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Mood and Judgment of Subjective Probabilities: Evidence from the U.S. Index Option Market

DORON KLIGER[1] and ORI LEVY[2]
[1] *University of Haifa, Israel. E-mail: kliger@econ.haifa.ac.il;*
[2] *The University of Haifa, Israel. E-mail: orilevy@econ.haifa.ac.il*

Abstract. Numerous psychological studies show that weather conditions affect people's mood and that mood states are correlated with people's subjective evaluation of future probabilities. In this paper, a new approach is developed and *asset market* data are employed to test the mood-subjective probability relation. Cloud cover and precipitation volume serve as two mood proxies. Our statistical analysis suggests that bad mood states are characterized by investors placing higher probabilities on adverse events.

Key words: mood, state prices, subjective probabilities, weather

JEL classification codes: D81.

1. Introduction

Numerous psychological studies claim that mood states influence individuals' subjective evaluation of future event probabilities, in a way that bad mood increases the subjective probability of undesired outcomes.[1] The goal of this paper is to test whether mood affects the subjective beliefs of capital market participants. To the best of our knowledge, *asset market data* were not previously employed to test the conjecture that subjective evaluations of future uncertainties are mood-related. This paper constitutes an attempt to fill this gap.

Accumulated evidence suggests that weather conditions, such as humidity levels, number of sunshine hours, and precipitation volume, are correlated with people's mood.[2] To date, the relation between psychological factors and returns has been empirically supported.[3] We aim at delving into the generating mechanism of

[1] For example, Bower (1983), Butler and Mathews (1983), Johnson and Tversky (1983), Schwarz and Clore (1983), Kavanagh and Bower (1985), Butler and Mathews (1987), Mayer et al. (1992), Wright and Bower (1992), Constans and Mathews (1993), and Mayer and Hanson (1995).

[2] For example, Cunningham (1979), Sanders and Brizzolara (1982), Howarth and Hoffman (1984), and Eagles (1994).

[3] Saunders (1993) and Hirshleifer and Shumway (2001) examine the effect of weather conditions on stock returns; Kamstra et al. (2000) use daylight-savings time changes to document the impact of sleep patterns on stock market returns; Kamstra et al. (2001) examine relations between stock

that relation and shedding light on the role of mood in the markets, by analyzing the impact of mood on investors' subjective beliefs regarding the market prospects.[4]

In our suggested setup, investors are assumed to maximize their intertemporal preferences, so that the discounted ratio of marginal utilities characterizes their intertemporal marginal rate of substitution (or Stochastic Discount Factor, SDF). However, when computing subjective expectations regarding future uncertainty, the investors' mood is allowed to interfere. In particular, to introduce the possibility of bad mood states affecting subjective probabilities of adverse events (i.e., "loss states"), the subjective Probability Distribution Function (PDF) is modelled as a *mixture* of the "true" physical PDF and an alternative, adverse PDF. Comparing the parametric SDF and state-by-state, mood-adjusted SDF estimates implied by the asset market data, we derive restrictions on the dynamics of *state prices*.[5]

Using repeated cross-sections of index option prices in the US to recover state prices and two weather variables, total cloud cover and precipitation volume, to proxy for investors' mood, these restrictions are then tested – the null (fully-rational) hypothesis, stating that subjective PDFs are independent of mood states, versus the alternative hypothesis, postulating that good (bad) mood is associated with an optimistic (pessimistic) evaluation of future uncertainties.

We proceed as follows. Section 2 suggests a way to incorporate the dependence of the subjective PDF on investors' mood. Section 3 implements the proposed framework. Section 4 concludes.

2. Theory

It is well-known that if markets are complete (in the Arrow–Debreu sense), absence of arbitrage implies that every asset-pricing model can be written in the following form (see, e.g., Cochrane (2001) for a textbook treatment),

$$E_t^s[M_{t+1} \otimes R_{t+1}] = I', \tag{1}$$

where $E_t^s[\cdot]$ denotes subjective expectation conditional on the time-t information set, Ω_t, $M'_{t+1} \equiv (M_{t+1,1}, \ldots, M_{t+1,S})$ is the one-period-ahead $(1 \cdot S)$ unique, positive SDF, S being the total number of states of nature; R_{t+1} is an $(S \cdot N)$ matrix of state-by-state gross rates of return of the N assets comprising the market;

market returns and the length of the day (claimed to be responsible for changes in investors' mood and thus their attitudes toward risk); and Kramer (2001) links variations in intraday equity returns to variations in investors' mood (and thus in risk aversion) throughout the day. Hirshleifer (2001) provides a comprehensive survey on psychology and asset prices.

[4] Various "market advantages" are discussed in Sunder (1995), who provides a comprehensive survey on experimental work with asset markets.

[5] State price is the price of a contingent claim that promises one unit of currency in one particular state, and nothing otherwise.

and I is the $(N \cdot 1)$ unity vector. Furthermore, each state-specific discount factor is defined by,

$$M_{t+1,s} = \left[\frac{P_{t,s}}{\Pi_{t,s}}\right] > 0, \quad s = 1, \ldots, S, \tag{2}$$

where $P_{t,s}$ is the price of a claim that guarantees one \$US in state 5 and nothing otherwise;[6] is the subjective (from investors' perspective) probability of state s occurring, and $\Pi_t \equiv (\Pi_{t,1}, \ldots, \Pi_{t,S})$ is the subjective PDF.

To capture the idea that bad mood is associated with a pessimistic evaluation of future uncertainties, let the investors' uncertainty regarding future PDFs be represented by the following parameterization,

$$\Pi_t = (1 - \epsilon) \cdot \Pi_t^* + \epsilon \cdot \tilde{\Pi}_t. \tag{3}$$

In words, the subjective PDF, Π_t, is a mixture of the "true" physical PDF, Π_t^*, with a weight of $(1 - \epsilon)$, $0 \le \epsilon \le 1$, and an alternative PDF, $\tilde{\Pi}_t$, with a weight of ϵ. To convey the idea that bad mood adversely affects investors' beliefs, we assume that $\tilde{\Pi}_t$ is bounded from above by the "at-the-money" state (a state where investors neither gain nor lose at the period's end). If $\epsilon = 0$, $\Pi_t = \Pi_t^*$, the "standard" setup. On the other extreme, if $\epsilon = 1$, $\Pi_t = \tilde{\Pi}_t$, so that investors are in the worst mood: the physical environment is completely overlooked, and only the adverse scenario's payoff is considered. Bad mood in general is described by assigning some positive weight, $\epsilon > 0$, for $\tilde{\Pi}_t$. The worse the mood, the larger is ϵ.

Consequently, the "at-the-money" SDF (cf. Equation (2))may be written as follows:

$$M_{t+1,s^{\mathrm{atm}}} \equiv \left[\frac{P_{t,s^{\mathrm{atm}}}}{(1 - \epsilon) \cdot \Pi^*_{t,s^{\mathrm{atm}}}}\right], \tag{4}$$

where s^{atm} denotes the "at-the-money" state.[7] Finally, since investors are assumed to maximize the subjective expectation of a time-separable utility function, the one-period-ahead SDF is of the following form (see, e.g., Hansen and Singleton (1982)),

$$M_{t+1,s} = \beta \cdot \left[\frac{\partial U(Eq_{t+1,s}, \cdot)/\partial Eq_{t+1,s}}{\partial U(Eq_t, \cdot)/\partial Eq_t}\right], \quad s = 1, \ldots S, \tag{5}$$

where $U(\cdot)$ is the vNM utility function; $Eq_{t+1,s}$ is the sth state price of equity; $\partial U(Eq_{t+1,s}, \cdot)/\partial Eq_{t+1,s}$, $s = 1, \ldots, S$ is the time $(t+1)$, state s, marginal utility;

[6] The continuous version of $P_t \equiv (P_{t,1}, \ldots, P_{t,s})$ is referred to in the literature as the "state price density".

[7] This result may be achieved with a richer formalization of uncertainty, known as ϵ-contamination (Epstein and Wang (1994) and Ait-Sahalia and Brandt (2001)), in which investors consider a set of alternative prior PDFs rather than only one.

$\partial U(Eq_t, \cdot)/\partial Eq_t$ is the contemporaneous marginal utility; and $\beta \equiv 1/(1+\rho)$, $\rho > 0$ being the subjective rate of time preference.

In Section 3, testable restrictions on the dynamics of state prices for the null hypothesis asserting that subjective PDFs are independent of mood versus the alternative hypothesis asserting that bad mood is associated with a pessimistic evaluation of future uncertainties are set forth, by comparing SDFs in Equations (5) and (4). As stated there, we claim that it is advantageous to focus the analysis *at-the-money* (exploiting the fact that we are able to recover state prices on a *state-by-state* basis), since at-the-money, the SDF is equal to the subjective discount factor ($\partial U(Eq_{t+1,s}, \cdot)/\partial Eq_{t+1,s^{\text{atm}}} = \partial U(Eq_t, \cdot)/\partial Eq_t$, and thus $M_{t+1,s^{\text{atm}}} = \beta$).

3. Analysis

3.1. THE DATA

Option data used in this analysis were provided to us by Jens Jackwerth and Mark Rubinstein.[8] The dataset extends from December 1987, immediately after the October 1987 crash, through December 1995, and includes 74 independent cross-sections of option prices for which there were no arbitrage violations.[9] To back out time-dependent state prices, $(P_{t,s})_{s\in S, t\in T}$, we build on Breeden and Litzenberger (1978) and use prices of European call options written on the S&P500 index, and traded on the Chicago Board Options Exchange (see Appendix A for details). These prices are sampled on a monthly basis and are averages of bid and ask quotes adjusted by a penalty parameter. Table I describes the selected sample.

Overall, the dataset consists of 1140 options, with 6 to 26 options in a cross-section and an average of 15.4. The cross-sectional time-to-expiration ranges from 23 to 43 days, with an average of 31.6. At-the-money volatility, implied by the Black and Scholes (1973) pricing equation ranges from 9.2% to 35.7% (in December 1987), averaging 15.7%.

Investors' mood is proxied by two weather variables, Sky Coverage from Sunrise to Sunset (SCSS) and Precipitation (PRCP). The weather data are collected at LaGuardia Field, New York City and were obtained from the National Climatic Data Center (NCDC). Figure 1 depicts the sky coverage data. The precipitation data are described in the rightmost column of Table I.

The cloud coverage variable is reported by the NCDC on a scale from 0 to 10, where 10 indicates total cloud coverage. Notice that the sky was completely covered with clouds (SCSS = 10) in about a third of the days. For the econometric analysis, we construct the following dummy variables: D_{TCC}, where $D_{\text{TCC}} = 1$ indicates total cloud coverage (i.e., days where SCSS = 10), and D_{PRCP}, where

[8] A comprehensive description of the data can be found in Jackwerth and Rubinstein (1996) and Jackwerth (2000).

[9] Rubinstein (1994), Jackwerth and Rubinstein (1996), and Christensen and Prabhala (1998) document a "regime shift" in option prices following the October 1987 crash.

Table I. Data description

	No. of options	Time to expiration	Volatility	PRCP
		(days)	(%)	(Inch)
Mean	15.41	31.61	15.73	14.16
Median	15.00	30.00	14.26	0.00
Max	26.00	43.00	35.72	212.00
Min.	6.00	23.00	9.17	0.00
Std. dev	4.58	4.06	5.42	38.52
No. obs.		74		

The table describes the 74 cross-sections in the dataset. Volatility (the third column) is the annual, at-the-money volatility implied by the Black and Scholes (1973) option pricing formula. PRCP (the rightmost column) is the precipitation level, measured in inches. The sample extends from December 1987 through December 1995.

$D_{\mathrm{PRCP}} = 1$ indicates rainy days (i.e., days where PRCP > 0, which are roughly a third of the days considered).

Our choice of the cutoff point for the cloud coverage variable follows Saunders' (1993) observation (p. 1339) that "100 percent cloud cover days are quite different from other days, including 90 percent cloud cover days. Approximately 85 percent of all rain occurs on 100 percent cloud cover days. Partially cloudy days, most of which have no rain, are not particularly depressing, even when a little rain falls. Therefore, one would not reasonably expect significant differences in weather-induced mood influences between days with 30 percent cloud cover versus days with 80 or 90 percent cloud cover". Modifying the cloud coverage indicator such that $D_{\mathrm{TCC}} = 1$ if the cloud coverage is 90 percent or more (i.e., days where SCSS = 9, 10), hardly alters our results.

3.2. EMPIRICAL SETUP

We focus the analysis on the status-quo state, i.e., on the state where investors neither gain nor lose during the period. Clearly,

$$\frac{\partial U(Eq_{t+1,s},\ \cdot)}{\partial Eq_{t+1,s^{\mathrm{atm}}}} = \frac{\partial U(Eq_t,\ \cdot)}{\partial Eq_t}, \tag{6}$$

where s^{atm} denotes the status-quo (at-the-money) state, i.e., $Eq_{t+1} = Eq_t$. Consequently, using Equations (5) and (4) the status-quo SDF equals the subjective discount factor β,

$$M_{t+1,s^{\mathrm{atm}}} = \left[\frac{P_{t,s^{\mathrm{atm}}}}{\Pi^*_{t,s^{\mathrm{atm}}}\ \cdot\ (1-\epsilon_t)}\right] = \beta. \tag{7}$$

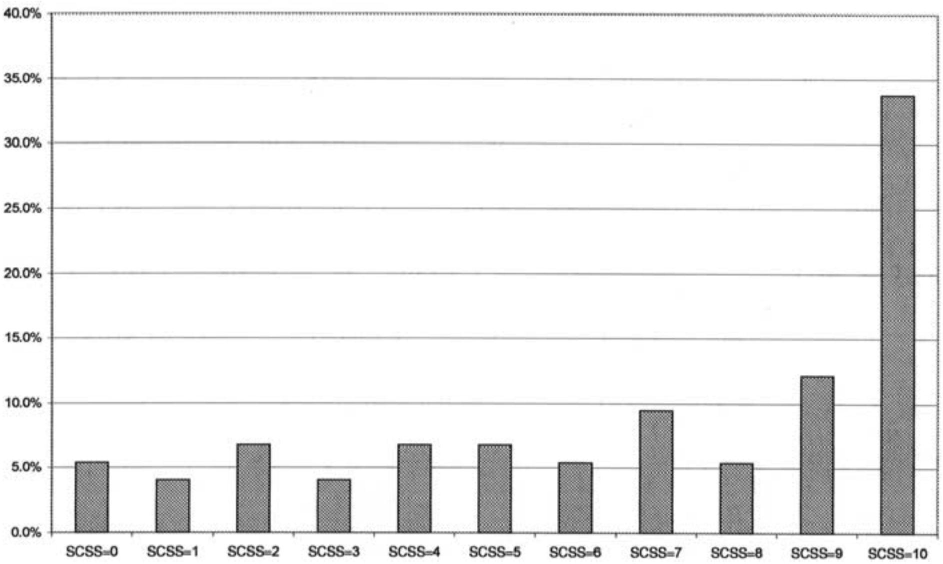

Figure 1. The figure describes the distribution of "Sky Coverage from Sunrise to Sunset" (SCSS). SCSS is reported by the National Climatic Data Center on a scale from 0 to 10, where 10 indicates total cloud coverage. Data are collected at LaGuardia Field, New York City. The number of included observations is 74.

Stating in logarithmic form, Equation (7) becomes:

$$\log(M_{t+1,s^{\text{atm}}}) = \log(P_{t,s^{\text{atm}}}) - \log(\Pi_{t,s^{\text{atm}}}) + mood_t = \log\beta, \tag{8}$$

where

$$mood_t \equiv -\log(1-\epsilon_t). \tag{9}$$

The variable *mood* represents investors' mood/pessimism regarding future uncertainties, as $\frac{\partial mood}{\partial \epsilon} > 0$. Arranging Equation (8) and defining $p_{t,s^{\text{atm}}} \equiv \log(P_{t,s^{\text{atm}}})$, and $\pi_t^{*\text{atm}} = \log(\Pi^*_{t,s^{\text{atm}}})$, yields:

$$p_{t,s^{\text{atm}}} = \log\beta + \pi_t^{*\text{atm}} - mood_t, \tag{10}$$

In essence, Equation (10) provides the basis for estimating the role investors' mood plays in the determination of subjective probabilities. The at-the-money analysis is justified since if the subjective PDF is independent of mood, then all state prices are mood-independent.

For estimating the at-the-money state prices, $p_{s^{\text{atm}}}$, we draw on, for every t, the method of Breeden and Litzenberger (1978) and use successive triplets of option prices, ordered by their strike prices (cf. Equation (A.5)) The resulting price is standardized through a division by the size of the state to give a price per rate of return range of 1%.

The mill hypothesis-subjective PDFs are independent of mood-is tested at-the-money and specified as,

$$H_0 \; : \; \frac{\partial p_{s^{\mathrm{atm}}}}{\partial mood} = 0, \tag{11}$$

while the conjecture that bad mood is associated with a pessimistic evaluation of future uncertainties implies the following alternative,

$$H_A \; : \; \frac{\partial p_{s^{\mathrm{atm}}}}{\partial mood} < 0, \tag{12}$$

To employ the relation derived in Equation (10) two variables ought to be controlled for: (i) the unobserved at-the-money physical PDF, and (ii) the options' time-to-expiration. Then, a proxy for investors' mood has to be used. We henceforth deal with these three empirical issues.

First, to control for the at-the-money PDF, we assume that the natural logarithm of the at-the-money PDF is proxied by its lagged value,

$$\pi_t^{*\mathrm{atm}} = \pi_{t-1}^{*\mathrm{atm}} + \xi_t. \tag{13}$$

We thus obtain the following first-difference equation,

$$p_{t,s^{\mathrm{atm}}} - p_{t-1,s^{\mathrm{atm}}} = -(mood_t - mood_{t-1}) + \xi_t. \tag{14}$$

Secondly, to control for the variability in the options' time-to-expiration, we append the number of days until the options' expiration, τ, to the tested empirical relation (see below). Note that at-the-money state prices are negatively related to the time-to-expiration, $(\partial p_{s^{\mathrm{atm}}}/\partial\tau) < 0$, for two reasons: (i) the larger τ, the later the contingent payoff is paid, and (ii) the larger τ, the lower the probability of being at-the-money (as at-the-money states are near the center of the probability distribution function when a short horizon is considered). Therefore, we conjecture the following,

$$\frac{\partial p_{s^{\mathrm{atm}}}}{\partial \tau} < 0. \tag{15}$$

Lastly, to proxy for investors' (unobserved) mood, we consider the two weather variables, total cloud coverage (SCSS) and precipitation volume (PRCP).

3.3. RESULTS

In accordance with the above analysis, we specify the following linear equation, and alternatively use each of the two weather variables (D_{TCC}, D_{PRCP}) to proxy for investors' mood: to proxy for investors' mood:

$$\Delta p_{s^{\mathrm{atm}}} = \alpha_1 \cdot \Delta mood + \alpha_2 \cdot \Delta\tau + \eta_t, \tag{16}$$

where Δ is the first-difference operator, $\Delta X \equiv X_t - X_{t-1}$, and η_t is a random variable representing the adjustment process of the at-the-money PDF, ξ_t, and (possibly serially-correlated) noise in estimating the at-the-money state prices. Using this equation, the null hypothesis (subjective PDFs are independent of mood states, Equation (11) may be tested against its alternative (bad mood is associated with pessimistic evaluation of future uncertainty, Equation (12)) as follows,

$$H_0 : \alpha_1 = 0, \tag{17}$$

and

$$H_A : \alpha_1 < 0. \tag{18}$$

In addition, we expect the coefficient controlling for the options' time-to-expiration, α_2, to be negative.

Equation (16) is estimated using the Generalized Method of Moments (GMM) of Hansen (1982). The vector of instrumental variables $Z_t \in \Omega_t$ consists of first differences of the weather variable, of the time-to-expiration, and a constant.[10] Note that the system is over-identified (the number of orthogonality conditions (3) exceeds the number of parameters to be estimated (2)). The estimation results appear in the first and second columns of Table II ("*Basic Specification*").

As can be seen in the table, the estimate of the mood coefficient, α_1, is significantly negative for both weather variables proxying investors' mood: it equals -0.059 when cloud coverage proxies mood, and -0.037 when precipitation is taken as a mood proxy, with probabilities (one-sided test) of 0% and 3.5%, respectively. In addition, and as expected, the estimates of α_2 are negative (-0.009 and -0.008, respectively) and significantly different from zero in both empirical specifications (probability of 0% in both cases). Lastly, testing the over-identifying restrictions using the J statistic indicates that the specification cannot be rejected (respective probabilities of 77% and 80%).

In order to rule out the possibility that the estimated effect of mood on the judgment of subjective probabilities captures variability in the rate of time preferences, we use the subjective discount factor, $\log(1/1 + \rho_t)$, where ρ_t is the time-t subjective rate of time preference.[11] For empirical purposes, we use the risk-free interest rate, i.e., postulating $\rho_t = R_t^F$. We expect the discount factor to be positively related to the state price, $p_{s^{\mathrm{atm}}}$, as heavier discounting (a smaller discount factor) reduces the present value of future payoffs. More importantly, as far as the mood-subjective probability relation exists in asset markets, α_1 should remain negative.

[10] In the estimated specifications henceforth, first differences or, alternatively, levels of the variables comprise the instrument list. The various instrument specifications hardly change the regression results. We thus report only the results obtained with first differences as instruments.

[11] See, e.g., Harris and Laibson (2001) for a particular example of a time-varying subjective discount function.

Table II. Estimation results

Specification	Basic		Augmented 1	
Mood proxy	TCC	PRCP	TCC	PRCP
α_1 (mood)	−0.059	−0.037	−0.060	−0.036
	(0.002)	(0.035)	(0.002)	(0.034)
α_2 (time)	−0.009	−0.008	−0.009	−0.008
	(0.000)	(0.000)	(0.000)	(0.000)
α_3 (discounting)			−0.609	−0.242
			(0.248)	(0.403)
R^2	0.163	0.123	0.167	0.123
Adj. R^2	0.151	0.110	0.143	0.098
χ^2	0.0818	0.0683	0.0796	0.0671
Prob.	0.7749	0.7939	0.7778	0.7956
No. obs. (adjusting for endpoints)	73			

The table presents GMM estimation results, as discussed in Section 3, where definitions of the two cases as well as economic interpretations of the different parameters are given. Probabilities (one-sided test) appear in parentheses.

We thus augment Equation (16) with the first difference of the subjective discount factor proxy, to obtain:

$$\Delta p_{s^{\text{atm}}} = \Delta mood + \alpha_2 \cdot \Delta\tau + \alpha_3 \cdot \Delta(\log(1/1+\rho)) + \eta_t. \qquad (19)$$

As can be seen in Table II (third and fourth columns, "*Augmented 1*"), the estimate for the subjective discount factor, α_3 is negative, though not significantly different from zero. The lack of significance may be due to the relative insensitivity of near-future (one month) payoffs to the discount rate. Nevertheless, the result which is of interest to us remains intact: the estimate for α_1 is practically unchanged and remains significant.

Next, to control for the extensively documented "January effect" (see, e.g., Thaler (1987) for a summary of the empirical evidence), we add a dummy variable, D_{Jan}, where $D_{\text{Jan}} = 1$ indicates January observations, to obtain:

$$\begin{aligned}\Delta p_{s^{\text{atm}}} &= \alpha_1 \cdot \Delta mood + \alpha_2 \cdot \Delta\tau + \alpha_3 \cdot \Delta(\log(1/1+\rho)) \\ &\quad + \alpha_4 \cdot \Delta D_{\text{Jan}} + \eta_t. \end{aligned} \qquad (20)$$

The results appear in Table III (first and second columns, "*Augmented 2*"). Clearly, the introduction of the January dummy is innocuous with respect to estimates of

To rule out the possibility that changes in wealth bias our results, we append the first difference of the (natural logarithm of) the index level (Δ(log *Index*)) to the estimated relations:

Table III. Estimation results

Specification	Augmented 2		Augmented 3	
Mood proxy	TCC	PRCP	TCC	PRCP
α_1 (mood)	−0.061	−0.036	−0.054	−0.033
	(0.001)	(0.023)	(0.001)	(0.026)
α_2 (time)	−0.009	−0.008	−0.009	−0.008
	(0.000)	(0.000)	(0.000)	(0.000)
α_3 (discounting)	−0.618	−0.241	−0.593	−0.180
	(0.243)	(0.402)	(0.188)	(0.400)
α_4 (January)	0.006	−0.002	−0.003	−0.006
	(0.428)	(0.474)	(0.451)	(0.406)
α_5 (index)			0.469	0.583
			(0.0218)	(0.011)
R^2	0.1671	0.1236	0.2112	0.1801
Adj. R^2	0.1309	0.0855	0.1641	0.1312
χ^2	0.0798	0.0671	0.0093	0.0093
Prob.	0.7778	0.7957	0.9233	0.9232
No. obs. (adjusting for endpoints)	73		72	

The table presents GMM estimation results, as discussed in Section 3, where definitions of the two cases as well as economic interpretations of the different parameters are given. Probabilities (one-sided test) appear in parentheses.

$$\Delta p_{s^{\text{atm}}} = \alpha_1 \cdot \Delta mood + \alpha_2 \cdot \Delta\tau + \alpha_3 \cdot \Delta(\log(1/1+\rho)) + \alpha_4\,\Delta D_{\text{Jan}} + \alpha_5 \cdot \Delta(\Delta(\log \mathit{Index})) + \eta_t. \tag{21}$$

As indicated above, Saunders (1993) arid Hirshleifer and Shumway (2001) find that SCSS (proxying for investors' mood) is correlated with stock market returns. Consequently, the inclusion of Δ (log *Index*) in the estimated regressions should make the rejection of the null hypothesis ($\alpha_1 = 0$) more difficult.

The estimation results (third arid fourth columns in Table III, "*Augmented 3*") reveal that the coefficient of the index level, α_5, is positive and significant.[12] The latter may be the result of investors putting more (less) weight on states away from the center of the PDF whenever the market is "low" ("high"), resulting in lower (higher) probabilities of being at-the-money. Once again, when cloud coverage is

[12] Since the first difference of rates of return is one of the independent variables in Equation (21), we adjusted the sample such that the total number of included observations is 72. The latter practice is qualitatively inconsequential.

used to proxy for investors' mood, as well as when precipitation volume proxies mood, the estimate for α_1 remains negative and significant.

Overall, the empirical results suggest that investors' mood is responsible for biases in their judgment, such that they exaggerate the probability of undesired results when in a bad mood.

4. Conclusions

Numerous psychological studies show that mood is correlated with people's subjective evaluation of future probabilities. Building on another robust finding, stating that weather conditions are correlated with people's mood, this paper has offered a novel empirical methodology, using asset *market data*, to test the conjecture that subjective evaluations of future uncertainties are mood-related. Empirical evidence were provided using estimates of state prices recovered from repeated cross-sections of option prices.

In our setup, investors were assumed to maximize the subjective expectation of a time-separable utility function, but allowed to be mood-swayed when parameterizing future uncertainties, an idea captured through modelling of the subjective PDF as a *mixture* of the "true" physical PDF and an alternative, adverse PDF. Comparing parametric and asset market-implied SDFs, exploiting the fact that state-by-state estimates of the latter are tractable, we derived testable restrictions on the dynamics of state prices for the null (fully rational) hypothesis stating that subjective PDFs are independent of mood states, versus the alternative hypothesis postulating that bad mood is associated with pessimistic evaluation of future uncertainties. Investors' mood was proxied by two weather variables, total cloud cover and precipitation volume, where overcast and rainy days indicated investors experiencing a gloomy mood.

Our statistical analysis, based on US price data on European call options written on the S&P500 index for the period ranging from December 1987 through December 1995 suggested that emotions exert an influence on judgments of market participants. Indeed, bad mood was found to be characterized by investors placing higher-than-usual probabilities on adverse events.

Appendix A. State Prices

Consider the option pricing interpretation of Cox and Ross (1976):

$$\begin{aligned} C_t &= \exp(-R_t^F \cdot \tau) \cdot E_t^{RN}[\max(0, Eq_{t+\tau,s} - K)] \\ &= \exp(-R_t^F \cdot \tau) \cdot \int_{-\infty}^{\infty} \Pi_{t,s}^{RN} \cdot \max(0, Eq_{t+\tau,s} - K)\, \mathrm{d}Eq_{t+\tau,s}, \qquad \text{(A.1)} \end{aligned}$$

where C_t is the current price of a European call option with strike price K, R_t^F is the risk-free rate till the option's expiration, τ is the time-to-expiration, E_t^{RN} denotes the conditional expectation operator according to the risk-neutral PDF, $Eq_{t+\tau,s}$ is the sth state expiration-date underlying asset's price, and $\Pi^{RN}_{t,s}$ is the expiration-date risk-neutral probability of the sth state. Differentiating (A.1) with respect to K yields,

$$\frac{\partial C_t}{\partial K} = -\exp(-R^F_t \cdot \tau) \cdot \int_K^\infty \Pi^{RN}_{t,s} \cdot \mathrm{d}Eq_{t+\tau,s}. \tag{A.2}$$

Differentiating with respect to K once more yields,

$$P_{t,s} = \exp(-R^F_t \cdot \tau) \cdot \Pi^{RN}_{t,s} = \left.\frac{\partial^2 C_t}{\partial K^2}\right|_{K=Eq_{t+\tau,s}}, \tag{A.3}$$

where (Breeden and Litzenberger (1978)),

$$\left.\frac{\partial^2 C_t}{\partial K^2}\right|_{K=Eq_{t+\tau,s}} = \lim_{\Delta\to 0} \frac{C_t(Eq_{t+\tau,s}+\Delta) - C_t(Eq_{t+\tau,s)}}{\Delta^2} - \frac{C_t(Eq_{t+\tau,s}) - C_t(Eq_{t+\tau,s}-\Delta)}{\Delta^2}. \tag{A.4}$$

Practically, the sth state price is approximated by pricing a "butterfly spread" centered around $K = Eq_{t+\tau,s}$ – a short position of two European call options with strike prices $K = Eq_{t+\tau,s}$ at a price of C_t $(K = Eq_{t+\tau,s})$ each, and long two European call options with strike prices $K = (Eq_{t+\tau,s} + \Delta)$ and $K = (Eq_{t+\tau,s} - \Delta)$ at respective prices of C_t $(K = Eq_{t+\tau,s} + \Delta)$ and C_t $(K = Eq_{t+\tau,s} - \Delta)$. This position promises an expiration-date payoff of A conditional on state $Eq_{t+\tau,s}$ occurring. Dividing by A to normalize the payoff to unity, the sth state price is obtained:

$$\frac{[C_t(Eq_{t+\tau,s}+\Delta) - C_t(Eq_{t+\tau,s})]}{\Delta} - \frac{[C_t(Eq_{t+\tau,s}) - C_t(Eq_{t+\tau,s}-\Delta)]}{\Delta}. \tag{A.5}$$

References

Ait-Sahalia, Y. and Brandt, M. W. (2001), 'Variable selection for portfolio choice', *Journal of Finance* **56**, 1297–1351.

Black, F. and Scholes, M. (1973), 'The valuation of options and corporate liabilities', *Journal of Political Economy* **81**, 637–654.

Bower, G. H. (1983), 'Affect and cognition', *Philosophical Transactions of the Royal Society of London* **B302**, 387–402.

Breeden, D. and Litzenberger, R. (1978), 'Prices of state-contingent claims implicit in options prices', *Journal of Business* **51**, 621–651.

Butler, G. and Mathews, A. (1983), 'Cognitive processes in anxiety', *Advances in Behavior Research and Therapy*, **5**, 51–62.

Butler, G. and Mathews, A. (1987), ‘Anticipatory anxiety and risk perception’, *Cognitive Therapy and Research* **91**, 551–565.

Christensen, B. T. and Prabirala, N. R. (1998), ‘The relation between implied and realized volatility’, *Journal of Financial Economics* **50**, 125–150.

Cochrane, J. H.: 2001, *Asset Pricing*, Princeton University Press, Princeton, NJ.

Constans, J. J. and Mathews, A. M. (1993), ‘Mood and the subjective risk of future events’, *Cognition and Emotion* **7**(6), 545–560.

Cox, J. C. and Boss, S. A. (1976), ‘The evaluation of options for alternative stochastic processes’, *Journal of Financial Economics* **3**, 145–166.

Cunningham, M. R. (1979), ‘Weather, mood and helping behavior: Quasi-experiments with the sunshine Samaritan’, *Journal of Personality and Social Psychology* **37**, 1947–1956.

Eagles, J. M. (1994), ‘The relationship between mood and daily hours of sunlight in rapid cycling bipolar illness’, *Biological Psychiatry* **36**, 422–424.

Epstein, L. G. and Wang, T. (1994), ‘Asset pricing under Knightian uncertainty’, *Econometrica* **62**, 283–322.

Hansen, L. P.: (1982), Large sample properties of generalized method o moments estimators’, *Econometrica* **50**, 1029–1054.

Hansen, L. P. and Singleton, K.: 1982, ‘Generalized instrumental variables estimation of non-linear rational expectations models’, *Econometrica* **50**, 1269–1286.

Harris, C. and Laibson, D. (2001), ‘Dynamic choices of hyperbolic consumers’, *Econometrica* **69**(4), 935–957.

Hirshleifer, D. (2001), ‘Investor psychology and asset pricing’, *Journal of Finance* **56**, 1533–1597.

Hirshleifer, D. and Shumway, T. (2001), Good day sunshine: Stock returns and the weather’, *Journal of Finance*, forthcoming.

Howarth, E. and Hoffman, M. S. (1984), ‘A multidimensional approach to the relationship between mood and weather’, *British Journal of Psychology* **75**, 15–23.

Jackwerth, J. C. (2000), ‘Recovering risk aversion from option prices and realized returns’, *Review of Financial Studies* **13**(2), 433–451.

Jackwerth, J. C. and Rubinstein, M. (1996), ‘Recovering probability distributions from option prices’, *Journal of Finance* **51**, 1611–1631.

Johnson E. J. and Tversky, A.: (1983), ‘Affect, generalization, and the perception of risk’, *Journal of Personality and Social Psychology* **45**(1), 20–31.

Kamstra, M., Kramer L., and Levi, M.: (2001), ‘Winter blues: A SAD stock market cycle’, *American Economic Review*, forthcoming.

Kamstra, M. J., Kramer, L. A., and Levi, M. D.: (2000), ‘Losing sleep at the market: The aylight-savings anomaly’, *American Economic Review* **90**(4), 1005–1011.

Kavanagh, D. and Bower, G. (1985), ‘Mood and self-efficacy: Impact of joy and sadness on risk as feeling perceived capabilities’, *Cognitive Therapy and Research* **9**, 507–525.

Kramer, L. A. (2001), ‘Intraday stock returns, time-varying risk premia, and diurnal mood variation’, *Working Paper*.

Mayer, J. and Hanson, E. (1995), ‘Mood-congruent judgment over time’, *Personality and Social Psychology Bulletin* **21**, 237–244.

Mayer, J., Gaschke, Y., Braverman, D., and Evans, T. (1992), Mood-congruent judgment is a general effect’, *Journal of Personality and Social Psychology* **63**, 119–132.

Rubinstein, M.: (1994), ‘Implied binomial trees’, *Journal of Finance* **49**(3), 771–818.

Sanders, J. L. and Brizzolara, M. S. (1982), ‘Relationships between weather and mood’, *Journal of General Psychology* **107**, 155–156.

Saunders, E. M. J.: 1993, ‘Stock prices and wall street weather’, *American Economic Review* **83**, 1337–1345.

Schwarz, N. and Clore, G. (1983), 'Mood, misattribution, and judgments of well-being: Information and directive functions of affective states', *Journal of Personality and Social Psychology* **15**, 513–523.

Sunder, S. (1995), 'Experimental asset markets: A survey', in John Kagel and Alvin Both, eds., *The Handbook of Experimental Economics*, Princeton University Press, Princeton, New Jersey.

Thaler, R. (1987), 'Anomalies: Seasonal movements in security prices II: weekend, holiday, turn of the month, and intraday effects', *Journal of Economic Perspectives* **1**(2), 169-177.

Wright, W. F. and Bower, G. H. (1992), 'Mood effects on subjective probability assessments', *Organizational Behavior and Human Decision Processes* **52**, 276-291.