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Mood-misattribution effect on energy markets: a biorhythm approach

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Mood-misattribution effect on energy markets: a biorhythm approach*

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Abstract

This paper investigates the relationship between emotion and European energy forward prices of oil, gas, coal and electricity during normal times and periods of extreme price movements relying on the biorhythm approach. To this end, we use the Seasonal Affective Disorder (SAD) variable to study the impact of emotion on energy market dynamics. Estimating OLS and quantile regressions, we find that seasonal patterns have a significant impact during extreme volatility periods only. Further investigations reveal that the SAD affect is significant during periods of price decrease, but insignificant during price increase. The out-of-sample predictive ability properties are also investigated and show that our "SAD model" outperforms significantly the pure "macroeconomic one".

JEL Classification: G02, C21, Q40
Keywords: energy forward markets, mood-misattribution, behavioral finance, extreme price movements, quantile regression.

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1 Introduction

Understanding energy price dynamics is a rather difficult task given its apparent erratic behavior and the various potential factors that may be at play (Sadorsky, 1999; Hamilton, 2003; Kilian, 2008, among others). Strong fluctuations increase energy market risks which lead in turn to distinct market apprehension and perception. Regarding the traditional economic and financial approaches, a rational agent is defined as someone who used all available information to anticipate future evolutions and allocate his portfolio, so that anticipations are well established on average. Under this hypothesis, rational investors will always choose equities with the best benefit-risk trade off in the Efficient Market Hypothesis (EMH) sense.

With regard to the development of behavioral finance (Shleifer, 2000; Thaler, 2005, among others), this traditional approach seems to be too restrictive in the sense that individual rationality appears to be bounded (Simon, 1982, 1987a and 1987b). In this context, the economic agent is not a simple calculator but a human with biaises whose decision-making process is influenced by cognitive and emotional resentments. This characteristic leads to distinct asset valuations among investors which can create excess volatility in financial markets (Black, 1986). The seminal work of Damasio (1994) shows that emotion can affect behavior and play a crucial role in the decision process where lack of feelings leads to suboptimal choices. In this way, recent researches in behavioral finance have studied the influence of emotions through the mood misattribution impact on decision-making. According to Loewentein et al. (2001), the mood misattribution perspective relies on the hypothesis that individuals who take their decision under risk and uncertainty are unconsciously influenced by their relative emotional states even if moods are unrelated to their choices (Schwarz and Clore, 1983).

Recent studies have shown significant mood impact on equity pricing.[1] However, they focus on specific classes of assets. In order to bring new elements to the recent energy prices increase and assuming that excess volatility could be due in part, to some investors influenced by their emotional states, we investigate the impact of mood misattribution on forward energy market dynamics such as oil, gas, coal and electricity during both "normal times" and periods of extreme (upward and downward) price movements. By relying on forward energy prices, we are able to account for both fundamental and speculative pressures (Joëts and Mignon, 2011).[2]

[1] See references in Section 3.

[2] Indeed, the forward energy market can result in both physical delivery and speculative purposes.

In order to investigate mood effect, a biorhythm approach is adopted considering the Seasonal Affective Disorder (SAD) framework developed by Kamstra et al. (2003). This approach known as 'winter blues' considers that seasonal variation in the number of hours of sunlight per day can lead to anxious state which in turn can affect risk apprehension and decision-making. Therefore, the SAD variable can be seen as an approximation of emotion which can affect the energy market behavior. Assuming that feelings influence behavior and risk perception of investors, we analyze mood effect on energy market variations in an in-sample and out-of-sample contexts. Both normal and extreme volatility periods are considered using OLS and quantile regression approaches.

Our contribution is fourfold. First, the relationship between emotion and energy markets is studied using biorhytm approach through the SAD proxy variable. Second, by relying on European forward prices of oil, coal, gas and electricity, we purge short-run demand and supply from noise that affects market fluctuations, and account for both fundamental and speculative pressures. Third, we investigate the emotional phenomenon of energy market dynamics considering normal and extreme market circumstances. Finally, we compare the out-of-sample properties of our *SAD model* against a pure *macroeconomic model* in term of predictive ability to see which strategy is the more fitted.

The rest of the paper is organized as follows. Section 2 presents the theoretical research background on which the investigation of investors' feelings is based. Section 3 reviews the existing literature on mood misattribution and equity pricing. Empirical application on energy markets is displayed in Section 4, and Section 5 concludes the article.

2 Mood influences on investor decision-making under uncertainty

In the traditional portfolio choice theories, the process of investors' decision is assumed to be quantitatively characterized by the weight of costs and benefits of all possible outcomes. In this perspective, rational investors choose the outcome with the best risk-benefit trade off (see Markowitz, 1952; Sharpe, 1964, among others). This type of behavior is what Loewenstein et al. (2001) describe as a *'consequentialist perspective'* which does not account for the emotional impact on the decision-making process. However, in practice these traditional approaches may be viewed as unrealistic since feelings play a crucial role in the perception of the environment, especially under risky and uncertain context (see, Zajonc, 1980; Schwarz, 1990; Forgas, 1995; Isen, 2000; Loewenstein et al., 2001, among others).

Behavioral finance coupled with the reconsideration of the rational investor concept bring to the light the recent interest in feelings impact on economic behavior leading to the development of a new class of models. The latters introduce anticipated emotions which are defined as emotions that are expected to be experienced by investors given a certain outcome level. This concept has been developed through the Loomes and Sugden (1982)'s regret model and applied in finance in the myopic loss aversion theory of Benartzi and Thaler (1995). Despite the fact that anticipated emotions constitute an advance over the traditional consequentialism approach, this concept appears to be relatively restrictive in the sense that it considers anticipated feelings rather than feelings experienced at the time of decision-making. According to Schwarz (1990), it seems coherent that people make different investment decisions depending on their positive and negative moods even if mood is unrelated to the decision context (Schwarz and Clore, 1983).

To overcome this limit, Loewenstein et al. (2001) develop the risk-as-feelings model which incorporates emotions influence at the time of making decision by allowing anticipated emotions, subjective probabilities and extra factors (i.e. mood, ...) that affect decision-making.[3] In their model framework, Loewenstein et al. (2001) suppose that investors' decisions under risky and uncertain environment are strongly affected by feeling perception. The authors use the three following premises derived from psychology : i) Cognitive evaluations include emotional reactions[4], ii) Emotions inform cognitive evaluations[5], and iii) Feelings can affect behavior.[6] According to Loewenstein et al. (2001)'s risk-as-feeling model, decision-making is the consequence of the interconnected processes of cognition evaluation and emotions which in turn affect behavior.

In a complementary way of Loewenstein et al. (2001), Forgas (1995) develops an Affect Infusion Model (AIM) which covers the extent to which people rely to their respective feelings. Forgas argues that emotions influence decision process depending on the risky and uncertain choice environment context. In this framework, he defines two kinds of strategies depending on the situation. The first one is the Low Affect Infusion Strategies (LAIS), used under familiar situations which involve less riskier and low complexity

[3]For more details, see the excellent survey of Dowling and Lucey (2005).

[4]According to Zajonc (1980), emotions are considered to be postcognitive.

[5]Researches in psychology show that optimistic and pessimistic behaviors tend to be linked to good and negative moods (see, Isen et al., 1978; Bower, 1981; Johnson and Tversky, 1983; Bower, 1991, among others).

[6]According to pioneer works of Damasio (1994), people with impaired ability to feeling emotions tend to make suboptimal decisions under risky and uncertain environment.

circumstances. The second one is the High Affect Infusion Strategies (HAIS) which are employed for more complex decision processes, under highly risky context. According to the AIM of Forgas (1995), feeling becomes predominant as risk and uncertainty increase. For instance, under optimal porfolio choice, investor should be characterized by HAIS framework where decision-making would be strongly dependent to her mood states.

According to this literature, feelings appear to have an influence on economic and financial behaviors. In a risky context, many factors can influence decision-making even if they are not related to decision. Mood is therefore seen as information as well as human misattribution emotions.

3 Mood-as-information and misattribution: literature review

In the literature, two types of feeling determinants are considered: the mood misattribution and the affect heuristic. While the later argues that people's decision-making is governed by images and associated feelings that are induced by decision process, the former maintains that mood can be induced by the environmental context such as weather, biorhythms and social events. These determinants leading to mood fluctuations are likely to affect investors' decision process and therefore financial stock markets.

Recent researches on behavioral and emotional finance mainly focus on mood misattribution by studying empirical evidence of mood fluctuations on equity returns. These factors influencing the positive and negative mood states are likely to modify the risk assessments. Saunders (1993), focusing on weather-based influences[7] on mood and behaviour, examines the potential impact of weather on both Dow Jones Industrial index from 1927 to 1989 and NYSE/AMEX indices from 1962 to 1989. Under the hypothesis that bad and good weathers lead to pessimistic and optimistic moods respectively and in turn to lower and higher returns, Saunders investigates the relationship between New York equity prices and the level of cloud cover in New York. He finds a significant relationship between both variables showing that mood misattribution effect can exist and be exploited in portfolio consideration. Hirshleifer and Shumway (2003) extended Saunders' analysis by considering the relationship between the de-seasonalized cloud cover and daily equity returns in 26 international markets from 1982 to 1997. Their results confirm a significant negative relationship between cloud cover and

[7]Psychological studies have seen that fluctuations of hours of sunshine can induce fluctuations in mood (see, Persinger, 1975; Howarth and Hoffman, 1984; Eagles, 1994).

equity returns and the fact that weather affects stock returns variabilities.[8] Cao and Wei (2002) based on psychological evidences, find significant impact of temperature on equity returns of eight financial markets from July 3, 1962 to July 3, 2001. Lower temperatures lead to higher returns while higher temperatures lead either to higher or lower stocks.

In the mood misattribution research, other studies have extended reflexion to broader proxies related to human biorhythms, and investigated misattribute impact of biological cycles on equity returns. Kamstra et al. (2000), assuming that an interruption of body's circadian cycle can cause anxiety and depression (Coren, 1996), investigate the influence of interruptions to sleep patterns induced, twice a year, by Daylight Savings Time Changes (DSTCs) on equity returns of US, Canadian, German and UK markets. They find a significant negative relationship between returns and DSTCs reflecting a negative impact of such biological effect. Kamstra et al. (2003) further investigate the potential impact of biorhythms and emotions on investment decisions by considering a depressive phenomenon known as Seasonal Affective Disorder (SAD) or 'winter blues'. This phenomenon is characterized by the fact that seasonal variation in hours of sunlight in the day can lead to anxious states (Cohen et al., 1992; Rosenthal, 1998) which in turn can affect risk apprehension. Due to different SAD effects depending on latitude locations, the authors investigate SAD/returns relationship including major equity indexes in both Northern and Southern Hemisphere countries. They find a significant SAD effect leading to seasonal pattern in returns. Then, due to SAD effect, equity returns are predicted to be lower between Autumn Equinox and Winter Solstice. Moreover an asymmetric component appears between fall and winter. Investors are considered to be risk averse and shun risky assets during fall while they seem to resume their risky holding during winter. Recently, to check the robustess of global mood influences, Dowling and Lucey (2005, 2008) investigate the impact of seven mood proxies variables (i.e. weather data (precipitation, temperature, wind, geomagnetic storms) and biorhythm data (SAD, DSTCs, lunar phases)) on returns and variance of 37 global equity markets from 12th December 1994 to 10th November 2004 using various robust econometric methods (GARCH specifications). They find that SAD effect is the most predominant one on equity pricing which means that winter blues is significant in both returns and variance of stocks.

These studies put forward that mood misattribution effect exists and tends to influence equity prices fluctuations. However, beyond this scope of research, it appears to be primordial to assess feeling effects on a most widely class of assets. In this way, we investigate the relationship between mood

[8] High and low cloud covers are associated to low and high stock returns respectively.

and energy market dynamics to see whether recent price fluctuations can be attributed to emotional considerations. Specifically, we distinguish between usual and extreme phases, and focus on the relation between mood misattribution and market variations by considering SAD approach: mood is proxied by SAD variable, while regular and extreme variations by both OLS and quantile regressions.

4 Empirical investigation

4.1 Data description

We consider daily data over the January 3, 2005 to December 31, 2010 period. We rely on European forward prices at 1 month of oil, gas, coal, and electricity. Energy prices data are extracted from the Platt's Information Energy Agency. To control for the economic and financial environment that may impact all energy price series (such as increasing demand from Asian emerging countries or speculation), we rely on a European equity futures price index—which has the advantage of being available at a daily frequency. This variable also allows considering energy markets as financial assets and controls for the recent financial turmoil. Our retained equity variable is the Dow Jones Euro Stoxx 50, the European leading stock index for futures contracts, extracted from Datastream. In order to account the energy prices risk premium, the euro/dollar US exchange rate is considered as a control variable. Basic statistical characteristics are reported in Table 1. They reveal that all energy return series are asymmetric (oil, gas and electricity returns are right skewed while coal returns are left skewed) and leptokurtic, indicating fat tail distributions. Due to the specific nature of electricity market (i.e. non-storability, inelasticity of the supply,...), returns are frequently affected by regime switching causing tails behavior higher than fossil energies (1.7 and 25 for the skewness and kurtosis respectively).

The mood proxy data defined as SAD variable, is calculated following Kamstra et al. (2003)'s formula. It gives an approximation of both the reduction of hours of daylight from Autumn Equinox to Winter Solstice, and the lengthening of the day from Winter Solstice to Spring Equinox.[9]

SAD variable is defined as follows:

[9] In Northern Hemisphere countries, Autumn Equinox, Winter Solstice, and Spring Equinox start respectively at September 21st, December 21st, and March 20th. In Southern Hemisphere countries they begin at March 21st, June 21st, and September 20th. For more details, see Kamstra et al. (2003).

$$SAD_t = \begin{cases} H_t - 12 & \text{for trading days in the fall and winter} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where H_t is the time from sunset to sunrise at a particular location. Value 12 denotes roughly average number of hours of night over the entire year at any location. Therefore, SAD_t is constructed to reflect the relative length of night in fall and winter compared to the mean annual length of 12 hours. According to psychological considerations, SAD is characterized as a binary variable which varies only over the fall and winter.

Following Kamstra et al. (2003), H_t, the number of hours of night is different depending on the country location and can be calculated using standard approximation from spherical trigonometry.

$$H_t = \begin{cases} 24 - 7.72 \times \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan\left(\lambda_t\right)\right] & \text{in the Northern Hemisphere} \\ 7.72 \times \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan\left(\lambda_t\right)\right] & \text{in the Southern Hemisphere} \end{cases} \tag{2}$$

where "arccos" is the *arc cosine*, δ the latitude which depends on countries location[10], and λ_t the sun's declination angle defined as follows:

$$\lambda_t = 0.4102 \times \sin\left[\left(\frac{2\pi\delta}{365}\right)(julian_t - 80.25)\right] \tag{3}$$

where "$julian_t$" sets for the number position of the day in the year numbered from 1 to 365.[11]

According to Kamstra et al. (2003), SAD variable is defined by $(H_t - 12)$ from Autumn Equinox to Spring Equinox and 0 otherwise. In this framework, during SAD period, investors are considered to be risk averse and to allocate their portfolios to safer assets affecting negatively energy market dynamics. On the contrary, from Spring Equinox to Autumn one, no SAD effect exists. Beside, SAD phenomenon is deeply influenced by geographical location. Therefore, we expect to have stronger impact in Northern Hemisphere countries rather than Southern Hemisphere countries, the later being closest to the equator where seasonal variations in daylight are small.

[10] Following Kamstra et al. (2003), we distinguished Northern Hemisphere and Southern Hemisphere countries by averaging larger markets in North and South latitudes respectively (for more details, see Appendix).

[11] $julian_t$ is equal to 1 for January 1, 2 for January 2, and so on.

4.2 Results and analysis

In order to investigate mood-misattribution effect on energy markets during regular and extreme price movements, we adopt the traditional OLS framework as well as the quantile regression approach introduced by Koenker and Basset (1978).

Consider the following linear model:

$$Y_t = X_t^{'}\beta + \nu_t \tag{4}$$

where Y and X are the endogeneous and exogeneous variables respectively, ν being the error term. In the traditional OLS framework, the dependent variable is supposed to fluctuate randomly around the conditional mean of the conditional distribution of Y ($E\left[Y/X,\beta\right]$), allowing to study the influence of exogeneous variables under regular time perspective. On the contrary, quantile analysis allows to examine the manner in which a set of explanatory variables can affect the conditional distribution of the dependent variable. By this approach, we focus on extreme occurrences considering different quantiles of the conditional distribution. In order to account for both upward and downward price movements, two quantiles are considered ($\theta = 0.05$ and 0.95).

The following regressions are estimated

$$r_t^{(i)} = \alpha + \beta SAD_t^{(j)} + \gamma Stoxx_t + \delta Rate_t + \varepsilon_t^{(i)} \tag{5}$$

where $r_t^{(i)}$ is the log-returns series for energy i (oil, gas, coal and electricity respectively). $SAD_t^{(j)}$ is the emotional proxy variable at j hemisphere (Northern and Southern Hemispheres respectively). $Stoxx_t$ and $Rate_t$ are the control variables for the economic and financial environment.

Table 2 reports the results of the OLS estimation of Equation (5) considering SAD effect on forward energy markets at 1 month during normal times. Distinguishing Northern and Southern Hemisphere countries, estimations reveal that SAD component has no any significant impact on energy market fluctuations in regular circumstances. More precisely, emotions do not affect energy markets when price movements are "usual" which corroborates the fact that during normal times, energy price dynamics are mainly governed by fundamentals. Regarding to the extreme market perspectives, Table 3 reports SAD effect on energy returns using quantile regression approach. A geographic differentiation is considered as well as downward and upward price movements. We see that SAD has different impacts depending on the hemisphere location. Considering Northern Hemisphere, results show that during periods of prices decrease, energy markets are influenced by emotional effects. Indeed, regarding to the left-tail behavior, SAD variables are significant and have negative impact for each market. This phenomenon reflects a mood-misattribution bias where environment leads to depressive states which in turn affects risk perception of investors. Moods are unrelated to energy portfolio choices, however investors are negatively affected by their emotions which self-sustain risk aversion behavior. Under SAD framework, energy prices decreases may be partly explained by emotional considerations which tend to affect investors' risk apprehension. Extreme movements are inherently associated with higher risk situation. From the upward point of view, SAD variable doesn't have any effect on energy markets. Considering Southern Hemisphere, we observe the opposite phenomenon regarding SAD effect on energy markets. As before, SAD is significant for each market during periods of price decrease, however, this impact appears to be positive on risk perception. It is not surprising to find lack of negative seasonal patterns in Southern Hemisphere countries because they are located closest to the equator where seasonal variations in daylight are quite small. Therefore, investors from Southern Hemisphere countries are less influenced by SAD components.

Investors who suffer from SAD effect are supposed to be risk averse and shun risky assets during fall and to resume their risky holding during winter. Therefore, SAD should have negative impact during fall and positive effect during winter.[12] To further investigate the asymmetric seasonal phenomenon between fall and winter during extreme volatility situations, we estimate the following quantile regression allowing both SAD fall and winter variables:

$$r_t^{(i)} = \alpha + \beta_1 SAD_t^{fall(j)} + \beta_2 SAD_t^{win(j)} + \gamma Stoxx_t + \delta Rate_t + \varepsilon_t^{(i)} \tag{4}$$

where $SAD_t^{fall(j)}$ is conducted from September 21 to December 20 for Northern Hemisphere countries, and from March 21 to June 20 for Southern Hemisphere countries. $SAD_t^{win(j)}$ runs from December 21 to March 20 for North, and from June 21 to September 20 for South.

Table 4 reports the asymmetric effect of SAD variables on energy markets at 1 month during extreme variations. Regarding Northern Hemisphere

[12] According to SAD principle, the predicted negative effect during fall is the result of decrease in hours of sunlight. During winter, the predicted positive effect is due to an increase in hours of sunlight.

countries, SAD variable during fall has the expected effect (significant and negative) in downside risk context for each market. Investors are risk averse during fall and allocate their portfolios to safest assets which tend to impact energy downside risk. From upside point of view, SAD variable is significant and positive during winter for oil, gas and electricity markets only. Regarding the asymmetric component, from Winter Solstice to Spring Equinox, investors' moods are heightened leading them to become more willing to resume the risk of their respective investments. From Southern Hemisphere perspective, both SAD fall and winter appear to have significant and positive effect in downside risk. Mood and energy prices are positively related which indicate the relative lower impact of emotion, in terms of seasonal variations, for countries closest to equator.

Our results are consistent with Forgas (1995)'s analysis which considers that agents are more influenced by moods under extreme situations rather than during normal ones. Extreme movements being inherently associated with high risk situation, recent energy prices fluctuations may be due in part to a misattribute emotional phenomenon which appears to be significant and negative during periods of price decrease only for Northern Hemisphere countries. Surprisingly, this phenomenon is no longer valid during periods of price increase reflecting that other factors should be considered.

4.3 Out-of-sample Predictive Ability of SAD approach

Previous section shows that SAD variable, as a proxy for emotion, impacts signficantly energy prices dynamic during extreme downward fluctuation periods. This phenomenon appears to be preponderant in Northern Hemisphere countries which are considered to be more influenced by variations of hours of daylight. Considering that forecasting is central to apprehend energy prices dynamic in economic decision-making for government institutions and regulatory authorities, we investigate the out-of-sample properties of our *SAD model* against a pure *macroeconomic model* in term of predictive ability. The former is of the form of Equation (5), while the latter removes the effect of the SAD variable. In this way, we use the conditional Giacomini-White (2006)'s approach to evaluate the relative merit of the two forecast alternatives. Giacomini and White (2006) propose a test of Conditional Predictive Ability which allows to compare the forecast properties of two models, given a general loss function.[13] Their test allows to directly reflect the effect of estimation uncertainty on relative forecast performance.

[13] This literature was initiated by Diebold and Mariano (1995), West (1996), McCracken (2000), Clark and McCracken (2001), Corradi et al. (2001), and Chao et al. (2001), to name few.

Moreover, it considers a less restrictive framework than previous methodologies since it permits a unified treatment of nested and nonnested models and also can accommodate more general estimation procedures in the derivation of the forecast.

Suppose one wants to compare the accuracy of the two competing forecasts for the τ-steps-ahead of the variable $Y_{t+\tau}$, using a loss function $L_{t+\tau}(.)$ and the information set $\mathcal{F}_t$. Giacomini and White (2006) propose to test the following null hypothesis:

$$H_0 : E\left[L_{t+\tau}(Y_{t+\tau}, \widehat{f}_{t,m_f}) - L_{t+\tau}(Y_{t+\tau}, \widehat{g}_{t,m_g})|\mathcal{F}_t\right] = 0 \tag{5}$$

$$\equiv E\left[\Delta L_{m,t+\tau}|\mathcal{F}_t\right] = 0$$

where $\widehat{f}_{t,m_f} \equiv f\left(W_t, ..., W_{t-m_{f+1}}; \widehat{\beta}_{t,m}\right)$ and $\widehat{g}_{t,m_g} \equiv f\left(W_t, ..., W_{t-m_{g+1}}; \widehat{\beta}_{t,m}\right)$ are measurable functions of a stochastic process W defined on a complete probability space $(\Omega, \mathcal{F}, P)$. The expectations are conditional to the set of information $\mathcal{F}_t$. The null hypothesis says that one cannot predict which forecasting methods will be accurate at the $t + \tau$ target horizon. Following Giacomini and White (2006), the test statistic is of the form:

$$T^h_{m,n} = n\left(n^{-1}\sum_{t=m}^{T-1} h_t \Delta L_{m,t+1}\right)' \widehat{\Omega}_n^{-1}\left(n^{-1}\sum_{t=m}^{T-1} h_t \Delta L_{m,t+1}\right) \tag{6}$$

$$= n\overline{Z}'_{m,n}\widehat{\Omega}_n^{-1}\overline{Z}_{m,n} \sim \chi^2_{q,1-q}$$

where $\overline{Z}_{m,n} \equiv n^{-1}\sum_{t=m}^{T-1} Z_{m,t+1}$, $Z_{m,t+1} \equiv h_t\Delta L_{m,t+1}$, and $\widehat{\Omega}_n \equiv n^{-1}n^{-1}\sum_{t=m}^{T-1} Z_{m,t+1}\times Z'_{m,t+1}$ is a $q \times q$ matrix. h_t is the test function which can be chosen by researchers to include variables that are relevant to help distinguish between the two models.[14]

As suggested by the authors, in order to compare the accuracy of the two competing approaches (*SAD model* vs *macroeconomic model*) we consider rolling window estimators.[15] Due to the relevance of SAD effect, we focus on Northern Hemisphere countries and downturn movements only. Our

[14] We use the moving average of past loss differences.

[15] As clearly mentioned by the authors, this limited memory approach is privileged for two reasons: (i) it imposes no restrictions on the estimators other than finite memory, and (ii) the analysis required is straightforward (see Giacomini and White, 2006).

in-sample estimation goes from January 3, 2005 to February 7, 2009 and produces sequences of τ-step-ahead forecasts for $\tau = 1$ using rolling window estimation procedure with $m = m_f = m_g = 1174 + \tau$. Then, in order to choose the best forecasting model, we use the two-step decision rule procedure proposed by Giacomini and White (2006):

1. Step 1: Regress $\Delta L_{m,t+1} = L_{t+\tau}\left(Y_{t+\tau}, \widehat{f}_{t,m_f}\right) - L_{t+\tau}\left(Y_{t+\tau}, \widehat{g}_{t,mg}\right)$ on h_t over the out-of-sample period and let $\widehat{\delta}_n$ the regression coefficient. Apply test and, in case of rejection of the null, proceed to step 2.

2. Step 2: $\widehat{\delta}_n' h_T \approx E\left[\Delta L_{m,t+1} | \mathcal{F}_t\right]$ indicates the decision rule: if $\widehat{\delta}_n' h_T > c$, the performance of g is better, whereas if $\widehat{\delta}_n' h_T < c$, f is the best choice ($c = 0$, is a user-specified threshold value). In our case, g and f are the *SAD model* and the *macroeconomic model* respectively.

Table 5 gathers results of the two-step test procedure for each energy market. The first step indicates that for each energy price the null hypothesis is rejected. Therefore, the two competing models (*SAD model* and *macroeconomic model*) are not equally accurate on average. It means that whatever the forecast target date $t + \tau$, one model outperforms the other one in term of forecast performance. The second step allows to choose the suitable model strategy by indicating the proportion of time one model outperforms the other. Results in Table 5 reveal that for each energy price, the *SAD model* outperforms the *macroeconomic model* in forecasting performance. Our *SAD model* is therefore more adequate to apprehend the energy prices dynamic reinforcing our finding in favor of the emotional component of the markets. This finding appears to be particulary relevant in the sense that it shows that extreme energy prices fluctuation could be dictated by irrational movements without any economic foundation.

5 Conclusion

This paper investigates the relationship between emotion and European energy forward prices during normal times and periods of extreme price movements. Relying on mood-misattribution hypothesis, we use Seasonal Affective Disorder (SAD) variable as a proxy to analyze the seasonal patterns effect on energy risk apprehension. Using both OLS and quantile biorhytm approach, we show that SAD phenomenon appears to be significant during extreme fluctuations only. More precisely, emotions affect energy market dynamics during periods of price decrease. However, this effect tends to be different depending on the geographical location. Indeed, while

Northern Hemisphere countries are primarily affected by negative seasonal relationships, SAD affects positively Southern Hemisphere countries which is consistent with the fact that seasonal variations of daylight are smaller for this group. Paying a particular attention to the asymmetric effect between fall and winter, we show a negative impact of SAD during fall and a positive one during winter for Northern countries, consistent with the seasonal hypothesis. Our findings put foward the key role played by feelings in phase of price falling. The significant role played by emotion in markets dynamic is confirmed in term of forecast performance. The out-of-sample investigation comparing the predictive ability of *SAD model* against pure *macroeconomic model* indicates that the emotional model outperforms significantly the economic model. Therefore, feelings appear to be preponderant in prices dynamic. Future researchs might be focused on the relative performance of the SAD model on portfolio allocation.

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Appendix

- Latitude data description

To construct simplest latitude values, we select larger markets in North and South Hemispheres respectively, then average each latitude in order to obtain two representatives values for North and South geographical locations. For North latitude, we obtain 48.89° by selecting and averaging: Turkey (Ankara), US (Washington), Canada (Ottawa), Italy (Roma), Switzerland (Bern), Austria (Vienna), France (Paris), Luxembourd, Belgium (Brussels), Germany (Berlin), UK (London), Netherlands (Amsterdam), Ireland (Dublin), Denmark (Copenhagen), Norway (Olso), Sweden (Stockholm), Finland (Helsinki), China (Beijing), and Japan (Tokyo).
For South latitude, we obtain 30.33° by choosing: New-Zealand (Wellington), Indonesia (Jakarta), South Africa (Johannesburg), Chile (Santiago), Australia (Camberra), and Argentina (Buenos Aires).

Table 1: Summary statistics for the daily energy forward returns at 1 month

	Brent	Gas	Coal	Electricity
Mean	0.00053	0.00017	0.00038	−0.00062
Variance	0.00053	0.00035	0.00033	0.00088
Skewness	0.13679	0.00327	−0.57407	1.76840
Kurtosis	8.97939	6.47279	9.93896	25.31240
Jarque-Bera test	2333.29 (0.00)	785.431 (0.00)	3221.56 (0.00)	33236.7 (0.00)

Notes: p-values for corresponding null hypotheses are reported in parentheses.

Table 2: SAD effect on energy forward markets under normal times

	Oil	Gas	Coal	Electricity
	Northern Hemisphere			
α	0.0006 (0.89)	0.002 (1.38)	0.0003 (0.64)	-0.0004 (-0.45)
βSAD_t	$-9.27E-05$ (-0.23)	-0.001 (-1.52)	$9.72E-05$ (0.33)	-0.0001 (-0.26)
$\gamma Stoxx_t$	0.017 (0.43)	0.054 (0.64)	0.322 (10.69^a)	-0.018 (-0.34)
$\delta Rate_t$	-0.047 (-0.51)	1.224 (6.36^a)	0.518 (7.59^a)	0.276 (2.32^a)
	Southern Hemisphere			
α	0.0005 (0.77)	-0.001 (-0.34)	-0.0001 (-0.01)	-0.0008 (-0.89)
βSAD_t	$1.57E-05$ (0.02)	0.001 (1.07)	0.0006 (1.48)	0.0005 (0.55)
$\gamma Stoxx_t$	0.007 (0.18)	0.062 (0.74)	0.324 (10.70^a)	-0.023 (-0.44)
$\delta Rate_t$	-0.021 (-0.23)	1.178 (6.15^a)	0.514 (7.50^a)	0.285 (2.38^a)

Notes: Between parentheses t-stats. ^{a} denotes rejection of the null hypothesis at 1%, 5% or 10% significance level.

Table 3: SAD effect on energy forward markets under extreme price movements

	Northern Hemisphere							
	Oil		Gas		Coal		Electricity	
	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)
α	−0.033 (-21.53^a)	0.031 (22.24^a)	−0.050 (-14.74^a)	0.060 (9.55^a)	−0.024 (-13.26^a)	0.026 (13.82^a)	−0.033 (-15.17^a)	0.034 (11.84^a)
βSAD_t	−0.001 (-2.31^a)	0.001 (1.45)	−0.007 (-3.65^a)	0.001 (0.49)	−0.002 (-1.69^a)	0.0003 (0.34)	−0.003 (-3.08^a)	0.003 (1.14)
$\gamma Stoxx_t$	0.159 (2.24^a)	−0.077 (-2.30^a)	0.082 (0.80)	0.076 (0.20)	0.410 (6.07^a)	0.305 (3.34^a)	0.176 (2.10^a)	−0.332 (−0.48)
$\delta Rate_t$	−0.195 (−0.93)	−0.088 (−0.42)	1.371 (3.77^a)	0.624 (0.61)	0.84 (4.82^a)	0.459 (2.52^a)	−0.048 (−0.120)	1.011 (1.76^a)
	Southern Hemisphere							
α	−0.038 (-16.50^a)	0.035 (21.40^a)	−0.070 (-13.84^a)	0.064 (11.15^a)	−0.030 (-13.49^a)	0.025 (15.01^a)	−0.042 (-17.09^a)	0.037 (9.55^a)
βSAD_t	0.003 (2.26^a)	−0.002 (−1.39)	0.013 (3.85^a)	−0.002 (−0.45)	0.004 (2.54^a)	0.002 (1.19)	0.005 (2.90^a)	−0.001 (−0.79)
$\gamma Stoxx_t$	0.216 (3.19^a)	−0.101 (-2.26^a)	0.146 (1.72^a)	0.082 (0.18)	0.387 (12.00^a)	0.282 (2.83^a)	0.210 (3.07^a)	−0.160 (0.25)
$\delta Rate_t$	−0.242 (−1.18)	0.038 (0.259)	1.291 (3.25^a)	0.572 (0.526)	0.86 (7.14^a)	0.505 (2.92^a)	−0.121 (−0.463)	0.89 (1.58)

Notes: Between parentheses t-stats. ^{a} denotes rejection of the null hypothesis at 1%, 5% or 10% significance level. UR and DR denote upward and downward price movements respectively.

Table 4: Asymmetric SAD effect on energy forward markets under extreme price movements

	Northern Hemisphere							
	Oil		Gas		Coal		Electricity	
	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)
α	−0.033	0.031	−0.050	0.059	−0.024	0.027	−0.033	0.034
	(-20.86^a)	(22.80^a)	(-14.68^a)	(9.18^a)	(-13.75^a)	(15.25^a)	(-14.61^*)	(12.99^a)
$\beta_1 SAD_t^{fall}$	−0.003	−0.0002	−0.007	0.003	−0.002	−0.009	−0.003	0.005
	(-1.97^a)	(−0.28)	(-3.64^a)	(0.68)	(-2.85^a)	(−0.67)	(-2.37^a)	(1.59)
$\beta_2 SAD_t^{win}$	−0.001	0.002	−0.007	0.001	−0.001	0.003	−0.005	0.001
	(−1.04)	(2.06^a)	(0.23)	(-1.70^a)	(−0.63)	(0.44)	(−0.25)	(-1.98^a)
$\gamma Stoxx_t$	0.159	−0.082	0.082	0.054	0.403	0.278	0.172	−0.117
	(1.89^a)	(-1.87^a)	(0.802^a)	(0.118)	(7.61^a)	(2.71^a)	(2.37^a)	(−0.25)
$\delta Rate_t$	−0.200	0.006	1.371	0.661	0.774	0.554	0.043	0.960
	(−0.89)	(0.046)	(3.75^a)	(0.57)	(4.30^a)	(5.02^a)	(0.12)	(2.78^a)
	Southern Hemisphere							
α	−0.038	0.035	−0.070	0.064	−0.029	0.025	−0.042	0.040
	(-16.42^a)	(21.54^a)	(-13.29^a)	(11.10^a)	(-13.47^a)	(15.00^a)	(-17.42^a)	(9.40^a)
$\beta_1 SAD_t^{fall}$	0.004	−0.002	0.015	−0.002	0.004	0.002	0.006	−0.007
	(2.71^a)	(−1.26)	(3.98^a)	(−0.41)	(2.06^a)	(1.17)	(2.59^a)	(−1.62)
$\beta_2 SAD_t^{win}$	0.003	−0.003	0.012	−0.002	0.003	0.002	0.007	−0.001
	(1.65^a)	(−1.15)	(2.95^a)	(−0.37)	(2.44^a)	(0.86)	(3.25^a)	(−0.41)
$\gamma Stoxx_t$	0.219	−0.106	0.117	0.081	0.392	0.283	0.221	0.354
	(3.33^a)	(-2.37^a)	(1.02)	(0.16)	(12.01^a)	(2.69^a)	(3.58^a)	(3.46^a)
$\delta Rate_t$	−0.267	0.066	1.409	0.582	0.865	0.499	−0.149	0.651
	(−1.30)	(0.50)	(3.62^a)	(0.49)	(7.26^a)	(2.71^a)	(−0.61)	(1.25)

Notes: Between parentheses t-stats. ^{a} denotes rejection of the null hypothesis at 1%, 5% or 10% significance level. UR and DR denote upward and downward price movements respectively.

Table 5: Conditional Predictive Ability Test

Model strategy	macroeconomic model			
	Brent	Gas	Coal	Electricity
SAD model	196.83 (0.00*)	262.36 (0.00*)	182.94 (0.00*)	165.65 (0.00*)
	[0.98+]	[1.00+]	[1.00+]	[1.00+]

Notes: Between parentheses p-values. * denotes rejection of the null hypothesis at 1% significance level. Between brackets the proportion of time the method in the column outperforms the method in the row over the out-of-sample period, according to the Giacomini and White (2006)'s decision rule. + indicates that the SAD model outperforms the macroeconomic model more than 50% of the time.