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Volatility Aversion in the Options Market Based on News Sentiment

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The author identifies and explains asymmetric reactions in the implied volatility of S&P 500 Index options across the term structure based on news sentiment. The asymmetry of the reaction is more pronounced for fear (proxied by put options) than for greed (proxied by call options). This asymmetry is termed factor volatility aversion, which is more pronounced the shorter the time to maturity of the option.

Are investors "irrational" because they overreact to new information? Numerous studies have asked and attempted to answer this question. The stream of behavioral finance literature would argue that overreaction is a form of irrationality.[1] In particular, implied volatility across the "term structure" of options is an interesting realm to look into because overreactions can be neatly dissected in terms of time to maturity and potential falling or rising prices. Stein [1989] nicely shows that long-maturity options (2-month) tend to "overreact" to changes in the implied volatility of short-maturity options (1-month). In his study, Stein [1989] posits that "it would be very interesting to know whether investors in long-dated options also tend to overreact [...]." Unfortunately, Stein [1989] states that the data series used to test for this hypothesis was of insufficient quality.[2]

The objective of this study is to test whether fluctuations in implied volatilities of S&P 500 options across the term structure can be explained with a novel dataset comprising sentiment in news. The idea to test this hypothesis with news sentiment stems from the attention sentiment in news has received in various recent studies and due to existing theories.[3] For instance, Engle and Ng [1993] define a news impact curve, which measures how new information is incorporated into volatility estimates. The authors find asymmetry in the volatility response to news and show that asymmetric volatility models, in which good and bad news have different predictability for future volatility, have been laid out in several studies.[4] Existing research has established theoretically that volatility responds to news in an asymmetric fashion. This study attempts to explain the

[1] See, for instance, Hong and Stein [1999], Daniel et al. [1998], Barberis et al. [1998], among others.

[2] Other studies that look at behavioral biases and their asset pricing impact in the options markets are Poteshman [2001], Poteshman and Serbin [2003], and Mahani and Poteshman [2004], among others.

[3] See Tetlock [2007], Leinweber and Sisk [2011], Tetlock et al. [2008], Uhl et al. [2015], Schmeling and Wagner [2015], Hillert et al. [2014], Goldberg and Grisse [2013], Gilbert et al. [2010], among others.

[4] See Black [1976], Christie [1982], French, Schwert and Stambaugh [1987], and Schwert [1990].

asymmetry in implied volatility empirically with a new measure called "news sentiment." Section 1 discusses the related literature, while Section 2 establishes a theory for the hypothesis. Section 3 explains the data used and discusses the empirical results. Section 4 concludes.

NEWS SENTIMENT IN RELATION TO STOCKS AND OPTIONS

Intuitively and based on the behavioral finance literature, news should have an impact on financial assets (and their volatility), as new information can cause investors to react quickly and sometimes (ir)rationally. In other words, it has been shown that investors tend to overreact.[5] Previous research has shown that investor sentiment can explain (ir)rational reactions of investors. Barberis et al. [1998] formulate a model of investor sentiment, which identifies a possible cause: the misreaction of the options market to changes in market volatility. The reasons they identify are conservatism and the representativeness heuristic. Since individuals are slow to change their beliefs in the face of new evidence, they act conservatively, as shown by Edwards [1968]. The representativeness heuristic is based on the theory of Kahneman and Tversky [1974]: the probability of an uncertain event is typically evaluated by the degree to which it is similar in its essential properties to the parent population. It reflects the salient features of the process by which it is generated. Furthermore, Daniel et al. [1998] construct a different model of investor sentiment, which is based on overconfidence and self-attribution.

Given that there are already different and competing models of investor sentiment, we do not want to formulate a competing model of investor sentiment in this study, but rather we want to test whether fluctuations in implied volatility can be related to changes in sentiment from news. Tetlock [2007] shows, for example, that negative sentiment in news can cause falling stock prices. Ho et al. [2013] show that news sentiment impacts asset volatility by examining the dynamic relationship between firm-level return volatility of the constituent stocks in the Dow Jones Composite Average and public news sentiment.

Poteshman [2001] also finds that misreactions in the options market can be explained by changes in market volatility, which is in line with the model of investor sentiment by Barberis et al [1998]. With this study, we want to go further by identifying what causes changes in implied market volatility. We posit that this can be empirically explained by sentiment in the news, as market participants constantly monitor the news flow and react to it. As topics in news flow change (and therefore the sentiment), investors react not only to new information, but also to a change in sentiment. Since it is difficult to determine which news topics are influential for or are being looked at by investors, we define a measure of sentiment that encompasses the broadest possible range of news topics. This consists of news related to macroeconomic events, such as central bank policy, geopolitical happenings, and macroeconomic indicator announcements, among others.[6]

In relation to the impact of news on implied volatility, Han [2008] investigates whether investor sentiment on the stock market affects prices of S&P 500 options. He finds that the index option volatility smile is steeper (flatter) and the risk-neutral skewness of monthly index returns is more (less) negative when market sentiment becomes more bearish (bullish). These effects cannot be explained by rational perfect-market-based option pricing models. Therefore, the cause of these effects is worth looking into. Based on the previous findings in the literature, it is of interest to evaluate what drives changes in implied volatilities of options across the term structure and whether potential changes can be explained with changes in news sentiment.

LOSS AND VOLATILITY AVERSION

Let us first consider the theoretical framework for loss averse behavior. As Kahneman and Tversky [1974] outline in their Prospect Theory, losses hurt more than gains give joy. Put differently, there is a kink in the utility function of an investor if we consider behavioral aspects compared to traditional mean-variance approaches. Kahneman and Tversky [1979] call this behavior *loss aversion*. Based on this theory, the following standard value function applies:

$$v(X_{t+1}) = \begin{cases} X_{t+1} & \text{for} \quad X_{t+1} \geq 0 \\ \lambda X_{t+1} & \quad X_{t+1} < 0, \end{cases} \tag{1}$$

[5] See, for instance, Stein [1989] and Hong and Stein [1999].

[6] See the third section for a more detailed explanation on the data used.

where $\lambda > 1$ is the loss aversion factor, and v is the expected utility of the outcomes to the individual making the decision of the value of the asset X. In an attempt to explain the observed reaction in implied volatility, we apply a smiliar theoretical foundation as in Barberis and Huang [2001]. In their assessment, they introduce a variable $z_{i,t}$ to the above value function, which tracks prior gains or losses on a specific asset i, and define the dependence between z and λ in the form of

$$\lambda(z_{i,t}) = \lambda + k(z_{i,t} - 1),$$

with $z_{i,t} > 1$ and $k > 0$, so that the following value function v is obtained:

$$v(X_{i,t+1}, z_{i,t}) = \begin{cases} X_{i,t+1} & \text{for} \quad X_{i,t+1} \geq 0 \\ \lambda(z_{i,t}) X_{i,t+1} & \quad X_{i,t+1} < 0 \end{cases} \tag{2}$$

For this study, we let X refer to implied volatility and i to the respective moneyness of either put or call options on the S&P 500 Index for each time to maturity T.[7] Given that we are not dealing with gains or losses in this study but with implied volatility, which is always positive, we consider first differences for all variables involved.[8] Therefore, we obtain a slightly different value function for implied volatilities of the form

$$v(\Delta X_{i,t+1}, z_{i,t}) = \begin{cases} \Delta X_{i,t+1} & \text{for} \quad \Delta X_{i,t+1} \leq 0 \\ \varsigma(\Delta z_{j,t}) \Delta X_{i,t+1} & \quad \Delta X_{i,t+1} > 0, \end{cases} \tag{3}$$

where $\Delta X_{i,t}$ refers to changes in implied volatility and i to the respective moneyness (ranging from 80% to 120%) of either put or call options on the S&P 500 Index for each time to maturity T. $\Delta z_{j,t}$ refers to changes in news sentiment and j to the respective positive or negative macro news sentiment scores. ζ is what we call in this context the *volatility aversion* factor and it is, in line with the specification of λ and as in Stein [1989], obtained by an AR(1)-regression model:

$$\Delta IV_t^M = k + \varsigma \Delta z_{j,t} + IV_{t-1} + \alpha \Delta S\&P500_{t-1} + \varepsilon_t, \tag{4}$$

with $z_{j,t}$ referring to positive or negative news sentiment, ΔIV_t^M to implied volatility, and i to the respective moneyness of either put or call options on the S&P 500 Index for each time to maturity T. $\Delta S\&P500_{t-1}$ are lagged returns of the S&P 500 price index as the control variable, ε_t refers to the error term, and k, to a constant. In order to test for *volatility aversion* ζ in options based on changes in news sentiment, we run several empirical tests in the following section. We therefore want to test the hypothesis that changes in news sentiment is one factor that can cause and explain reactions in the options market, and potentially, volatility aversion.

EMPIRICAL ANALYSIS

Data

In order to test for the above hypothesis, the financial market dataset used in this study relates to the S&P 500 price index, its implied volatility, and its option skew. For implied volatility of the S&P 500 price index, we obtain implied volatility data for out-of-the-money (OTM) and at-the-money (ATM) put and call options, readily available from and calculated by Thomson Reuters Datastream. The data are available from December 2007 to February 2016, with maturities ranging from 1 month to 3 years and moneynesses between 80% and 120%.

Exhibit 1 shows summary statistics for implied volatilities across the various maturities. For ease of reading, we have summarized all moneynesses per maturity, that is, for each maturity we show the minimum and maximum across the moneynesses (ranging from 80% to 120%). A moneyness of 100% refers to put and call options that are at-the-money (ATM), moneyness values below 100% refer to out-of-the-money (OTM) put options, and moneyness values above 100% refer to out-of-the-money (OTM) call options. Each implied volatility variable has 2,148 observations and ranges from December 2007 to February 2016. Across the different maturities, we can see that the minimum values are increasing from 1 month to 3 years, whereas the maximum values are decreasing from 1-month to 3-year maturities. That means that the range of implied volatilities is narrowing the farther the time to maturity of

[7] We have chosen options on the S&P 500 Index because these are the most liquid and most traded options. Furthermore, Stein [1989], among others, has also used S&P 500 Index options.

[8] This is also based on unit root tests that we ran, which showed that first differences are warranted for obtaining stationarity in the data.

EXHIBIT 1
Summary Statistics of Implied Volatilities of S&P 500 Index Options

	1 m		2 m		3 m		6 m		9 m		1 y		2 y		3 y	
Maturities	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**
Mean	16.7	39.8	16.0	33.1	15.9	31.3	15.7	29.4	15.9	28.5	16.4	28.0	18.3	26.8	19.8	26.5
Median	13.6	37.1	13.1	30.7	13.2	29.2	13.6	27.8	13.8	27.3	14.5	27.0	16.7	26.2	18.2	26.0
Maximum	65.7	95.7	58.7	80.3	51.5	74.8	48.8	65.4	46.0	60.1	43.9	55.8	41.0	48.8	39.4	43.0
Minimum	7.5	26.7	7.3	23.0	7.6	21.7	8.9	20.0	9.3	19.6	9.4	18.4	10.9	19.2	8.3	17.5
Std. Dev.	5.3	10.0	5.0	8.8	5.3	8.2	5.9	7.2	6.0	6.7	5.9	6.3	5.0	5.4	4.3	5.2
Skewness	2.2	3.2	2.0	3.3	18	3.0	1.6	2.3	1.4	1.9	1.3	1.7	1.1	1.7	0.9	1.7
Observations	2,148		2,148		2,148		2,148		2,148		2,148		2,148		2,148	

Notes: This exhibit shows the summary statistics of the implied volatilities for the moneynesses ranging from 80% to 120% for the respective time to maturities (ranging from 1 month to 3 years). A moneyness of 100% refers to put and call options which are at-the-money (ATM), moneyness values below 100% refer to out-of-the-money (OTM) put options, and moneyness values above 100% refer to out-of-the-money (OTM) call options. Each implied volatility variable has 2,148 observations.

the option. This might potentially be a first indication of more pronounced reactions in shorter-dated options, which we will look at in more detail later.

News sentiment data are obtained from Thomson Reuters News Analytics (TRNA). The data are available from January 2003 to February 2016. TRNA is an algorithmic text-analysis tool that is able to describe news items with more than 80 pieces of metadata, such as timestamp (down to the millisecond), sentiment class (indicating whether the overall tone of the article is positive, neutral, or negative), sentiment probabilities (the share of each sentiment class of a news item in terms of a probability, consisting of positive, neutral, and negative and adding up to 100%), subjects (news items are tagged with codes that relate to specific subjects), and news item count. The sentiment algorithm is based on two main construction techniques for Natural Language Processing (NPL). First, a large set of both positive and negative words is determined using the "bag-of-words" approach.[9] Second, the algorithm was trained by input of several hundred economists and financial market experts who classified a fixed number of news articles into positive and negative. These were then put into the adaptive algorithm, enabling it to classify articles as positive, neutral, and negative sentiment. The algorithm achieves the overall classification by assigning percentage shares of positive, neutral, and negative to each single news piece.

EXHIBIT 2
Summary Statistics of News Sentiment

	Positive Macro News Sentiment	Negative Macro News Sentiment
Mean	0.382275	0.332521
Median	0.38763	0.326208
Maximum	0.85122	0.819143
Minimum	0.055628	0.007846
Std. Dev.	0.045833	0.058757
Skewness	–0.918516	2.287069
Kurtosis	23.67094	20.74686
Observations	2,148	2,148

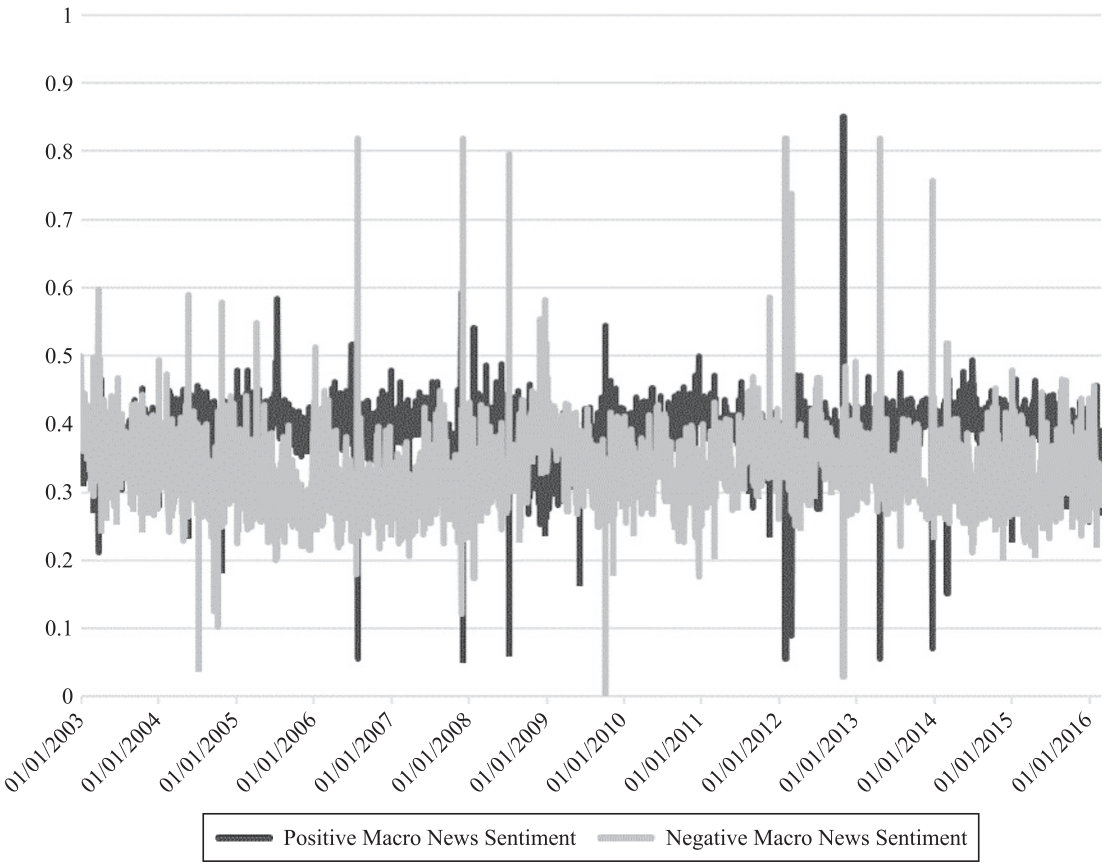
Notes: This exhibit shows summary statistics for positive and negative macro and micro news sentiment, ranging from May 2007 to February 2016 with 2,148 total observations. These time series are based on sentiment from 8,631,352 news articles.

In order to examine news sentiment as broadly as possible, we have constructed a specific measure: sentiment based on macro news. *Macro news* is a variable that refers to any news related to monetary or fiscal policy, economic indicators, credit or government debt ratings, or geopolitical events.[10] In total, we consider 8,631,352

[9] One of the most popular bag-of-words approaches is based on the Harvard IV dictionary.

[10] Various subject codes from TRNA were taken, such as AID, BOMB, CRIM, DEF, DIP, DIS, ENV, JUDIC, LAW, POL, SECUR, WAR, VIO, VOTE, BOJ, CEN, ECI, EMU, ECB, EU, FED, G7, IMF, INT, JOB, MCE, PLCY, PMI, SNB, STIR, WASH, AAA, ABS, DBT, EUB, EUR, GVD, IGD, MMT, MTG, MUNI.

EXHIBIT 3
Daily Macro News Sentiment



Note: This exhibit shows the daily values of the average of both positive and negative macro sentiment probability shares of each article, ranging from 0 to 1.

news articles to generate the particular macro news sentiment time series.

For this study, we want to focus on the sentiment probabilities in order to distinguish between positive and negative news sentiment, and potentially an asymmetric reaction based on volatility aversion. For each day, we take the average of each sentiment probability (for both positive and negative) in order to obtain daily values.

Exhibit 2 shows summary statistics of the news sentiment probabilities. All summary statistics, such as mean, median, maximum, and minimum are quite aligned and evenly distributed. The skewness for positive macro sentiment is negative, whereas it is positive for negative macro sentiment. Exhibit 3 shows daily values of both positive and negative (i.e., sentiment probabilities) macro news sentiment. The time series are stationary, which is confirmed by respective unit root tests.

Econometric Analysis

Stein [1989] formulates a regression model while assuming a continuous-time mean-reverting AR(1)-process with a constant long-run mean and a constant coefficient of mean-reversion in order to test for overreactions in S&P 500 options. More recently, Christoffersen et al. [2012] have replicated Stein's analysis. However, they interpret the results differently and assume a variance-dependent pricing kernel as opposed to an anomaly of rational expectations. Therefore, in this study, we want to focus on novel data in order to examine what kind of reactions there are in the options market based on news sentiment. In order to test for a potential reaction of options (and namely in implied volatility) by changes in news

Exhibit 4

t-Statistics of News Sentiment Regression Coefficients

Below are reported *t*-statistics for the respective news sentiment coefficients based on the specified regressions. T-statistics in bold indicate statistical significance at the 10% level.

Sample (adjusted): 12/05/2007 2/26/2016

Included Observations: 2,148

Dependent Variable (differences) Implied Volatility (1-month maturity)

	80%	85%	90%	95%	100%	105%	110%	115%	120%
Independent Variables (differences)									
Positive Macro News Sentiment	–0.939	**–3.283**	**–2.993**	**–3.090**	**–3.496**	–1.641	**–2.095**	–0.781	–0.323
Negative Macro News Sentiment	0.516	1.885	2.411	3.005	2.768	1.715	1.698	0.801	0.500

Dependent Variable (differences) Implied Volatility (2-month maturity)

	80%	85%	90%	95%	100%	105%	110%	115%	120%
Independent Variables (differences)									
Positive Macro News Sentiment	**–5.106**	**–6.068**	**–4.976**	**–4.715**	**–4.018**	**–3.250**	**–3.543**	**–2.717**	–1.560
Negative Macro News Sentiment	2.397	3.479	3.111	3.793	3.162	2.337	2.856	1.899	1.200

Dependent Variable (differences) Implied Volatility (3-month maturity)

	80%	85%	90%	95%	100%	105%	110%	115%	120%
Independent Variables (differences)									
Positive Macro News Sentiment	**–6.511**	**–6.169**	**–5.117**	**–6.552**	**–4.516**	**–3.588**	**–2.930**	**–2.342**	**–1.975**
Negative Macro News Sentiment	3.673	2.795	3.315	3.638	2.977	3.252	2.505	1.904	1.499

Dependent Variable (differences) Implied Volatility (6-month maturity)

	80%	85%	90%	95%	100%	105%	110%	115%	120%
Independent Variables (differences)									
Positive Macro News Sentiment	**–4.524**	**–3.632**	**–5.568**	**–6.289**	**–3.900**	**–2.674**	**–2.943**	**–3.101**	**–2.624**
Negative Macro News Sentiment	2.674	2.970	4.081	4.140	2.470	2.473	2.429	2.658	2.259

Dependent Variable (differences) Implied Volatility (9-month maturity)

	80%	85%	90%	95%	100%	105%	110%	115%	120%
Independent Variables (differences)									
Positive Macro News Sentiment	**–3.233**	**–3.654**	**–3.851**	**–6.040**	**–5.592**	**–3.432**	**–2.904**	**–2.179**	**–2.881**
Negative Macro News Sentiment	2.287	3.347	3.125	3.466	2.778	2.580	2.879	2.018	2.650

Dependent Variable (differences) Implied Volatility (1-year maturity)

	80%	85%	90%	95%	100%	105%	110%	115%	120%
Independent Variables (differences)									
Positive Macro News Sentiment	–1.367	**–4.586**	**–4.786**	**–4.361**	**–4.462**	**–2.518**	**–2.213**	**–1.727**	**–2.463**
Negative Macro News Sentiment	1.150	3.092	3.831	2.268	2.783	1.915	2.325	1.828	1.914

Dependent Variable (differences) Implied Volatility (2-year maturity)

	80%	85%	90%	95%	100%	105%	110%	115%	120%
Independent Variables (differences)									
Positive Macro News Sentiment	**–3.008**	**–2.697**	**–3.318**	**–3.839**	**–4.071**	–1.550	**–2.302**	**–2.124**	**–2.585**
Negative Macro News Sentiment	2.891	2.155	3.122	2.971	2.979	1.946	2.174	1.894	2.159

Dependent Variable (differences) Implied Volatility (3-year maturity)

	80%	85%	90%	95%	100%	105%	110%	115%	120%
Independent Variables (differences)									
Positive Macro News Sentiment	**–2.237**	**–2.500**	–0.408	**–2.659**	**–3.543**	0.012	–0.976	**–3.020**	**–3.738**
Negative Macro News Sentiment	2.812	2.014	1.342	2.650	2.412	0.888	0.703	1.033	1.317

Notes: This exhibit shows the t-statistics and statistical significance of the news sentiment regression coefficients from the following ordinary least squares regression: $\Delta IV_t^M = k + \varrho \Delta NS_t + \alpha \Delta S\&P500_{t-1} + \beta IV_{t-1} + \varepsilon_t$, *where* IV_t^M *is the implied volatility at the respective moneyness M, NS refers to positive and negative macro news sentiment, and* ε_t *to the error term. The exhibit shows that 124 news sentiment regression coefficients out of a total of 144 regressions are statistically significant at the 10% level.*

sentiment, we formulate an AR(1)-model of the following form:

$$\Delta IV_t^M = k + \varsigma \Delta NS_t + \beta IV_{t-1}^M + \alpha \Delta S\&P500_{t-1} + \varepsilon_t \quad (5)$$

where k is a constant, ΔIV_t^M is the change of the implied volatility at the respective moneyness M, ΔNS_t refers to changes in news sentiment (both for positive and negative macro news sentiment, respectively), $\Delta S\&P500_{t-1}$ are lagged returns of the S&P 500 price index as the control variable, and ε_t is the error term. Contrary to Stein [1989], we include news sentiment NS in the equation as an independent variable, as we want to test the hypothesis that changes in implied volatilities of S&P 500 options across the term structure can be explained by changes in news sentiment. Dickey–Fuller [1981] tests were performed in order to check against non-stationarity for levels of the respective variables IV_t^M, $S\&P500_{t-1}$, and NS_t as well as for first differences. Given that the unit root hypothesis for these tests and the respective variables in levels were repeatedly not rejected for all cases, first differences were used. For the first differences in the respective variables, the unit root hypothesis could be rejected.[11]

In total, we run 144 regressions of the above form for implied volatilities of S&P 500 put and call ATM and OTM options with maturities between 1 month and 3 years with positive and negative macro news sentiment as independent variables. Out of the 144 obtained news sentiment coefficients from the AR(1)-regressions, 124 are statistically significant. Exhibit 4 reports t-statistics of the respective news sentiment regression coefficients and their statistical significance. In order to get an easier handle on the results of these numerous regressions, we construct 3-D surfaces, which we call "implied volatility surfaces" based on news sentiment. The idea is the same as with traditional implied volatility surfaces. The first of the three dimensions of these surfaces is the respective moneyness of the S&P 500 options. A value of 1 means that the S&P 500 options (both put and call) are at-the-money. Values below 1 refer to out-of-the-money put options, and values above 1 refer to out-of-the-money call options. The second dimension is the time to maturity, ranging from 1 month to 36 months. The third dimension is the coefficient of news sentiment from the above regression. An advantage of this 3-D surface is that we can see the sensitivities of news sentiment on implied volatility for various maturities and moneynesses.

We consider the results in such a graphical form, as we intend to easily discern between different reactions based on news sentiment and in order to potentially identify asymmetric reactions based on volatility aversion. If investors were to react rationally (symmetrically) to changes in sentiment on any kind of news, we would expect that these changes have the same or similar effects across moneyness of the options. In other words, we could expect the surface to be "flat." However, as we will see, this is not the case.

Exhibit 5 illustrates the results from the regressions with positive macro news sentiment as the independent variable. The following conclusions can be drawn: all coefficients from the regressions are negative (except one), which means that when positive sentiment increases, implied volatility goes down. Put differently, investors appreciate more positive news so that implied volatility decreases. However, there are differences of these effects in maturities and moneyness. Positive macro news sentiment can explain changes in implied volatility of short-maturity OTM put options much more than short-maturity OTM call options or ATM put and call options. Changes in implied volatilities of longer-dated options cannot be explained very well by positive macro news sentiment, as the regression coefficients converge to 0.

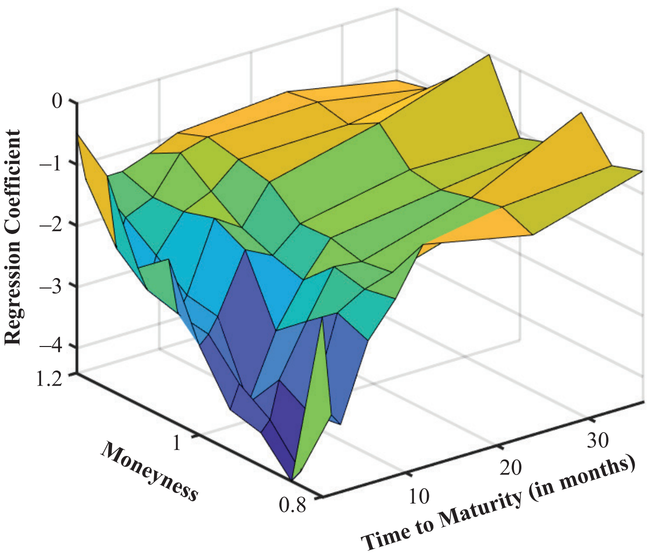
Exhibit 6 shows the results from the regressions with negative macro news sentiment as the independent variable. The following conclusions can be drawn: all regression coefficients are positive, which means that when negative sentiment increases, implied volatility goes up. Therefore, investors show fear when sentiment worsens. However, there are differences of these effects in maturities and moneyness. Contrary to Exhibit 5, the largest explanatory power of negative macro news sentiment is around ATM put and call options. The explanatory effects decrease the further out-of-the-money the respective put and call options get. In line with positive macro news sentiment, changes in implied volatilities of longer-dated options cannot be explained very well by negative macro news sentiment, as the regression coefficients converge to 0.

Combining the findings from the regressions of both positive and negative macro news sentiment, we can summarize the following: when both positive and negative news sentiment worsen, implied volatility of ATM and OTM put and call options on the S&P 500 increases. This effect is more pronounced for OTM

[11] These findings are in line with Poterba and Summers [1986] as well as with Stein [1989].

Exhibit 5

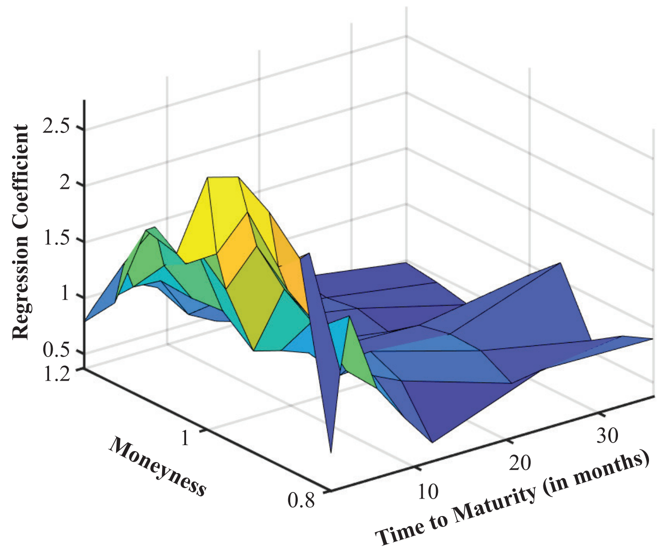
Implied Volatility Surface Based on Positive Macro News Sentiment



Notes: This exhibit shows the surface based on regression coefficients from the following ordinary least squares regression: $\Delta IV_t^M = k + \varsigma \Delta MacroP_t + \alpha \Delta S\&P500_{t-1} + \beta IV_{t-1} + \varepsilon_t$, *where* IV_t^M *is the implied volatility at the respective moneyness M, MacroPt refers to positive macro news sentiment,* $S\&P500_{t-1}$ *to lagged returns of the S&P 500 equity index, and* ε_t *to the error term. The exhibit shows that investors overreact much more strongly to changes in positive macro news sentiment for short-dated deep out-of-the-money put options than for call options. For longer-dated options, investors basically neither over- nor underreact to changes in positive macro news sentiment, as the regression coefficients converge toward 0.*

Exhibit 6

Implied Volatility Surface Based on Negative Macro News Sentiment



Notes: This exhibit shows the surface based on regression coefficients from the following ordinary least squares regression: $\Delta IV_t^M = k + \varsigma \Delta MacroN_t + \alpha \Delta S\&P500_{t-1} + \beta IV_{t-1} + \varepsilon_t$, *where* IV_t^M *is the implied volatility at the respective moneyness M, MacroNt refers to negative macro news sentiment,* $S\&P500_{t-1}$ *to lagged returns of the S&P 500 equity index, and* ε_t *to the error term. The exhibit shows that investors overreact the most to changes in negative macro news sentiment for both short-dated at-the-money put and call options. It appears that changes in negative macro news sentiment do not cause significant changes in implied volatilities in deep out-of-the-money put and call options. For longer-dated options, investors basically neither over- nor underreact to changes in positive macro news sentiment, as the regression coefficients converge toward 0.*

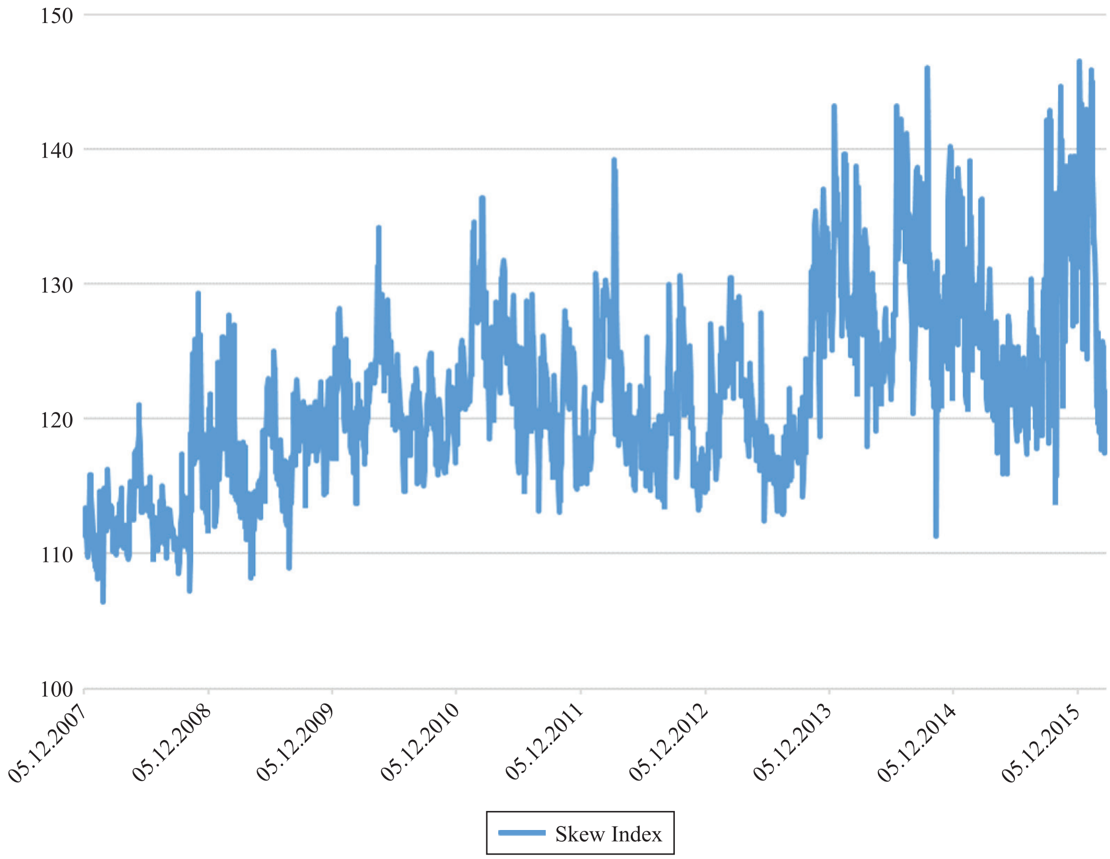
put options, that is, there is an asymmetry of the news sentiment effect: fear (change in implied volatility of put options) is more pronounced than greed (change in implied volatility of call options). The news sentiment effect becomes more pronounced (higher regression coefficient) the shorter the time to maturity of the option. This implies that investors can discount and differentiate between time horizons and are less influenced by changes in news sentiment as the time to maturity of an option increases. We can therefore conclude that there are differing reactions in the options market due to changes in news sentiment. However, these reactions based on news sentiment are not evenly distributed, but are rather centered around short-maturity put options. Hence, we can conclude that volatility aversion is present in the options market.

Robustness Checks

We run several robustness checks in order to verify our findings. Bakshi and Kapadia [2003] give insights into sources of skewness, as they document differential pricing of individual equity options versus market indexes and relate it to variations of skewness by showing how risk aversion introduces skewness in the risk-neutral density, so that skewness is a first starting point to look into. In line with Han [2008], we consider option skew in order to cross-check our earlier findings of asymmetric reactions (i.e., skew) based on changes in news sentiment. We use the so-called SKEW index of the CBOE to test for this in a simple and straightforward

EXHIBIT 7

The Skew Index



Note: This exhibit shows the development of the Skew Index from May 2007 to February 2016.

manner.[12] As defined by the CBOE, the SKEW Index is an index derived from the price of S&P 500 tail risk. Similar to VIX, the price of S&P 500 tail risk is calculated from the prices of S&P 500 out-of-the-money options. SKEW typically ranges from 100 to 150. A SKEW value of 100 means that the perceived distribution of S&P 500 log-returns is normal, and the probability of outlier returns is therefore negligible. As SKEW rises above 100, the left tail of the S&P 500 distribution acquires more weight, and the probabilities of outlier returns become more significant. One can estimate these probabilities from the value of SKEW. Since an increase in perceived tail risk increases the relative demand for low strike puts, increases in SKEW also correspond to an overall steepening of the curve of implied volatilities, familiar to option traders as the *skew*." Exhibit 7 shows a graphical representation of the skew index from May 2007 to February 2016. It can be seen that a *skew* has always been present in the history of the sample period—an indication that the perceived distribution of S&P 500 log-returns was not normal, at any time! This simple yet powerful observation might confirm our findings that there are asymmetric reactions in the options markets.

We run a simple linear regression based on the findings and hypothesis of Han [2008], who shows that a skew can be explained by sentiment among investors. We therefore define the following AR(1)-model as in Stein [1989] and as above:

$$\Delta Skew_t = k + \varsigma \Delta NS_t + \gamma \Delta Skew_{t-1} + \varepsilon_t, \qquad (6)$$

[12] See CBOE SKEW Index, available at https://www.cboe.com/products/vix-index-volatility/volatility-indicators/skew.

Exhibit 8

Regression Estimates for Skew Index and News Sentiment

OLS Model Estimates

Regression Coefficients of OLS Model, *t*-statistics in [ ] below coefficients
Sample (adjusted): 12/06/2007 2/26/2016
Included Observations: 2,147

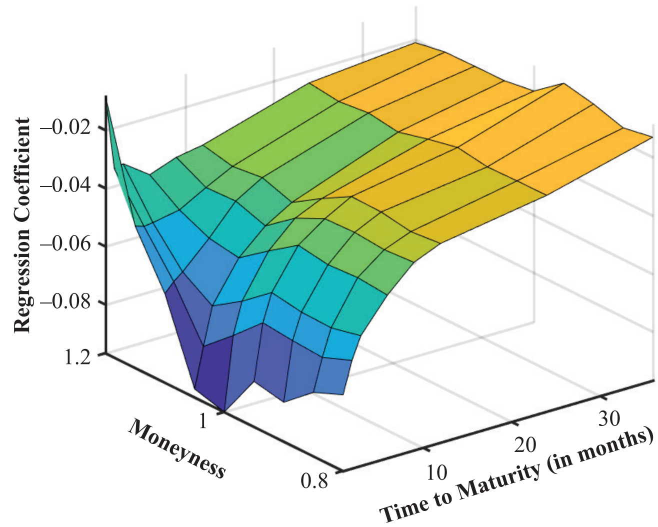
Dependent Variable	Skew Index (Differences) 1	Skew Index (Differences) 2
Independent Variables		
Positive Macro News	4.451196	
Sentiment (in differences)	[2.962761]***	
Negative Macro News		–1.418934
Sentiment (in differences)		[–1.181452]
Constant	0.003243	0.003395
	[0.062803]	[0.065673]
AR(1)	–0.320472	–0.320169
	[–25.67376]***	[–25.69977]***
R-Squared	0.105469	0.102719
Adjusted R-Squared	0.104216	0.101463
Standard Error of Regression	3.127473	3.132277
Log likelihood	–5492.577	–5495.872
F-Statistic	84.22271	81.77521

*Notes: *** denotes statistical significance at the 1% level.*

This exhibit shows regression estimates of the Skew Index with positive and negative macro news sentiment.

Exhibit 9

Implied Volatility Surface Based on S&P 500 Price Index



Notes: This exhibit shows the surface based on regression coefficients from the following ordinary least squares regression: $\Delta IV_t^M = k + \alpha\Delta SP500_t + \beta IV_{t-1} + \varepsilon_t$, where IV_t^M is the implied volatility at the respective moneyness M, SP500 refers to prices of the S&P 500 Index, and ε_t to the error term. The exhibit shows that investors overreact the most to changes in S&P 500 prices for both short-dated at-the-money put and call options. Put differently, we observe the typical "volatility smile" for short-dated options. For longer-dated options, investors basically neither over- nor underreact to changes in S&P 500 prices, as the regression coefficients converge towards 0.

where k is a constant, $Skew_t$ refers to the CBOE Skew Index, NS_t to both positive and negative macro news sentiment, and ε_t is the error term. Exhibit 8 shows the results. It can be seen that positive macro news sentiment is statistically significant in explaining the Skew Index. However, negative macro sentiment is not statistically significant. This confirms two main things: first, it confirms a present skew, and, second, it shows that positive sentiment has explanatory power for the skew index. Rightly so, negative sentiment does not have explanatory power for the skew index, as negative sentiment would only be helpful in explaining changes in the skew index if the "other side" (i.e., values of the Skew Index below 100) of the skew were present, but this is not the case.

Furthermore, we test with a "more traditional" factor for explaining implied volatility and generating implied volatility surfaces with changes in prices of the underlying of the options, that is, returns of the S&P 500 Index itself. We want to test for differences between returns of the S&P 500 Index and news sentiment. We run the following AR(1)-models in line with (6):

$$\Delta IV_t^M = k + \alpha\Delta SP500_t + \beta IV_{t-1} + \varepsilon_t, \tag{7}$$

where $SP500_t$ refers to prices of the S&P 500 Index, IV_t^M to the implied volatilities of the respective moneyness and maturities, and ε_t to the error term. Exhibit 9 shows the implied volatility surface based on prices of the S&P 500 Index. In the exhibit, we identify a pattern for short-dated options which looks similar to a "volatility smile." Implied volatilities for ATM put and call options can be better explained by changes in S&P 500 prices (i.e., changes in the market environment) than for OTM put or call options. A typical volatility smile graph would show that implied volatilities are higher for OTM put or call options than for ATM put or call options, whereas the standard option pricing model according to Black and Scholes [1973] would consider equally high implied volatilities for OTM and ATM put and call options.[13] Furthermore, the smile is teetering off as the time to maturity of the options increases and the regression coefficients are rather small (in absolute numbers), or close to 0. The exhibit shows a different picture than the one we obtained for news sentiment—both in terms of explanatory power and magnitude, confirming our findings. In sum, our findings justify the presence of a volatility smile in short-dated options.

The implications of this cross-check are therefore manifold: we can assume that the implied volatility in OTM put and call options is influenced by a different factor, as S&P 500 Index returns explain changes in implied volatilities of short-dated OTM put and call options less than implied volatilities of short-dated ATM put and call options. Implied volatilities of both ATM and OTM put and call options can hardly be explained. We can therefore posit that implied volatilities react in short-dated options (up to 9 months) based on changes in news sentiment. Two interesting follow-up topics arise based on our findings that could be examined in further research: first, further cross-checks for what drives changes in implied volatilities for longer-dated options can be done; and second, are there any other channels of information, which trigger changes in implied volatility?

CONCLUSION

We test implied volatility across the "term structure" of options because investor reactions can be neatly dissected in terms of time to maturity and potential falling or rising prices. Previous studies have established that volatility responds to news in an asymmetric fashion. This paper attempts to explain the asymmetry in implied volatility with a new measure of news sentiment across the term structure of S&P 500 options (for maturities ranging from 1 month to 3 years).

We find that when both positive and negative news sentiment worsen, implied volatility of ATM and OTM put and call options on the S&P 500 increases. This effect is more pronounced for OTM put options, that is, there is an asymmetry of the news sentiment effect: fear (change in implied volatility of put options) is more pronounced than greed (change in implied volatility of call options), which is in turn related to volatility aversion. The news sentiment effect becomes more pronounced (higher regression coefficient) the shorter the time to maturity of the option. This implies that investors can discount and differentiate between time horizons and are less influenced by changes in news sentiment as the time to maturity of an option increases.

We can therefore conclude that investors in the options market react to changes in news sentiment. However, these reactions based on news sentiment are not evenly distributed, but are rather centered around short-maturity put options. We term this asymmetry *volatility aversion*. This factor is neither evenly nor linearly distributed and varies significantly depending on the sentiment of the news, time to maturity of the option, and moneyness.

[13] See Hull [2003] for a detailed explanation of the volatility smile.

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