Edinburgh Research Explorer

Keeping a weather eye on prediction markets: improving forecasts by accounting for environmental conditions

Keeping a weather eye on prediction markets: The influence of environmental conditions on forecasting accuracy.

Abstract

Prediction markets are increasingly being embraced as a mechanism for eliciting and aggregating dispersed information and providing a means of deriving probabilistic forecasts of future uncertain events. The efficient market hypothesis postulates that prediction market prices should incorporate all information relevant to the performance of the contracts traded. This paper shows that this may not be the case in relation to information regarding environmental factors such as the weather and atmospheric conditions. In the context of horseracing betting markets, we demonstrate that even after the effects of these factors on the contestants (horses and jockeys) has been discounted, the accuracy of probabilities derived from market prices are systematically affected by the prevailing weather and atmospheric conditions. By correcting for this phenomenon, we show that significantly better forecasts can be derived from prediction markets, and that these have substantial economic value.

1. Introduction

Recent years have seen a substantial and growing interest in prediction markets as instruments for improving forecasts by appropriately aggregating and weighing information spread across many individuals. Prediction markets are organised to allow participants to trade contracts where the payoffs are dependent on a specified uncertain event, and the market prices can be interpreted as forecasts of the probability of the event (Paton et al., 2009). The ability of prediction market prices to fully reflect all relevant information is traditionally grounded on the efficient market hypothesis (EMH) (Fama, 1970). This assumes that decision-makers in financial markets rationally assess the likelihood of all possible future outcomes and make financial asset allocations that optimally represent their degree of beliefs, having taken into consideration their risk-reward trade-offs. It has been argued that prediction markets are one of the most efficient mechanisms for aggregating asymmetrically dispersed private and public information, as decision-makers in these markets have incentives to continue trading until the

information they hold is fully incorporated into market prices (Spann and Skiera, 2009). This argument is supported by the growing evidence that probabilities derived from prediction markets outperform sophisticated forecasting methods (Spann, 2003; Tziralis and Tatsiopoulos, 2007) and by the fact that an increasing number of corporations use prediction markets as decision support tools (Cowgill et al., 2009; Soukhoroukova et al., 2012).

Despite the clear strengths of prediction markets, they have been shown to suffer from pricing anomalies, whereby final prices can fail to appropriately reflect all relevant information. These anomalies include the favourite-longshot bias (FLB) (where decision-makers systematically under-estimate/over-estimate the winning probabilities of the most/least likely outcomes) (Smith and Vaughan Williams, 2010; Cain et al., 2002), and pricing anomalies arising from herding (Soosung and Salmon, 2004), over and under-reaction to new information (Poteshman, 2001), anchoring (Johnson et al., 2009), and representativeness bias (Tassoni, 1996).

The psychology and decision-making literatures suggest that these pricing anomalies can often arise from participants' moods, emotions and feelings[1] (referred to collectively hereafter as mood). Empirical research has shown that 'mood misattribution' can occur, whereby current, transient factors unrelated to the decision can affect mood and this can lead to judgments that depart from those expected from fully rational decision makers (Lucey and Dowling, 2005). Furthermore, it has been shown that mood can be influenced by weather and atmospheric conditions (referred to hereafter as environmental conditions (EC)). Consequently, mood fluctuations caused by EC can potentially decrease the ability of decision-makers to make probabilistic judgments that account for all relevant rational considerations and can diminish their ability to effectively learn from feedback. Mood fluctuations caused by EC can potentially impair these key ingredients of effective prediction markets (Vosgerau, 2010) and may therefore reduce the accuracy of forecasts derived from these markets.

---

[1] The distinction between mood, emotion and feelings is not consistent in the psychology literature (Oatley and Jenkins, 1996). Mood is defined as a distinctive emotional tone or attitude expressed for a short period of time. Emotion is an affective state of mind, deriving from feelings, moods, sensations and relationships with others. Feelings is a term that is often used to describe either mood or emotions. Rather than attempting to distinguish the effects of mood, emotions and feelings we simply refer to these collectively as 'mood' and examine their combined effects throughout the paper.

Individuals are often unaware of the extent to which EC affect their mood and under-estimate the degree to which these in turn affect the quality of their decisions, especially when facing complexity, risk and/or uncertainty (Loewenstein, 2000; Bechara et al., 1997). Consequently, the degree to which EC affect the accuracy of prediction market forecasts may have been neglected. To help shed light on this aspect of prediction markets, we examine to what extent EC systematically affect the quality of forecasts derived from prediction markets and to what extent, by accounting for EC, it is possible to improve forecasts derived from these markets.

To explore whether EC can affect the quality of predictions derived from prediction markets we choose a market where these factors have a very good chance of not being influential. If the effects of EC are affecting the quality of predictions in this market then this is also likely to be the case in a wide variety of prediction markets. Specifically, we examine a prediction market renowned for the accuracy of its forecasts, namely the horseracing betting market. In fact, forecasts from sports betting markets have been shown to outperform expert predictions (Forrest and Simmons, 2000), statistical models using fundamental variables (Benter, 1994), and aggregated fast and frugal predictions made by lay people (Serwe and Frings, 2006; Spann and Skiera, 2009). The accuracy of the forecasts derived from these markets has been tied to the fact that participants can engage in a large number of similar markets (Paton and Vaughan Williams, 2005), enabling them to learn the factors that influence horseracing performance. An additional benefit these markets offer for examining our research question is that they have a specific contract end-point, at which all uncertainty is resolved (an unequivocal outcome occurs), thus enabling a clear assessment of forecast accuracy.

In summary, these prediction market conditions offer an ideal setting for examining our research questions. They offer a setting in which the prediction market participants have a stronger likelihood of not being influenced by EC than in many other market settings. Therefore, if we find that environmental conditions are affecting the accuracy of predictions derived from prices in horserace betting markets, we can be fairly confident that this will be the case in other prediction markets. Furthermore, the unequivocal nature of the outcome in these markets allows us to test to what extent adjusting prices to account for environmental factors leads to better forecasts.

Our results demonstrate that the accuracy of probability forecasts derived from final prices in horserace betting markets can be substantially improved by understanding and correcting for situations where we expect EC to affect prices. Specifically, our results reveal that: (i) pricing anomalies associated with EC are present in prediction markets since the accuracy of forecasts derived from final prices appear to be affected by mood misattribution; (ii) forecasting accuracy can be significantly improved when correcting for this mood misattribution, (iii) recognising and correcting probability forecasts for mood misattribution can lead to substantial economic gain.

The remainder of the paper is organised as follows. In section 2, we discuss the influence that EC may have on decision making and we use this discussion to motivate our hypotheses. In section 3, we discuss the features of the different mechanisms of sports prediction markets, and introduce the data used in this research. In section 4, we describe the methods employed to test our proposed hypotheses. The empirical results are reported and discussed in section 5. Finally, in section 6 we draw conclusions and identify important implications of our research for prediction markets and wider decision making contexts.

2. Environmental conditions, mood and prediction market forecasts

2.1 The role of mood, emotion and feelings in decision-making

The dual-process theory of decision-making and information processing suggests that there are two fundamental systems of thinking that operate in parallel and depend on each other for guidance when making decisions. Logic and normative rules prevail in the analytic system. This system is normally effortful and requires conscious control during the judgment process. By contrast, intuition, mood, emotions and feelings are thought to drive the experiential system of decision-making. This system involves quick information processing since, for the most part, this is automatically performed by the subconscious mind. Mood, emotions and feelings are often the first reactions when processing information (because of the relatively higher process speeds of the experiential system). Consequently, they subsequently provide initial guidance to the analytic system when assessing information and making cognitive evaluations about future outcomes (Slovic et al., 2004). In fact, the dual process theory

postulates that fully rational analytic reasoning, as required by the EMH, cannot function effectively unless it is guided by mood (Zajonc, 1980; Kahneman and Frederick, 2002; Sloman, 1996).

Loewenstein et al's. (2001) risk-as-feelings model supplements the dual-process theory by incorporating the idea that mood influences 'every' aspect of the decision-making process. This model incorporates the view that decisions under conditions of risk and uncertainty are largely evaluated at the cognitive level, based fundamentally on logical and rational outcome predictions and cost-benefit analysis. However, the model postulates that mood, triggered by the anticipation of future outcomes, the evaluation of subjective probabilities and the environmental circumstances may exert an external influence on these evaluations.

In sum, research suggests that mood is an important factor affecting decision-making. It can effectively aid decision-making, as illustrated by the fundamental role played by intuition and instinct in enabling human survival and evolution. However, mood can have a direct effect on decision quality. In particular, the consensus to emerge from previous research is that good mood leads to more optimistic judgments of future outcomes (Isen et al., 1978), greater use of irrelevant information (Sinclair and Mark, 1995), heavier reliance on the experiential system of thinking and on previous experiences, the use of more simplistic stereotyping and simplification heuristics (Forgas, 1995), less engagement in critical modes of thinking and greater susceptibility to distractions (Hirshleifer and Shumway, 2003). By contrast, decision makers in bad mood states tend to make more pessimistic judgments of future outcomes (Isen et al., 1978), undertake more critical information processing (Isen et al., 1978), engage in more analytical and reasoning activities and react more efficiently to relevant news (Sinclair and Mark, 1995).

2.2 The effect of environmental factors on emotions, mood and feelings

Empirical evidence suggests that a range of environmental factors influence mood. The conventional view is that 'good' EC, induce positive mood and 'bad' EC induce bad mood (Lockard et al., 1976; Schwarz and Clore, 1983). For instance, higher temperatures and atmospheric pressures, clear skies, absence of rain and geomagnetic storms, good air quality, and lower humidity and less wind have been linked to individuals experiencing positive mood states, whereas lower temperatures and

atmospheric pressures, cloudy and rainy days, geomagnetic storms, poor air quality, higher humidity and more wind have been associated with low mood[2].

There is also evidence that mood can be influenced by moon cycles. For instance, the higher illuminance levels emitted during full moon nights have been found to disrupt sleeping patterns, which in turn leads to negative moods (Kelley, 1942; Cajochen et al. 2013; Armitage, 2007). Furthermore, the shortening of daylight during winter months has been linked to seasonal affective disorder (SAD), a medical condition which causes individuals to experience consistent low moods and depression (Kamstra et al., 2003).

2.3 Empirical evidence linking environmental conditions to market outcomes

Most studies that have investigated to what extent EC, via their influence on mood, affect decision making in a naturalistic environment, have been conducted in financial markets. However, those studies that have explored the effect of the EC on equity returns[3], have reached no consensus about the direction of such influence. For instance, some studies suggest that negative moods (e.g. during geomagnetic storms, cloudy and rainy days, after a full moon night, and during the months of autumn and winter) lead to more pessimistic judgments about future outcomes, causing investors to be more prone to sell stocks; thus driving stock prices down and leading to negative returns. Some studies also show that positive moods can lead to more optimistic judgments about future outcomes, increasing investors willingness to buy stocks; thus driving stock prices up and leading to positive returns (Denissen et al., 2008; Goetzmann et al., 2015; Kamstra et al., 2003). However, other studies suggest that negative moods are associated with positive equity returns, thus, suggesting the opposite relationship between mood and returns.

Dowling and Lucey (2005) argue that although EC have an influence on optimism, they may have an even greater influence on the level of analytical reasoning adopted when making decisions. This they argue is the key factor causing good mood states to be associated to negative equity returns. For example, they suggest that investors in negative (positive) mood states are more likely to undertake

---

[2] For a detailed review on the mechanisms by which these occur, see: Keller (2005): temperature and atmospheric pressure; Eagles (1994): cloud cover; Bagby et al. (1996): rain; Persinger and Levesque (1983): geomagnetic storms and wind speed.

[3] These have examined most EC, other than air quality.

more (less) critical information processing and to be more (less) likely to effectively incorporate relevant information when making their investment decisions; factors which lead to higher (lower) equity returns.

Hirshleifer and Shumway's (2003) study further illustrates the mixed conclusions concerning the relationship between mood and returns in financial markets. In particular, they provided evidence that temperature, rain and sunshine were significantly correlated with stock returns across 25 countries. However, the direction of their influence on returns varied depending on the location of the stock market studied.

In summary, several studies have attempted to explore whether mood misattribution affects stock returns. However, definitive conclusions of such an effect cannot be drawn from these studies, as some researchers have found that EC appear to affect asset prices (e.g., Chang et al., 2008; Cao and Wei, 2005; Lucey and Dowling, 2005; Hirshleifer and Shumway, 2003) whereas other studies reveal that EC have no such influence on asset prices (e.g., Jacobsen and Marquering, 2008; Goetzmann and Zhu 2005; Pardo and Valor, 2003).

Shortcomings in previous research may have led to these mixed conclusions. In particular, there were often large time differences between the trades taking place and the weather observations, most studies did not incorporate a wide set of EC variables and there are difficulties in developing an unequivocal measure of the influence on market prices due to the infinitely lived nature of the assets being studied (e.g., stocks). In addition, no study in the context of financial markets has examined the influence that EC induced mood misattribution has on calibration of prices.

Our research question is designed to fill this research gap and we develop a methodology designed to overcome the shortcomings of previous research. This methodology is used to test the following two hypotheses, derived directly from the literature discussed above which suggests that EC can influence mood and that, via mood misattribution, this can lead to pricing anomalies:

H1. Environmental conditions that are expected to lead to good (bad) mood have a systematic, negative (positive) influence on the accuracy of forecasts derived from prices in prediction markets.

As discussed in detail in section 3.1, final contract prices, and consequently returns, in horseracing markets reflect the ability of decision makers to accurately predict winning probabilities of horses. Therefore, from the literature presented here on the influence of EC on decision-making, we postulate that EC may influence the analytical effort displayed by decision-makers, which in turn may influence the calibration of their forecasts.

If we find evidence to support H1, we propose the following:

H2. The accuracy of probability estimates derived from final market prices in prediction markets can be improved by correcting for the influences of environmental conditions.

3. Data

3.1 Different prediction market mechanisms in sports markets

The mechanisms underlying prediction markets can vary. However, their ultimate purpose is to provide an appropriate means for aggregating individuals' beliefs on the likelihood of future events (Vaughan Williams, 2011).

Previous sports prediction market research has largely examined pari-mutuel and betting exchange mechanisms. In the former, all bets on a particular event are combined together in a pool, the market organiser then removes its commission and payoffs are calculated to distribute the remaining betting volume among the winning bets. In this form of prediction market, the winning probability of each contestant is represented by the proportional dollar amount placed by individuals on particular contestants. Betting exchanges on the other hand work in a similar manner to traditional financial markets, where individuals trade contracts between themselves, either by buying or selling a contract on a specified event. In this form of prediction market, the market organiser commission is only charged on winning contracts. Both these forms of prediction market may be described as 'person-to-person' betting, in that the market organisers simply charge a commission to provide the infrastructure to allow individuals to trade against each other on the basis of their beliefs concerning the outcome of events.

A relatively less studied prediction market mechanism is that of bookmaker markets, sometimes referred as 'quote driven' prediction markets. In this market setting, bookmakers act as market makers,

quoting the contract prices (odds) that they are willing to offer individuals to place bets on particular events or contestants, and individuals can either bet or not at the quoted prices. Therefore, alongside bettors, bookmakers are also important decision-makers in determining final contract prices, as they are financially susceptible to the outcome of the event (i.e. they are financially dependent on the outcome of events as they participate by taking the opposite side of every contract (bet) traded). The quoted prices are determined by the price-setting behaviour of the market maker. For example, in order to avoid substantial losses, bookmakers could quote prices that aim to reflect true outcome probabilities, thus, allowing them to earn a long-term profit equal to the average commission charged. The bookmakers can assess these probabilities based on their own assessment of the relevant information, together with the relative volumes of betting on different outcomes. Alternatively, bookmakers can quote odds that attract levels of betting volumes on each outcome, such that whatever the event outcome, they earn a profit equal to the commission charged. Based on these price-setting behaviours, contract prices in this prediction market setting reflect both the bookmaker's and the bettors' beliefs concerning the outcome of the event (Franck et al., 2010).

The few studies that compare forecasting accuracy between different prediction market mechanisms mainly compare the accuracy of bookmakers' odds and prices from the leading UK betting exchange, Betfair. The results suggest that Betfair prices provide slightly higher prediction power (Franck et al., 2010; Strumbelj, 2014), but this difference is not statistically significant (Strumbelj, 2014). In fact, it is widely documented that quote driven prediction markets are very efficient at aggregating individuals' beliefs and knowledge concerning future outcomes, as evidenced by the high forecasting performance derived from final prices (Boulier and Stekler, 2003; Forrest et al., 2005; Sung and Johnson, 2007). Consequently, we employ bookmaker odds when testing our hypotheses.

3.2 Sources of data

The horseracing data were obtained from Raceform Ltd and covers all flat races in the United Kingdom between 2002 and 2016, inclusive. It consists of starting times, finishing positions, race class, number of bends, an indicator for handicap (0 for non-handicap and 1 for handicap) races, and bookmakers' starting prices (SP) for each of the 73,457 horses and 2,717 jockeys in the 87,402 flat races run at 43

race tracks across the United Kingdom during this fifteen year period. Races occur in all months of the year on different going conditions, with the majority of races taking place between May and September (61.31%) and on good/fast conditions (79.9%).

In order to avoid overfitting and to enable us to estimate accuracy improvements which may be possible from incorporating EC into forecasts, the research sample is divided in two parts: the in-sample (training set) data consists of races run between 2002-13 and represents approximately 80% of the data and the out-of-sample (holdout sample) is composed of races run between 2014-16[4].

The EC data were obtained from the Met Office Integrated Data Archive System. The database contained hourly data from weather stations across the United Kingdom. The closest weather stations to each individual racetrack were identified using their respective zip codes and these were used to identify the EC prior to each race start time. The EC were captured in variables measuring the temperature, wind speed, cloud cover, geomagnetic activity, humidity, atmospheric pressure, rain amount, air quality, and moon cycles. Our review of the psychological and medical literature revealed that geomagnetic storms and full moon days may deteriorate mood, and therefore improve the quality of decisions. Consequently, following Dowling and Lucey (2005) we coded '*geomagnetic storms*' as 1 and 0 to indicate when geomagnetic activity is, respectively, greater than and less than or equal to 29; 1 indicating the occurrence of a geomagnetic storm. In addition, '*full moon*' was coded 1 and 0 to indicate the days when a full moon does and does not occur, respectively. We also derived a numerical estimate for the seasonal affective disorder (*SAD*) based on Kamstra et al's (2003)[5] methodology. The descriptive statistics of the horseracing and EC variables are presented in Table 1.

---

[4] To ensure the robustness of our analysis to different cut-off points when determining the training and holdout samples, we conducted our analysis on different training and holdout samples, composed of different racing calendar years and compared the results with the ones reported in Tables 3, 4 and 5. Summary statistics (i.e. adjusted and pseudo R^2, signs of coefficients and their respective significance levels) remained consistent with the results reported in Tables 3 and 4. Equally, the relative economic performance of the betting strategies presented in Table 5 remained consistent across different samples. The results of these robustness checks suggest that the results presented in Tables 3, 4 and 5 are robust to different cut-off points for dividing the sample into training and holdout datasets.

[5] Derived by

$$SAD_t = \left\{ \begin{array}{l} \left\{ \left\{ 24 - 8.72 \ x \ arcos \left[-tan\left(\frac{2\pi\sigma}{360}\right) tan\left(0.4102 \ x \ sin\left(\left(\frac{2\pi}{365}\right)(Julian_t - 80.25) \right) \right) \right] \right\} - 12 \ for \ racing \ days \ in \ the \ fall \ and \ winter \right. \\ \qquad\qquad\qquad\qquad\qquad\qquad\qquad Zero \ Otherwise \end{array} \right.$$

where, Julian ranges from 1 to 365(6), representing the number of the day in each year and δ is the latitude in degrees of race tracks.

[Table 1 about here]

4. Method

To test our hypotheses, we must investigate: (i) which EC factors influence the accuracy of forecasts derived from market prices and (ii) to what extent forecasting accuracy derived from market prices can be improved by correcting for the influences of EC. To achieve this, we first employ regression analysis to determine the EC factors that influence Brier scores, a widely adopted score function that measures the accuracy of probabilistic forecasts; thereby enabling us to test H1. To test H2, we employ conditional logit models to measure the degree to which forecast accuracy can be improved by correcting for the likely influences of EC on probability estimates derived from market prices. This is achieved by comparing the accuracy of probabilities forecasts generated by conditional logit models incorporating the following predictors: (a) EC and probabilities derived from market prices and (b) probabilities derived from market prices. We use the coefficients of these models, estimated on the basis of the training sample data, to forecast winning probabilities for the holdout sample. We then base Kelly betting strategies on the probability estimates derived from these models and compare the returns obtained, in order to test H2. We now further examine the details of our methodology.

4.1 Deseasonalized Variables

Acclimatisation is an important biological mechanism that needs to be considered when studying decision-making, as it moderates the influence of EC on mood. In particular, there is evidence that individuals have the ability to acclimatize to seasonal changes in the environment. This can potentially reduce or exacerbate the expected influence of EC on mood (Young et al., 1986). Furthermore, acclimatisation also allows individuals to maintain the stability of internal functions across a range of different EC (Hancock and Vasmatzidis, 2003). Consequently, the influence of the raw EC on decision-making may be moderated by an individual's ability to acclimatise to the current seasonal conditions. This can potentially lead to raw EC having a different influence on mood at different times of the year (e.g. an above average temperature may improve mood during the winter and cause a deterioration in mood in the summer). To address this, we follow Hirshleifer and Shumway's (2003) methodology and

deseasonalized[6] the EC included in the regression analyses (with the exception of geomagnetic storms, full moon and SAD, as they do not follow seasonal patterns). The expectation is that the deseasonalized variables will provide a better measure of the influence of EC on mood (and consequently on decision-making), as EC are adjusted to better represent the ability of individuals to acclimatise.

In addition, the process of deseasonalyzing EC variables, reduces the seasonal correlation among EC variables. For example, by deseasonalyzing the weather variables we ensure that worse weather conditions would not exclusively be observed during winter months and *vice versa* for summer months. In particular, by deseasonalyzing an EC variable, poorer weather conditions would occur if the EC variable in question were below the *expected* weather condition for a particular month. Therefore, poorer conditions can be observed all year round and not exclusively during winter months. This process of deseasonalyzing weather variables has also been used by several authors to reduce the correlation among weather variables (for an example, see Lu and Chou, 2012).

4.2 Combining environmental conditions variables

A statistical model including a wide range of EC may lead to spurious and biased estimates due to underlying associations among the variables (Jacobsen and Marquering, 2008). Temperature, wind, atmospheric pressure, cloud cover, humidity, rain and air quality, for example, are not independent, as changes in one of these variables may affect the others (Ahrens et al., 2012). In particular, a reduction in atmospheric pressure can lead to rain, and rain and cloud cover are highly correlated. One way of handling this issue would be to discard EC variables that have a strong association. However, our review of the psychology and decision-making literatures revealed that mood can be influenced by a combination of different EC (e.g. Persinger and Levesque, 1983; Tarquini *et al.,* 1998; Denissen et al., 2008).

In these circumstances, discarding EC variables may lead to a model that fails to represent the true underlying influence of EC on prediction market prices. An alternative approach is to adopt a data reduction technique. We believe that this approach is more suitable to our study, as in data reduction all

---

[6] The deseasonalization procedure involves subtracting the monthly average from the raw environmental condition in question.

variables are retained. To achieve this, we employ principal component analysis, which allows the possibility of retaining information from all EC variables observed in a particular race. Principal component analysis aggregates the interdependent EC variables into a smaller set of uncorrelated composite variables, called principal components (PC). It achieves this by defining an orthogonal linear weighted combination of the EC variables observed on race *j*:

$$
\begin{aligned}
PC_1 &= \alpha_{11}X_{1j} + \alpha_{12}X_{2j} + \cdots + \alpha_{1n}X_{nj} \\
&\quad\vdots \\
PC_m &= \alpha_{m1}X_{1j} + \alpha_{m2}X_{2j} + \cdots + \alpha_{mn}X_{nj}
\end{aligned}
\tag{1}
$$

where α_{mn} is the weight for the *m*th principal component and the *n*th EC variable *X*. The weights for each PC are defined by the eigenvector of the correlation matrix of the EC variables. The PCs are defined in such a way that the first component accounts for the largest amount of variance σ^2 among the EC variables, where for each PC the sum of the squared weights $\alpha_{11}^2 + \alpha_{12}^2 + \cdots + \alpha_{1n}^2$ is equal to one. The proportional variance accounted by each PC is given by σ_m^2/n. PCs with resulting eigenvalues lower than one account for less variance among the EC variables than had been contributed by an individual EC variable. This may render components' scores unreliable (Kaiser, 1958). Consequently, we adopt the Kaiser criterion and only consider PCs that achieve eigenvalues greater than one.

Having established which components were to be retained, a varimax orthogonal rotation with Kaiser normalization is performed in order to constrain PCs to be uncorrelated. The PC analysis revealed that three components achieved eigenvalues greater than one. These three components, as shown in Table 2, accounted for 61.63% of total variance among the deseasonalized EC. We labelled the resulting PCs in a manner to best represent the highest component weights. Consequently, component one was labelled '*warmer, sunnier and drier conditions*' (based on component weights of 0.533, -0.447 and -0.534 for deseasonalized *temperature*, *cloud cover* and *humidity*, respectively), component two was labelled '*poorer weather*'[7] (based on component weights of 0.767 and -0.62 for deseasonalized *wind speed* and *air pressure*, respectively), and component three was labelled '*wetter*

---

[7] This label reflects the understanding that lower atmospheric pressure leads to greater wind speeds, and greater wind speeds are associated to poorer weather conditions, such as cloudier and rainier days (Trujillo and Thurman, 2001).

weather and poorer air quality' (based on component weights of 0.696 and 0.548 for deseasonalized rain and air quality, respectively). The resulting three components were used, in addition to *SAD*, *geomagnetic storms* and *full moon* as predictors for the subsequent analyses.

[Table 2 about here]

4.3   Preference variables

The performance of a horse is determined by a large range of factors (Benter et al., 1996). Based on medical and psychological literature, Costa Sperb et al. (2017) predicted that ECs are likely to impact the performance of horses and jockeys. This relationship is due to the ECs' influence on the horse's and jockey's physiological and metabolic capabilities and on their current state of mind/mood. As a result, the authors developed a methodology that forecasts a horse's winning probability based on a range of ECs. Costa Sperb et al. (2017) refer to this as a 'preference variable' methodology, since it identifies under which ECs horses and jockeys perform well (i.e. for which they display a 'preference'). Consequently, in order to capture the influence that EC may exert on final prices in prediction markets, it is first necessary to control for the effect that these conditions may have on a horse's and jockeys' performance. Including these 'preference variables' in our model allows us to control for the influence of EC on the performance of horses and jockeys. This approach, therefore, enables us to isolate the influence of EC on the calibration of final market prices (potentially resulting from the ECs effects on the bettors' moods).

4.4   Assessing influence of environmental conditions on forecast accuracy

In order to test H1, that EC have a systematic influence on the accuracy of forecasts derived from prices in prediction markets, we employ the Brier score (Brier, 1950) as our measure of forecast accuracy. This is selected because it is widely used to assess the accuracy of probabilistic, mutually exclusive discrete outcomes in sports (e.g. Corral and Rodriguez, 2010; Strumbelj and Sikonja, 2010; McHale and Morton, 2011).

The Brier score for a total of *N* runners in a race is defined as follows:

$$BS_j = \frac{1}{N}\sum_{i=1}^{N}\left(f_{ij}-o_{ij}\right)^2 \tag{2}$$

where f_{ij} is the odds implied probability[8] for the horse and jockey pair i in race j and o_{ij} is the actual outcome of the race (i.e. 1 for the winner and 0 otherwise). Brier scores can vary between 0 and 1, where 0 represents perfect prediction accuracy (i.e. lower Brier scores indicate better forecasts). Importantly, the Brier score is minimized when the true probabilities are estimated, therefore, providing a robust measure of prediction accuracy derived from final prices.

To establish whether EC influence the quality of probability estimates derived from final prices, we determine to what extent the Brier score is influenced by three key variables: *Horseracing Factors, Preference Variable Variance* and *Environmental Conditions.* This is achieved by estimating the following model, using the training data:

$$\text{Brier score}_j = \alpha + \beta_1 Preference\ Variable\ Variance_j + \beta_k Horseracing\ Factors_j \\ + \beta_k Environmental\ Conditons_j + \varepsilon \tag{3}$$

We now define each of the three variables in this model.

Horseracing Factors: Previous research has indicated that the accuracy of forecasts derived from prices in horseracing markets may be influenced by race specific factors such as: number of runners (Gramm and Owens, 2005), whether the race is a handicap (Brown, 2016), the number of bends that horses encounter in the race (Johnson et al., 2010), the class of the race (Sung et al., 2012), whether the race is run at a weekend (Sung et al., 2012), whether the race is the first or last of the day at a particular racetrack (Johnson and Bruce, 1993) and the bookmaker commission charged on the race (Vaughan Williams and Paton, 1998). We include all these factors in the regression as control variables, together referred to as 'Horseracing Factors'.

Preference Variable Variance: The accuracy of forecasts derived from final prices in betting markets is sensitive to the level of uncertainty of the race outcomes (Moul and Keller, 2014). We believe that this uncertainty is likely to be linked to the variance of the preference variable probabilities across

---

[8]Odds implied probabilities *f* are the probabilities derived from final betting prices (SP) where the probabilities for a particular race are constrained to sum to 1, defined as $f_{ij} = \dfrac{\left(\frac{1}{SP_{ij}+1}\right)}{\left(\Sigma_{i=1}^{N}\frac{1}{SP_{ij}+1}\right)}$

horses in a given race. For example, a lower variance observed for the horses' preference variable probability estimates in a given race suggests that it is more difficult to distinguish the influence of EC on the performance of individual horses and jockeys (i.e. higher outcome uncertainty). This, we believe is likely to lead to poorer, less calibrated judgments, which in turn may suggest that the accuracy of forecasts derived from market prices will be lower. Consequently, we control for the influence of preference variable variance on forecasting accuracy by including *Preference Variable Variance* in our regression (Eq. 3).

Environmental Conditions: In order to assess the impact of EC on forecast accuracy, we include a range of EC variables in the regression (Eq. 3). In particular, we include the PCA components derived in the manner outlined in 4.2, together with variables to capture SAD, geomagnetic storms and full moon. A statistically significant negative coefficient for EC variables associated with poorer mood (i.e. *wetter weather and poorer air quality* and *poorer weather* components, geomagnetic storms, full moon and SAD), and a statistically significant positive coefficient for the EC variable associated with better mood (i.e. *warmer, sunnier and drier weather* component) would be indicative of a mood misattribution bias, therefore, providing evidence to support H1.

4.5   Improving forecasting accuracy by accounting for the influence of environmental condition variables on market prices

In order to test H2, we examine the extent to which the accuracy of forecasts derived from market prices can be improved by correcting for mood misattribution bias. To achieve this, we employ the most widely used modelling procedure in assessing the degree to which odds in horseracing prediction markets reflect all available information, namely, conditional logit (Johnson and Bruce, 2001). The aim of the conditional logit model (referred to CL hereafter) is to derive the winning probability p_{ij} of a horse and jockey pair i in race j, such that the sum of the winning probabilities for all horses in each race is constrained to be one. These probabilities are estimated using a vector of h predictors $\mathbf{Y}_{ij} = \left[Y_{ij}^1, \dots, Y_{ij}^h\right]$, which capture information in respect to each jockey and horse pair i in race j. A particular

advantage of this model is that the winning probability estimates of each horse are conditional on the competitiveness of the race.

To estimate the CL model, a 'winningness' index W_{ij} is derived for every pair of horse and jockey i in race j, such that

$$W_{ij} = \sum_{r=1}^{h} \beta_r Y_{ij}^r + \varepsilon_{ij} \tag{4}$$

where β_r is a coefficient which measures the importance of predictor Y_{ij}^r in determining the likelihood of horse and jockey pair i winning race j, and ε_{ij} is an independent error term distributed according to the double exponential distribution. W_{ij} is calculated such that the horse and jockey pair that wins a particular race is determined to be the one with the highest winningness index in that race. Thus, the estimated probability of the horse and jockey pair K winning race j (p_{Kj}) composed of N_j runners is estimated by:

$$p_{Kj} = Prob(W_{Kj} > W_{ij}, i - 1, 2 \dots N_j, i \neq K) \tag{5}$$

Therefore,

$$p_{Kj} = Prob\left(\sum_{r=1}^{h} \beta_r (Y_{Kj}^r) + \varepsilon_{Kj} > \sum_{r=1}^{h} \beta_r (Y_{ij}^r) + \varepsilon_{ij}, i = 1, 2 \dots N_j, i \neq K\right) \tag{6}$$

The W_{ij} cannot be observed directly. However, whether horse i wins race j can be observed as a win/lose binary variable t_{ij} defined such that:

$$\begin{cases} t_{ij} = 1 \; if \; W_{ij} = Max\left(W_{1j}, W_{2j,} \dots, W_{N_j j}\right) \\ \qquad t_{ij} = 0 \; otherwise \end{cases} \tag{7}$$

The probability of the horse and jockey pair K winning race j can be represented by:

$$p_{Kj} = Prob\left(t_{Kj} = 1 | (p_{ij}), i = 1, 2 \dots, N_j\right) \tag{8}$$

such that the conditional winning probability for the horse and jockey pair i in race j can be derived as follows:

$$p_{ij} = \frac{exp\left(\sum_{r=1}^{h} \beta_r Y_{ij}^r\right)}{\sum_{i=1}^{N_j} exp\left(\sum_{r=1}^{h} \beta_r Y_{ij}^r\right)} \tag{9}$$

where β_r are estimated using maximum likelihood procedures.

In order to test H2, that the accuracy of probability estimates derived from final market prices in prediction markets can be improved by correcting for the likely influences of EC, we estimate three separate CL models using the training data. We then compare the ability of these models to predict winning probabilities. The first, called 'benchmark CL', incorporates winning probabilities derived from market prices as a single predictor. The second model, called 'preference CL', incorporates winning probabilities derived from market prices and EC preference variables (as outlined in section 4.3) as predictors. Lastly, the model called 'EC CL' incorporates winning probabilities derived from market prices, EC preference variable and interaction terms between the EC principal components and market price probabilities, as predictors.

A statistically significant coefficient for the EC preference variable in the EC CL model will indicate that market prices do not fully incorporate information concerning the impact of EC on the performance of horses and jockeys. Statistically significant interaction terms between the EC principal components and market price probabilities will provide supplementary evidence of a mood misattribution bias, as all relevant information concerning the impact of EC on the performance of horses and jockeys should have already been discounted by market prices and the EC preference variable.

We use coefficients estimated for these three CL models (i.e. 'benchmark CL', preference CL' and 'EC CL') using the training sample, to develop winning probability estimates for the holdout sample races. These are used as the basis of three separate Kelly betting strategies (1956) on the holdout sample races. Kelly betting is employed as its final performance is directly dependent on the accuracy of the forecast probabilities (MacLean et al., 1992). Comparing the returns achievable by the three Kelly betting strategies provides a means of examining the predictive value of correcting for any possible mood-induced misattribution bias (i.e. exploring to what extent the returns from employing the EC CL

model outperform those achievable when employing the benchmark CL and preference CL models); therefore, providing a further test of H2.

Kelly betting assumes that a fraction $f_j(i)$ of wealth is bet on the horse and jockey pair i in race j. Let $f_j = \sum_{i=1}^{N_j} f_j(i)$ be the total fraction of wealth bet on race j with N_j runners. Given that the horse and jockey pair K wins race j (with odds O_{Kj}), the current wealth is projected to increase by a factor of $1 - \sum_{i=1}^{N_j} f_j(i) + f_j(K)(O_{Kj} + 1)$. Kelly betting involves selecting f_j that maximises the expected log of winnings, $F(f_j)$, such as:

$$F(f_j) = \sum_{K=1}^{N_j} p_{Kj}^{\varphi} log \left(f_j(K)(O_{Kj} + 1) + 1 - \sum_{i=1}^{N_j} f_j(i) \right) \qquad (10)$$

where p_{Kj}^{φ} are the predicted winning probabilities (as estimated by the 'benchmark CL', the 'preference CL' and the 'EC CL' models). Therefore, Kelly betting selects bets that maximize the expected log returns over all potential winners using the input model probabilities, p_{Kj}^{φ}.

Employing the Kelly betting strategy can lead to very large bets being recommended as wealth levels increase later in the sequence of bets or as a consequence of bets where a large fraction of wealth ($f_j(i)$) is prescribed (Benter, 1994). In order to avoid the success of a betting strategy being artificially biased by the sequence of betting or the result of one or two large bets, we employ a fractional Kelly strategy without re-investment of winnings. Specifically, the bank size used to calculate the size of bets is returned to its initial amount after each bet, independently of the outcome of that bet. In addition, we employ a 0.5 Kelly strategy, whereby we bet 50% of the recommended Kelly bet ($f_j(i)$) in a given race. This is done in order to prevent individual large bets substantially altering the final economic performance of the betting strategy. Consequently, adopting a 0.5 Kelly without re-investment of the winnings ensures that the performance of a betting strategy is more representative of the collective forecast value of the predicted winning probabilities (p_{Kj}^{φ}) rather than (un)fortunate outcomes from a few large bets.

An initial wealth of $1,000 is assumed for all three Kelly betting strategies and we measure the success of the betting strategies by determining the total increase from the initial wealth as a result of applying the strategy. Should a Kelly betting strategy on the holdout data produce better returns when it is based on winning probabilities estimated using the EC CL model (incorporating market prices, EC preference variables and environmental conditions) compared to when based on probability estimates from the 'benchmark CL' and the 'preference CL' models, this will provide further evidence to support H2. Specifically, this will imply that significantly higher returns can be achieved by correcting for the influence of EC on the quality of probability estimates derived from market prices.

5   Results

The first set of results relate to our tests to detect any possible EC induced mood misattribution bias in the winning probability forecasts derived from the final market prices. The second set of results is aimed at examining to what extent it is possible to improve probability estimates derived from market prices by correcting for any misattribution bias present.

5.1 The influence of environmental conditions on the accuracy of forecasts derived from prices in prediction markets.

The results of estimating a linear regression in the form of Eq. 3, to examine the impact of EC on the accuracy of forecasts derived from prices in prediction markets, are summarized in Table 3. These results show that six of the eight horserace factors have a significant effect on forecast accuracy, as measured by the Brier score. This suggests that it was important to control for these factors when assessing the impact of EC on the accuracy of forecasts derived from prices in prediction markets.

The significant, positive coefficient of the *preference variable variance* indicates that larger disparities between the effect of EC on the performance of individual horses and jockeys in the race leads to market prices which deviate further from their correct value (i.e. forecasts derived from these prices will be less accurate). This suggests that decision makers are not appropriately identifying the effect EC on the performance of individual horses and jockeys, because greater disparities between the effect of EC on the performance of individual horses and jockeys should enable market participants to better distinguish each horse/jockey's chance of success, thereby improving forecasting accuracy.

The results relating to the influence of the six EC variables on forecasting accuracy is revealing. They suggest that mood misattribution may affect the accuracy of forecasts derived from final prices, therefore, providing evidence to support H1. Specifically, *warmer, sunnier and drier weather* and *poorer weather* EC components and *SAD* are significant in explaining forecasting accuracy (t-values of -2.15, -2.00 and -1.96, respectively), even after controlling for horserace factors and *preference variable variance*.

The negative coefficient for the *poorer weather* component and *SAD* are consistent with the notion that poorer moods are associated with more analytical and logical reasoning. In particular, these results suggest that poorer moods, induced by the EC related to these variables, are associated with more accurate forecasts derived from market prices (i.e. lower Brier score).

However, the negative coefficient for the *warmer, sunnier and drier weather* component suggests the opposite. Specifically, one might expect that positive mood induced by higher temperatures and lower cloud cover and humidity would lead to greater reliance on the experiential system of thinking; thus leading to poorer forecast calibration (i.e. a positive coefficient indicating larger Brier scores). However, we find the opposite effect. This unexpected result may arise because the *warmer, sunnier and drier weather* component is not exclusively allocating weights to EC variables associated with better mood. For instance, this component has a large and positive weight on air quality, and larger values for air quality are associated with poorer mood. This factor may moderate, or perhaps in our case out-weigh, the positive influence on mood of the other large EC component weights, consequently resulting in the negative coefficient observed for this component. Importantly, this may demonstrate the relevance of the combined influence of different EC on mood, therefore illustrating the importance of including all relevant EC variables when assessing their effect on decision-making.

Importantly, the fact that we find a systematic relationship between EC and the accuracy of forecasts derived from market prices, even after the impact of these EC on the performances of horses and jockeys has been taken into account, suggests that it may be possible to improve probability estimates derived from market prices by correcting for the influence of the identified bias.

[Table 3 about here]

5.2 Improving the accuracy of forecasts derived from market prices by accounting for the influence of environmental conditions

We evaluated the extent to which forecasts of winning probabilities derived from market prices can be improved by correcting for any EC induced mood misattribution bias. To achieve this we estimated three CL models using the training data and compared their ability to predict winning probabilities. The first CL model, labelled 'benchmark CL', was estimated using market prices as a single covariate. The second CL model, labelled 'preference CL', was estimated using market prices and preference variables as covariates. Lastly, a CL model labelled 'EC CL' is estimated using market prices, preference variables and interaction terms between EC variables and market prices as covariates. The results of estimating these three CL models are presented in Table 4.

[Table 4 about here]

The results of estimating the 'benchmark CL' model indicate that market prices (z-score of 196.75) alone are highly significant in explaining winning probabilities (pseudo-R^2 = 0.1627). This result is in line with the evidence that decision-makers in sports prediction markets are amongst the most sophisticated forecasters, and that final prices from this particular market provide a good guide to winning probabilities (Figlewski, 1979; Smith and Vaughan Williams, 2010).

The results of estimating the 'preference CL', show that the coefficient for the market price probabilities remains highly significant (z-score 193.52), indicating that market prices alone are still highly significant predictors. The *EC preference variable* was also significant at the 1% level (z-score 2.62), indicating that market prices are not fully accounting for the influence of the environment on performance. The positive coefficient of this *EC preference variable* is what might be expected, suggesting that horses and jockeys with greater preferences for the EC experienced on the day of the race, are more likely to win.

In the 'EC CL' model, market prices and the *EC preference variable* are still highly significant (z-score 124.57 and 2.61, respectively). In addition, the *warmer, sunnier and drier weather component* and the *poorer weather component* were also significant at the 1% level (z-scores of 2.61 and 2.56, respectively). These results are consistent with the regression analysis presented in Table 3, suggesting that EC have an influence on the quality of forecasts derived from final market prices in this prediction

market. *Geomagnetic storms* and *SAD* are only significant at the 10% level (z-scores of 1.83 and 1.73, respectively).

Taken together, these results provide further indication of a mood misattribution bias present in this prediction market as all relevant influence of EC on performance should be fully discounted in market prices and the EC preference variable. However, the results indicate that although market price probabilities are still highly significant, the *EC preference variable* incorporates fundamental performance-related information concerning the preferences of horses and jockeys for certain EC that is not contained in market prices. Furthermore, even after controlling for horses' and jockeys' preferences for certain EC, the EC are still systematically influencing the predictive power of market prices. In particular, the model incorporating the interaction terms between market price probabilities and EC ('EC CL') better explains the results of races in the training dataset than the 'preference CL' and 'benchmark CL' models (pseudo-R^2 of 0.1629, 0.1628 and 0.1627 for the ECCL, preference variable CL and benchmark CL, respectively). This suggests that the accuracy of forecasts derived from market prices can be improved by correcting for the mood misattribution bias detected.

To confirm this, we conducted log-likelihood ratio tests (LR) to examine if the difference in explanatory power arising from incorporating the EC related information is statistically significant (see Johnson et al., 2009). In particular, we calculated $LR_1 = 2[(L_P) - (L_B)]$, where L_P and L_B are the log-likelihoods of the 'preference CL' and 'benchmark CL' models. We found that LR_1 = 8.86 ($\chi^2_1[.01]$=6.63), suggesting that market prices are not fully incorporating the impact of EC on the performances of horses and jockeys. We also calculated $LR_2 = 2[(L_{EC}) - (L_P)]$, where L_{EC} and L_P are the log-likelihoods of the 'EC CL' and 'preference CL' models and found that LR_2 = 18.80, ($\chi^2_6[.01]$=16.81). This suggests that market prices suffer from mood misattribution bias. In particular, even after controlling for the influence of EC on performance, the same EC still significantly affect winning probability forecasts derived from market prices.

Taken together, these results indicate that forecasts of winning probabilities derived from market prices are highly predictive of final race outcomes. They also demonstrate that whilst participants in this betting market largely take account of the influence of the EC on the performance of horses and jockeys, the quality of their decisions are affected by environmental conditions. In

addition, they suggest that by controlling for the influence of EC on performance as well as correcting prices for the presence of a mood misattribution bias induced by environmental conditions, we should be able to significantly improve probability forecasts derived from market prices.

Consequently, we examined the degree of improvement in forecasting accuracy which can be achieved by correcting for the mood misattribution bias. To achieve this, we used the three models presented in Table 4 (i.e. estimated using the training races) to forecast winning probabilities for the races during the holdout period (01 Jan, 2014 – 31 Dec, 2016). These probabilities were used as inputs to develop a 0.5 Kelly betting strategy (with an initial wealth of $1,000) without reinvestment of the winnings (as outlined in section 4.5). The results of applying this strategy, using probabilities derived from the 'benchmark CL', 'preference CL' and 'EC CL' models, are presented in Table 5.

[Table 5 about here]

The overall rate of return (ROR) for the 'benchmark CL', 'preference CL' and 'EC CL' are -7.05%, 0.38% and 1.44% respectively. Clearly, the ROR of the 'preference CL' model is substantially larger than the ROR obtained for the 'benchmark CL' (a difference in ROR of 7.43%). In addition, the difference in ROR between the 'EC CL' and 'preference CL' is 1.06%, representing a proportional improvement of 279%.

When comparing the ROR from the strategies displayed in Table 5, for bets in different odds ranges, it can be observed that the 'EC CL' has the best economic performance for bets at odds probabilities greater than 20%. For example, the 'EC CL' is the only strategy achieving a positive ROR at odds probabilities greater than 50% (i.e. ROR of 0.96%, cf. to ROR of -2.14% and -0.93% for the 'benchmark CL' and 'preference CL', respectively), as well as achieving the highest ROR for odds probabilities between 20 and 50% (i.e. ROR of 5.04% cf. to ROR of -13.67% and 3.20% for the 'benchmark CL' and 'preference CL', respectively). Conversely, the 'EC CL' has the poorest economic performance for odds probabilities less than or equal to 20% (i.e. ROR of -41.75%%, cf. to RORs of -21.45% and -31.33% for the 'benchmark CL' and 'preference CL', respectively). However, the small number of bets related to some of these categories prevent us drawing any firm conclusions related to these different odds probability ranges.

A bootstrap procedure was used to determine whether the differences in the returns between the three strategies ('benchmark CL', the 'preference variable CL' and the 'EC CL') were significant. This was achieved by drawing random samples of races from the holdout period, with replacement, with each sample composed of the same number of observations as in the holdout period. This procedure was repeated 1000 times. Then, for each of the resulting 1000 samples, we determined the return from a 50% Kelly betting strategy based on winning probabilities forecast by the 'benchmark CL', the 'preference variable CL' and the 'EC CL'. The resulting distributions of returns were used to test whether the difference in returns achievable by these three strategies were statistically significant. In fact, t-tests showed that the differences in returns obtained from winning probability forecasts based on the 'benchmark CL' and the 'preference CL' and between the 'preference CL' and 'EC CL' models were significantly different at the 1% level ($t(1000) = 35.59$, and 3.45, respectively).

These results indicate that the model accounting for the effect of EC on market prices ('EC CL') provides additional information over that incorporated in those models that simply include market prices ('benchmark CL') and the influence of EC on horse and jockey performance ('preference CL') (i.e. the returns achievable from winning probability forecasts derived from the 'EC CL' model are significantly greater than those possible using either of the other models). These results support H2, confirming the significance of the influence of EC on the forecast accuracy of probabilities derived from market prices.

We further investigated the influence of ECs on the forecast accuracy of market prices. In particular, we examined which ECs had the greatest impact on the forecasting accuracy of odds-implied probabilities. To achieve this, we examined the ROR from a betting strategy which employs probabilities corrected for the influence of particular individual EC conditions on the accuracy of odds probabilities (i.e. using 'EC CL'), and compared the returns achieved for this strategy under different ECs. If, as proposed in H1, good (bad) mood leads to worse (better) calibrated forecasts, then we expect larger (smaller) inaccuracies in odds-implied probabilities (i.e. the betting strategy using the corrected odds-implied probabilities should achieve higher (lower) ROR), under ECs associated with more positive (negative) mood. In conducting this analysis, we categorised EC variables into those associated

with positive and negative mood on the basis of the literature referred to in footnote 2. The results of this analysis are displayed in Table 6.

[Table 6 about here]

The results demonstrate that substantially greater RORs are achieved under ECs that have been shown to induce more positive mood. Interestingly, positive RORs were achieved under all ECs associated with positive mood and negative RORs were achieved under all ECs associated with negative mood. Consequently, these results provide further evidence of the influence of EC on prediction calibration. In particular, these results suggest that ECs associated with good mood have a negative influence on the forecasting accuracy of market prices, providing further evidence to support H1.

6   Conclusion

Our principal aims were to identify to what extent forecast probabilities derived from market prices in prediction markets are affected by environmental conditions. The results offer an interesting insight into the degree to which EC may affect individuals' information processing ability concerning future states of the world.

The results suggest that decision-makers in prediction markets studied are skilful at making probabilistic forecasts of event outcomes. However, under certain EC, market prices deviate from rational asset pricing, thus, leading to less accurate probability forecasts.

To our best knowledge, this is the first paper to investigate the influence of EC-induced mood on prices in a prediction market, where the EC themselves are also important factors when estimating the fundamental performance of the contracts traded. For instance, the nature of the prediction market studied means that participants are 'nudged' to consider EC, as they influence the fundamental performance of horses and jockeys. Psychology studies have demonstrated that when individuals are nudged about the ECs, their decisions are less likely to be influenced by the effects of ECs (Schwarz and Clore, 1983). However, despite the fact that one might expect bettors in horserace betting markets to be alert to the effect of ECs, we observe a significant influence of ECs on market prices. This suggests that the effect of EC on market prices is likely to be even more significant in other prediction markets where participants do not feel the need to actively consider EC.

The only logical way in which the EC examined could influence prices in these markets is through their effect on the performances of horses and jockeys. However, we controlled for the influence of EC on the performances of horses and jockeys. Consequently, our results strongly suggest that mood misattribution bias negatively influences the accuracy of forecasts derived from final market prices.

We demonstrated a systematic link between current EC and the forecast accuracy of market prices, as measured by the Brier score. In fact, we showed that the *warmer, sunnier and drier weather*, and the *poorer weather* components and *SAD* had a statistically significant influence on Brier score. This is a surprising result, especially considering that the estimated model included eight control variables that accounted for factors shown in previous research to influence forecast accuracy and that the model controlled for the influence of the EC on the performance of horses and jockeys. These results provide a clear indication of the presence of an EC-induced mood misattribution bias, and suggest the possibility of improving probability estimates derived from market prices by correcting for this bias.

We observed that although winning probability forecasts derived from market prices are highly predictive, they do not fully account for the influence of EC on the performances of horses and jockeys. In addition, even after controlling for such effects, misattribution bias still led to sub-optimal probability estimates. We demonstrated that it is possible to improve significantly the forecast accuracy of market price probabilities by correcting for the misattribution bias detected and we demonstrated that this could lead to substantial improvements in the rate of return derived from a betting strategy based on the adjusted winning probability forecasts.

There is no appealing explanation from traditional EMH as to why the EC studied here should have any effect on market prices, other than through their influence on the performance of horses and jockeys. However, our results are consistent with the psychological literature which suggests that EC influence mood and judgements about the future, therefore, affecting the quality of forecasts about future states of the world.

Our study suggests that even in prediction markets composed of skilled and experienced participants, the participants' judgements are influenced by EC, leading to less accurate forecasts. By

correcting for this phenomenon, we show that significantly better forecasts can be achieved, and that these have substantial economic value.

In sum, we are led to the clear conclusion that when the purpose of a prediction market is to derive accurate probabilistic estimates from final contract prices, forecast accuracy can be substantially improved by understanding and correcting for situations where prediction markets systematically under-perform. Consequently, the implications of this research are far reaching.

The effective use of prediction markets have helped many organisations predict uncertain and complex outcomes, such as predicting the results of political events, demand for products, production costs across business units, and the likelihood of success of design innovations (Healy et al., 2010; Soukhoroukova et al., 2012). Our results suggest that the underlying value of prediction markets to organisations can be greatly improved by identifying and correcting for conditions under which individuals systematically make sub-optimal estimations about future states of the world.

Table 1 Descriptive statistics of horseracing and environmental conditions variables

Variable	Mean	Std. Dev.	Min	Max
Bookmaker commission (%)	0.17	0.08	0.01	0.95
No. runners	10.01	3.56	2	36

Race class	4.59	1.39	1	7
No. Bends	1.52	1.53	0	8
Temperature (°C)	14.25	5.68	-4.40	33.20
Wind speed (Km/h)	9.04	4.58	0	36
Cloud (varies from '0' clear sky to '9' complete covered)	4.98	3.04	0	9
Humidity (%)	70.54	16.40	19.30	100
Atmospheric pressure (hPa)	1014.62	9.70	965.80	1044.30
Rain amount (millimetres)	0.10	0.60	0	28
Air quality (varies from '1' perfect air quality to '10' hazardous air quality)	3.15	0.95	1	10
Geomagnetic storms ('1' indicates days during geomagnetic storms, '0' otherwise)	0.42	0.49	0	1
Full moon ('1' indicates days after a full moon night, '0' otherwise)	0.23	0.42	0	1
SAD (indicates the lengthening of night hours, from the expected 12hrs, for different days of the year and geographic locations)	0.80	1.42	0	5.05

Table 2 Principal component factor loadings with Kaiser normalised varimax rotation based on deseasonalized environmental conditions

Environmental Condition Variable (deseasonalized)	Component 1 Warmer, sunnier and drier weather	Component 2 Poorer weather	Component 3 Wetter weather and poorer air quality
Temperature	0.533	0.063	0.189
Air Quality	0.419	-0.073	0.548
Wind Speed	0.115	0.767	-0.210
Pressure	0.124	-0.620	-0.254
Humidity	-0.534	-0.072	0.262
Cloud Cover	-0.447	0.092	0.045
Rain	-0.165	0.067	0.696
Eigenvalue	1.99	1.28	1.05
Proportional Variance Explained	0.2838	0.1820	0.1505
Cumulative Variance Explained	0.2838	0.4658	0.6163

Table 3 The influence of environmental conditions on Brier scores (i.e. forecast accuracy) of forecasts derived from market prices

	Variables	Coef.	Std. Error	*t*-value	
	Intercept	0.16216	0.00200	81.08	**
Environmental conditions	*Warmer, sunnier and drier weather component*	-0.00019	0.00009	-2.15	*
	Poorer weather component	-0.00022	0.00011	-2.00	*
	Wetter weather and poorer air quality component	-0.00003	0.00012	-0.27	
	Geomagnetic storms	0.00027	0.00025	1.07	
	Full moon	0.00019	0.00029	0.64	
	SAD	-0.00018	0.00009	-1.96	*
Horseracing factors	*Bookmaker commission*	-0.00419	0.00188	-2.23	*
	No. Runners	-0.00654	0.00004	-149.16	**
	Handicap races	0.00728	0.00026	27.49	**
	Weekend races	0.00016	0.00029	0.54	
	Last race	0.00010	0.00037	0.26	
	First race	-0.00104	0.00036	-2.91	**
	Race class	-0.00168	0.00010	-17.47	**
	No. Bends	-0.00039	0.00008	-4.73	**
Preference	*Preference Variable Variance*	0.34539	0.04887	7.07	**
	Adjusted R ²	0.3513			

Note:
*Indicates significance at the 5% level
**Indicates significance at the 1% level
Negative (positive) coefficients indicate lower (higher) Brier scores, thus representing more (less) accurate forecasts. Tests for multicollinearity among explanatory variables reveal variance inflation factors (VIF) and tolerances well within acceptable limits (max values of 1.64 and 0.62, respectively) (Blaikie, 2003).

Table 4 Results of estimating the 'benchmark CL', 'preference CL', and 'EC CL' models based on the training data (01 Jan, 2002 – 31 Dec, 2013)

	Benchmark CL			Preference CL			EC CL		
	Coefficient	Std. Error	Z-score	Coefficient	Std. Error	Z-score	Coefficient	Std. Error	Z-score
Market price probabilities	1.15342	0.00586	196.75**	1.150782	0.005947	193.52	1.14072	0.00916	124.57**
EC Preference variable				0.062071	0.023723	2.62	0.06184	0.02371	2.61**
Market price probs. ×*warmer, sunnier and drier weather* component							0.01093	0.00419	2.61 **
Market price probs. ×*poorer weather component*							0.01343	0.00525	2.56**
Market price probs. ×*wetter weather and poorer air quality* component							-0.00457	0.00573	-0.80
Market price probs. × *geomagnetic storms*							0.02189	0.01199	1.83
Market price probs. ×*full moon*							-0.02135	0.01381	-1.55
Market price probs. ×*SAD*							0.00722	0.00418	1.73
Log-likelihood	-130066.63			-130062.20			-130052.30		
Pseudo-R^2	0.1627			0.1628			0.1629		

Note:

*Indicates significant at the 5% level

**Indicates significant at the 1% level

Tests for multicollinearity among explanatory variables reveal variance inflation factors (VIF) and tolerances well within acceptable limits (max values of 1.31 and 0.76, respectively) (Blaikie, 2003).

Table 5 Rates of return achieved using a 0.5 Kelly betting strategy using winning probabilities forecast for the holdout races (01 Jan, 2014 – 31 Dec, 2016) by the 'benchmark CL', the 'preference CL' and the 'EC CL' models, with coefficients estimated using the training data (01 Jan, 2002 – 31 Dec, 2013).

Odds Probabilities:	No. bets	No. races with profit	Amt. bet ($)	Profit ($)	Rate of ret. without reinvestment %
Benchmark CL					
>50%	449	256	8156.74	-174.46	-2.14%
≤50% and >20%	606	214	5675.17	-775.54	-13.67%
≤20%	38	6	170.12	-36.49	-21.45%
Total	**1093**	**476**	**14002.04**	**-986.49**	**-7.05%**
Preference CL					
>50%	449	260	9474.32	-88.33	-0.93%
≤50% and >20%	761	266	8103.76	259.43	3.20%
≤20%	61	5	326.99	-102.46	-31.33%
Total	**1271**	**531**	**17905.07**	**68.64**	**0.38%**
EC CL					
>50%	451	258	11566.12	110.54	0.96%
≤50% and >20%	841	295	10928.79	551.31	5.04%
≤20%	115	11	781.09	-326.08	-41.75%
Total	**1404**	**564**	**23276.00**	**335.77**	**1.44%**

Table 6 Rates of return achieved for the 0.5 Kelly betting strategy based on estimates from the 'EC CL' model for different EC.

	Environmental condition	Amt. bet ($)	Profit ($)	Rate of ret. without reinvestment %
Conditions associated with good mood	*No full moon*	20119.15	397.54	1.98%
	No geomagnetic storms	9792.47	645.01	6.59%
	Not SAD months	16060.27	1041.80	6.49%
	No rain	21765.38	617.50	2.84%
	Clear skies (cloud cover ≤ 3)	8034.20	237.39	2.95%
	Positive deseasonalized atmospheric pressure	10422.00	481.41	4.62%
	Low wind conditions (≤ 5km/h)	2412.81	487.54	20.21%
	Good air quality (air quality index ≤ 3)	20956.58	434.32	2.07%
	Positive deseasonalized temperature	12092.96	361.40	2.99%
	Lower humidity (≤ 60%)	7556.08	375.53	4.97%
Conditions associated with bad mood	*Full moon*	3156.85	-61.76	-1.96%
	Geomagnetic storms	13483.53	-309.23	-2.29%
	SAD months	7215.72	-706.02	-9.78%
	Raining days	1510.62	-281.72	-18.65%
	Cloudy days (cloud cover ≥ 7)	10533.41	-517.15	-4.91%
	Negative deseasonalized atmospheric pressure	12853.99	-145.63	-1.13%
	Windy (>5km/h)	20863.18	-151.76	-0.73%
	Poor air Quality (air quality index ≥4)	2319.41	-98.54	-4.25%
	Negative deseasonalized temperature	11183.03	-25.62	-0.23%
	Higher humidity (> 60%)	15719.92	-39.75	-0.25%

References

Ahrens, C., Jackson, P. and Jackson, C. (2012). *Meteorology today: An introduction to weather, climate, and the environment.* Andover: Cengage Learning.

Armitage, R. (2007). Sleep and circadian rhythms in mood disorders. *Acta Psychiatrica Scandinavica,* 115, 104-115.

Bagby, R., Shuller, D., Levitt, A., Joffe, R. and Harkness, K. (1996). Seasonal and non-seasonal depression and the five-factor model of personality. *Journal of Affective Disorders*, 28 (2-3), 89-95.

Bechara, A., Damasio, A., Tranel, D. and Damasio, A. (1997). Deciding advantageously before knowing the advantageous strategy. *Science*, 275, 1293-1295.

Benter, W. (1994). Computer based horserace handicapping and wagering systems: A report. *Efficiency of Racetrack Betting Markets,* 183-198.

Benter, W., Miel, G. and Turnburgh, P. (1996). Modelling distance preference in thoroughbred racehorses, *Proceedings of Third Conference on Mathematics and Computers in Sport*. Bond University: Queensland, 207-218.

Blaikie, N. (2003). *Analyzing quantitative data.* London: Sage.

Boulier, B. and Stekler, H. (2003). Predicting the outcomes of National football league games. *International Journal of Forecasting,* 24, 285-300.

Brier G. W. (1950). Verification of weather forecasts expressed in terms of probability. *Monthly Weather Review*, 78, 1–3.

Brown, A. (2016). The distribution of information in speculative markets: A natural experiment. *The European Journal of Finance,* 22(2), 105-119.

Cain, M., Law, D. and Peel, D. (2002). Is one price enough to value a state contingent asset correctly? Evidence from a gambling market. *Applied Financial Economics,* 12, 33-38.

Cajochen, C., Altanay-Ekici, S., Munch, M., Frey, S., Knoblauch, V. and Wirz-Justice, A. (2013). Evidence that the lunar cycle influences human sleep. *Current biology,* 23(15), 1485-1488.

Cao, M. and Wei, J. (2005). Stock returns: A note on temperature anomaly. *Journal of Banking and Finance,* 29, 1559-1573.

Chang, S., Chen, S., Chou, R. and Lin, Y. (2008). Weather and intraday patterns in stock returns and trading activity. *Journal of Banking and Finance*, 32, 1754-1766.

Corral, J. and Rodriguez, J. (2010). Are differences in rankings good predictors for Grand Slam tennis matches? *International Journal of Forecasting,* 26, 551-563.

Costa Sperb, L.F., Sung, M. Ma, T. and Johnson, J. E. V. (2017). Determining preference for weather and atmospheric conditions: Methodology and an application. *University of Southampton Working Paper*. https://eprints.soton.ac.uk/415092/

Cowgill, B., Wolfers, J. and Zitzewitz, E. (2009). Using prediction markets to track information flows: Evidence from Google. *Working paper*, Google Inc., Mountain View, CA.

Denissen, J., Penke, L., Butalid, L. and Aken, M. (2008). The effects of weather on daily mood: A multilevel approach. *Emotion,* 8(5), 662-667.

Dowling, M. and Lucey, B. (2005). Weather, biorhythms, beliefs and stock returns – Some preliminary Irish evidence. *International Review of Financial Analysis,* 14, 337-355.

Eagles, J.M. (1994). The Relationship between Mood and Daily Hours of Sunlight in Rapid Cycling Bipolar Illness. *Biological Psychiatry*, 36, 422-424.

Fama, E. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance,* 25 (2), 283-417.

Figlewski, S. (1979). Subjective information and market efficiency in a betting model. *The Journal of Political Economy,* 75-88.

Forgas, J. (1995). Mood and judgment: The affect infusion model (Aim). *Psychological Bulletin,* 117, 39-66.

Forrest, D., Goddard, J. and Simmons, R. (2005). Odds-setters as forecasters: The case of English football. *International Journal of Forecasting,* 21, 551-564.

Forrest, D. and Simons, R. (2000). Forecasting sport: The behaviour and performance of football tipsters. *International Journal of Forecasting*, 16, 317-331.

Franck, E., Verbeek, E. and Nuesch, S. (2010). Prediction accuracy of different market structures – bookmakers versus a betting exchange. *International Journal of Forecasting*, 26(3), 448-459.

Goetzmann, W., Kim, D., Kumar, A. and Wang, Q. (2015). Weather-induced mood, institutional investors, and stock returns. *Review of Financial Studies,* 28(1), 73-111.

Goetzmann, W. and Zhu, N. (2005). Rain or shine: Where is the weather effect? *European Financial Management,* 11 (5), 559-578.

Gramm, M. and Owens, D. (2005). Determinants of betting market efficiency. *Applied Economic Letters,* 12(3), 181-185.

Hancock, P. and Vazmatzidis, I. (2003). Effects of heat stress on cognitive performance: the current state of knowledge. *International Journal of Hyperthermia,* 19(3), 355-372.

Healy, P., Linardi, S., Lowery, J. and Ledyard, J. (2010). Prediction markets: Alternative mechanisms for complex environments with fewer traders. *Management Science,* 56(11), 1977-1996.

Hirshleifer, D. and Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *Journal of Finance,* 58(3), 1009-1032.

Isen, A., Shalker, T., Clark, M. and Karp, L. (1978). Affect, accessibility of material in memory, and behaviour: A cognitive loop? *Journal of Personality and Social Psychology,* 36: 1-12.

Jacobsen, B. and Marquering, W. (2008). Is it the weather? *Journal of Banking and Finance*, 32, 526-540.

Johnson, J.E.V. and Bruce, A. (2001). Calibration of subjective probability judgments in a naturalistic setting. *Organizational Behaviour and Human Decision Processes,* 85(2), 265-290.

Johnson, J.E.V. and Bruce, A. (1993). Gluck's second law: An empirical investigation of horserace betting in early and late races. *Psychological Reports,* 72, 1251-1258.

Johnson, J.E.V., O'Brien, R. and Sung, M. (2010). Assessing bettors' ability to process dynamic information: Policy implications. *Southern Economic Journal,* 76(4), 906-931.

Johnson, J.E.V., Schnytzer, A. and Liu, S. (2009). To what extent do investors in a financial market anchor their judgments excessively? Evidence from the Hong Kong horserace betting market. *Journal of Behavioral Decision Making,* 22(4), 410-434.

Kahneman, D. and Frederick, S. (2002). Representativeness revisited: Psychology for behavioural economics. In Gilovich, T., Griffin, D. and Kahneman, D. (Eds.), *Heuristics and Biases: The psychology of intuitive judgment* (pp. 49-81). New York: Cambridge University Press.

Kaiser, H. (1958). The varimax criterion for analytic rotation in factor analysis. Psychometrika, 23, 669-702.

Kamstra, M., Kramer, L. and Levi, M. (2003). Winter Blues: a SAD stock market cycle. *American Economic Review,* 93, 324-333.

Keller, M.C., Fredrickson, B.L., Ybarra, O., Côté, S., Johnson, K., Mikels, J., Conway, A., Wager, T. (2005). A warm heart and a clear head: The contingent effects of weather on mood and cognition. *Psychological Science*, 16(9), 724-731

Kelley, D.M., (1942). Mania and the moon. *Psychoanalytic Review* 9, 406–426.

Kelly, J. (1956). A new interpretation of information rate. *IRE Transactions on Information Theory,* 2(3), 185-189.

Lockard, J., McDonald, L., Clifford, D. and Martinez, R. (1976). Panhandling: Sharing of resources. *Science,* 191, 406-408.

Loewenstein, G. (2000). Emotions in economic theory and economic behaviour. *American Economic Review,* 65, 426-432.

Loewenstein, G., Weber, E., Hsee, C. and Welch, N. (2001). Risk as feelings. *Psychological Bulletin,* 127(2), 267-286.

Lu, J. and Chou, R. (2012). Does the weather have impacts on returns and trading activities in order-driven stock markets? Evidence from China. *Journal of Empirical Finance,* 19, 79-93.

Lucey, B. and Dowling, M. (2005). The role of feelings in investor decision-making. *Journal of Economic Surveys*, 19(2), 211-237.

MacLean, L., Ziemba, W. and Blazenko, G. (1992). Growth versus security in dynamic investment analysis. *Management Science,* 38(11), 1562-1585.

McHale, I. and Morton, A. (2011). A Bradley-Terry type model for forecasting tennis match results. *International Journal of Forecasting,* 27, 619-630.

Moul, C. and Keller, J. (2014). Time to unbridle US thoroughbred racetracks? Lessons from Australian Bookies. *Review of Industrial Organization,* 44(3), 211-239.

Oatley, K. and Jenkins, J. (1996). *Understanding emotions.* Oxford Blackwell Publishers.

Pardo, A. and Valor, E. (2003). Spanish stock returns: Where is the weather effect? *European Financial Management,* 9(1), 117-126.

Paton, D., Siegel, D. and Vaughan Williams, L. (2009).The growth of gambling and prediction markets: Economic and financial implications. *Economica*, 76, 219-224.

Paton, D. and Vaughan Williams, L. (2005). Forecasting outcomes in spread betting markets: Can bettors use "quarbs" to beat the book? *Journal of Forecasting,* 24, 139-154.

Persinger, M. and Levesque, B. (1983). Geophysical variables and behaviour: the weather matrix accommodates large portions of variance of measured daily mood. *Perceptual and Motor Skills*, 57, 868–870.

Poteshman, A. (2001). Underreaction, overreaction, and increasing misreaction to information in the options market. *The Journal of Finance,* 56(3), 851-876.

Schwarz, N. and Clore, G. (1983). Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. *Journal of Personality and Social Psychology,* 45, 513-523.

Serwe, S. and Frings, C. (2006). Who will win Wimbledon? The recognition heuristic in predicting sports events. *Journal of Behavioural Decision Making,* 19(4), 321-332.

Sinclair, R. and Mark, M. (1995). The effects of mood state on judgmental accuracy: Processing strategy and mechanism. *Cognition and Emotion,* 9, 417-438.

Sloman, A. (1996). The empirical case for two systems of reasoning. *Psychological Bulletin,* 119, 3-22.

Slovic, P., Finucane, M., Peters, E. and MacGregor, D. (2004). Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk and uncertainty. *Risk Analysis,* 24(2), 311-322.

Smith, M. and Vaughan Williams, L. (2010). Forecasting horserace outcomes: New evidence of odds bias in UK betting market. *International Journal of Forecasting,* 26,543-550.

Soukhoroukova, A., Spann, M. and Skiera, B. (2012). Sourcing, filtering, and evaluating new product ideas: An empirical exploration of the performance of idea markets. *Journal of Product Innovation Management,* 29(1), 100-112.

Soosung, H. and Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance,* 11(4), 585-616.

Spann, S. (2003). Internet-based virtual stock markets for business forecasting. *Management Science*, 49, 1310-1326.

Spann, M. and Skiera, B. (2009). Sports forecasting: a comparison of the forecast accuracy of prediction markets, betting odds and tipsters. *Journal of Forecasting,* 28(1), 55-72.

Strumbelj, E. (2014). On determining probabilistic forecasts from betting odds. *International Journal of Forecasting,* 30(4), 934-943.

Strumbelj, E. and Sikonja, M. (2010). Online bookmakers' odds as forecasts: The case of European soccer leagues. *International Journal of Forecasting,* 26, 482-488.

Sung, M. and Johnson, J.E.V. (2007). Comparing the effectiveness of one- and two-step conditional logit models for predicting outcomes in a speculative marker. *Journal of Prediction Markets,* 1, 43-59.

Sung, M., Johnson, J.E.V. and Peirson, J. (2012). Discovering a profitable trading strategy in an apparently efficient market: Exploiting the actions of less informed traders in speculative markets. *Journal of Business Finance and Accounting,* 39(7), 1131-1159.

Tarquini, B., Perfetto, F. and R. Tarquini (1998). Melatonin and seasonal depression. *Recenti Progressi in Medicina,* 89(8), 395-403.

Tassoni, C. (1996). Representativeness in the market for bets on National Football League games. *Behavioral Decision Making,* 9(2), 115-124.

Trujillo, A. and Thurman, H. (2001). *Essentials of Oceanography.* London: Pearson.

Tziralis, T. and Tatsiopoulos, I. (2007). Prediction markets: an extended literature review. *Journal of Prediction Markets*, 1, 75-91.

Vaughan Williams, L. (2011). *Prediction Markets: Theory and practice.* London: Routledge.

Vaughan Williams, L., and Paton, D. (1998). Why are some favourite-longshot biases positive and other negative? *Applied Economics,* 30(11), 1505-1510.

Vosgerau, J. (2010). How prevalent is wishful thinking? Misattribution of arousal causes optimism and pessimism in subjective probabilities. *Journal of Experimental Psychology: General,* 1, 32-48.

Young, A., Muza, S., Sawka, M., Gonzalez, R, and Pandolf, K. (1986). Human thermoregulatory responses to cold are altered by repeated cold water immersion. *Journal of Applied Physiology,* 60(5), 1542-1548.

Zajonc, R. (1980). Feeling and thinking: Preferences need no inferences. *American Psychologist,* 35, 151-175.