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Does the Weather Affect Stock Market Volatility?

Lazaros Symeonidis[1], George Daskalakis[2] and Raphael N. Markellos[3,⋆]

[1] *ICMA Centre, Henley Business School, University of Reading, UK*

[2] *Norwich Business School, University of East Anglia, UK*

[3] *Dept. of Management Science & Technology, Athens University of Economics and Business, Greece*

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Abstract. This paper investigates the empirical association between stock market volatility and investor mood-proxies related to the weather (cloudiness, temperature and precipitation) and the environment (nighttime length). Overall, our results suggest that cloudiness and length of nighttime are inversely related to historical, implied and realized measures of volatility. The strength of association seems to vary with the location of an exchange on Earth with respect to the equator. Weather deviations from seasonal norms and dummies representing extreme weather conditions do not offer additional explanatory power in our datasets.

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⋆ Corresponding author: Associate Professor, Department of Management Science and Technology, Athens University of Economics and Business, Office 915, 47A Evelpidon Str., Athens, GR 113 62, Greece, Tel: 0030 210 820 3671, Fax: 0030 210 882 8078, rmarkel@aueb.gr. Visiting Research Fellow, Centre for Research in International Economics and Finance (CIFER), Department of Economics, Loughborough University, UK.

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1. Introduction

Investment professionals appear to have been well aware of the behavioral effects of the weather for over a century now. Characteristically, Samuel A. Nelson (1902, p. 163) reports: "*During normal markets, brokers have observed that the psychological factor is so strong that speculators are not disposed to trade as freely and confidently in wet and stormy weather as they are during the dry days when the sun is shining, and mankind is cheerful and optimistic*".[1] More recently, several papers have investigated in depth the links between stock market returns and prevailing weather conditions. The main empirical finding in this literature is the so-called 'sunshine effect' according to which cloudiness, as measured by cloud cover, has a significant negative correlation with daily equity index returns (see Saunders, 1993; Hirshleifer and Shumway, 2003 and Chang et al., 2008 among others). This relationship has been explained using arguments from psychology on the basis of "mood misattribution". Simply put, sunny weather is thought to influence the mood of some investors making them more optimistic and thus more willing to enter into long positions, which in turn leads to higher returns. Other weather and environmental variables which have been considered in the financial literature as mood-proxies include, among others, temperature (e.g., Cao and Wei, 2005), daylight savings time changes (see, e.g., Kamstra et al., 2000) and the 'Seasonal Affective Disorder' (SAD, see, e.g., Kamstra et al., 2003; Garrett et al., 2005).

Rather than concentrating on expected returns, a recent strand of research has examined the effect of weather and environmental factors on volatility. This is of great academic and practical interest since volatility underlies a variety of key financial decisions, problems and applications in asset valuation, portfolio theory, derivatives pricing, risk management, etc. The main obstacle in this research is that volatility is largely unobservable. In the present paper, we consider all three of the most widely used proxies: historical, implied and realized volatility (for a detailed description of these and relevant references see Poon and Granger,

[1] Nelson collected and published the Wall Street Journal editorials of the legendary Charles H. Dow in a book which formed the basis of what later became known as Dow Theory and Technical Analysis.

2003, and Mills and Markellos, 2008). Specifically, we extend in four main directions the empirical literature which examines the impact on volatility of cloudiness, variation in nighttime hours, temperature and precipitation, respectively. First, in addition to the three deseasonalised weather variables, we consider also the effect of absolute deviations from seasonal norms and of dummies which reflect extreme weather conditions. This is because mood variations could be potentially better correlated with the magnitudes of deviations, or, with extreme deviations of weather, from seasonal norms, respectively. For example, we may feel particularly uncomfortable when the weather is (significantly) hotter or colder than expected during a particular season. In this manner, deviations of weather variables from seasonal averages may then lead to variations in mood states and to shifts in volatility. Since the strength of association between weather/environmental variables and stock market returns has been found to depend also on stock exchange location (see, e.g., Keef and Roush, 2007), we also consider the effect of latitude when looking at international data. Second, we analyze the effects on historical volatility using an ARCH-type model on the extensive dataset of Hirshleifer and Shumway (2003) which consists of stock market index returns for 26 stock exchanges internationally between 1982 and 1997. Third, we analyze four implied volatility indices for the CBOE (namely: VIX, VXO, VXN and VXD) along with the term structure of the VIX volatility index (7 volatility duration buckets). Implied volatility is derived from traded options and is a measure of expected volatility as this is perceived by investors in the derivatives market. The variety of indices used enhances the robustness of our results and allows us to see if the effect of weather and of environmental factors depends on the composition of the volatility index and the underlying option market investment horizon. Finally, we analyze realized volatility which is constructed on the basis of high-frequency returns for the S&P 500 index. Realized volatility offers a great advantage in that it is considered as the most accurate representation of the unobserved volatility process.

Empirical evidence is mixed between the existing studies that have investigated the effects of weather and environmental conditions on volatility. Chang et al. (2008) show that New York City cloudiness has a significant positive effect on intraday volatility of NYSE firms over the entire trading day. Two volatility proxies are used by these authors: one based on the range of the intraday prices and the other on the basis of the standard deviation of the bid-ask mid-point returns. Both of these proxies are uncommon in the literature and their accuracy is unknown. Dowling and Lucey (2008) study the empirical effect of seven mood-proxies on both the returns and variances of 37 national equity market indices and 21 small capitalization indices. They employ GARCH-type processes to approximate and model the variations in the conditional variance of returns. Their results show that wind, precipitation, geomagnetic storms, daylight savings time changes and the SAD are all positively related to conditional volatility for most of the indices considered. Kaplanski and Levy (2009) consider the effect of SAD and temperature on the VIX option's implied volatility index which is traded in the Chicago Board Options Exchange (CBOE). They use also a measure of so-called 'actual' volatility based on the historical standard deviation of a monthly window of daily returns. The authors find that the number of daylight hours (temperature) is negatively (positively) related only to the 'perceived' volatility proxied by the VIX and not to the 'actual' historical volatility measure. Another study which indirectly shows a positive relationship between volatility and bad weather is Kliger and Levy (2003). These authors find using S&P 500 index options data that bad mood, as proxied by total cloud cover and precipitation, make investors place higher-than-usual probabilities on adverse events.

At a theoretical level, our research effort is motivated by Mehra and Sah (2002) who show that even small fluctuations in investors' attitudes towards risk, which could result from weather-related shifts in their mood states, can have a non-negligible impact on market volatility. Chang et al. (2008), mention two competing, but not mutually exclusive, explanations with contradictory empirical implications for the relationship between weather and volatility. On the one hand, since poorer social moods can be associated with more disagreement in valuation opinions among investors, bad weather can be expected to be inversely related to market volatility (see Harris and Raviv, 1993; Shalen, 1993; Baker and Stein, 2004; Lucey and Dowling, 2005, among others for a thorough discussion). On the other hand, studies such as Brown (1999), Gervais and Odean (2001), and Statman et al. (2006), suggest that when investors are in a good mood, which can be associated with fair weather, then they tend to trade more, which in turn increases volatility. A third explanation has been given by Kaplanski and Levy (2009), who argue that if SAD induces seasonality in returns, and returns are negatively correlated with volatility, then SAD can indirectly create seasonality in volatility in the opposite direction. We can assume that a similar indirect effect on volatility holds also for other weather and environmental conditions which may affect returns. Finally, another explanation of a positive association between bad weather and volatility could be based on psychological studies which link poor mood with an increase in the subjective probability of undesired outcomes (see Kliger and Levy, 2003 and the references therein).

2. Empirical Application

We use three weather and one environmental variable sampled at daily intervals: sky cover (*SKC*), temperature (*TEMP*), precipitation (*PRECIP*), and the variation in the number of hours of night, respectively (the acronym used for this variable is *SAD* since it captures the Seasonal Affective Disorder; see Kamstra et al., 2003). All weather variables are obtained from the International Surface Weather Observations (ISWO, see www.ncdc.noaa.gov). *SKC* is measured by sky cover, ranging from 0 (clear) to 8 (overcast), and is calculated as the average cloud cover for each day from 6 a.m. to 4 p.m. local time for each city. *TEMP* and *PRECIP* are measured in degrees Fahrenheit and inches, respectively. Following Kaplanski and Levy (2009), the temperature variable for each city is calculated as the average value between the daily maximum and minimum temperature divided by 52.27. In order to assess the impact of the variation in the length of night that causes the SAD effect, we follow the procedure described in Kamstra et al. (2003). As in Hirshleifer and Shumway (2003) and Dowling and Lucey (2008), due to the highly seasonal nature of the weather variables we deseasonalize *SKC*, *TEMP* and *PRECIP* by subtracting from each observation its weekly average. Magnitudes of deviations are then calculated as the absolute deseasonalised values for *SKC*, *TEMP* and *PRECIP*, respectively. Finally, dummies representing positive and negative extreme conditions for each weather variable are constructed by assigning the value 1 when the deseasonalised value belongs in the top or lower 20% percentile, respectively, and zero otherwise.[2] In this manner, we obtain 6 'extreme weather' dummies (denoted with a superscript '+' and '–' when observations in the top and lower 20% percentile are used, respectively): SKC^{+}, SKC^{-}, $TEMP^{+}$, $TEMP^{-}$, $PRECIP^{+}$, $PRECIP^{-}$.

2.1 Historical Volatility

In order to model the historical volatility with respect to weather conditions, we select the so-called GJR-GARCH(1,1) process (Glosten et al., 1993):

$$\sigma_{i,t}^{2}=c_{i}+b_{i}\sigma_{i,t-1}^{2}+\alpha_{i}e_{i,t-1}^{2}+g_{i}I_{\{e_{t-1}<0\}}e_{i,t-1}^{2}+\sum_{j=1}^{4}\gamma_{ij}W_{ij,t} \tag{1}$$

This model is chosen since it is flexible enough to capture asymmetries in the volatility process and appears to fit well various datasets (for a similar application see Dowling and Lucey, 2008). In (1), $\sigma_{i,t}^{2}$ is the conditional variance of market i at time t, and $e_{i,t-1}$ the residual series from the conditional mean equation of equity market returns ($r_{i,t}$). In order to avoid making any restrictive assumptions about the data generating process, we assume for simplicity that returns result from an AR(1) process with a drift so that $r_{i,t}=\mu_{i}+\rho_{i}r_{i,t-1}+e_{i,t}$. Also, $e_{i,t}=\sigma_{i,t}z_{i,t}$, where $z_{i,t}\sim \mathrm{N}(0,1)$ are the standardized disturbances. $W_{ij,t}$ corresponds to the matrix of the variables considered. This includes also the deseasonalised and absolute deseasonalised values for the weather variables, extreme weather dummies, and the *SAD*. For our analysis we employ the dataset compiled by Hirshleifer and Shumway (2003) that contains daily index returns from 26 international stock exchanges for the period 1982 to 1997. For each index at a time, we estimate equation (1) through the Maximum Likelihood (ML) approach.

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[2] The use of other 'extreme' percentiles, e.g., ±10%, and ±5% leads to comparable results and conclusions.

The GJR-GARCH(1,1) estimation results are presented in Table 1.[3] Using a two-tailed test as in Hirshleifer and Shumway (2003), we can conclude that for the 26 cities considered, most of the statistically significant coefficients at the 95% level associated with *SAD* and *SKC* are negative (13 out of 19 and 10 out of 13, respectively). The statistically significant coefficients for *TEMP* are mainly positive (9 out of the 15 significant coefficients), while the results on *PRECIP* are mixed, with 7 statistically significant coefficients being positive and 5 negative. Similar results to the above are obtained when absolute values or dummies for the weather variables are used. The only exception is *PRECIP* where a more clearly negative relationship now emerges (11 out 16, 9 out of 15 and 10 out of 13 negative significant coefficients for $|PRECIP|$, $PRECIP^{+}$ and $PRECIP^{-}$, respectively).

Motivated by Parker and Tavassoli (2000), who show that the effect of weather on economic behavior depends on the location of a place on Earth with respect to the equator, we investigate now if latitude can explain variations in the effect of weather on volatility across countries. In a relevant paper, Keef and Roush (2007) show that in the Hirshleifer and Shumway (2003) dataset, the influence of cloud cover on stock returns becomes more negative as absolute latitude increases. In order to study the potential effect of location, we calculate the absolute latitude (i.e., ignoring if it is north or south of the equator) for each city and transform it to a decimal. We then separate our sample of cities in two groups: those with above average absolute latitude (Group A: Amsterdam, Brussels, Copenhagen, Dublin, Helsinki, Istanbul, London, Madrid, Milan, New York, Oslo, Paris, Stockholm, Vienna, Zurich) and those with below average absolute latitude (Group B: Athens, Bangkok, Buenos Aires, Johannesburg, Kuala Lumpur, Manila, Rio de Janeiro, Santiago, Singapore, Sydney, Taipei). By examining the average value of the statistically significant coefficients at the 95%

[3] For brevity we only report the coefficients of the variables for each city under investigation. It is interesting to note that the g_i coefficients for all cities in the GJR-GARCH(1,1) models were found to be statistically significant and positive, thus suggesting the presence of an asymmetric effect of negative residuals (or of 'bad' news). This is a common finding in the empirical literature which is known as the leverage effect. Other ARCH-type specifications that we also tested led to comparable findings. All omitted results are available upon request by the authors.

level we can conclude that the strongest effect of latitude exists for the *SAD* variable. Specifically, the average *SAD* significant coefficient for the 8 cities in Group B is -0.3110, which is 28.9 times larger in magnitude than the average value of -0.0104 for the 11 cities in Group A. This is somewhat unexpected since we use the latitude-corrected procedure proposed by Kamstra et al. (2003) in calculating the *SAD* variable. It could be that the effect of latitude is more prominent than that accounted for in our SAD-proxy. The average coefficient for the negative/positive latitude countries is -0.0300/-0.0106 (1.84 times larger) for *SKC*, 0.2733/-0.0735 for *TEMP* (4.72 times smaller) and 0.0118/-0.1267 for *PRECIP* (6.7 times larger).

In order to enhance the robustness of our results, we examine the significance of the parameters via a Wald test for each estimated regression. The null hypothesis in these tests is that the coefficients of the weather variables in each variance equation are all zero, i.e., $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$. In all cases except one, the test statistics reject the null hypothesis that the coefficients of the mood-proxies considered are jointly insignificant. This uniform evidence of mood-proxy effects on stock market volatility is indeed quite impressive. However, it should be pointed out that these joint tests are not independent to each other due to the covariance between the different stock market indices considered. Finally, as in Chang et al. (2008), in order to assess the stability of the estimates, we repeat the analysis across various subsamples. The results, not reported here due to space limitations, are similar to those presented in Table 1 and our conclusions remain the same.

2.2 Implied Volatility

Implied volatility is obtained by inverting financial option pricing formulae using observed option prices. The vast majority of empirical evidence shows that implied volatility provides better forecasts compared to historical volatility models and GARCH in particular (see Poon and Granger, 2003). Volatility indices (V) can be constructed by taking weighted averages of implied volatilities from options with different configurations in terms of maturity and moneyness. For the purposes of the present paper, each implied volatility index is related to our mood-proxies according to the following regression framework:

$$V_{i,t} = a_i + \sum_{j=1}^{4} b_{ij} W_{ij,t} + \varphi_{i,1} V_{i,t-1} + \varphi_{i,2} V_{i,t-2} + u_{i,t} \tag{2}$$

where $V_{i,t}$ is the closing value of the implied volatility index i on day t. Lagged $V_{i,t}$ are included in the test regression in order to capture the persistence in volatility. These index-by-index regressions are estimated using ordinary least squares (OLS) assuming Newey and West (1987) HAC standard errors and covariances. To assess the joint influence of the weather and environmental factors on implied volatility we also perform various joint estimations. In particular, we estimate a pooled OLS model by stacking all observations in a large panel. In this model the intercepts and coefficients are assumed to be the same across all indices. Since the pooled OLS model is based on the unrealistic assumption that the errors are uncorrelated, we also estimate a fixed effects model, assuming Panel Corrected Standard Errors (PCSE) for the coefficient covariance matrix. This specification allows for contemporaneously correlated and heteroskedastic errors (see Wooldridge, 2002, for a description).

In estimating regression (2), we employ data for the *VIX* (02/01/1990–27/06/2008), *VXO* (02/01/1990–27/06/2008), *VXN* (05/02/2001–27/06/2008) and *VXD* (07/10/1997–27/06/2008) volatility indices, which are traded in the CBOE (see www.cboe.com).[4] Thus, the focus from a weather perspective is in the area of Chicago. The *VXO* is estimated following Whaley (1993), and represents the implied volatility of a synthetic at-the-money option on the S&P 100 which has a constant 30 calendar days to expiry. The *VIX* is calculated in a model-free manner as a weighted sum of out-of-the-money S&P 500 call and put option prices at two nearby maturities across all available strikes. Carr and Wu (2006) show that squared values of

[4] While implied volatility indices have been recently developed for a variety of other countries (e.g., the VDAX-NEW in Germany, the VX1 and VX6 in France, the VSTOXX in the Eurex, the VSMI in Switzerland, the MVX in Canada, etc.), these have a rather limited number of observations and are thinly traded.

the *VIX* approximate the 30-day conditional risk-neutral expectation of the return variance or, in other words, the 30-day variance swap rate. Employing the same methodology used for the *VIX*, the *VXN* is estimated as a proxy for the volatility of near-term NASDAQ-100 options. Finally, the *VXD* is based on real-time prices of options on the Dow Jones Industrial Average (DJIA) with a 30-day expiration. In estimating (2) we also employ the recently released data on the term structure of the *VIX*. This is a representation of implied volatility from particular S&P 500 (so-called SPX) index option expirations. It is calculated by applying the *VIX* methodology to a single strip of *SPX* options having the same expiration date. Unlike the *VIX*, the term structure data do not give constant maturity volatility. Using the data obtained by the CBOE we group the term structure expirations in 7 buckets corresponding to an average of 16.69 (*VIX1*), 50.04 (*VIX2*), 84.52 (*VIX3*), 146.63 (*VIX4*), 234.23 (*VIX5*), 331.08 (*VIX6*) and 469.52 (*VIX7*) calendar days, respectively. The term structure can provide potentially useful information since it reflects variations in perceptions of volatility across derivative market investment horizons.

The regression coefficients for the variables under study against the volatility indices are summarized in Table 2. Although most of the coefficients are not statistically significant, the negative sign for *SAD* and *SKC* is in line with the results obtained for historical volatility. However, statistically significant negative coefficients for both the *SAD* and *SKC* are obtained if they are estimated with the pooled OLS model and the fixed effects model for the four implied volatility indices. Coefficients for *TEMP* and *PRECIP* are mostly positive. Moreover, in this case we also find some statistically significant coefficients. The results for the absolute values and dummies allow similar conclusions. The only exception is that when magnitudes of extreme positive temperatures are used, we obtain several statistically significant negative coefficients.

2.3 Realized Volatility

A recent development in the financial literature is the emergence of the so-called integrated or realized variance (*RV*) estimator (for a review see Andersen et al., 2009). This nonpametric estimator measures the quadratic variation of the underlying diffusion process in continuous time. It can be simply approximated in discrete time by taking the sum of squared returns within a fixed time interval. The popularity of realized variance has to do with the fact that it allows us, in the continuous time limit, to approximate the, ex post, instantaneous variance over any time interval, to any desired degree of accuracy, by just sampling at sufficiently high-frequencies. Under certain assumptions it can be proven that *RV* is a uniformly consistent and unbiased estimator of the unobserved, true variability of the process. However, it has been shown that microstructures pose a natural limit to the accuracy of the estimator.

In the present paper we use *RV* estimates constructed from high-frequency S&P 500 index returns over the period 05/01/1993 to 31/12/1997 (this dataset has been put together by Huang et al., 2007 and can be downloaded from Jun Yu's homepage). From the daily variance figures we calculate volatilities as the annualized standard deviations (these will be referred to simply as *RV*'s hereafter). As with the implied volatility indices in (2), *RV* estimates are then used as a dependent variable in the following regression framework:

$$RV_t = a + \sum_{j=1}^{4} b_j W_{j,t} + \phi_1 RV_{i,t-1} + \phi_2 RV_{t-2} + u_t \tag{3}$$

The regression results are contained in Table 2 and are roughly in line with those previously obtained for implied volatility. Specifically, coefficient estimates for *SAD*, *SKC* and *PRECIP* are insignificant at the 95% level. The coefficients for *SAD*, *SKC* and *TEMP* are negative. When absolute values and extreme weather dummies are used, the coefficients for both cloudiness and variation in the hours of night (precipitation) are consistently negative (positive). Statistically significant positive coefficients are obtained only for *TEMP* and for |*PRECIP*|. However, these results should be deemed preliminary since the period employed for the realized volatility is particularly short. Thus, there is a realistic chance of not being able to capture the annual seasonalities investigated in the present paper.

3. Discussion of Results and Conclusions

The empirical results in this paper suggest that SAD and cloudiness are negatively associated with various measures of stock market volatility. In line with Dowling and Lucey (2008), we find that historical volatility according to a GJR-GARCH(1,1) model is significantly inversely related to the mood-proxies associated with cloudiness and variation in nighttime hours for 26 stock exchanges and cities internationally between 1982 and 1997. Despite the fact that we use a latitude-corrected SAD-proxy, we find that the effect of this variable depends on the location of a city on Earth with respect to the equator. Our results concerning implied volatility and realized volatility offer some additional support. Specifically, implied volatility indices for the CBOE and realized S&P 500 index returns tend to be negatively related with cloudiness and variation in nighttime hours. However, the underlying coefficients are statistically significant only in a pooled sample of four implied volatility indices. The direction of association for the SAD-proxy and the VIX implied volatility index is consistent with that reported by Kaplanski and Levy (2009). Our disparity with respect to statistical significance is possibly due to the adoption of a different sample. In general, our analysis suggests that absolute deviations of weather variables from seasonal norms and dummies related to extreme weather conditions do not offer additional explanatory power in attempts to model volatility.

Our results are consistent with the explanation that good mood is associated with increased trading and volatility, respectively. As mentioned, it could also be the case that we are simply observing the indirect result of the ‘leverage effect’. Our results are unlikely to be influenced by data-snooping since we use several different but comparable volatility datasets to evaluate our hypothesis and we validate our results, when possible, using subsamples of our original data. It would be useful to evaluate also the economic significance of our results, as in Hirshleifer and Shumway (2003). However, building volatility trading strategies is far from straightforward since it requires combined derivative positions.

This note adds to the empirical literature but does not extend our theoretical understanding of the relationship between weather and financial markets. The psychological effects involved in weather are both interesting and complex and deserve further research. A potentially useful direction could consider the heterogeneity in trade responsiveness to weather and environmental-related changes in mood. For example, Levy and Galili (2008) show that males, low income, and young individuals tend to be net buyers on cloudy days. To the extent that these groups have differences in characteristics such as risk aversion, the variations in investor mix could affect intertemporal market returns and volatility. We believe that it would also be interesting to explore rational causes in addition to the behavioral explanations that have been discussed. For example, extending the arguments by Goetzmann and Zhu (2005), if market participants tend to leave early on rainy days in order to beat the rush, then we can expect a negative impact of cloudiness on liquidity and volatility, respectively. Indeed, as Loughran and Schultz (2004) demonstrate, trading volume is significantly lower during blizzards in a city, since investors may take longer to get to work as a result of, for example, the need to shovel snow or dig out cars. This leaves less time for trading. In general, during bad weather it can be expected that commuting times of investors will also be significantly longer. Alternative explanations could be based on the effect of weather on the cognitive behaviors of market participants (see Keller et al., 2005, *inter alia*). It could be that volatility increases due to weather-related shifts in information consumption by investors. It is well known that social interaction has a significant effect on stock prices (Hong et al., 2004). It could be that during sunny weather investors tend to socialize and communicate more which increases the amount of effective information and volatility.

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Table 1. Weather and environmental variable coefficient estimation results for GJR-GARCH (1,1) models

City	*SAD*	*SKC*	*TEMP*	*PRECIP*	*SAD*	*|SKC|*	*|TEMP|*	*|PRECIP|*	*SAD*	*SKC*$^{+}$	*TEMP*$^{+}$	*PRECIP*$^{+}$	*SAD*	*SKC*$^{-}$	*TEMP*$^{-}$	*PRECIP*$^{-}$
Amsterdam	-0.0013*	0.0003	-0.0307	0.0131	-0.0013*	-0.0032	-0.0107	0.0273	-0.0016*	-0.0425*	0.0120	0.0100	-0.0014*	-0.0167	0.0416*	0.0072
Athens	-0.0168*	-0.0152	0.0921*	0.4046*	0.0001	-0.0322*	0.1908*	-0.1214*	-0.1287*	-0.2838*	-0.3466*	-0.3000*	-0.0041	-0.1426*	-0.0411	-0.0452*
Bangkok	-0.9262*	-0.0858*	-0.3354*	-0.2719	-1.0962*	-0.0858*	-0.2796*	-0.3775*	-0.0172*	0.1366*	-0.1475*	0.0043	-0.0023	-0.0866*	-0.0298†	-0.0282*
Brussels	-0.0336*	-0.0234*	-0.2053*	0.0326	0.0005	-0.0079*	0.0763*	0.0129	-0.0005	0.0022	0.0248*	-0.0042	-0.0004	-0.0348*	0.0257*	-0.0112*
Buenos Aires	-0.0520*	0.0073	1.0727*	0.2690*	-1.3218*	-0.1919*	-1.7288*	-0.5463*	-1.1284*	0.6392	-1.6592*	9.3083*	-1.0584*	-6.0919*	-3.4042*	-0.8313
Copenhagen	0.0020*	-0.0099*	0.0336*	0.0002	0.0019*	-0.0025	0.0004	0.0003*	0.0019*	-0.0045	0.0086	0.0341*	0.0017*	0.0192*	0.0257*	0.0289*
Dublin	0.0032*	0.0059	-0.0062	-0.1156*	0.0003	0.0435*	-0.2460*	-0.0997*	0.0039*	0.0119	0.0411*	-0.0573*	0.0025	0.0894*	-0.0923*	-0.0649*
Helsinki	0.0031*	0.0130*	-0.0203	0.1819*	0.0028*	0.0091*	0.0342	0.2291*	0.0007	-0.0177	0.0364*	0.1273*	0.0052*	-0.0243†	-0.0802*	0.0097
Istanbul	-0.0486*	0.0168†	-0.1617*	-0.0725	-0.0126*	-0.0200*	0.0521	-0.1322*	-0.0105*	0.0081	0.1039*	-0.0297	-0.0192*	0.0202	0.0961†	-0.0230
Johannesburg	-0.0332*	-0.0206*	0.0942*	-0.0769	-0.0410*	-0.0346*	0.1275*	-0.0364†	-0.0421*	0.0456*	0.0493*	-0.1682*	-0.0162*	0.1573*	0.0124	-0.0310*
Kuala Lumpur	-0.1290	-0.1285*	0.7736*	0.0890*	-0.2400*	0.1302*	-0.3238*	0.0605*	-0.3412*	0.0762*	0.0644*	0.1560*	-0.4812*	0.0696*	-0.1221*	-0.0870*
London	0.0010	0.0136*	-0.1047*	-0.0632	0.0009	0.0089*	-0.0689*	0.0515*	0.0007	-0.0053	0.0156	0.0123	0.0004	0.0288*	0.0348*	0.0120†
Madrid	0.0084*	-0.0073*	0.0913*	-0.3324*	0.0091*	-0.0005	0.0852*	-0.0122	0.0069*	0.0101	0.0897*	-0.0606*	0.0066*	0.0332*	-0.0694*	-0.0049
Manila	-0.3335*	0.1446*	0.0899	-0.7232*	-0.1188*	-0.1122*	0.7654*	-0.4327*	0.0459	0.0033	0.4351*	-0.0764†	0.0783*	-0.2460*	0.0120	-0.0986*
Milan	0.0006	0.0090	0.0729*	0.0237	0.0007	-0.0075	0.0836*	-0.0226	0.0005	-0.0230	0.0060	-0.0333†	0.0015	-0.0427	-0.1092*	0.0147
New York	0.0008	-0.0006	0.0090	0.0292	0.0008	0.0025	-0.0049	-0.0045	0.0014	0.0042	-0.0127	0.0306*	0.0009	0.0193*	-0.0053	-0.0034
Oslo	0.0069*	0.0120	-0.0306	0.0346	0.0065*	0.0137*	-0.0557	0.0845	0.0067*	-0.0408	0.0554†	0.0397	0.0094*	-0.0379	-0.0565	0.0224
Paris	0.0029	0.0019	0.0281	-0.1195	0.0032	-0.0090†	0.0717*	0.0472	0.0019	-0.0109	0.0075	0.0208	0.0016	-0.0208	0.0444*	0.0115
Rio de Janeiro	-0.1882*	-0.0833*	0.2460	-2.6280†	-3.0451*	-0.5208*	-1.5970*	-11.8309*	-1.3841*	-0.2764	-0.0333	-3.8580*	-1.0722*	1.1492*	-1.7443*	-2.7482*
Santiago	-0.0050	-0.0064*	0.0279†	0.0589*	-0.0060	-0.0015	0.0152	0.0074	-0.0064†	-0.0116	0.0235	0.0156	-0.0072*	0.0103	-0.0112	0.0143
Singapore	-0.9300*	-0.0115	0.1542*	-0.0357*	-0.6851*	-0.0413*	0.2526*	-0.0253*	-0.6621*	0.0370*	0.0761*	-0.1126*	-0.4578*	0.0160	-0.0013	-0.1033*
Stockholm	0.0079*	-0.0067	-0.0411	0.1409	0.0073*	0.0059	-0.0893*	0.0712	0.0074*	0.0226	-0.0236	0.0583*	0.0076*	0.0820*	0.0161	0.0404*
Sydney	-0.0085*	-0.0111†	0.0614*	0.0244	-0.0074*	0.0042	0.0214	-0.0371*	-0.0048	0.0018	0.0692*	-0.0184	-0.0097*	0.0516*	-0.0360	-0.0191
Taipei	0.0090	0.0001	0.0091	0.3505*	0.0205*	0.0050	0.0130	0.1665*	-0.6358*	-0.8704*	-0.9583*	-1.0975*	0.0231*	-0.0193	0.0521	0.1154*
Vienna	-0.0524*	-0.0337*	-0.1679*	-0.3318*	-0.0981*	-0.0212*	-0.0903*	-0.4843*	-0.0321*	-0.1731*	-0.1687*	-0.2917*	-0.0004	0.0267*	0.0085†	0.0052
Zurich	-0.0099*	-0.0263*	-0.1464*	-0.0355*	0.0016	-0.0410*	-0.0474*	-0.0424*	0.0083*	0.0214†	-0.0286*	-0.0618*	0.0055*	-0.0080	-0.0189*	-0.0516*

Note: A star (dagger) denotes statistical significance of a coefficient at the 95% (90%) level using a two-tailed test.

Table 2. Effect of weather and environmental mood-proxies on CBOE implied volatility indices and S&P 500 realized volatility

Volatility	***SAD***	***SKC***	***TEMP***	***PRECIP***
VIX	-0.0138	-0.0203*	0.0066	0.1772*
VXO	-0.0109	-0.0189*	-0.0004	0.1742*
VXN	-0.0179	-0.0124	0.0008	0.1068
VXD	-0.0231	-0.0310*	0.0014	0.2275†
Pooled OLS	-0.0172*	-0.0188*	0.0028	0.1678*
Fixed Effects	-0.5549	-0.0154*	-0.0063	0.0560
VIX1	-0.0115	-0.0201	0.0071	0.1432
VIX2	-0.0128	-0.0117	0.0061	0.0921
VIX3	-0.0142	-0.0074	0.0044	0.0836
VIX4	-0.0131	-0.0064	0.0039	0.0774*
VIX5	-0.0113	0.0021	0.0030	-0.0045
VIX6	-0.0014	0.0030	0.0033	0.0564
VIX7	-0.0110	0.0046	-0.0015	-0.0006
RV	-0.0006	-0.0006	-0.0246*	0.0012
	SAD	**|*SKC*|**	**|*TEMP*|**	**|*PRECIP*|**
VIX	-0.0072	0.0144	-0.0143*	0.1619*
VXO	-0.0115	-0.0006	-0.0212*	0.1460*
VXN	-0.0138	-0.0480	-0.0185	0.2453†
VXD	-0.0108	-0.0295	-0.0173	0.2806*
Pooled OLS	-0.0116	-0.0119	-0.0170*	0.2400*
Fixed Effects	-0.5408	-0.0025	-0.0013	0.1008
VIX1	-0.0108	-0.0309	-0.0235	0.1011
VIX2	-0.0118	-0.0248	-0.0115*	0.1021
VIX3	-0.0130	-0.0100	-0.0096*	0.0857
VIX4	-0.0121	-0.0275*	-0.0078*	0.1025*
VIX5	-0.0120	-0.0158	-0.0074*	-0.0057
VIX6	0.0003	-0.0140	-0.0064*	0.1145*
VIX7	-0.0108	0.0122	-0.0092*	-0.0118
RV	-0.0005	-0.0005	-0.0014	0.0070*
	SAD	***SKC⁺***	***TEMP⁺***	***PRECIP⁺***
VIX	-0.0112	-0.0546	0.0013	0.0582
VXO	-0.0136	-0.0825	-0.0492	0.0362
VXN	-0.0253	-0.1337†	0.0963	-0.0153
VXD	-0.0223	-0.0908	-0.0530	0.0182
Pooled OLS	-0.0171*	-0.0690*	-0.0250	0.0490
Fixed Effects	-0.5572	-0.0615*	-0.0210	-0.0079
VIX1	-0.0111	-0.0923	-0.0813	-0.0075
VIX2	-0.0126	-0.0574	-0.0548	-0.0142
VIX3	-0.0139	-0.0371	-0.0371	0.0148
VIX4	-0.0129	-0.0716*	-0.0371	0.0542†
VIX5	-0.0110	-0.0251	-0.0216	0.0247
VIX6	-0.0024	-0.0404	0.0412	0.0748†
VIX7	-0.0121	0.0519†	0.0665*	-0.0500†
RV	-0.0005	-0.0012	-0.0033	0.0055
	SAD	***SKC⁻***	***TEMP⁻***	***PRECIP⁻***
VIX	-0.0134	0.0430	0.0490	-0.0414
VXO	-0.0124	0.0346	0.0109	0.0274
VXN	-0.0229	-0.0561	0.0973	0.0734
VXD	-0.0174	-0.0028	0.0313	0.0026
Pooled OLS	-0.0153†	-0.0128	0.0342	0.0282
Fixed Effects	-0.5469	0.0325	0.0007	-0.0205
VIX1	-0.0117	0.0100	-0.0258	-0.0189
VIX2	-0.0146	-0.0235	0.0407	-0.0160
VIX3	-0.0148	-0.0118	-0.0006	-0.0112
VIX4	-0.0142	-0.0348	0.0254	-0.0059
VIX5	-0.0104	-0.0244	-0.0054	0.0259
VIX6	-0.0004	-0.0289	-0.0312	0.0132
VIX7	-0.0123	-0.0324	0.0248	-0.0157
RV	-0.0007	-0.0024	0.0019	0.0011

Note: A star (dagger) denotes statistical significance of a coefficient at the 95% (90%) level using a two-tailed test.