regressing the Cross-Sectional Dispersion $CSAD$ against a set of exogenous variables. The return of the respective option written on the market index with type cp , moneyness m and maturity M is denoted by $R_{mkt,t}^{cp,m,M}$. The dummy variable D_t takes the value of 1 if the index option return at t is negative and the value of zero otherwise. The dummy variables D_t^L and D_t^U take the value of 1 if the respective index option return at t is located in the 5% lower and upper tail, respectively, of the distribution, and the value of zero otherwise. The term CNS_t is a measure of volatility risk. The variable OI_t refers to the index options' open interest at t (measured in millions). The dummy variables $D_t^{OI,L}$ and $D_t^{OI,U}$ take the value of 1 if the open interest of index options at t is located in the distribution's lower and upper 5% tail, respectively, and the value of 0 otherwise. The regression results are presented separately for calls and puts, across three different moneyness levels, namely OTM, ATM and ITM (with absolute deltas of 0.25, 0.50 and 0.75, respectively). The Table reports the estimated coefficients, their statistical significance, and the Adjusted R^2 . Statistical significance at the 5% level is denoted by *, and it is based on Newey and West (1987) HAC standard errors. The sample runs from January 1996 to December 2012.

Table 4: Herding Regressions - Macroeconomic Announcements and Crises

moneyness	Calls			Puts		
	OTM	ATM	ITM	OTM	ATM	ITM
constant	0.0242*	0.0129*	0.0142*	0.0177*	0.0081*	0.0057*
$(1 - D_t)R_{mkt,t}^{cp,m,M}$	0.2752*	0.2760*	0.2502*	0.2755*	0.2708*	0.2782*
$D_t R_{mkt,t}^{cp,m,M}$	-0.1726*	-0.2131*	-0.1962*	-0.1797*	-0.2117*	-0.2266*
$(1 - D_t)(R_{mkt,t}^{cp,m,M})^2$	0.0131*	0.0153*	0.0369*	0.0057*	0.0185*	0.0163*
$D_t(R_{mkt,t}^{cp,m,M})^2$	0.1117*	0.0814*	0.1020*	0.1148*	0.1012*	0.0901*
D_t^L	0.0091*	0.0038	0.0031	0.0070	0.0006	0.0061*
D_t^U	0.0282*	0.0263*	0.0179*	0.0374*	0.0262*	0.0226*
CNS_t	-0.0420*	-0.0099*	-0.0077*	-0.0275*	-0.0153*	-0.0191*
OI_t	0.0060*	0.0039*	0.0023*	0.0050*	0.0040*	0.0029*
$D_t^{OI,L}$	-0.0304*	-0.0214*	-0.0143*	-0.0226*	-0.0207*	-0.0153*
$D_t^{OI,U}$	-0.0203*	-0.0150*	-0.0087*	-0.0191*	-0.0162*	-0.0122*
D_t^{macro}	-0.0021*	-0.0011*	-0.0010*	-0.0017*	-0.0008*	-0.0008*
$D_t^{cr.dotcom}$	0.0053	0.0047*	0.0032	0.0054	0.0040*	0.0029
$D_t^{cr.subprime}$	-0.0078*	-0.0040*	-0.0016*	-0.0055*	-0.0047*	-0.0040*
$AdjR^2$	0.97	0.97	0.96	0.97	0.97	0.97

Notes: This Table reports the results of regressing the Cross-Sectional Dispersion $CSAD$ against a set of exogenous variables. The return of the respective option written on the market index with type cp , moneyness m and maturity M is denoted by $R_{mkt,t}^{cp,m,M}$. The dummy variable D_t takes the value of 1 if the index option return at t is negative and the value of zero otherwise. The dummy variables D_t^L and D_t^U take the value of 1 if the respective index option return at t is located in the 5% lower and upper tail, respectively, of the distribution, and the value of zero otherwise. The term CNS_t is a measure of volatility risk. The variable OI_t refers to the index options' open interest at t (measured in millions). The dummy variables $D_t^{OI,L}$ and $D_t^{OI,U}$ take the value of 1 if the open interest of index options at t is located in the distribution's lower and upper 5% tail, respectively, and the value of 0 otherwise. The dummy variable D_t^{macro} takes the value of 1 on dates of US macroeconomic announcements, and the value of 0 otherwise. The dummy variables $D_t^{cr.dotcom}$ and $D_t^{cr.subprime}$ take the value of 1 during the dot-com bubble collapse (March 2000 to August 2002) and the US subprime crisis (September 2007 to March 2009), respectively, and the value of 0 otherwise. The regression results are presented separately for calls and puts, across three different moneyness levels, namely OTM, ATM and ITM (with absolute deltas of 0.25, 0.50 and 0.75, respectively). The Table reports the estimated coefficients, their statistical significance, and the Adjusted R^2 . Statistical significance at the 5% level is denoted by *, and it is based on Newey and West (1987) HAC standard errors. The sample runs from January 1996 to December 2012.

Table 5: Herding Regressions - Dispersion of Analysts' Forecasts

moneyness	Calls			Puts		
	OTM	ATM	ITM	OTM	ATM	ITM
constant	0.0254*	0.0134*	0.0160*	0.0167*	0.0058*	0.0046*
$(1 - D_t)R_{mkt,t}^{cp,m,M}$	0.2751*	0.2759*	0.2498*	0.2755*	0.2709*	0.2784*
$D_t R_{mkt,t}^{cp,m,M}$	-0.1725*	-0.2131*	-0.1961*	-0.1796*	-0.2116*	-0.2268*
$(1 - D_t)(R_{mkt,t}^{cp,m,M})^2$	0.0131*	0.0154*	0.0370*	0.0057*	0.0186*	0.0163*
$D_t(R_{mkt,t}^{cp,m,M})^2$	0.1116*	0.0814*	0.1023*	0.1151*	0.1021*	0.0903*
D_t^L	0.0091*	0.0037	0.0029	0.0070	0.0005	0.0060*
D_t^U	0.0284*	0.0263*	0.0180*	0.0374*	0.0261*	0.0226*
CNS_t	-0.0418*	-0.0098*	-0.0074*	-0.0276*	-0.0157*	-0.0193*
OI_t	0.0061*	0.0039*	0.0025*	0.0049*	0.0037*	0.0028*
$D_t^{OI,L}$	-0.0315*	-0.0219*	-0.0158*	-0.0217*	-0.0188*	-0.0144*
$D_t^{OI,U}$	-0.0209*	-0.0152*	-0.0096*	-0.0186*	-0.0151*	-0.0117*
D_t^{macro}	-0.0021*	-0.0011*	-0.0009*	-0.0017*	-0.0009*	-0.0009*
$D_t^{cr.dotcom}$	0.0060	0.0050*	0.0041	0.0048	0.0028*	0.0024
$D_t^{cr.subprime}$	-0.0079*	-0.0041*	-0.0018*	-0.0054*	-0.0045*	-0.0039*
FD_t	-0.0010	-0.0004*	-0.0014*	-0.0008*	-0.0018	-0.0008*
$AdjR^2$	0.97	0.97	0.96	0.97	0.97	0.97

Notes: This Table reports the results of regressing the Cross-Sectional Dispersion $CSAD$ against a set of exogenous variables. The return of the respective option written on the market index with type cp , moneyness m and maturity M is denoted by $R_{mkt,t}^{cp,m,M}$. The dummy variable D_t takes the value of 1 if the index option return at t is negative and the value of zero otherwise. The dummy variables D_t^L and D_t^U take the value of 1 if the respective index option return at t is located in the 5% lower and upper tail, respectively, of the distribution, and the value of zero otherwise. The term CNS_t is a measure of volatility risk. The variable OI_t refers to the index options' open interest at t (measured in millions). The dummy variables $D_t^{OI,L}$ and $D_t^{OI,U}$ take the value of 1 if the open interest of index options at t is located in the distribution's lower and upper 5% tail, respectively, and the value of 0 otherwise. The dummy variable D_t^{macro} takes the value of 1 on dates of US macroeconomic announcements, and the value of 0 otherwise. The dummy variables $D_t^{cr.dotcom}$ and $D_t^{cr.subprime}$ take the value of 1 during the dot-com bubble collapse (March 2000 to August 2002) and the US subprime crisis (September 2007 to March 2009), respectively, and the value of 0 otherwise. The variable FD_t refers to the mean (normalized) dispersion of analysts' forecasts in the cross-section of underlying stocks at t . The regression results are presented separately for calls and puts, across three different moneyness levels, namely OTM, ATM and ITM (with absolute deltas of 0.25, 0.50 and 0.75, respectively). The Table reports the estimated coefficients, their statistical significance, and the Adjusted R^2 . Statistical significance at the 5% level is denoted by *, and it is based on Newey and West (1987) HAC standard errors. The sample runs from January 1996 to December 2012.

Table 6: Herding Regressions - Underlying *CSAD* and Index return

moneyness	Calls			Puts		
	OTM	ATM	ITM	OTM	ATM	ITM
constant	0.0357*	0.0192*	0.0194*	0.0301*	0.0126*	0.0108*
$(1 - D_t)R_{mkt,t}^{cp,m,M}$	0.2780*	0.2801*	0.2545*	0.2796*	0.2757*	0.2834*
$D_t R_{mkt,t}^{cp,m,M}$	-0.1728*	-0.2149*	-0.1998*	-0.1781*	-0.2126*	-0.2310*
$(1 - D_t)(R_{mkt,t}^{cp,m,M})^2$	0.0126*	0.0144*	0.0356*	0.0055*	0.0181*	0.0154*
$D_t(R_{mkt,t}^{cp,m,M})^2$	0.1171*	0.0872*	0.1049*	0.1242*	0.1085*	0.0904*
D_t^L	0.0088*	0.0031	0.0028	0.0063	-0.0002	0.0057*
D_t^U	0.0286*	0.0265*	0.0183*	0.0364*	0.0255*	0.0218*
CNS_t	-0.0325*	-0.0024*	-0.0039*	-0.0188*	-0.0090*	-0.0138*
OI_t	0.0059*	0.0038*	0.0025*	0.0047*	0.0036*	0.0027*
$D_t^{OI,L}$	-0.0325*	-0.0228*	-0.0164*	-0.0227*	-0.0196*	-0.0149*
$D_t^{OI,U}$	-0.0159*	-0.0107*	-0.0069*	-0.0131*	-0.0106*	-0.0085*
D_t^{macro}	-0.0017*	-0.0007*	-0.0007*	-0.0012*	-0.0005*	-0.0006*
$D_t^{cr.dotcom}$	0.0098	0.0074*	0.0056	0.0097	0.0055*	0.0048
$D_t^{cr.subprime}$	-0.0028*	0.0002*	0.0008*	0.0005*	-0.0001*	-0.0004*
FD_t	-0.0027	-0.0014*	-0.0020*	-0.0014*	0.0006	-0.0002*
$CSAD_t^S$	-0.3544*	-0.1988	-0.1201	-0.4609*	-0.2388*	-0.2278*
$(R_{mkt,t}^S)^2$	-3.4441	-5.5684	-3.6008	-3.0896	-4.8756	-2.6152
$AdjR^2$	0.97	0.97	0.96	0.97	0.97	0.97

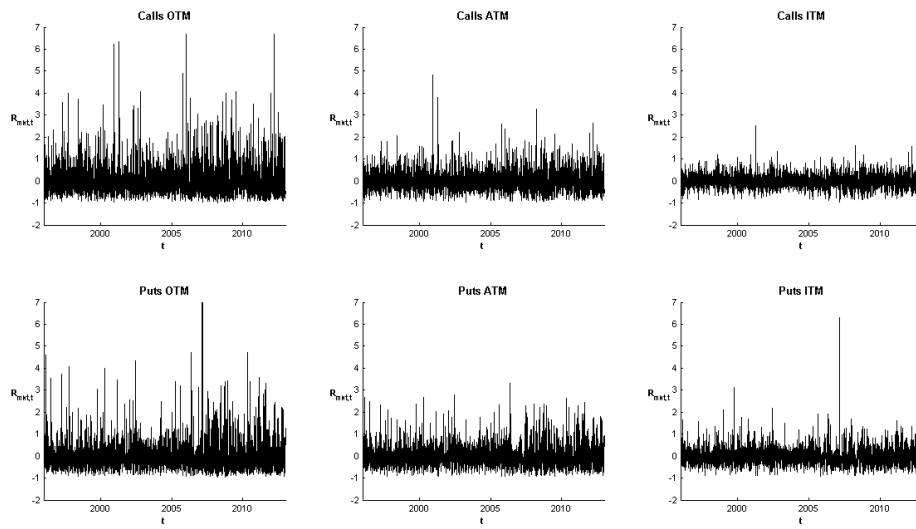
Notes: This Table reports the results of regressing the Cross-Sectional Dispersion *CSAD* against a set of exogenous variables. The return of the respective option written on the market index with type *cp*, moneyness *m* and maturity *M* is denoted by $R_{mkt,t}^{cp,m,M}$. The dummy variable D_t takes the value of 1 if the index option return at t is negative and the value of zero otherwise. The dummy variables D_t^L and D_t^U take the value of 1 if the respective index option return at t is located in the 5% lower and upper tail, respectively, of the distribution, and the value of zero otherwise. The term CNS_t is a measure of volatility risk. The variable OI_t refers to the index options' open interest at t (measured in millions). The dummy variables $D_t^{OI,L}$ and $D_t^{OI,U}$ take the value of 1 if the open interest of index options at t is located in the distribution's lower and upper 5% tail, respectively, and the value of 0 otherwise. The dummy variable D_t^{macro} takes the value of 1 on dates of US macroeconomic announcements, and the value of 0 otherwise. The dummy variables $D_t^{cr.dotcom}$ and $D_t^{cr.subprime}$ take the value of 1 during the dot-com bubble collapse (March 2000 to August 2002) and the US subprime crisis (September 2007 to March 2009), respectively, and the value of 0 otherwise. The variable FD_t refers to the mean (normalized) dispersion of analysts' forecasts in the cross-section of underlying stocks at t . The variables $CSAD_t^S$ and $R_{mkt,t}^S$ denote the cross-sectional dispersion and the index return, respectively, of the underlying equity market. The regression results are presented separately for calls and puts, across three different moneyness levels, namely OTM, ATM and ITM (with absolute deltas of 0.25, 0.50 and 0.75, respectively). The Table reports the estimated coefficients, their statistical significance, and the Adjusted R^2 . Statistical significance at the 5% level is denoted by *, and it is based on Newey and West (1987) HAC standard errors. The sample runs from January 1996 to December 2012.

Table 7: Herding Regressions - Systematic Dummies Times Squared Returns

moneyness	Calls			Puts		
	OTM	ATM	ITM	OTM	ATM	ITM
constant	0.0799*	0.0458*	0.0331*	0.0652*	0.0429*	0.0323*
$(1 - D_t)R_{mkt,t}^{cp,m,M}$	0.2920	0.2838*	0.2569*	0.2789*	0.2895*	0.2922*
$D_t R_{mkt,t}^{cp,m,M}$	-0.1681*	-0.2090*	-0.2094*	-0.1767*	-0.2241*	-0.2426*
$(1 - D_t)(R_{mkt,t}^{cp,m,M})^2$	0.0145*	0.0438*	0.0923*	0.0318*	0.0423*	0.0431*
$D_t(R_{mkt,t}^{cp,m,M})^2$	0.1555*	0.1359*	0.1310*	0.1757*	0.1498*	0.1257*
D_t^L	0.0113*	0.0045	0.0066	0.0072	0.0004	0.0055*
D_t^U	0.0313*	0.0191*	0.0127*	0.0310*	0.0218*	0.0204*
CNS_t	-0.0482*	-0.0308*	-0.0163*	-0.0331*	-0.0224*	-0.0220*
$D_t^{OI < MA}(R_{mkt,t}^{cp,m,M})^2$	0.0004	-0.0108*	-0.0211*	-0.0142*	-0.0187*	-0.0193*
$D_t^{OI,L}(R_{mkt,t}^{cp,m,M})^2$	-0.0761*	-0.1391*	-0.1941*	-0.0449*	-0.0761*	-0.1615*
$D_t^{OI,U}(R_{mkt,t}^{cp,m,M})^2$	0.0070	0.0277*	0.0417*	-0.0049*	0.0059	-0.0284*
$D_t^{macro}(R_{mkt,t}^{cp,m,M})^2$	-0.0049*	-0.0027*	-0.0013*	-0.0097*	-0.0092*	-0.0015*
$D_t^{cr.dotcom}(R_{mkt,t}^{cp,m,M})^2$	0.0101*	0.0243*	0.0521*	0.0162*	0.0212*	0.0333*
$D_t^{cr.subprime}(R_{mkt,t}^{cp,m,M})^2$	-0.0095*	-0.0214*	-0.0390*	-0.0098*	-0.0176*	-0.0207*
$D_t^{FD > MA}(R_{mkt,t}^{cp,m,M})^2$	0.0000	-0.0023	-0.0037	-0.0121*	-0.0102*	-0.0095*
$CSAD_t^S$	-1.5948*	-0.8537*	-0.4821*	-1.3305*	-1.0322*	-0.7793*
$(R_{mkt,t}^S)^2$	4.7524	-4.6994	-5.3847	3.1780	-1.0100	-0.8470
$Adj R^2$	0.96	0.96	0.95	0.97	0.96	0.97

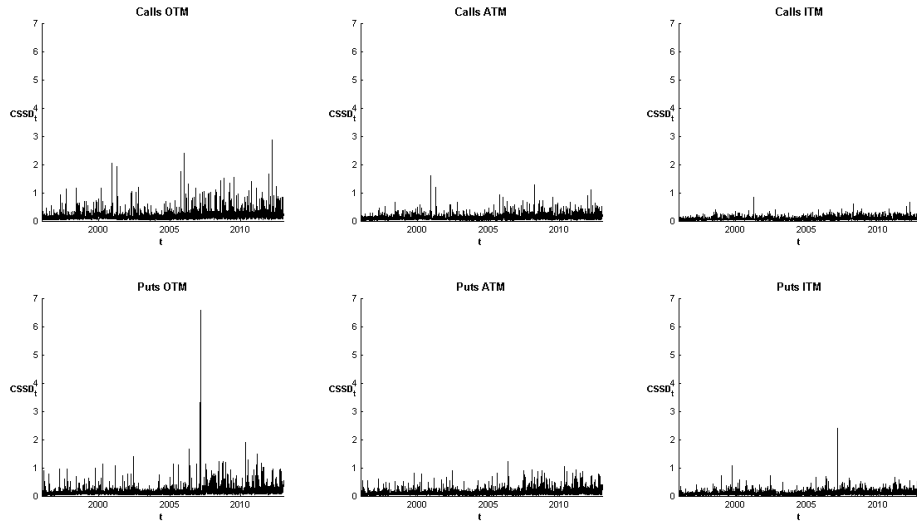
Notes: This Table reports the results of regressing the Cross-Sectional Dispersion $CSAD$ against a set of exogenous variables. The return of the respective option written on the market index with type cp , moneyness m and maturity M is denoted by $R_{mkt,t}^{cp,m,M}$. The dummy variable D_t takes the value of 1 if the index option return at t is negative and the value of zero otherwise. The dummy variables D_t^L and D_t^U take the value of 1 if the respective index option return at t is located in the 5% lower and upper tail, respectively, of the distribution, and the value of 0 otherwise. The term CNS_t is a measure of volatility risk. The variable $D_t^{OI < MA}$ takes the value of 1 if the index options' open interest at t is lower than its 30-day moving average, and the value of 0 otherwise. The variables $D_t^{OI,L}$ and $D_t^{OI,U}$ take the value of 1 if the open interest of index options at t is located in the distribution's lower and upper 5% tail, respectively, and the value of 0 otherwise. The dummy variable D_t^{macro} takes the value of 1 on dates of US macroeconomic announcements, and the value of 0 otherwise. The dummy variables $D_t^{cr.dotcom}$ and $D_t^{cr.subprime}$ take the value of 1 during the dot-com bubble collapse (March 2000 to August 2002) and the US subprime crisis (September 2007 to March 2009), respectively, and the value of 0 otherwise. The variable $D_t^{FD > MA}$ takes the value of 1 if the mean (normalized) dispersion of analysts' forecasts in the cross-section of underlying stocks at t is greater than its 30-day moving average, and that of 0 otherwise. The variables $CSAD_t^S$ and $R_{mkt,t}^S$ denote the cross-sectional dispersion and the index return, respectively, of the underlying equity market. The regression results are presented separately for calls and puts, across three different moneyness levels, namely OTM, ATM and ITM. The Table reports the estimated coefficients, their statistical significance, and the Adjusted R^2 . Statistical significance at the 5% level is denoted by *, and it is based on Newey and West (1987) HAC standard errors. The sample runs from January 1996 to December 2012.

Figure 1: Time-Series of Daily Index Option Returns



Notes: This Figure plots the time-series of daily returns of options written on the S&P 500 index. The upper panel refers to calls and the lower panel to puts. Each subplot refers to different moneyness levels, namely OTM, ATM and ITM (with absolute deltas of 0.25, 0.50 and 0.75, respectively). The sample period runs from January 1996 to December 2012.

Figure 2: Time-Series of Daily Cross-Sectional Dispersion



Notes: This Figure plots the daily time-series of Cross-Sectional Dispersion ($CSAD$) of options written on individual stocks around the index option return. $CSAD$ is computed as

$$CSAD_t^{cp,m,M} = \frac{\sum_{i=1}^N |R_{i,t}^{cp,m,M} - R_{mkt,t}^{cp,m,M}|}{N-1}$$

where $R_{i,t}^{cp,m,M}$ ($R_{mkt,t}^{cp,m,M}$) is the daily arithmetic return at time t of an option written on the individual stock i (on the market index) with type cp , moneyness m , and maturity M , while N is the number of individual stocks for which option returns are available at t . The upper panel refers to calls and the lower panel to puts. Each subplot refers to different moneyness levels, namely OTM, ATM and ITM (with absolute deltas of 0.25, 0.50 and 0.75, respectively). The sample period runs from January 1996 to December 2012.