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Challenges to rationality: An examination on the influence of environmental conditions on decision making in real-world financial markets

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<u>Abstract</u>

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by Luis Felipe Costa Sperb

This thesis, which is divided into three papers, investigates the influence of weather and other atmospheric conditions on decision making in naturalistic environments and its implications for market efficiency and forecasting. The decision setting chosen is the UK horserace betting market. The distinctive features of this setting which enables to investigate behaviour more clearly than in other financial markets is the generation of an unequivocal outcome (a winner) within a finite time frame, thus offering an objective benchmark to inspect decision making anomalies and factors which may have caused them.

The first paper investigates the influence of weather and other atmospheric factors on the performance of horses and jockeys, and the extent to which probability estimates derived from betting markets odds can be improved by incorporating this influence. The findings suggest that bettors do not fully account for such influence on horserace performance, and by correcting such inefficiency in odds, forecasting power was significantly improved. It was also demonstrated that substantial economic gains were attainable when adopting forecasts that make full use of information related to the influence of weather and other atmospheric conditions on the performance of horses and jockeys. The findings of this paper have important implications as they may suggest that in a far wider variety of naturalistic contexts, decision makers may not be making full use of relevant information that is publicly available. This is likely to lead to sub-optimal decisions and, in particular reduce forecasting performance, leading to misleading forecasts.

The second paper explores whether the calibration of probabilistic forecasts derived from betting odds are affected by weather and other atmospheric conditions, via misattribution of mood, as well as the extent to which these probability estimates can be

improved by correcting for any misattribution of mood detected. This paper shows that after discounting the effects of the prevailing weather and other atmospheric conditions on the performance of horses and jockeys, the accuracy of probabilistic forecasts derived from betting odds are systematically affected by the same conditions. By correcting for misattribution of mood, this paper shows that significantly better forecasts can be derived from betting odds, and that these have substantial economic value. The principal conclusion from this paper is that when the purpose of a financial market is to derive accurate probabilistic estimates from final contract prices, forecast accuracy can be substantially improved by understanding and correcting for situations where markets systematically under-perform.

The third paper addresses the conflicting and inconclusive evidence of the existence of weather effects, via misattribution of mood, on market efficiency in naturalistic financial markets. A review on research on weather-induced misattribution of mood in naturalistic financial markets indicates that shortcomings in previous research may be the foundation to these conflicting and inconclusive results. This paper then proposes that investigating the influence of weather-induced misattribution of mood on the level of favourite-longshot bias (FLB) (a phenomenon whereby favourites/longshots are under-/over-bet) displayed in horserace betting markets addresses all shortcomings identified in previous research. The results show that under weather conditions when individuals are expected to experience good mood (cf. bad mood), they over-/under-estimate the winning probabilities of longshot/favourite contestants at a greater extent, and that such effect inflict substantial economic cost on decision makers. Remarkably, these results remain significant when controlling for various factors known to influence the FLB, hence providing robust evidence to support the conclusions that weather-induced misattribution of mood can significantly affect decision making in a naturalistic financial market, and that (in horserace markets) it is weather conditions associated with good mood which damage decision quality. Importantly, the results of this paper suggest that decision anomalies may be innate to the human decision making process.

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Declaration of authorship

I, **Luis Felipe Costa Sperb**, declare that this thesis, **"Challenges to rationality: An examination on the influence of environmental conditions on decision making in real-world financial markets"**, and the work presented in it are my own and have been generated by me as the result of my own original research. I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;

2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;

3. Where I have consulted the published work of others, this is always clearly attributed;

4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;

5. I have acknowledged all main sources of help;

6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;

7. Either none of this work has been published before submission, with the exception of a version of Chapter 3, which is to be published in the forthcoming special edition of the *International Journal of Forecasting* on prediction markets*:* "**Keep a weather eye on prediction markets: The influence of environmental conditions on forecasting accuracy**".

This thesis is based on work done by myself jointly with my supervisors, **Professors Tiejun Ma**, **Ming-Chien Sung** and **Johnnie E. V. Johnson** (Business School, University of Southampton), who each provided advice and suggestions based on earlier drafts of the work.

Signed:

Date: 09/01/2019

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1. Introduction

The axiom that individuals rationally and effectively deliberate on all available options prior to making a decision is crucial to normative decision models. Decisions in this context are normally regarded as informationally efficient. That is, market prices are expected to aggregate and reflect investors' beliefs, which is to say, market prices effectively reflect information (Blume and Easley, 1992). However, empirical evidence have contradicted this by showing that decision makers are susceptible to judgmental and behavioural biases when making decisions under conditions of risk and uncertainty (e.g., Loewenstein, 2000; Johnson et al., 2009). Motivated by this, in recent years, there has been a substantial growing interest in the scientific enquiry about the underlying factors influencing decision making under risk and uncertainty. Among these factors, many laboratory-based research in psychology and neuroscience have shown that weather and atmospheric conditions (referred collectively to environmental conditions, hereafter) exert an influence on judgment and decision making processes, which may lead to sub-optimal decision outcomes (Slovic et al., 2004). However, the influence that environmental conditions may exercise on judgment and decision making in naturalistic environments is still a relatively under-researched field. Although laboratory settings allow scientists to manipulate conditions in order to identify relationships between the variables at interest, such manufactured conditions may fail to capture the richness and complexity of naturalistic settings. This, in turn, can lead to conclusions that omit elements that are often only present in real-world environments or capture behaviour that departs from that of the real natural behaviour, as individuals often behave differently when they know they are being observed (Bruce and Johnson, 1997). Such difficulties have been argued to be more prevalent in decision environments that involve high stakes and levels of risk and uncertainty (e.g. in financial decisions), as in these conditions it is difficult to replicate real-world decision conditions in laboratory experiments. In addition, in the laboratory it is difficult to give individuals the level of meaningful (economic) incentives to make optimal decisions which they receive in the real-world (Johnson et al., 2009). Thus, it is essential for evidence to be retrieved from research conducted in naturalistic decision environments to provide external validity to the theoretical foundations of phenomena uncovered in laboratory settings. Consequently, this thesis is aimed at investigating the influence of environmental conditions on decision making under risk and uncertainty in naturalistic settings where individuals have large economic incentives to make optimal decisions.

To achieve this aim, this thesis proposes that the UK horserace betting market provides an ideal naturalistic environment to investigate the extent to which environmental conditions influence decisions. For instance, this market offers abundant opportunities for decision makers to learn from outcome feedback, as participants can bet in a large number of similar markets (Paton and Vaughan Williams, 2005). In addition, this market setting is highly liquid (e.g. the betting volume in the UK bookmaker horserace market surpassed £600M in 2016 (Statista, 2017)). These characteristics have been shown to improve the manner in which information is employed by market participants (i.e. market efficiency: Johnson and Bruce, 2001). In fact, horserace bettors have been shown to make accurate judgments, as they have been shown to outperform decisions made by experts, statistical models using fundamental variables, and aggregated fast and frugal predictions made by lay people (e.g., Bolger and Wright, 1994; Serwe and Frings, 2006; Spann and Skiera, 2009; Benter, 1994; Forrest and Simmons, 2000). Importantly, this market setting offers the additional benefit of having a specific contract end-point, at which all uncertainty is resolved (an unequivocal outcome occurs) once the race is over (Thaler and Ziemba, 1988). Thus, at the end of a race, the objective probability of success, as determined *ex post* by race outcomes, can be compared against the market's subjective probability estimates (contained in market prices)[1] (Johnstone, 2012), facilitating the investigation of factors that may cause any judgmental and behavioural biases. Furthermore, UK horseracing takes place all year round and, consequently, bettors, horses and jockeys are exposed to a myriad of environmental conditions.

[1] Throughout this thesis, market prices will be used to represent the aggregate beliefs of market participants (i.e., the beliefs of the 'representative bettor'). In general, such perspective has been widely accepted in the literature as economic 'natural selection' in market dynamics favours correctly informed bettors over misinformed bettors, rendering markets an efficient means of aggregating beliefs (e.g., Fama, 1970; Blume and Easley, 2006). It is important to note that under certain market conditions (e.g., immature and incomplete markets), it might be possible for misinformed bettors to prevail (i.e., they may come to dominate the market) due to systematic differences in utility functions between misinformed and correctly informed traders (Blume and Easley, 1992; Sandroni, 2000). That is, it is possible that under these market conditions market prices might not fully reflect the aggregate informational content of bettors' beliefs, but rather differences in their utility functions. Due to the subjectivist nature in establishing the extent of market maturity and completeness, in addition to considering the wide academic support on the theoretical underpinning of market dynamics favouring correctly informed bettors to prevail in the market, this thesis incorporates the generalised view that market prices reflect the beliefs of the representative bettor.

In summary, the characteristics of the UK horserace betting market provide an ideal setting for examining the influence of environmental conditions on individuals' decisions in a naturalistic environment. They offer the opportunity of investigating the influence of a myriad of environmental conditions on decision outcomes, as well as a setting in which market participants have a strong likelihood of not being influenced by these environmental conditions. Therefore, if it is found evidence that environmental conditions are affecting the quality of predictions derived from prices in horserace betting markets, it is highly likely that in other naturalistic contexts the quality of decisions may also be influenced by environmental conditions.

In the context of horseracing, environmental conditions may influence decision quality via two channels: (i) via the cognitive ability of individuals in accounting for the influence of environmental conditions on the performance of horses and jockeys; (ii) via a direct influence of environmental conditions on individuals' rational reasoning process.

The former is based on the ability of bettors to distinguish, and fully incorporate in their decisions the unique ways in which environmental conditions may influence the performance of horses and jockeys. For instance, medical and psychological literature show that environmental conditions can affect horses' and jockeys' physiological and metabolic capabilities and their current state of mind, which in turn can influence their athletic performance (e.g., Persinger and Levesque, 1983; Tarquini et al., 1998; Adams, 1987; Hodgson and McConaghy, 1994). This, linked with the highly interactive nature of the sport (i.e. horses and jockeys interact and communicate with one another and the environment), may lead to the emergence of behaviour that is less readily discernible and difficult to predict (Bellomo, 2008). Therefore, the ability to incorporate such information effectively when making decisions depends upon the cognitive ability of decision makers to understand and untangle the difficult and opaque influence that environmental conditions may exert on the performance of horses and jockeys (Johnson et al., 2006; Brehmer, 1992).

Environmental conditions may also exert a direct influence on individuals' rational reasoning process. Many psychology and neuroscience literature have shown that environmental conditions may influence individuals' mood (Lockard et al., 1976; Schwarz and Clore, 1983), and in turn mood can affect our judgment and decision making process, potentially leading to sub-optimal decision outcomes (e.g., Slovic et al., 2004).

More specifically, psychology research postulates that fully rational reasoning cannot function unless it is guided by mood (Slovic et al*.,* 2004), and that mood guides every aspect of a decision process, as cognition and consciousness are revised and reconstructed with changes in mood (Loewenstein et al., 2001; Slovic et al., 2004; Csikszentmihalyi and Larson, 1984). Importantly, when decisions involve greater levels of risk and uncertainty, the deliberation costs of achieving an optimal decision become highly burdensome and resource intensive (Forgas, 1995). In such situations, cognitive evaluations seek greater support from current mood and emotions, leading to sub-optimal outcomes, which are often regarded as 'satisfactory' by the decision maker (Loewenstein et al., 2001). This, in turn, can lead to the emergence of decision biases. Most commonly, it has been suggested that mood can impair rationality through 'misattribution of mood', a condition whereby mood, influenced by transient factors unrelated to the decision, impair individuals' ability to effectively process information leading to poor judgments (Lucey and Dowling, 2005). Conventionally, misattribution of mood can influence decisions by affecting risk preferences (Isen et al., 1978; Kamstra et al., 2003), by leading individuals to become more prone to use simplistic stereotyping and simplification heuristics (Forgas, 1995), to increase reliance on the experiential system of thinking and on previous experiences; leading individuals to become more prone to use irrelevant information (Forgas, 1995; Sinclair and Mark, 1995), and to engage less in analytical modes of thinking (Hirshleifer and Shumway, 2003).

The influence of environmental conditions on decision making, via the two channels discussed, is examined in three separate papers, which are all related to the principal aim of the research. Overall, the results presented in these papers demonstrate that to a large extent sub-optimal decisions are correlated with environmental conditions. More specifically, I find that decision makers fail to fully incorporate in their decisions the influence of environmental conditions on the behaviour, and ultimately the performance, of horses and jockeys. Furthermore, evidence suggests that environmental conditions may also exert a direct influence on decision makers' rational reasoning processes, leading to a reduction in the quality of probabilistic assessments. Noteworthy, it is shown that the accuracy of probabilistic assessments derived from betting odds can be significantly improved by incorporating the influence of environmental conditions on performance of horses and jockeys, as well as by correcting for the direct influence that these conditions may exert on the rational reasoning process. Moreover, the results demonstrate that sub-optimal decisions attributed to the environmental conditions can lead to substantial financial consequences.

Chapter 2, titled "**Sports forecasting under the weather: Using environmental factors to enhance forecasting in sport**", explores the influence of environmental conditions on performance outcomes of living beings in a naturalistic setting, and the extent to which probability estimates derived from contract prices can be improved by incorporating this influence. The literature survey suggests that performance of living beings are highly challenging to predict as it is difficult to accommodate for the emergence of new behavioural and performance patterns stimulated by changes in environmental conditions (Dawkins, 1976). When studying behaviour of living beings, many researchers were able to demonstrate an influence of environmental conditions on past performance (Suping et al., 1999; Forgas 1989; Etnier et al., 2006). However, to my best knowledge, no forecasting study has directly fully accounted for these conditions to improve forecasting performance. Although environmental conditions are truly exogenous variables that are regionally unequivocally observable, measurable, and predictable (Bauer et al., 2015), the ability to use such information for prediction purposes depends on the cognitive ability of decision makers in understanding their true underlying relationship in relation to performance (Johnson et al., 2006; Brehmer, 1992). Consequently, it is argued that environmental factors may be neglected by many decision makers because of the extensive cognitive demands required to process the highly dynamic, and often opaque influence of environmental conditions on the performance of living beings.

To provide empirical evidence to substantiate the claims in the preceding paragraph, this paper explores the extent to which the influence of environmental conditions on performance of living beings can be incorporated to improve predictive power in a naturalistic setting. To achieve this I set a difficult benchmark by exploring a naturalistic setting where the decision makers are renowned for the accuracy of their forecasts, and where the performance of contracts traded are determined by living beings. More specifically, the context studied is horseracing betting markets, where market prices reflect decision makers' degree of belief of the winning probabilities of individual competitors. Hence, this paper formulates a methodology to measure the influence of a myriad of environmental conditions on the fundamental performance of horses and jockeys, and investigates the extent to which market prices incorporate such influence.

This paper also examines to what extent it is possible to improve forecasting predictive power, over that achievable using market prices, by incorporating the influence of environmental conditions on the performance of horses and jockeys.

The results of the analysis in this paper demonstrate that environmental conditions have an effect on the performance of horses and jockeys, and that prices for the market studied do not fully account for such influence. By correcting such inefficiency in market prices, forecasting performance was significantly improved. It also demonstrated that substantial economic improvements are attainable when adopting forecasts that make full use of the influence of environmental conditions on the performance of horses and jockeys. The findings of this paper are important as they suggest that in a far wider variety of contexts decision makers may not be making full use of relevant information that is publicly available. In particular, it is likely that the effect of environmental factors may be even greater in settings where decision makers have less incentive to make accurate judgments and where they do not receive immediate and regular outcome feedback. This is likely to lead to a number of decision errors and, in particular reduce forecasting performance.

Chapter 3 consists of a paper that has been accepted for publication in the forthcoming special edition of the *International Journal of Forecasting* on prediction markets*:* "**Keep a weather eye on prediction markets: The influence of environmental conditions on forecasting accuracy**". This paper investigates whether probabilistic forecasts derived from market prices in a naturalistic setting are affected by environmental conditions, via misattribution of mood, as well as the extent to which these probability estimates can be improved by correcting for any misattribution of mood detected. More specifically, by discounting the influence of environmental conditions on the performance of assets traded, this paper investigates whether the direct impact posed by environmental conditions on the rational reasoning process of market participants can lead to poor forecasts.

Based on the efficient market hypothesis (EMH) (Fama, 1970), all relevant information regarding the performance of contracts traded should already be fully incorporated in final prices, and deviations from this hypothesis are considered to arise from decision making irrationalities. Although the EMH does not provide explanations for observed market irrationalities, literature in psychology and neuroscience provide evidence that mood experienced at the time decisions are made can lead to deviations from fully rational behaviour (Loewenstein, 2000; Bechara et al., 1997). Furthermore, through a mechanism called 'misattribution of mood', individuals allow mood influenced by transient factors unrelated to the decision at hand to affect decision outcomes (Lucey and Dowling, 2005). This theory, combined with the evidence that environmental conditions may affect individuals' moods (e.g., Lockard et al., 1976; Schwarz and Clore, 1983), suggests that environmental conditions experienced at the time decisions are made may lead to sub-optimal probabilistic forecasts. This may arise from individuals wrongfully accounting for factors unrelated to the decision at hand, thus causing a negative influence on decision quality about future events. Evidence is found to support this argument, and consequently I also examined the extent to which probability estimates derived from market prices can be improved by correcting for the existence of the influence of environmental conditions on decisions.

Consequently, this paper explores the extent to which mood induced by environmental conditions influence decisions in a market that is renowned by the accuracy of participants' forecasts, namely horseracing betting markets. Firstly, the effect of environmental conditions on the fundamental performance of the contracts traded are controlled for by employing the 'preference variable methodology' developed in paper 1 (i.e. I control for the effects discussed in paper 1). In the context studied, market prices are aimed at reflecting the fundamental performance of competitors, and the performance of horses and jockeys are influenced by environmental conditions. Therefore, employing the preference variable methodology I control for the influence of environmental conditions which are related to the decision making in this market context, thus making it possible to investigate the extent to which the direct impact of environmental conditions on judgments can lead to a reduction in the calibration of probabilistic forecasts.

Regression analysis is employed to measure the extent to which probabilistic forecasts, as derived from market prices, are directly influenced by environmental conditions. The regression analysis incorporates numerous control variables that have been shown in previous research to influence calibration of market prices. Since there is no logical explanation for environmental conditions to influence probabilistic assessments contained in market prices beyond their influence on the fundamental performance of horses and jockeys (i.e. via the preference variable), any significant relationship between forecast calibration and environmental conditions will provide evidence of misattribution of mood induced by the prevailing environmental conditions. Lastly, this chapter investigates the extent which probabilistic forecasts derived from market prices can be improved by correcting for any identified mood misattribution bias.

The results of this paper offer interesting insights into how environmental conditions affect individuals' information processing ability about future states of the world. They suggest that decision makers in the market studied are skilful at making probabilistic predictions of event outcomes. However, under certain environmental conditions, market prices deviate from that required from rational asset pricing, thus leading to less accurate probabilistic judgments and sub-optimal forecasts. The regression analysis demonstrated a systematic link between environmental conditions and forecast calibration derived from market prices. For instance, deteriorating weather conditions, geomagnetic storms and warmer, sunnier, and drier conditions were significantly associated with influencing forecast calibration, hence indicating the presence of misattribution of mood. This, in turn, indicates the possibility of improving probability estimates derived from market prices by correcting for the misattribution of mood detected. This paper then demonstrates that this is the case by developing a means of improving these forecasts (i.e. correcting the influence of misattribution of mood on forecast calibration). I observed that although probabilities derived from market prices are highly predictive of final results, they do not fully account for the influence of environmental conditions on performance of horses and jockeys, and in part their predictive power was negatively influenced by environmental conditions-induced misattribution of mood. Lastly, this paper empirically demonstrates the substantial economic gains are achievable by correcting for the influence of environmental conditions on calibration of probabilistic assessments derived from market prices.

Chapter 4, titled "**Does good weather lead people to make good decisions? Evidence from a real-world financial decision making environment**", is aimed at further contributing to the understanding of the direct influence of environmental conditions on the rational reasoning process, by addressing the identified causes underlying the disagreement in conclusions from previous research on the influence of weather-induced misattribution of mood on decision outcomes in real-world financial markets. Conventionally, the focus of previous research in financial markets was majorly centred on studying the influence of mood, associated with the prevailing weather and atmospheric conditions, on equity returns. Some studies provide evidence that there is such an influence existent in financial markets (e.g., Chang et al., 2008; Dowling and Lucey, 2005), however, some studies suggest the contrary (e.g., Lu and Chou, 2012; Goetzmann and Zhu, 2005). Those studies that find an influence of weather on equity returns, have reached no consensus regarding the direction of such influence (i.e., whether weather conditions associated with positive moods improve or worsen market efficiency and equity returns), consequently providing conflicting evidence on how weather may affect decision making in a naturalistic financial setting. Furthermore, some authors have questioned mood as a valid channel by which environmental conditions influence market returns.

In sum, the evidence available from previous research may be insufficient to derive a conclusive answer to the question of whether individuals' weather-induced mood may pose an influence on decision making in a naturalistic financial market setting. In addition, previous research fails to provide definitive answers to whether it is weather conditions associated with positive or negative moods that reduce decision quality and market efficiency. This paper then argues that investigating the influence of mood, induced by the prevailing weather conditions, on equity returns in traditional financial markets may not provide an adequate naturalistic context to capture the extent to which individuals' decisions may be affected. For instance, the neuroscience and psychology literature indicate that mood can affect one's cognitive abilities and risk taking preferences (e.g., good/bad mood lead to higher/lower cognitive errors and risk taking behaviour (e.g., Forgas, 1995; Sinclair and Mark, 1995; Isen et al., 1978)). However, it has been shown that these mechanisms may have opposing effects on equity returns (e.g., higher risk taking may lead to higher returns (Denissen et al., 2008), while higher cognitive errors may lead to lower returns (Dowling and Lucey, 2005)). Consequently, this could potentially be an important factor causing the conflicting results from previous research. For example, Lu and Chou (2012) show that market activity, such as turnover and liquidity, are significantly influenced by investors' mood. However, they found that equity returns were not. This further illustrates that although investment behaviour may indeed be influenced by mood, the mechanisms by which they affect equity returns (i.e. via the risk taking and cognitive errors proposition) may be important factors impairing the ability of previous research to uncovering the extent to which mood influences decision quality in a naturalistic setting and the economic significance of such influence.

This paper proposes a novel means of overcoming the drawbacks of previous research, in order to provide robust evidence to establish mood as valid channel by which environmental conditions affect judgments and thus, provide further evidence to expand our understanding of the extent to which weather-induced mood may influence decision quality. In particular, I employ data from a naturalistic financial market, which circumvents the difficulties presented by traditional financial markets when studying the influence of mood on decision making. Namely, the horserace betting market is argued to provide an ideal naturalistic context to capture the influence of weather-induced misattribution of mood on investment decisions. Traditional financial markets and horserace betting markets share many similarities (e.g. assets can be easily traded due to their high liquidity, information about asset performance is widely available to the public and future outcomes are uncertain (Thaler and Ziemba, 1988)). Therefore, this suggests that if weather-induced mood can influence decisions in financial markets, it could also influence decisions in horseracing betting markets. Importantly, it is argued that a characteristic that makes horseracing markets an ideal setting to derive conclusive evidence on the influence of mood on decision making, is the existence of the favourite-longshot bias (FLB) (i.e. a phenomenon whereby market participants under-/over-estimate the winning probabilities on favourites/longshots) in the market. For instance, it is widely accepted in the literature that the FLB may be explained by more cognitive errors displayed by bettors when assessing low probability events and by heightened risk-preferences (e.g., Quandt, 1986; Snowberg and Wolfers, 2010). Since these are both expected to increase the FLB, this setting should lead to a less ambiguous set of results than those reported using traditional financial market data (i.e. greater/less risk taking and more/less cognitive errors would cause larger/lower levels of FLB). Therefore, as the FLB may be caused by individuals displaying more cognitive errors and a greater tendency to take risks, then weather-induced mood which is expected to influence both these factors in the same direction, is likely to have a high chance of affecting the level of FLB present in the market.

Regression analysis is employed to measure the extent to which misattribution of mood can affect decision making, via an influence on FLB, in horseracing betting markets. First, temperature is selected as the environmental condition variable to measure the expected mood of investors. This is motivated by the evidence that mood associated with temperature can influence cognition and risk preferences in a manner which is homologous with the explanations of the existence of FLB. More specifically, higher (lower) temperatures have been shown to be associated with improving (deteriorating) mood and to lead to higher (lower) cognitive errors and risk taking (e.g., Keller et al., 2005; Howarth and Hoffman (1984). Subsequently, the influence of temperature-induced mood on FLB is investigated via two methodological approaches: (i) whether bettors' subjective probabilities, as contained within market prices, under-/over-estimate the winning probabilities on favourites/longshots; and (ii) whether abnormal returns occur on favourites/longshots. To enhance the validity of results and to establish temperature-induced mood as a the channel affecting decisions, the regression analysis conducted in these approaches incorporate numerous control variables that have been shown in previous research to influence FLB, as well as variables to control for a likely influence of temperature on performance of horses and jockeys.

The results of this paper demonstrate that mood, influenced by temperature, is significantly associated with the level of FLB displayed by bettors in the market studied. More specifically, the results reveal that under temperature conditions when decisions makers are expected to experience good mood, the FLB is more pronounced in market prices (i.e. subjective probabilities, derived from betting odds, under-/over-estimate the objective winning probabilities on favourites/longshots at a greater extent), and that this has a significant effect on returns (i.e. net returns on longshot contestants are significantly lower when decisions makers are expected to experience good mood). Importantly, by addressing the shortcomings identified in previous research on weather-induced misattribution of mood conducted in real-world financial markets, the results in this chapter show that selecting an appropriate decision context and approach is necessary to provide robust evidence to discipline the debate on the extent in which mood influences decision making in a naturalistic setting.

The combined results of the three papers in this thesis provide novel and interesting insights of the impact of a myriad of environmental conditions on decision making in naturalistic financial markets. Normative decision models are built on the theoretical foundations that individuals rationally and effectively deliberate on all available options prior to making fully rational and optimal decisions. This, by definition, fails to provide an adequate explanation for the existence of decision making biases and anomalies present in naturalistic decision environments (i.e., in normative decision models, decision inefficiencies are only attributed to irrationality of individuals). To the best of my knowledge, this is the first academic research to investigate in depth the extent to which decision makers incorporate the influence of environmental conditions on the performance of assets traded, as well as the direct effect of environmental conditions on the rational reasoning process of market participants. The overall findings of this thesis suggest that decision makers in the market studied are skilful at making probabilistic predictions of event outcomes. However, under certain environmental circumstances, market prices deviate from rational levels (as defended by normative decision models), thus leading to sub-optimal probabilistic judgments. Specifically, in the context of horseracing, this thesis shows that environmental conditions influence decisions in two ways: (i) decisions made by market participants did not fully account the influence of environmental conditions on the performance of horses and jockeys; (ii) misattribution of mood, induced by environmental conditions, directly influenced individuals' decision making process.

The empirical evidence of the influence of environmental conditions on decision making can help enhance our understanding of human decision rationality in the following ways. By showing that decision makers do not fully incorporate the influence of truly exogenous, observable, measurable and predictable environmental conditions on the performance of horses and jockeys, it is argued that although transparency and availability of information may be a necessary condition for optimal decision making, they by themselves are not sufficient conditions to achieve such aims. Undoubtedly, transparency can provide strong foundations to support optimal decisions. However, as shown in paper 1, even when information is fully transparent, decision makers may not fully discount information that is opaque and less readily discernible. Hence, this finding shows that decision makers are rational to a large extent. However, their inability of effectively using publicly available information that is opaque and less readily discernible for prediction purposes suggest that (under certain circumstances) human rationality may be restricted by our cognitive limitations. Furthermore, the finding of a direct influence of environmental conditions on decision quality (i.e. via misattribution of mood, as shown in paper 2 and further supported in paper 3), helps corroborate the theoretical foundation that behavioural factors are important pillars supporting fully rational and analytical reasoning, as postulated by normative decision models. For example, if human cognition, by design, allows mood associated with environmental conditions to actively participate in the process of achieving decision outcomes, and individuals are often unaware of their current moods (Loewenstein et al., 2001), this may indicate that under certain (mood) conditions we may not be able to attain full rational control over our decisions. Importantly, this suggests that decisions that depart from that expected by the normative decision models may be, in fact, inherent in the fundamental decision making process.

2. Sports forecasting under the weather: Using environmental factors to enhance forecasting in sport

Abstract

Little attention has been given to measuring the influence of environmental factors (weather and atmospheric factors) when forecasting performance in sport. Neglecting these influences may lead to sub-optimal forecasts, since the medical and psychology literatures provide strong evidence of their influence on performance in sport. Consequently, this paper develops a modelling procedure to maximise the extraction of information concerning the influence of a myriad of environmental conditions on the performance of competitors in sport. Specifically, it examines the influence of a range of weather and atmospheric factors on the performance of both horses and jockeys in over 31,000 UK horseraces. To achieve this, weather and atmospheric conditions data from the Met Office Integrated Data Archive System (temperature, wind speed, cloud cover, geomagnetic activity, humidity, atmospheric pressure, precipitation, air quality, and moon cycles) are employed to forecast the performance of horses and jockeys. The findings demonstrate that the forecast model is effective at capturing the influence of these environmental factors on performance, and that it is possible to employ this approach to substantially improve forecast power and accuracy. The results also demonstrate the economic significance of incorporating the influence of weather and atmospheric conditions when forecasting performance in sport.

2.1 Introduction

Order provides structure to aid understanding of underlying phenomena and can provide a solid basis for deriving forecasts. However, order may not necessarily be observed in sports contests, particularly because performance is ultimately delivered by living beings. Mistakenly assuming order may in fact lead to misunderstanding of the underlying processes and ultimately to poor forecasts.

Living organisms consist of different active cells, tissues, organs and a myriad of specialised body components. These, linked with their ability to interact and communicate with one another and the environment, lead to the emergence of behaviour that is often opaque and difficult to predict (Bellomo, 2008). Conventionally, species are assumed to behave in a relatively common manner, the particular behaviour of a single organism being determined by how it adapts and responds to its various interactions with other organisms and to its environment (Dawkins, 1976). Where more than one species interact (e.g., in horseracing), predicting the emergence of behaviour is particularly challenging. What is clear is that predicting behaviour of living beings is a difficult and complex task, some more so than others, and their performance cannot be effectively forecast in isolation from their environment.

When studying behaviour of living beings, scientists often use historical records to help understand the general influences of external and internal conditions. However, when predicting behaviour determined by the actions of more than a singular species, hindsight may not necessarily lead to foresight, as it may be difficult to fully accommodate the emergence of new behavioural and performance patterns stimulated by changes in external stimuli and the environment. For example, research has shown that weather and atmospheric conditions (which are collectively referred to as environmental conditions, hereafter) can have an important influence on mood (Howarth and Rothman, 1984), cognitive performance (Hancock and Vazmatzidis, 2003) and athletic abilities (Suping et al., 1999). Consequently, it is likely that environmental factors are particularly important in predicting sports outcomes, as sport performance is determined by contestants' cognitive abilities, mood and physical skills (Forgas, 1989; Parkin et al., 1999; Etnier, et al., 2006). However, studies designed to forecast performance in a range of sports have failed to directly account for environmental factors or have failed to provide robust evidence concerning the true influence of the environment on performance. Borghesi (2008, 2007) uses the medical and physiology literatures to identify possible influences of environmental conditions on American football performance. However, the author does not incorporate their influence on sport performance to improve forecasting. Rather the author examines the correlation of market prices and these conditions, and explores the possibility of earning above average returns by including the environmental conditions alongside market prices.

Other authors have acknowledged the importance of environmental factors on the ability of contestants and final results (e.g., Cain et al., 2003; Brown, 2016; Makropoulou and Markellos, 2011; Chung and Hwang, 2010). Nevertheless, these studies only provide speculative claims about their influence with no empirical evidence. Therefore, to my best knowledge, no academic literature has directly attempted to use environmental factors to improve forecasting power in sports.

Clearly, there should be no impediments to using environmental conditions for forecasting purposes, as they can form the basis of truly exogenous variables that are regionally unequivocally observable, measurable, and predictable to a high degree of accuracy (Bauer et al., 2015). However, the ability to use such information effectively depends upon the cognitive ability of decision makers to understand and predict complex, and often opaque manners in which individual species respond to external stimuli and the environment (Brehmer, 1992).

The absence of environmental factors from previous sports forecasting studies may be explained by the complexity of the process. However, this is potentially an important omission as not fully accounting for the impact of environmental conditions on fundamental performance in sports may lead to sub-optimal forecasts. This motivates the broad research question examined in this paper: To what extent can accounting for environmental factors improve forecasts of performance in sports? To answer this question, this paper develops a methodology for making use of environmental factors when forecasting performance in sports. The literature survey indicates that environmental conditions are rarely employed in forecasting sports' outcomes and this research demonstrates that significant improvements in accuracy can be achieved when they are employed. To achieve this paper's objectives, the forecasts developed which incorporate the influence of environmental conditions on performance are compared against a difficult benchmark, namely the probabilities derived from odds on sporting event outcomes formed in a liquid betting market.

The remainder of this paper proceeds as follows. Section 2.2 discusses the influence of decision complexity when making forecasts. In section 2.3, the sport studied in this paper is introduced, as well the research hypotheses. In addition, this section explores the medical and psychology literatures addressing the influence of environmental factors on performance in sport. In section 2.4, the data used in this research is introduced. Section 2.5 develops a methodology to capture the influence of a myriad of environmental factors on performance in sports and describes how improvements in forecasts are measured when accounting for these factors. In section 2.6, the results are presented and discussed. Finally, section 2.7 draws conclusions and identify important implications for forecasting in sports and in wider contexts.

2.2. Complexity of a decision and Forecasting

The complexity of a decision concerning future states of the world is related to a range of factors, including the volume and heterogeneity of information (Doerner, 1980; Timmermans, 1993), the dynamic nature of the context being studied (Hogarth, 1987) and the ability to discriminate alternatives based on individual attributes (Tversky, 1972). Discriminability is, in turn, determined by relative similarity (Biggs et al., 1985; Bockenholt, 1991), ambiguity (Ritov and Baron, 1990), ability to unravel and incorporate relevant opaque attributes of interrelated variables or constructs (Brehmer, 1992), and the complexity of the relationships between the decision attributes (Sung and Johnson, 2009). With an increase in decision complexity, a decision maker's ability to discriminate relationships diminishes and feedback tends to become more ambiguous (Brehmer and Allard, 1991). This makes it difficult to learn and to develop solutions that are logically correct (Berry and Broadbent, 1984), thus making it difficult to understand and predict behaviour and future states of the world. Consequently, when trying to forecast the behaviour of such constructs, individuals may avoid incorporating information that is not fully comprehended (as imprecision in one or more parameters may lead to misleading forecasts) or they may increasingly rely on simplification and heuristics (Payne et al., 1993). In either case, this is likely to lead to an increase in the number of errors (Reason, 1990) and systematic biases (Harvey et al., 1994; Kahneman and Tversky, 1982), to less accurate probability judgments (Wright et al., 1996) and to a reduction in the quality of forecasts (Goodwin and Wright, 1994).

Consequently, it is predicated that the complexity in understanding the manner in which living beings respond to environmental factors often leads to a failure to fully use available environmental information when making forecasts. To support this claim, this paper explores the extent to which forecasting performance can be improved by incorporating environmental factors, in a field that is renowned for the accuracy of its forecasts. In particular, the forecasts developed incorporating the influence of environmental conditions on performance are compared to the odds related to the outcome of the sporting event obtained from a liquid betting market. Odds in these markets effectively represent the combined probability forecasts of all market participants. Studies have consistently demonstrated that predictions based on final odds are better than forecasts based on many other methods, including aggregate fast and frugal predictions made by lay people (Serwe and Frings, 2006; Spann and Skiera, 2009), predictions of experts (Forrest and Simmons, 2000) and statistical models using fundamental variables (Benter, 1994). According to the efficient market hypothesis (Fama, 1970), odds should reflect all available information in the market, including the effect of past and current environmental conditions on performance (Figlewski, 1979), and should quickly adjust for changes (such as changes in the weather) before the start of the contest. Consequently, odds provide a testing benchmark of predictive accuracy. If it can be shown that the influence of environmental conditions on fundamental performance in sports have not been fully incorporated into final odds this will demonstrate that these factors are often neglected in sports forecasting. Furthermore, this paper compares the returns achievable from bets placed using (i) odds as the basis of forecasts of the probabilities of the outcome of the sporting events and (ii) probability forecasts that account for environmental conditions. The differences in the returns achievable will serve to demonstrate the importance of accounting for environmental conditions when forecasting performance in sports.

2.3. Horseracing and the influence of the environment on performance

2.3.1 Horseracing Markets

In order to answer the proposed research question concerning the extent to which accounting for environmental factors can improve forecasts of sports performance, a sport is chosen where the results are the subject of a well-established betting market. This then provides this research with a testing benchmark of the quality of the forecasts developed that incorporate the influence of environmental factors on performance. In particular, this paper examines thoroughbred horseraces and their associated betting markets. These provide the opportunity to explore the relative effect of different environmental conditions on the performance of both humans and animals engaged in a co-operative task in a naturalistic setting. In addition, predicting the results of horseraces is a difficult and complex task. The final outcome is determined by a large range of factors, including opaque and more difficult to discern constructs, such as horses' and jockeys' preferences for different distances and their individual ability to cope with different environmental conditions (Benter et al., 1996). Furthermore, thoroughbred races are outdoor events which occur all year round and, consequently, horses and jockeys are directly exposed to a myriad of environmental conditions. It is widely held in the horseracing literature that the performances of horses and jockeys are sensitive to environmental conditions (Figlewski, 1979; Johnson et al., 2010), but little hard evidence for this relationship exists. Consequently, this motivates the first hypothesis:

H1. The performances of horses and jockeys are affected by environmental conditions.

If evidence is found to support H1, then in order to answer the proposed research question, it will be important to develop a forecasting methodology which can effectively account for the relationship between environmental conditions and horses' and jockeys' performances. Consequently, such methodology is developed and uses to test the second hypothesis:

H2. The accuracy of winning probability forecasts can be improved by incorporating the influence of environmental conditions on the performance of horses and jockeys.

Simply establishing that it is possible to effectively forecast the impact of environmental conditions on the performances of horses and jockeys is not sufficient to fully answer the proposed research question. Rather, this paper is keen to establish to what extent these factors are generally considered by the public when forecasting the results of sporting events. To achieve this, it is necessary to identify whether a tough benchmark, a public forecast which has been shown to be well calibrated, already accounts for these factors. In addition, it is necessary to establish to what extent the forecasts produced by the methodology developed improve on these public forecasts. The well-known efficient market hypothesis (Fama, 1970) postulates that public odds fully incorporate all relevant information available to performance. For instance, it has been widely evidenced that odds provide powerful predictors of sports outcomes (Strumbelj and Sikonja, 2010; Forrest et al., 2005). In particular, it has been well established that odds on horseraces provide well-calibrated forecasts of each horse's winning probability (e.g. Lessmann et al., 2010; Johnson and Bruce, 2001). Therefore, odds provide a robust benchmark to test H2, as environmental conditions should be fully incorporated into odds[2].

If evidence is found to support H2, consequently, it is necessary to verify the economic significance of incorporating environmental conditions on the performance of horses and

[2] The recent strand of economic Darwinism literature postulates that investors that populate markets in the long-run have been shown to be the ones with logarithmic utility functions and with the most nearly correct beliefs (Johnstone, 2007b). As the examination of bettors' utility functions lies beyond the scope of this paper, in addition to the widely accepted view in the literature that market dynamics favours correctly informed bettors over misinformed bettors (e.g., Fama, 1970; Blume and Easley, 2006), this paper uses betting odds on the perspective of analysing the correspondence between forecasts of the representative bettor (i.e., the informational value contained in odds) and observed events (i.e., race outcomes).

jockeys. Economic improvements are directly associated with the accuracy of winning probability estimates (Johnstone, 2012; Lessmann et al., 2010). Hence, measuring the economic significance of incorporating environmental conditions on the performance of horses and jockeys will provide further evidence concerning the forecasting value of incorporating such influences. This motivates the testing of the third hypothesis:
H3. Economic gains can be made by using forecasts which account for the influence of environmental conditions on the performance of horses and jockeys.

2.3.2 The influence of environmental conditions on horses and jockeys

Horses and humans are likely to respond differently to different environmental conditions because each species possesses specialised body components and systems. In addition, individuals within a species have been shown to vary in terms of their reactions (Adamu et al., 2012). The factors that influence reaction to environmental conditions are now discussed.

The thermoregulatory function of mammals is directly impacted by exercise intensity and environmental factors. Vigorous exercise (e.g., running) demands enormous increases in horses' and humans' physiological capabilities in order to provide sufficient metabolic energy to perform mechanical activities whilst regulating body temperature. The latter is very important as there is a fine margin between normal and lethal body temperature: 3°C for horses and 4°C for humans (Castanheira et al., 2010; Gonzalez-Alonso et al., 1999). Therefore, in colder temperatures the thermoregulatory system increases its thermogenesis and vasoconstriction activities to elevate body temperature, and in hotter temperatures engages in vasodilatation and increases perspiration to dissipate excess heat (Hodgson and McConaghy, 1994). The environmental conditions that are directly associated with influencing the thermoregulatory efforts in mammals are temperature, wind, humidity and rain (Hodgson and McConaghy, 1994; Geor et al., 2000; Hargreaves et al., 1999).

Air quality and atmospheric pressure have a direct impact on the ability of living beings to transform oxygen into metabolic energy. When air quality is poor, the levels of carbon monoxide present in blood cells tend to increase, thus, decreasing the capacity of blood cells to carry oxygen around the body; negatively influencing muscular performance and coordination (Walborg et al., 1967; Adams, 1987). Air quality is also associated with airway restriction and respiratory illnesses (Pierson et al., 1986). Atmospheric pressure directly influences the pressure of oxygen, and the balance between the oxygen and blood pressure is critical for the diffusion of oxygen into blood cells. For example, lower atmospheric pressures reduce the body's ability to metabolize oxygen, leading to rapid muscle fatigue (Draper and Marshall, 2014).

Geomagnetic activity and sunlight exposure have been shown to influence the production of melatonin and serotonin by the pineal gland. Imbalances in these substances affect the stability of circadian rhythms, which are directly related to mood and sleep disturbances and anxiety (Persinger and Levesque, 1983; Tarquini et al., 1998). Lack of sunlight exposure has also been linked to depression, the most common form being the seasonal affective disorder (SAD). The latter is a mood disorder that is commonly most severe during the winter months due to the reduced length of daylight. The psychological literature also suggests that mood is sensitive to moon cycles, an effect which is mediated by the influence of sleeping patterns on mood. The illuminance level of a full moon is 250 times greater than in the new moon phase, providing sufficient light to disrupt sleep quality and circadian rhythms (Smith et al., 2014). For example, Cajochen et al. (2013) provided evidence that, even when subjects slept indoors, they slept on average 25 minutes less during full moon nights and experienced less deep sleep. Importantly, a disruption in sleeping patterns has been strongly linked to mood disorder, irritability, stress, anxiety and depression (Lentz et al., 1999; Armitage, 2007).

Based on this survey of the medical and psychological literature, the environmental factors that can affect performances of horses and humans can be categorised into two groups: (i) Those that have a direct influence on their thermoregulatory systems and their ability to transform oxygen into energy, thereby leading to a physical impact on performance (i.e. temperature, humidity, wind, degree of precipitation, atmospheric pressure[3] and air quality); (ii) Those factors that have a direct influence on circadian rhythms and sleeping patterns, which can impact performance via their influence on state of mind/mood (i.e. geomagnetic activity, SAD, cloud cover and moon cycles).

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[3] There is also literature supporting the view that atmospheric pressure may have a direct influence on mood. However, this evidence is mixed (for a review: Digon and Bock, 1966; Goldstein, 1972). By contrast, the impact of atmospheric pressure on oxygen metabolization is widely accepted in the medical and psychological literature.

2.4. Data

The horseracing data used to test the hypotheses was supplied by Raceform Ltd. It consists of race starting times, horses' finishing positions and bookmaker final odds of each of 31,160 different horses (and 1,526 different jockeys) running in 30,425 flat races at 38 racetracks across the United Kingdom from 2000 to 2005. The average number of runners in each race was 11.51 (with a mode of 12) and the average number of races per horse (jockey) during the sample period was 10.7 (213.19). Races take place throughout the year on different underfoot (going) conditions, but the majority of races take place between May and August (53.55%) and on good/fast going conditions (80.8%). In order to avoid overfitting, the dataset is divided in two parts. The training sample is composed of races run between 2000-04 and the holdout (out-of-sample) sample is composed of races run in 2005.

The environmental conditions data were obtained from the Met Office Integrated Data Archive System (2000-05). The closest weather stations for individual racetracks were identified using their respective zip codes and weather data was collected at the start of each race (as opposed to at the scheduled start time). The weather data employed included temperature, wind speed, cloud cover, geomagnetic activity, humidity, atmospheric pressure, precipitation, air quality, and moon cycles. A numerical estimate for the seasonal affective disorder (SAD) was derived using the method developed by Kamstra et al. (2003)[4].

5. Procedures

The forecasting model developed is aimed to incorporate the maximum amount of information related to the impact of each of the environmental conditions on the performances of horses and jockeys. To achieve this, the approach employed was based on four fundamental principles: First, it incorporates how individual horses and jockeys cope with different environmental conditions. Second, it ensures that the influence of environmental conditions on an individual horse's or jockey's performance is updated at the end of every race. This, ensures that the approach allows for the fact that their ability

[4] Derived by:

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

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 a given racetrack.

to handle different environmental conditions may evolve over time. Third, it incorporates the interaction of the ability of both horses and jockeys to handle the environmental conditions; as final performance may, at least in part, be a function of this interaction. Fourth, it adjusts performance estimates associated with different environmental conditions to account for competition. This is undertaken because a horse/jockey's performance is likely to be dependent on the competitiveness of the field.

Consequently, 'preference variables' are developed to account for the ability of individual horses and jockeys to cope with different environmental conditions (see Benter, 1994, 1996), as well as catering for the fact that this ability may change/evolve over time. Subsequently, conditional logit models are employed in order to account for the interaction between horses and jockeys and for the influence of competition on performance.

Although the performance of a horse is not independent of the performance of its jockey, and *vice versa,* I decided to test H1 by capturing the performance sensitivity of individual horses and jockeys to different environmental conditions, by adapting an approach suggested by Benter (1994, 1996). Specifically, from their performance in a given race, it is computed, for any given horse or jockey, an estimate of the possible direction and magnitude of the effect of different environmental conditions on that horse's (jockey's) future performances and a 'preference variable' related to each (individual) environmental condition is created. These are referred as 'preference variables' because individuals may cope differently with different environmental conditions. Consequently, this is captured in their 'preference' for (or ability to cope/thrive under) particular environmental conditions (Gustavsson and Waern, 2002).

The performance of a horse's or jockey's is measured in terms of their race finish position. Consequently, in order to make finishing positions comparable across races with different numbers of runners, finish positions are normalised (NFP) within the range 0.5 (winner) to -0.5 (last finisher).

As discussed in section 2.3.1, the performances of horses and jockeys may be related to a myriad of factors, including more persistent concepts such as their athletic abilities and some more temporary phenomenon such as the current weather. In an attempt to have a better measure of the influence of the current environmental conditions on present performance, the long-term athletic ability of a horse (jockey), estimated by its average NFP (based on races throughout its career prior to the start of today's race), is subtracted from the observed NFP of today's race:

$$\Delta NFP_{ij} = NFP_{ij} - \left(\sum_{j=1}^{i} NFP_{i(j-1)} \Big/ (j-1) \right) \tag{2.1}$$

In order to evaluate how today's performance is influenced by current environmental conditions, in addition to allowing that individual's performance is updated at the end of every race and to maximise the use of all performance information available, linear regressions are estimated for individual horses (jockeys) and for separate environmental conditions after each race. In other words, following the completion of race j for an individual horse (jockey) i, ΔNFP_{ij} is measured and this is related to a particular environmental condition (e.g., x_{1j}) observed for race j. In order to predict the change in NFP expected for the following race (j+1) associated with environmental condition x_1 (i. e. $\Delta NFP_{i(j+1)x_1}$), the coefficients of the following linear regression are estimated, using the results of horse (jockey) i's previous j races:

$$\Delta NFP_{ijx_1} = \alpha + \beta x_{1j} \tag{2.2}$$

Then, the coefficients estimated in Eq. 2.2 (α and β) at race j are used to predict horse (jockey) i's ΔNFP in race $j+1$ when environmental variable x_1 takes the value $x_{1,j+1}$ (i.e. *predicted* $\Delta NFP_{i(j+1)x_1} = \alpha + \beta x_{1,j+1}$). This procedure is repeated after every race for all horses (jockeys) until their last race and for every individual environmental condition variable.

Having derived preference variables related to each of the environmental conditions, it was observed high correlation between some of the horse's (and jockey's) preference variables (see Table 2.1). For example, the correlation between a horse's preference for wind and geomagnetic storms is 0.929 and the correlation between a jockey's preference for temperature and SAD is 0.681. Overall, 90% (40%) of horse (jockey) related preference variable correlations exceeded 0.5. Consequently, approaches were examined for avoiding multicollinearity in the forecasting model, as this might lead to biased and unstable regression coefficients and poor forecasting performance (Friedman and Wall, 2005). One way of handling this problem would be to discard preference variables that are highly correlated. However, the review of the medical and psychological literatures, suggests that particular body functions may be influenced by a combination of different environmental conditions (e.g. thermoregulatory functions of mammals are directly influenced by temperature, wind, humidity and rain). Consequently, discarding preference variables may lead to a prediction model that fails to represent the true underlying influence of environmental conditions on the performance of horses and jockeys. This could produce a forecasting model that may not provide consistent predictive performance on new datasets (George, 2000).

A second approach to avoiding multicollinearity is to adopt a data reduction technique. This alternative is more appropriate for this study, as in data reduction it is not necessary to discard correlated predictor variables information from all preference variables when predicting performance. To achieve this, principal component analysis (PCA) are employed rather than other data reduction techniques, because there is evidence that PCA works well in combining predictors for forecasting (Poncela et al., 2011) while avoiding multicollinearity (Goia et al., 2010).

PCA involves combining preference variables into a smaller set of variables, called principal components, while ensuring that the estimated principal components maximize the informational retention from the original variables. This approach, therefore, maintains the relative relationships between the variables (Giri, 2004). In particular, from an initial set of *n* correlated preference variables, PCA is employed to create principal components $PC_1 \ldots PC_k$ which are derived as linear weighted combinations of the original preferences γ:

$$\begin{gathered} PC_1 = \propto_{11} \gamma_{ij1} + \propto_{12} \gamma_{ij2} + \cdots + \propto_{1n} \gamma_{ijn} \\ \vdots \\ PC_k = \propto_{k1} \gamma_{ij1} + \propto_{k2} \gamma_{ij2} + \cdots + \propto_{kn} \gamma_{ijn} \end{gathered} \tag{2.3}$$

where α_{kn} is the weight of the *k*th principal component and the *n*th environmental condition preference variable γ for a horse or jockey i in race j. The weights of each α_{kn} are derived by the eigenvectors of the correlation matrix, and the variance σ_k^2 of each estimated principal component k, is given by the eigenvalue of the corresponding eigenvector. The order of the estimation of the components requires that the first principal component explains the largest possible degree of variance among preference variables, the second component explains the second largest possible degree of variance, and so on, up to PC_k. All the principal components are subject to $(a_{k1}^2 + a_{k2}^2 \ldots + a_{kn}^2) = 1$. The proportion of variation accounted for by individual components is given by σ_k^2/n, and the sum of the eigenvalues is equal to the number of original variables. Components with eigenvalues lower than 1 account for less variance than had been contributed by an individual variable and components' scores may be unreliable when their eigenvalues are lower than 1 (Kaiser, 1958).

Table 2.1. Correlation analysis of horse and jockey preference variables

		Horses										Jockeys									
		Temp.	Wind speed	Pressure	Precipitation amount	Humidity	Air quality	SAD	Cloud	Moon Phases	Geomag. Storms	Temp.	Wind speed	Pressure	Precipitation amount	Humidity	Air quality	SAD	Cloud	Moon Phases	Geomag. Storms
Horses	Temperature	1.000																			
	Wind speed	0.885	1.000																		
	Pressure	0.867	0.898	1.000																	
	Precipitation amount	0.467	0.479	0.465	1.000																
	Humidity	0.840	0.821	0.805	0.430	1.000															
	Air quality	0.888	0.900	0.876	0.476	0.827	1.000														
	SAD	0.809	0.755	0.734	0.445	0.710	0.744	1.000													
	Cloud	0.591	0.603	0.591	0.311	0.550	0.600	0.494	1.000												
	Moon Phases	0.599	0.618	0.605	0.314	0.558	0.609	0.500	0.413	1.000											
	Geomag. Storms	0.897	0.929	0.900	0.491	0.831	0.920	0.769	0.609	0.625	1.000										
Jockeys	Temperature	0.045	0.032	0.029	0.017	0.034	0.033	0.042	0.020	0.018	0.031	1.000									
	Wind speed	0.026	0.030	0.024	0.013	0.023	0.027	0.025	0.018	0.015	0.026	0.494	1.000								
	Pressure	0.021	0.022	0.027	0.012	0.020	0.023	0.020	0.013	0.013	0.022	0.510	0.535	1.000							
	Precipitation amount	-0.003	-0.001	-0.002	0.001	-0.002	-0.002	0.001	-0.004	-0.001	-0.003	0.077	0.087	0.095	1.000						
	Humidity	0.027	0.024	0.021	0.011	0.033	0.026	0.028	0.014	0.015	0.024	0.601	0.490	0.532	0.091	1.000					
	Air quality	0.026	0.025	0.022	0.013	0.023	0.033	0.024	0.017	0.014	0.025	0.546	0.488	0.491	0.090	0.514	1.000				
	SAD	0.036	0.027	0.023	0.017	0.031	0.030	0.054	0.017	0.016	0.026	0.681	0.474	0.493	0.113	0.557	0.507	1.000			
	Cloud	0.021	0.021	0.020	0.011	0.019	0.021	0.022	0.027	0.013	0.021	0.420	0.423	0.426	0.076	0.429	0.437	0.404	1.000		
	Moon Phases	0.021	0.022	0.021	0.009	0.020	0.022	0.019	0.016	0.022	0.022	0.498	0.508	0.513	0.090	0.500	0.488	0.483	0.428	1.000	
	Geomag. Storms	0.024	0.024	0.022	0.011	0.022	0.025	0.024	0.017	0.015	0.025	0.496	0.502	0.507	0.084	0.494	0.478	0.482	0.421	0.506	1.000

Consequently, the Kaiser criterion is adopted and only principal components with eigenvalues larger than 1 are considered. Having established which components were to be retained, a varimax orthogonal rotation with Kaiser normalization was performed in order to minimize the correlation among components while maximising the variance of the components loadings; thereby facilitating interpretation of the estimated components.

2.5.1 Validation procedures for environmental conditions preference variables

In order to assess the forecasting value of the principal components derived from the above procedure, a two-stage conditional logit regression model (CL) was adopted.

The CL model (McFadden, 1974) has been widely adopted in horserace forecast studies (e.g., Lessmann et al., 2009; Johnson et al., 2010; Bolton and Chapman, 1986). One of CL's distinctive advantages for this research stems from the fact that it enables the winning probability of a particular horse and jockey pair to be estimated in conjunction with the other horse and jockey pairs in a given race, thus, incorporating the within-race competition when estimating winning probabilities (Lessmann et al., 2010).

The two-stage CL approach involves estimating a CL model incorporating fundamental variables in the first stage (i.e. environmental preference principal components) to predict winning probabilities. This will provide a means of measuring the extent to which the performance of horses and jockeys are affected by environmental conditions; thus providing means to test H1. The probabilities generated in the first stage CL are used as predictors in a second CL model (stage 2), which also incorporates betting odds implied probabilities. There are important benefits of incorporating the probabilities generated in the first-stage into the second stage CL model (cf. to including the environmental preference components directly as predictors in the second stage). In particular, it has been shown that this enables more predictive information from fundamental variables in the first stage to be distilled (Sung and Johnson, 2007). If environmental preference components are included directly as predictors, the dominant predictive influence of betting odds may overwhelm the more subtle, although nonetheless important, predictive ability of the environmental preference components, when they are regressed together in a single stage model. Therefore, the two-stage methodology maximizes the extraction of the predictive information contained within fundamental variables, as environmental preference components will only compete for predictive importance among themselves in the first-stage (Sung and Johnson, 2007). By comparing the coefficients of betting odds-implied probabilities and the winning probabilities derived from the environmental preference components (from stage one) in the second stage CL, it will be possible to assess the extent to which incorporating the influence of environmental conditions on the performance of horses and jockeys can improve winning probability forecasts derived from betting odds; therefore providing a means of testing H2. The CL approach is now explained in further detail.

(*i*) *Stage one: Fundamental model*

Stage one only incorporates environmental conditions principal components as predictors. The formulation of the first stage CL model begins by estimating the horse and jockey pair *t*'s ability to win race *j*,

$$W_{tj} = \sum_{l=1}^{m} \beta(l) x_{tj}(l) + \varepsilon_{tj}, \tag{2.4}$$

where $\beta(l)$, for $l = 1,\ldots,m$, are the coefficients that determine the importance of the environmental conditions principal components ($x_{tj}(l)$) (i.e. measuring preferences for different environmental factors), and W_{tj} is a win/lose dichotomous variable for the horse and jockey pair *t*, in race *j* with *n* runners, defined as:

$$\begin{cases} w_{tj} = 1 \; if \; W_{tj} = Max\left(W_{1j}, W_{2j,} \ldots, W_{n_j j}\right) \\ w_{tj} = 0 \; otherwise \end{cases} \tag{2.5}$$

Assuming the independent errors ε_{tj} are identically distributed according to the double exponential distribution, the estimated winning probability for the horse and jockey pair *t*, p_{tj}, is given by:

$$p_{tj} = Pr\left(W_{tj} > W_{tj}, t = 1,2, \ldots, n_j\right) = \frac{exp\left[\sum_{l=1}^{m} \beta(l) x_{tj}(l)\right]}{\sum_{t=1}^{n_j} exp\left[\sum_{l=1}^{m} \beta(l) x_{tj}(l)\right]} \tag{2.6}$$

The coefficients $\beta(l)$ are estimated by maximizing the joint probability of observing all the race results in the training dataset. This procedure is achieved by maximizing the log-likelihood (*LL*) of the full model (i.e. one including all predictors variables in which are of interest):

$$\ln LL(full) = \sum_{j=1}^{N} \sum_{t=l}^{n_j} y_{tj} \, ln \, p_{tj} \;, \tag{2.7}$$

where $y_{tj} = 1$if horse and jockey pair *t* won race *j* and $y_{tj} = 0$ otherwise, and *N* is the total number of races in the training dataset. The McFadden's R^2 was computed to measure the degree to which the environmental conditions explain winning probabilities:

$$R^2 = 1 - \frac{lnLL(M_{Full})}{lnLL(M_{Null})} \tag{2.8}$$

where LL is the log-likelihood of the estimated model, and M_{Full} is the model with predictors (e.g. environmental conditions principal components) and M_{Null} is the model without predictors.

(*ii*) *Stage two: Combining fundamental and betting odds information*

In the second stage, a CL is estimated with two predictors: the natural logarithm of the environmental conditions probability estimates p^e for the horse and jockey pair t in race j (p^e_{tj}), as derived from stage one CL, and the natural logarithm of betting odds implied probabilities p^o for the horse and jockey pair t in race j, defined as $p^o_{tj} = 1/(odds_{tj} + 1)$. Consequently, the final estimated model probability in the second stage for the horse and jockey pair t in race j is obtained as follows:

$$p^f_{tj} = \frac{exp\left(\tau ln\left(p^e_{tj}\right) + \ \omega ln(p^o_{tj})\right)}{\sum_{t=1}^{nj} exp\left(\tau ln\left(p^e_{tj}\right) + \omega ln(p^o_{tj})\right)} \tag{2.9}$$

where τ and ω are parameters that are estimated using maximum likelihood procedures. If the parameter τ is statistically significant, this will suggest that betting odds are not fully incorporating the influence of environmental conditions on the performance of horses and jockeys.

In order to assess the additional predictive value of incorporating the influence of environmental conditions on performance, a log-likelihood ratio test (LR) was performed. This compares the amount of predictive information contained in the CL model incorporating both odds and environmental preference principal components as predictors with that contained in a CL model incorporating only betting odds probabilities as predictors (referred as benchmark CL hereafter). This test is calculated as $LR = -2\left[(L_B) - \left(L_f\right)\right]$, where L_f is the LL of the CL model containing odds and environmental conditions predictors, and L_B is the LL of a CL model only containing betting odds implied probabilities as a single predictor. The probability of the difference is distributed χ^2_n, where n is the difference between the total number of parameters estimated in the benchmark CL and second stage CL models. If the LR is statistically significant, it will provide evidence of the improved winning probability forecasts achievable by incorporating the influence of environmental conditions on the performance of horses and jockeys.

Next, the in-sample coefficient estimates of the benchmark CL and the second stage CL incorporating environmental conditions variables are used to forecast winning probabilities for the holdout sample. Comparing the calibration of the forecasts from these models will allow to test H2. The calibration of winning probability forecasts can be measured using the Brier scores (the arithmetic mean squared error of a model's forecast probabilities) and the area under the ROC (measuring the goodness-of-fit of discrete response models). Brier scores can vary between 0 and 1, where 0 is perfect prediction, and the area under the ROC curve varies between 0.5, indicating no prediction power, to 1, indicating perfect prediction. In a similar manner to Sung et al. (2016), out-of-sample forecast calibration was also measured by comparing the pseudo-R^2s from a CL model with predicted probabilities for the holdout races derived from the benchmark CL as covariate and from a CL model with the probabilities derived from the two stage CL as covariate. A CL modelling procedure develops coefficients for the covariates to maximise the probability of success for the horse and jockey pair that turns out to be the winner (i.e. maximises the winning probability for the eventual winning competitor given the explanatory variables entered in the model). Consequently, the pseudo-R^2 will provide an additional measure to compare the calibration of the winning probability forecasts derived from the benchmark CL and the two stage CL.

In order to test H3, it is necessary to assess the economic impact of incorporating the influence of environmental conditions on the performance of horses and jockeys when forecasting winning probabilities. To achieve this, two betting strategies are simulated, one based on winning probability forecasts which incorporate environmental conditions preferences (as computed by the two stage CL), and the other using winning probabilities derived from betting odds only, derived from the benchmark CL.

These winning probabilities are used as the basis of two separate Kelly betting strategies (Kelly 1956), and the returns obtained from these strategies on the holdout races are compared. The Kelly strategy is employed as its final performance is directly dependent on the calibration of the forecast probabilities (e.g., see: Johnstone, 2007, 2011, 2012; MacLean et al., 1992). Comparing the returns achievable by the two Kelly betting strategies will provide a means to assess the economic gains associated with predictive improvements of incorporating the influence of environmental conditions on the performance of horses and jockeys. The Kelly criterion assumes that a fraction $f_j(v)$ of wealth is bet on the horse and jockey pair v in race j. Let $f_j = \left(f_j(1), \dots, f_j(m_j)\right)$ be the total fraction of wealth bet on race *j* with m runners. Given that the horse and jockey pair t wins race *j,* the current wealth is projected to increase by a factor of $1 - \sum_{t=1}^{m_j} f_j(t) + f_j(t)(O_{tj} + 1)$. The Kelly criterion consists of selecting f_j that maximises the expected log winnings, $F(f_j)$, such as:

$$F(f_j) = \sum_{t=1}^{m_j} p_{tj}^{\varphi} log\left(f_j(t)(O_{tj} + 1) + 1 - \sum\nolimits_{i=t}^{m_j} f_j(t)\right) \tag{2.10}$$

where p_{tj}^{φ} are the predicted winning probabilities, as estimated by the benchmark CL for the strategy derived from betting odds, and by a two-stage CL model including environmental conditions adjusted winning probabilities.

As indicated by Benter (1994), employing the Kelly betting strategy, can lead to very large bets being recommended as wealth levels increase later in the sequence of bets. In order to avoid the success of a betting strategy being artificially biased by the result of one or two large bets in the sequence of betting, a fractional Kelly strategy without re-investment of winnings is employed. Specifically, a 0.5 Kelly strategy is employed, whereby it bets 50% of the recommended Kelly bet ($f_j(t)$) in a given race and the bank size used to calculate the size of bets is returned to unity after each bet, independently of the outcome of that bet.

The success of the betting strategy is measured by determining the total increase in wealth as a result of applying the strategy and by calculating the Sharpe-ratio (Sharpe, 1994). The latter is a widely adopted measure of risk-adjusted investment performance and involves computing the ratio of mean returns of a betting strategy to its standard deviation (Lessman et al., 2012).

Should a Kelly betting strategy on the holdout data produce better returns when it is based on winning probabilities estimated using the two stage CL model (incorporating both odds implied probabilities and probabilities based on the environmental preference components) than when based on winning probabilities derived from a CL model simply incorporating odds-implied probabilities, this will provide evidence to support H3. Specifically, this will imply that more calibrated forecasts and consequently, significantly higher returns can be achieved by incorporating environmental preference components when forecasting horserace performance.

2.6. Results

2.6.1 Environmental Preference Variables

A summary of the estimated individual horse and jockey preference variables for each of the environmental conditions are presented in Table 2.2. Interestingly, horses, on average, display a positive preference for all environmental conditions studied (i.e. perform better the higher the values of the environmental factors: e.g., in higher temperatures, air pressure etc.), whereas jockeys perform better the lower the values of these environmental factors. This observation is consistent with the *a priori* belief that humans and horses may respond differently to different environmental conditions due to their specialised body components and systems (Dawkins, 1976). As discussed in section 2.5.1, PCA was employed to combine the environmental conditions preference variables into uncorrelated components, with the objective of avoiding multicollinearity when predicting winning probabilities.

Table 2.2 Individual horse and jockey environmental preference variables: Summary statistics

		Mean	Std. Dev.	Min	Max
Horse Preferences	Wind	0.0077	0.0682	-0.3089	0.3271
	Pressure	0.0068	0.0631	-0.3469	0.3626
	Temperature	0.0078	0.0626	-0.2962	0.3783
	Humidity	0.0074	0.0686	-0.3613	0.4201
	Precipitation	0.0098	0.1675	-4.5244	3.2867
	Air quality	0.0084	0.0718	-0.3726	0.3562
	SAD	0.0089	0.0836	-0.4572	0.4542
	Cloud	0.0001	0.0777	-0.4590	0.4241
	Moon	0.0065	0.0860	-0.4245	0.4798
	Geomagnetic storms	0.0084	0.0740	-0.3630	0.3738
Jockey Preferences	Wind	-0.0008	0.0344	-1.7532	0.7972
	Pressure	-0.0008	0.0340	-0.8414	0.7386
	Temperature	-0.0004	0.0362	-0.7639	0.6509
	Humidity	-0.0007	0.0353	-0.8054	0.7878
	Precipitation	-0.0080	0.1062	-4.4143	4.4255
	Air quality	-0.0008	0.0359	-1.3175	1.4081
	SAD	-0.0005	0.0368	-0.5368	0.7826
	Cloud	-0.0004	0.0403	-1.6450	1.2461
	Moon	-0.0008	0.0344	-0.5581	0.5553
	Geomagnetic storms	-0.0007	0.0349	-1.2573	1.5349

The results of conducting the PCA with varimax rotation and Kaiser normalisation on all the estimated preference variables for horses and jockeys, using the training data related to races run between 1st January 2000 and 31st December 2004, are summarised in Table 2.3. In order to avoid overfitting when employing the environmental preference principle components in the forecasting procedures, all components' loadings were estimated using the training data only. For instance, for the out-of-sample forecasting procedures, the in-sample loadings, as displayed in Table 2.3, were paired with out-of-sample preference variables in order to estimate out-of-sample environmental preference principal components.

Table 2.3 Principal components (with eigenvalues > 1) and associated component loadings with Kaiser normalised varimax rotation, determined using the training dataset of races run between 1st January 2000 and 31st December 2004.

		Component 1	Component 2
Horse Preferences	Wind	**0.3540**	-0.0011
	Pressure	**0.3471**	-0.0022
	Temperature	**0.3527**	0.0006
	Humidity	**0.3305**	0.0002
	Precipitation	0.2044	-0.0022
	Air quality	**0.3514**	-0.0002
	SAD	**0.3120**	0.0039
	Cloud	0.2523	-0.0011
	Moon	0.2554	-0.0034
	Geomagnetic storms	**0.3592**	-0.0018
Jockey Preferences	Wind	0.0001	**0.3288**
	Pressure	-0.0010	**0.3365**
	Temperature	0.0037	**0.3565**
	Humidity	0.0001	**0.3441**
	Precipitation	-0.0030	0.0641
	Air quality	0.0004	**0.3323**
	SAD	0.0032	**0.3440**
	Cloud	0.0008	0.2893
	Moon	-0.0008	**0.3295**
	Geomagnetic storms	-0.0003	**0.3285**
Eigenvalue		7.184	4.919
Proportional Variance Explained		35.92%	24.60%
Cumulative Variance Explained		35.92%	60.52%

As indicated in section 2.5.1, to ensure that component scores are reliable, the Kaiser criterion (Kaiser, 1958) is adopted and only components with eigenvalues greater than one were included. This resulted in the two principal components displayed in Table 2.3, which together accounted for 60.52% of the total variance among the preference variables. In a similar manner to Fabrigar et al. (1999), preference loadings with magnitudes above 0.3 and below -0.3 were examined, as a means of determining the distinguishing features of each component. This led to the conclusion that component 1 is more representative of horses' preferences (referred to as *horse preference component*) and component 2 is more representative of jockey's preferences (referred to as *jockey preference component*). It is difficult to determine *a priori* the likely number and nature of components. However, the fact that these two components were identified is further confirmation of the belief that individuals 'within' a species (i.e. horses or jockeys in this case) respond and adapt similarly to environmental stimuli, and that different species respond and adapt differently.

Interestingly, no significant component reflected the categorisation of environmental variables into those that affect performance via physical or mood effects. This may be a reflection of the difficulty in isolating the specific influence on performance of different environmental conditions. For instance, when combined, a particular variable or set of variables can potentially magnify, diminish or counterbalance the impact on performance of other variables. For example, a horse with a preference for sunny conditions may be expected to perform well on a sunny day. However, if the same horse has a high preference for cooler temperatures and the current race is run in hot weather, its preference for cooler temperatures may diminish the positive influence of sunny conditions on performance. Consequently, as the overall impact of environmental conditions on performance will result from a combination of all factors acting together, this may hinder the PCA from extracting components that reflected the categorisation of environmental variables into those that affect performance via physical and mood effects.

2.6.2 Aggregate predictive value of environmental preference components

This section evaluates the relative degree of importance of horses' and jockeys' environmental preference components in determining winning probabilities by assessing the in-sample explanatory value of the two estimated environmental preference components. This was achieved by developing a CL model in the form of Eq. 2.6. This model included the horse preference and jockey preference components presented in Table 2.3. An interaction term between horse and jockey preferences was included in order to capture the simultaneous influence of environmental conditions on horse and jockey pairs.

Table 2.4 Coefficients and test statistics of a conditional logit model with horse and jockey environmental conditions preference components, estimated using the 25,123 races (18,470 horses) in the training sample period (1st Jan 2000-31st Dec 2004)

Variables	Coef.	Standardised Coef.	Std. error	Z-score (p-value)
Horse preference component	0.1225	0.3279	0.0029	40.90** (0.000)
Jockey preference component	0.0275	0.0598	0.0035	7.77** (0.000)
Interaction horse and jockey components	-0.0027	-0.0158	0.0013	-2.08* (0.037)
Log-likelihood		-41024.75		
pseudo-R^2		0.0213		

Note:

**Indicates significance at the 5% level*

***Indicates significance at the 1% level*

The results of estimating the CL model based on the training dataset are presented in Table 2.4. The signs of horse and jockey preference component coefficients are positive, which is consistent with *a priori* theoretical expectations that larger preferences should lead to higher predicted winning probabilities. In particular, horse and jockey components are composed of a combination of environmental conditions for which they have demonstrated a preference. Therefore, the positive coefficient suggests that, when combined, higher values for the environmental conditions for which horses/jockeys have shown a preference, lead to higher predicted winning probabilities.

The results also show that the horse/jockey interaction term is negative and statistically significant. One might expect this coefficient to be positive, since this would suggest that when both horses and jockeys have conditions which they favour, their overall performance should be significantly improved. However, this could suggest that current environmental conditions are influencing the performance of horses and jockeys in a slightly different manner, and the negative coefficient is moderating this simultaneous influence. For instance, the preference variables are only measuring the expected final performance relative to environmental conditions and do not provide any clues as to how/why this performance is achieved. For example, suppose that for a particular horse and jockey pair, they both exhibit a preference for high temperature. The horse's higher temperature preference may arise because it enables the horse to run faster in the early stage of a race, leading to above average performance. On the other hand, the higher temperature preference for the jockey may arise because s/he has found in previous races that in these conditions s/he has more energy to push a horse to sprint faster at the end of the race. If the jockey only acts on his/her preference s/he may hold the horse back in the early stages. In such circumstances the jockey's temperature preference may nullify the horse's advantage, leading to a negative interaction for this horse/jockey combination. In an attempt to measure the relative importance of the jockey and horse preference components, these components were standardised prior to estimating the CL models (by subtracting the mean of each variable and dividing it by its standard deviation). Under standardization, the predictors are measured on the same scale, and the resulting coefficients can, therefore, be interpreted as the magnitude of their importance when explaining winning probabilities. The standardised coefficients presented in Table 2.4 provide evidence that horse preferences account for most of the variation in winning probabilities, as the coefficient for the horse component is 5.48 times greater than the coefficient for the jockey component (standardized coefficients of 0.3279 and 0.0598 for the horse and jockey preference components, respectively). The significance of the horse and jockey preference components (z-scores of 40.90 and 7.77 for horse and jockey preference components, respectively) indicates that both variables extract valuable information concerning the influence of environmental conditions on the performances of horses and jockeys; providing support for H1.

2.6.3 Improvement in forecasting performance by incorporating the influence of environmental conditions

Having established the influence of environmental conditions on the performance of horses and jockeys, it is necessary to measure the extent to which incorporating this influence can improve winning probability forecasts. In particular, I assessed if betting odds, which represent the public's combined view of the winning probability, fully account for environmental factors. If evidence indicates that this is not the case, I assessed to what extent forecasts could be improved by incorporating these factors. This is accomplished this by comparing the forecasting performance of a CL simply incorporating odds implied probabilities (the benchmark model) and a two stage CL model (in the form of Eq. 2.9). The covariates of this latter model included the odds implied winning probabilities together with winning probabilities derived from a CL incorporating the horse and jockey environmental conditions preference principal components shown in Table 2.4. The coefficients for the horse and jockey environmental conditions preferences principal components were estimated on the training sample of races run between 2000 and 2004 (i.e. the coefficients shown in Table 2.4). In this initial analysis, both the benchmark CL model and the two stage CL model were estimated only using training races run between 2000 and 2004 and the results are displayed in Table 2.5.

Table 2.5 Coefficients and test statistics of the benchmark conditional logit model and the two-stage conditional logit model incorporating both odds implied probabilities and probabilities derived from a CL model incorporating environmental conditions principal components; all models being estimated using the training dataset of races between 2000 and 2004.

Variables	Benchmark CL			Two-stage CL		
	Coef.	Std. error	Z-score	Coef.	Std. error	Z-score (p-value)
Odds implied Probabilities	1.156	0.333	97.25**	1.142	0.126	90.78** (0.000)
Environmental conditions probabilities (stage one CL)				0.091	0.026	3.45** (0.001)
Log-likelihood		-35902.39			-35896.52	
pseudo-R^2		0.1435			0.1437	

Note:

***Indicates significance at the 1% level*

These results indicate that odds alone are highly significant in explaining winning probabilities (benchmark CL pseudo-R^2 0.1435, z = 97.25), confirming the importance of odds as a predictor of winning probabilities, as shown in several previous studies (Strumbelj and Sikonja, 2010; Johnson and Bruce, 2001). The results of estimating the two-stage CL model, indicate that betting odds do not fully account for the influence of environmental conditions on the performances of horses and jockeys. This is demonstrated by the fact that the environmental conditions probabilities variable is significant at the 1% level (z-score of 3.45) and the pseudo-R^2 for the two-stage CL model is greater than that for the benchmark CL model (0.1437 and 0.1435, respectively: Log-likelihood ratio test significant at the 1% level (LR = 11.75, $\chi_1[0.01]=6.63$)). These results suggest that the variable *environmental conditions probabilities* provides information that is not contained in odds, and that forecasts of winning probabilities can be improved by incorporating this variable in a CL forecasting model.

Next, I examined the degree to which the accuracy of winning probability forecasts could be improved by incorporating the influence of environmental conditions on performance. This entailed using the coefficients estimated using the training sample data for the models displayed in Table 2.5, to predict winning probabilities for each horse and jockey pair in the out-of-sample races, run between 1st January 2005 and 30th December 2005. The accuracy of these forecasts were evaluated against the actual results of the races and the resulting measures of goodness-of-fit of the forecasts are presented in Table 2.6. In order to enhance the validity of results, the measures of goodness-of-fit were also calculated in a 5-fold cross-validation procedure. In the cross-validation procedure, the parameters of the models displayed in Table 2.5 were estimated on a subset of 80% of races, and the resulting model was used to forecast winning probabilities for the remaining 20% of races. This process was repeated on 5 non-overlapping partitions of equal size of the dataset, and the resulting out-of-sample goodness-of-fit measures represent the average results observed on these 5 partitions.

Table 2.6 Accuracy of winning probabilities

	Holdout Sample (01 Jan-30 Dec 2005)			5-Fold Cross-validation		
Model	Pseudo-R^2	ROC Area	Brier Score	pseudo-R^2	ROC Area	Brier Score
Benchmark CL	0.0943	0.7714	0.0793	0.1029	0.7826	0.0772
Two-stage CL	0.0944	0.7716	0.0791	0.1031	0.7829	0.0770

Whichever measure of forecasting accuracy was employed (pseudo-R^2, ROC area and Brier Score), the holdout sample winning probability forecasts based on the model incorporating the influence of environmental conditions on the performances of horses and jockeys (i.e. the two-stage CL model) were more accurate than the benchmark CL model (which simply incorporated betting odds implied probabilities). This was the case for results based on forecasts across the whole of the holdout sample and for the mean 5-fold cross validation results.

Taken together, the results presented in Tables 5 and 6 provide strong support for H2, namely, that the accuracy of winning probability forecasts can be improved by incorporating the influence of environmental conditions on the performance of horses and jockeys.

6.4 The economic value of accounting for environmental conditions when forecasting winning probabilities

This section measures the economic significance of incorporating these environmental preference components probabilities when forecasting winning probabilities for a horse and jockey pair in the races run during the holdout period (01 Jan – 30 Dec 2005). To achieve this, winning probabilities were computed based on the benchmark CL model (simply incorporating odds-implied probabilities) and the two-stage CL model (which incorporated both odds-implied probabilities and those derived from the horse and jockey's environmental preference components). For each of these models, coefficients were estimated based on the training sample of races (results shown in Table 2.5), and these were used in a CL model to determine winning probabilities for horse/jockey pairs running in races during the holdout period. These probabilities are then used to develop a 50% Kelly betting strategy, as outlined in section 2.5.2. The results of applying these betting strategies are presented in Table 2.7.

Table 2.7 A comparison of returns from a 50% Kelly betting strategy based on probabilities derived from the benchmark CL model and a two-stage CL model incorporating both odds-implied probabilities and those derived from the horse and jockey's environmental preferences, for the 5302 races in the holdout period (1st Jan- 30th Dec 2005)

Probabilities derived from:	No. Bets	No. races with profit	Amt. bet ($)	Profit ($)	Rate of ret. without reinvestment %	Sharpe Ratio
Benchmark CL	1466	553	28880.00	-1007.49	-3.48%	-0.0231
Two-stage CL	805	180	13688.89	1357.12	9.91%	0.0257

It is clear from the results displayed in Table 2.7, that the inclusion of the horse and jockey environmental preference components substantially enhanced the profits achievable from the Kelly betting strategy. The betting strategy employing the probabilities forecast by the benchmark CL model returned a loss of 3.48% and a negative Sharpe ratio of 0.0231. Although this strategy achieved profitable returns for 553 races, the positive returns of such races were mainly obtained when betting on favourites (77%

of the profitable bets were derived from betting odds of less than 2), and the average overlay for these bets was 2.71% (i.e. the ratio of benchmark CL probabilities to odds implied probabilities). This suggests that even for these profitable bets, the average returns were small. By contrast, the betting strategy employing probabilities derived from a CL model which accounted for the environmental preference components produced a substantial profit of 9.91% and a Sharpe ratio of 0.0257.

A bootstrap procedure was employed to determine whether the improvements in returns were significant. Consequently, random samples of races were drawn from the holdout period, with replacement, with each sample composed of the same number of races as in the holdout period. This procedure was repeated 1000 times. Then, for each of these 1000 samples of races it was determined the returns achievable using a 50% Kelly betting strategy based on winning probabilities forecast by the benchmark CL and the two-stage CL models. The resulting distributions of returns were used to test whether the difference in returns achievable using the benchmark and the two-stage CL models were statistically significant. The resulting t-test showed that the returns obtained from winning probabilities derived from the benchmark and the two-stage CL models were significantly different at the 1% level ($t\,(1000) = 30.97$, $p < 0.01$).

These results provide strong support for H3, namely that economic gains can be made by employing forecasts which account for the influence of environmental conditions on the performance of horses and jockeys. Furthermore, these results demonstrate that the betting public, despite being noted for the accuracy of the odds-implied winning probabilities they produce, fail to fully account for environmental influences on the performance horse and jockeys. There are clear financial incentives in betting markets for producing accurate probability estimates. In fact, there is strong weight of evidence that horserace bettors are proficient at incorporating a range of complex factors which can influence the results of horseraces (Johnson et al., 2010; Lessmann et al., 2010). Consequently, the fact that odds fail to fully account for the impact of environmental factors on horse and jockey performance, suggests that this is also likely to be the case in other sporting arenas, where betting markets may be less mature.

2.7. Conclusion

This study, to my best knowledge, is the first to explore the value of incorporating environmental conditions when forecasting performance in the context of sports. A methodology is developed to maximise the extraction of the influence of a myriad of weather and atmospheric conditions on the performance of horses and jockeys, and it was demonstrated empirically, that it is possible to effectively employ this information to improve forecast performance.

This paper faced the modelling challenge that environmental conditions were common for all contestants within a single race. By reviewing medical and psychology literature, it was identified that the same environmental conditions may influence individual humans and horses in different ways. Consequently, it was introduced the notion of 'preference' for these different environmental conditions. This provided a means to capture the unique manner in which these environmental conditions influenced the individual performance of horses and jockeys.

Furthermore, this paper demonstrated that it is possible to overcome the technical challenge posed by the fact that many of the environmental preference variables are correlated. This was achieved by aggregating preference variables into principal components, through PCA. This allowed to avoid multicollinearity issues whilst allowing the forecast methodology to make use of all preference variables when making predictions. As a result of this process, two key components were identified which were termed *horse preferences* and *jockey preferences;* the former consisting of factors which had a greater influence on the performance of horses and the latter consisting of factors which had a greater influence on the performance of jockeys. The observed differential impact of environmental factors on horses and jockeys is further supported by the fact that individuals within a particular species respond and adapt to external stimuli in a common manner, and that response and adaptation may differ between species (Dawkins, 1976).

Perhaps most importantly this paper demonstrated that not fully accounting for environmental conditions is likely to lead to sub-optimal forecasts of performance in sport. The *a priori* belief was that betting odds should have fully incorporated the effect of environmental conditions on performance. However, the results showed that this was not the case even for highly liquid horseracing markets. In fact, they demonstrated that significant improvements in the accuracy of winning probability forecasts could be achieved by appropriately accounting for environmental preference variables. This paper also demonstrated that the economic penalty associated with not accounting for these factors is substantial.

The findings of this study are potentially significant for a far wider variety of forecasts than those related to sports performance. It is likely that environmental factors, via their direct impact on physical performance and via changes in mood, can affect decision makers in a range of settings. The results reported here suggest that forecasts related to the behaviour and performance of living beings is likely to be considerably enhanced by accounting for the impact of environmental factors and that this could be undertaken by adopting the approach introduced here. Further work is clearly needed to examine the results obtained in this paper are mirrored in other sports and in wider settings, but this study certainly suggests that accounting for weather and atmospheric conditions may well help to improve forecasting accuracy in a broad range of settings.

3. 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, this research demonstrates 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, it is shown that significantly better forecasts can be derived from prediction markets, and that these have substantial economic value.

3.1 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[5] (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.

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,

[5] 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.

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, this paper examines 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 I 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, the prediction market examined is 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 the research question posed in this paper 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 this paper's 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 this paper finds that environmental conditions are affecting the accuracy of predictions derived from prices in horserace betting markets, it can be fairly confidently suggested that this will be the case in other prediction markets. Furthermore, the unequivocal nature of the outcome in these markets allows to test to what extent adjusting prices to account for environmental factors leads to better forecasts.

The 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 EC are expected to affect prices. Specifically, the results in this paper 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. Section 3.2 discusses the influence that EC may have on decision making and this discussion is used to motivate the proposed hypotheses. Section 3.3 discusses the features of the different mechanisms of sports prediction markets, and introduce the data used in this research. Section 3.4 describes the methods employed to test the proposed hypotheses. The empirical results are reported and discussed in section 3.5. Finally, section 3.6 draws conclusions and identifies important implications of this research for prediction markets and wider decision making contexts.

3.2 Environmental conditions, mood and prediction market forecasts

3.2.1 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 an 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).

3.2.2 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 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 wind have been associated with low mood[6].

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

[6] 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.

been linked to seasonal affective disorder (SAD), a medical condition which causes individuals to experience consistent low moods and depression (Kamstra et al., 2003).

3.2.3 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[7], 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. For example, Dowling and Lucey (2005) suggest that investors in negative (positive) mood states are more likely to undertake 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

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

influence on asset prices (e.g., Jacobsen and Marquering, 2008; Goetzmann and Zhu 2005; Pardo and Valor, 2003).

Particularly, a general limitation observed from previous studies is that there were often large time differences between the trades taking place and the weather observations 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). These are important limitations as they may have led to the mixed conclusion on the effects of EC on stock returns. In addition, no study in the context of financial markets has examined the influence that EC induced mood misattribution has on calibration of prices.

The research question in this paper is designed to fill this research gap and a methodology is designed to overcome the limitations 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 3.3.1, 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, it is postulated that EC may influence the analytical effort displayed by decision makers, which in turn may influence the calibration of their forecasts. If evidence is found to support H1, the following is proposed:

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, this paper employs bookmaker odds when testing the proposed 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 the estimation of the 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[8].

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. The review of the psychological and medical literature revealed that geomagnetic

[8] To ensure the robustness of the analysis to different cut-off points when determining the training and holdout samples, the analysis was conducted on different training and holdout samples, composed of different racing calendar years and compared the results with the ones reported in Tables 3.3, 3.4 and 3.5. 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 3.3 and 3.4. Equally, the relative economic performance of the betting strategies presented in Table 3.5 remained consistent across different samples. The results of these robustness checks suggest that the results presented in Tables 3.3, 3.4 and 3.5 are robust to different cut-off points for dividing the sample intro training and holdout datasets.

storms and full moon days may deteriorate mood, and therefore improve the quality of decisions. Consequently, following Dowling and Lucey (2005) '*geomagnetic storms*' were coded 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. A numerical estimate for the seasonal affective disorder (*SAD*) was derived based on Kamstra et al.'s (2003)[9] methodology. The descriptive statistics of the horseracing and EC variables are presented in Table 3.1.

Table 3.1 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

[9] Derived by

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

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.

3.4. Method

To test the proposed hypotheses, the following must be investigated: (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, regression analysis are employed to determine the EC factors that influence Brier scores, a widely adopted score function that measures the accuracy of probabilistic forecasts; thereby providing empirical evidence to test H1. To test H2, conditional logit models are employed 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. The coefficients of these models, estimated on the basis of the training sample data, are used to forecast winning probabilities for the holdout sample. Then, in order to test H2, Kelly betting strategies are based on the probability estimates derived from these models and the obtained returns are compared. The next section further examines the details of the methodology.

3.4.1. Deseasonalized Variables

Acclimation 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 acclimate to seasonal changes in the environment. This can potentially reduce or exacerbate the expected influence of EC on mood (Young et al., 1986). Furthermore, acclimation 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 acclimate 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., a temperature of 15°C may improve mood during the winter and cause a deterioration of mood during the summer). To address this, following Hirshleifer and Shumway's (2003) methodology, the EC included in the regression analyses are deseasonalized[10] (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 acclimate.

In addition, the process of deseasonalyzing EC variables, reduces the seasonal correlation among EC variables. For example, by deseasonalyzing the weather variables it is ensured that deteriorating weather conditions would not exclusively be observed during winter months and *vice versa* for summer months. In particular, by deseasonalyzing an EC variable, a deteriorating weather condition would occur if the EC variable in question were below the 'expected' weather condition for a particular month. Therefore, deteriorating 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).

3.4.2. 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.

An alternative approach is to adopt a data reduction technique. It is argued that this approach is more suitable to this study, as in data reduction all variables are retained, thus allowing information from all EC variables to be analysed. To achieve this, principal component analysis is employed, 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).

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

It achieves this by defining an orthogonal linear weighted combination of the EC variables observed on race *j*:

$$\begin{aligned} PC_1 &= \alpha_{11}X_{1j} + \alpha_{12}X_{2j} + \cdots + \alpha_{1n}X_{nj} \\ &\vdots \\ PC_m &= \alpha_{m1}X_{1j} + \alpha_{m2}X_{2j} + \cdots + \alpha_{mn}X_{nj} \end{aligned} \tag{3.1}$$

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, the Kaiser criterion is adopted and only PCs that achieve eigenvalues greater than one are considered.

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 3.2, accounted for 61.63% of total variance among the deseasonalized EC. The resulting PCs were labelled 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 '*deteriorating weather*' [11] (based on component weights of 0.767 and -0.62 for deseasonalized *wind speed* and *air pressure*, respectively), and component three was labelled '*wetter 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.

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

Table 3.2 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 Deteriorating 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

3.4.3 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 the methodology allow to control for the influence of EC on the performance of horses and jockeys. This approach, therefore, enables the methodology employed to isolate the influence of EC on the calibration of final market prices (potentially resulting from the ECs effects on the bettors' moods).

3.4.4 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, the Brier score (Brier, 1950) is employed as the 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:

$$BS_j = \frac{1}{N}\sum_{i=1}^{N}\left(f_{ij} - o_{ij}\right)^2 \tag{3.2}$$

where f_{ij} is the odds implied probability[12] 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, it is determined 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:

$$\begin{aligned} \text{Brier score}_j = \alpha &+ \beta_1 Preference\ Variable\ Variance_j \\ &+ \beta_d Horseracing\ Factors_j \\ &+ \beta_q Environmental\ Conditons_j + \varepsilon \end{aligned} \tag{3.3}$$

Each of the three variables in this model are now defined.

Horseracing Factors (d): 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

[12] 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 $f_{ij} = \left(\frac{1}{SP_{ij}+1}\right) \Big/ \left(\sum_{i=1}^{N} \frac{1}{SP_{ij}+1}\right)$

(Johnson and Bruce, 1993) and the bookmaker commission charged on the race (Vaughan Williams and Paton, 1998). All these factors are included 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). In turn, it is believed that this uncertainty is likely to be linked to the variance of the preference variable probabilities across 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 can potentially lead to poorer, less calibrated judgments, which in turn may suggest that the accuracy of forecasts derived from market prices will be lower. Consequently, the influence of preference variable variance on forecasting accuracy is controlled by including *Preference Variable Variance* in the regression model (Eq. 3.3).

Environmental Conditions (q): In order to assess the impact of EC on forecast accuracy, a range of EC variables are included in the regression (Eq. 3.3). In particular, it is included 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 *deterioration 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.

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

In order to test H2, it is examined the extent to which the accuracy of forecasts derived from market prices can be improved by correcting for mood misattribution bias. To achieve this, it is employed 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 $\mathbf{Y}_{ij} = [Y_{ij}^1, \ldots, Y_{ij}^h]$, 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

$$W_{ij} = \sum_{r=1}^{h} \beta_r Y_{ij}^r + \varepsilon_{ij} \tag{3.4}$$

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:

$$p_{Kj} = Prob(W_{Kj} > W_{ij}, i - 1,2 \ldots N_j, i \neq K) \tag{3.5}$$

Therefore,

$$p_{Kj} = Prob\left(\sum_{r=1}^{h} \beta_r (Y_{Kj}^r) + \varepsilon_{Kj} > \sum_{r=1}^{h} \beta_r \left(Y_{ij}^r\right) + \varepsilon_{ij}, i = 1,2 \ldots N_j, i \neq K\right) \tag{3.6}$$

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:

$$\begin{cases} t_{ij} = 1 \; if \; W_{ij} = Max\left(W_{1j}, W_{2j,} \ldots, W_{N_j j}\right) \\ t_{ij} = 0 \; otherwise \end{cases} \tag{3.7}$$

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

$$p_{Kj} = Prob\left(t_{Kj} = 1 | (p_{ij}), i = 1,2 \ldots, N_j\right) \tag{3.8}$$

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

$$p_{ij} = \frac{exp\left(\sum_{r=1}^{h} \beta_r Y_{ij}^r\right)}{\sum_{i=1}^{N_j} exp\left(\sum_{r=1}^{h} \beta_r Y_{ij}^r\right)} \tag{3.9}$$

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, three separate CL models are estimated using the training data. Then, the ability of these models to predict winning probabilities is compared. 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 3.4.3) 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.

The coefficients estimated for these three CL models (i.e. 'benchmark CL', preference CL' and 'EC CL') using the training sample, are used 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 (e.g., see: Johnstone, 2007, 2011, 2012; 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:

$$F(f_j) = \sum_{K=1}^{N_j} p_{Kj}^{\varphi} log\left(f_j(K)\left(O_{Kj} + 1\right) + 1 - \sum_{i=1}^{N_j} f_j\,(i) \right) \qquad (3.10)$$

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, a fractional Kelly strategy without re-investment of winnings is employed. 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, it is employed a 0.5 Kelly strategy, whereby 50% of the recommended Kelly bet ($f_j(i)$) is placed 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 the success of the betting strategies are measured 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

3.5 Results

The first set of results relate to the 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.

3.5.1 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. 3.3, to examine the impact of EC on the accuracy of forecasts derived from prices in prediction markets, are summarized in Table 3.3. 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 *deteriorating 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*.

Table 3.3 The influence of environmental conditions on Brier scores (i.e. forecast accuracy) of forecasts derived from market prices

	Variables	Coef.	Std. Error	*t*-value (p-value)
	Intercept	0.16216	0.00200	81.08 (0.000)
Environmental conditions	*Warmer, sunnier and drier weather component*	-0.00019	0.00009	-2.15 (0.032)
	Deteriorating weather component	-0.00022	0.00011	-2.00 (0.046)
	Wetter weather and poorer air quality component	-0.00003	0.00012	-0.27 (0.787)
	Geomagnetic storms	0.00027	0.00025	1.07 (0.285)
	Full moon	0.00019	0.00029	0.64 (0.522)
	SAD	-0.00018	0.00009	-1.96 (0.049)
Horseracing factors	*Bookmaker commission*	-0.00419	0.00188	-2.23 (0.026)
	No. Runners	-0.00654	0.00004	-149.16 (0.000)
	Handicap races	0.00728	0.00026	27.49 (0.000)
	Weekend races	0.00016	0.00029	0.54 (0.589)
	Last race	0.00010	0.00037	0.26 (0.795)
	First race	-0.00104	0.00036	-2.91 (0.004)
	Race class	-0.00168	0.00010	-17.47 (0.000)
	No. Bends	-0.00039	0.00008	-4.73 (0.000)
Preference	*Preference Variable Variance*	0.34539	0.04887	7.07 (0.000)
	Adjusted R^2	0.3513		

The negative coefficient for the *deteriorating 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, the opposite effect is found. 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 this 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. This demonstrates the intricate nature of the combined influence of different EC on mood.

Importantly, the fact that this analysis finds 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.

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

This section evaluates 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, three CL models are estimated using the training data and their ability to predict winning probabilities are compared. 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 3.4.

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 *deteriorating 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 3.3, 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, log-likelihood ratio tests (LR) were conducted 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, LR was 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. It is 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.

Table 3.4 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 (p-value)	Coefficient	Std. Error	Z-score (p-value)	Coefficient	Std. Error	Z-score (p-value)
Market price probabilities	1.15342	0.00586	196.75** (0.000)	1.150782	0.005947	193.52** (0.000)	1.14072	0.00916	124.57** (0.000)
EC Preference variable				0.062071	0.023723	2.62** (0.009)	0.06184	0.02371	2.61** (0.009)
Market price probs. • *warmer, sunnier and drier weather* component							0.01093	0.00419	2.61** (0.009)
Market price probs. • *deteriorating weather component*							0.01343	0.00525	2.56** (0.010)
Market price probs. • *wetter weather and poorer air quality* component							-0.00457	0.00573	-0.80 (0.424)
Market price probs. • *geomagnetic storms*							0.02189	0.01199	1.83 (0.067)
Market price probs. • *full moon*							-0.02135	0.01381	-1.55 (0.121)
Market price probs. • *SAD*							0.00722	0.00418	1.73 (0.083)
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).

It was 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, it should be able to significantly improve probability forecasts derived from market prices.

Consequently, it is examined the degree of improvement in forecasting accuracy which can be achieved by correcting for the mood misattribution bias. To achieve this, the three models presented in Table 3.4 (i.e. estimated using the training races) are used 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) and without reinvestment of the winnings (as outlined in section 3.4.5). The results of applying this strategy, using probabilities derived from the 'benchmark CL', 'preference CL' and 'EC CL' models, are presented in Table 3.5.

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 3.5, 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 prevents the possibility of drawing any firm conclusions related to these different odds probability ranges.

Table 3.5 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%**

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, returns were determined 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.

The influence of ECs on the forecast accuracy of market prices is further investigated. In particular, it is examined which ECs had the greatest impact on the forecasting accuracy of odds-implied probabilities. To achieve this, 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') is examined, and the returns achieved for this strategy under different ECs are compared. If, as proposed in H1, good (bad) mood leads to worse (better) calibrated forecasts, then it is expected 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, EC variables were categorised 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 3.6.

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.

Table 3.6 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%

3.6 Conclusion

The principal aims of this paper 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 my 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, it is observed 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, the methods employed controlled for the influence of EC on the performances of horses and jockeys. Consequently, the results obtained in this paper suggest that mood misattribution bias negatively influences the accuracy of forecasts derived from final market prices.

It was demonstrated a systematic link between current EC and the forecast accuracy of market prices, as measured by the Brier score. In fact, the results showed that the *warmer, sunnier and drier weather*, and the *deteriorating 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.

It was observed that although winning probability forecasts derived from market prices were 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. Then, this paper demonstrated that it is possible to improve significantly the forecast accuracy of market price probabilities by correcting for the misattribution bias detected and it is 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, the results obtained are consistent with the psychological literature which suggests that EC influence mood and judgments about the future, therefore, affecting the quality of forecasts about future states of the world.

This study suggests that even in prediction markets composed of skilled and experienced participants, the participants' judgments are influenced by EC, leading to less accurate forecasts. By correcting for this phenomenon, it is shown that significantly better forecasts can be achieved, and that these have substantial economic value.

In sum, this paper leads 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). The results in this paper 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.

4. Does good weather lead people to make good decisions? Evidence from a real-world financial decision making environment

Abstract

Research in psychology and neuroscience show that weather conditions can affect one's current mood. Importantly, research also show that decision biases can arise from misattribution of mood, a condition whereby current mood impairs an individual's ability to effectively process information. However, research on misattribution of mood in naturalistic financial markets provide inconclusive evidence of the influence of weather-induced mood on decision making, and if such effect exists, whether weather conditions associated with good or bad moods damage decision quality. A review on these studies indicates that shortcomings in previous research may be the foundation to these inconclusive results. This paper then proposes that investigating the influence of misattribution of mood on the level of favourite-longshot bias (FLB) (a phenomenon whereby favourites/longshots are under-/over-bet) displayed in horserace betting markets addresses all shortcomings identified in previous research. Studying the decisions from over 87,000 races across the United Kingdom, the results show that under weather conditions when individuals are expected to experience good mood (cf. bad mood), they over-/under-estimate the winning probabilities of longshot/favourite contestants at a greater extent, and that such effect inflict substantial economic cost on decision makers. These results remain significant when controlling for various factors known to influence the FLB, hence providing robust evidence to support the conclusions that weather-induced misattribution of mood can significantly affect decision making in a naturalistic setting, and that (in horserace markets) it is weather conditions associated with good mood which damage decision quality.

4.1 Introduction

Normative decision models require that individuals rationally and effectively deliberate on all available options prior to making a decision. However, many laboratory-based studies in psychology and neuroscience have shown that a range of behavioural factors, including mood and emotions, may affect our judgment and our decision making processes, often leading to sub-optimal decision outcomes. However, it has also been suggested that these behavioural factors may also assist the rational decision process. In particular, cognition and consciousness are revised and reconstructed with changes in mood and emotions (Slovic et al., 2004; Csikszentmihalyi and Larson, 1984). Consequently, it has been proposed that behavioural factors are important pillars of fully rational reasoning.

It is well established that the decision making process is composed of two systems of thinking that operate in parallel (Kahneman, 2011). The analytic system is based on cognitive and rational information processing rules, where logic strongly supports decision outcomes. This system is computationally effortful as decisions require conscious appraisals of outcomes based on reason and evidence validation. Decisions made by the experiential system are oriented by feelings, mood and emotions, leading to decisions that are almost automatically handled by the subconscious mind. Due to the relatively quicker process speed of the experiential system, affective reactions are the first responses generated when making-decisions. These subsequently provide guidance to the information processing and cognitive evaluations performed by the analytic system of thinking (Zajonc, 1980). When decisions involve greater levels of risk and uncertainty, the analytic system's deliberation costs associated with achieving an optimal decision become highly burdensome and resource intensive. In such situations, the cognitive system relies to a greater extent on feelings, mood and emotions (referred to collectively hereafter as mood)[13], leading to sub-optimal outcomes which are regarded as 'satisfactory' by the decision maker. For example, the analytic system may consider that the marginal cost of cognitive deliberation is greater than the benefit of reaching an optimal decision in an uncertain context, therefore increasing reliance on the experiential system (Loewenstein et al., 2001).

Consequently, mood is an important element to consider when investigating decision making rationality. This is particularly the case in decision environments characterised by more uncertain conditions, where mood may assist decision making processes by enhancing decision agility (e.g., supporting the speedy selection of relevant alternatives and facts to be evaluated by the analytic system) (Bechara et al., 1994).

However, mood has also been linked with decision making biases. In particular, it has been suggested that mood can impair rationality through 'misattribution of mood',

[13] Mood, feelings and emotions have intersecting definitions in the literature (see: Oatley and Jenkins, 1996). Rather than attempting to distinguish the effects of mood, emotions and feelings, on decision making, these will be collectively referred as 'mood' and their combined effects are examined throughout the paper.

a condition whereby mood, influenced by transient factors unrelated to the decision, impair individuals' ability to effectively process information, leading to poor judgments (Lucey and Dowling, 2005). The main conclusion to emerge from the literature exploring the influence of misattribution of mood on decision quality, suggests that decisions made under good (cf. bad) mood states are more susceptible to cognitive errors, consequently leading to sub-optimal decision outcomes. For example, decision makers in good mood states are more prone to use simplistic stereotyping and simplification heuristics (Forgas, 1995), are more optimistic about future states of the world and increase risk taking (Isen et al., 1978; Kamstra et al., 2003), to engage less in analytical modes of thinking (Hirshleifer and Shumway, 2003) and to increase their reliance on the experiential system of thinking and on previous experiences, resulting in them being prone to use irrelevant information (Forgas, 1995; Sinclair and Mark, 1995). By contrast, individuals in bad mood states are prone to becoming more pessimistic about future states of the world and becoming more risk-averse (Isen et al., 1978; Kamstra et al., 2003). They have also been shown to undertake more cognitive information processing (Isen et al., 1978), to engage in more analytical and reasoning activities and to react more efficiently to relevant news (Sinclair and Mark, 1995).

Importantly, both medical and psychology studies provide evidence that mood can be influenced by current weather conditions. For example, it has been shown that good weather conditions, such as higher temperatures, can lead to better moods, and this relationship is reversed for bad weather conditions (Watson, 2000). Based on this evidence, several studies have investigated the influence of misattribution of mood, triggered by weather conditions, on rational asset valuations in naturalistic decision settings. Many of these studies find evidence that weather-induced mood misattribution influences equity returns (e.g., Chang et al., 2008; Cao and Wei, 2005; Lucey and Dowling, 2005), however, some studies find that weather-induced mood misattribution has no significant impact on equity returns (e.g., Goetzmann and Zhu 2005; Lu and Chou, 2012). A comprehensive review on these studies suggest that shortcomings in previous research may be the foundation to these conflicting conclusions.

Firstly, many studies did not discount the influence of relevant factors that may affect equity returns. Jacobsen and Marquering (2008) noted that the majority of studies that found evidence of the influence of weather-induced misattribution of mood on equity returns did not account for economic factors and well-known market anomalies that may affect returns. For instance, when attempting to replicate the findings from previous research, Jacobsen and Marquering (2008) showed that the influence of weather-induced misattribution of mood on returns was significantly diminished when discounting for the January effect and the 2008 financial crisis. Secondly, there were often large time discrepancies between trades taking place and weather observations. Commonly, previous studies focused on investigating the correlation of daily equity returns and average weather conditions in a trading day. Importantly, Chang et al. (2008) showed that although average weather conditions did not significantly affect average daily returns, weather conditions observed at the market open did pose a significant impact on returns in the first 30 minutes of trade; hence suggesting the importance in incorporating weather observations that more closely resemble the conditions when trades take place. Another challenge in uncovering the effect of misattribution of mood in financial markets, is posed by the difficulties in establishing an unequivocal measure of the influence of weather conditions on equity returns due to the infinitely duration of the assets being studied (e.g., stocks). For instance, the infinite duration of assets mean that at no point in time the true effects of weather conditions on asset value can be revealed with certainty.

Moreover, it is unclear whether it is weather associated with positive or negative moods which damage decision quality in naturalistic financial markets, as previous results may be sensitive to the mechanism via which mood, influenced by weather conditions, may affect equity returns. For instance, although mood may influence cognition and risk taking levels simultaneously, their relative importance may lead to polarised conclusions of the direction, and most importantly, of the existence of misattribution of mood on equity returns. From the studies that find an influence of weather on equity returns, it is evident that they have reached no consensus regarding the direction of such influence. For example, some studies provide evidence that positive moods caused by good weather conditions, lead to higher risk taking and more optimistic judgments about the future performance of the asset being traded. In particular, these conditions result in investors buying more stocks, consequently increasing stock prices, leading to positive equity returns (Denissen et al., 2008; Goetzmann et al., 2015; Kamstra et al., 2003). However, other studies find that positive moods are related to negative equity returns (Dowling and Lucey, 2005; Hirshleifer and Shumway, 2003). Dowling and Lucey (2005) argue that that a key factor causing good weather conditions (which are associated with positive moods) to be associated with negative equity returns is that, although weather conditions may have an influence on optimism and risk taking levels, they may pose an even greater influence on investors' cognition. For example, the authors argue that investors in good moods are more prone to engage in less critical thinking and analytical reasoning, consequently becoming more prone to errors when evaluating stocks, leading to negative returns.

Lastly, some authors have questioned investors' weather-induced mood as the principal channel in which weather conditions influence equity returns. For instance, Goetzmann and Zhu (2005) found that weather conditions influenced market makers' transaction costs, and that weather-induced transaction costs, in turn, affected equity returns. Furthermore, Apergis et al. (2016) show that the influence of weather conditions on equity prices could be explained by the impact that weather posed on key equity value-drivers, such as retail sales and energy prices.

The conflicting nature of the conclusions reached in these naturalistic studies suggests that the decision setting and research approaches employed may not be ideal for reaching conclusive evidence regarding the impact of weather-induced mood misattribution on decision making. Therefore, this research is aimed at overcoming the problems associated with previous studies in order to obtain reliable empirical evidence to contribute to the discussion of the impact of weather, via misattribution of mood, on decisions in a naturalistic environment. Consequently, this research proposes a novel decision setting and approach which addresses all shortcomings identified in previous studies.

To achieve this aim, I decided to explore the effects of mood, triggered by weather conditions, on decisions made in the horserace betting market. Traditional financial markets and horserace betting markets are very similar in the sense that assets can be easily traded due to their high liquidity, information about performance is widely available to the public and future outcomes are uncertain. However, the important advantages of studying horseracing markets include the relatively short horizon and finite nature of this market, which provides a setting where the final outcome is unequivocal (a winner is determined) and all uncertainty is resolved once the race is over (Thaler and Ziemba, 1988). Thus, at the end of a race, the objective probability of success, as determined *ex post* by race outcomes, can be compared against the market's subjective probability estimates (contained in betting odds) (Johnstone, 2012), facilitating the inspection of factors that may cause any decision bias detected (i.e., any influence of weather on decisions can be revealed once a race is finished)[14]. Additionally, it is possible in this setting to discount alternative channels by which weather might affect decisions, thus offering credible direct evidence of mood being a valid channel underpinning any decision bias detected. For instance, it is possible to control for the influence that weather may pose on fundamental performance of contracts traded (i.e., the influence of weather on horseracing performance), as well as for any potential influence that market makers' (i.e., bookmakers in horseracing markets) pricing policies may pose on betting odds. Furthermore, it is common in horseracing markets for the vast majority of betting volume occur in the last thirty minutes prior the start of a race (Makropoulou and Markellos, 2011). This provides a basis to capture weather observations that more closely resemble the environmental conditions in which decisions are made. Noteworthy, a longstanding empirical regularity present in horseracing markets is the favourite-longshot bias (referred to FLB hereafter). This bias refers to the observation that bettors under-estimate the winning probabilities of high-probability contestants (favourites) and over-estimate the winning probabilities of low-probability contestants (longshots). It has been well-documented that demand side explanations for the existence of the bias are based on two mechanisms: higher cognitive errors displayed by bettors when assessing low-probability events (Snowberg and Wolfers, 2010) and by heightened preference for riskier investment alternatives (Sung et al., 2009). Research indicates that misattribution of mood induced by the prevailing temperature can influence both of these mechanisms (e.g. Howarth and Hoffman, 1994), and may therefore explain, at least in part, the existence of FLB. Consequently, studying the influence of temperature on FLB in horseracing markets addresses all shortcomings identified in previous studies, thus providing an ideal approach and setting to achieve the proposed aim of this research. Specifically, if this research finds that temperature-induced mood fluctuations have an influence on the FLB

[14] The largest weight of evidence support the view that markets favour the survival of correctly informed bettors over misinformed bettors (i.e., the survival of bettors with 'informationally efficient' judgments), thus rendering market prices an efficient means of aggregating bettors' beliefs (see: Fama, 1970; Blume and Easley, 2006). It is important to note that literature also suggests that under certain market circumstances (e.g., immature markets) it is possible for bettors with sub-optimal beliefs to dominate the market due to systematic differences in utility functions between misinformed and correctly informed traders (Blume and Easley, 1992; Sandroni, 2000). That is, market prices may not fully reflect bettors' beliefs, but rather differences in utility functions between these two classes of bettors. As the examination of bettors' utility functions lies beyond the scope of this paper, in addition to the larger body of evidence indicating that in mature markets (such as the case of horseracing markets) bettors with the more accurate judgments are the ones who can survive in the market, this paper uses betting odds as a means of analysing the informational value of decisions made by the representative bettor (i.e., inspecting the influence of weather on the informational value contained in betting odds).

in horseracing markets, and that such influence withstands when discounting for alternative explanations of the FLB, it will provide robust evidence to discipline the debate on the influence of weather effects, via misattribution of mood, on decision making in a naturalistic setting.

The results of this research demonstrate that temperature-induced mood has a significant influence on the level of FLB displayed by bettors in the market studied. More specifically, the results reveal that: (i) when decisions makers are expected to experience positive mood (i.e., when the prevailing temperature is perceived as good), the FLB is more pronounced (i.e. subjective probabilities, derived from betting odds, under-/over-estimate the objective winning probabilities on favourites/longshots at a greater extent and that net returns on longshot competitors are significantly lower); (ii) these results withstand when discounting for alternative factors known to influence the FLB. Importantly, by addressing all shortcomings identified from previous studies, this research provides strong evidence to establish mood as a credible channel in which weather conditions may affect decision making, and that (in horseracing markets) it is temperature associated with good mood which damage decision quality.

The remainder of the paper is organised as follows. Section 4.2 presents a discussion of the causes of the FLB and on the influence that mood and temperature may have on decision making. This discussion is used to develop the research hypothesis to be tested. In section 4.3, the data used in this research is introduced. Section 4.4 describes the methodology employed to test the proposed hypothesis. The empirical results are reported and discussed in section 4.5. Section 4.6 presents a discussion of the findings, and in section 4.7 conclusions are drawn and the implications of this research are discussed.

4.2. Mood, temperature and the favourite-longshot bias

4.2.1. Favourite-longshot bias

A longstanding empirical regularity in betting markets is the existence of the traditional FLB, whereby favourites are disproportionately under-bet and longshots are over-bet. The bias was first observed by Griffith (1949), and since then its existence has been consistently documented in different horseracing markets across a variety of countries (e.g., *Australia*: Bird and McCrae, 1994; Snowberg and Wolfers, 2010; *New Zealand*: Feess et al., 2014; Gandar et al., 2001; Qiu, 2012; *UK*: Bruce and Johnson, 2000; Smith and Vaughan-Williams, 2010; Sung and Johnson, 2010; *USA:* Thaler and Ziemba, 1988; Gramm and Owens, 2005; Snowberg and Wolfers, 2010). The literature suggests that the FLB can be caused by a number of elements. Generally, these elements are categorised in supply and demand side factors.

Supply side explanations of the FLB are associated with technical particularities related to betting markets. Most commonly, they have been attributed to the pricing policy adopted by bookmakers in response to the incidence of insider trading. In bookmaker markets, also known as quote-driven betting markets, bookmakers act as market makers, quoting the market prices (odds) that they are willing to offer bettors to place bets on particular events or contestants, and bettors can either bet or not at the quoted prices. Consequently, insider traders are more likely to bet on bookmaker markets because they can secure the winning odds when bets are placed, therefore guaranteeing they obtain the expected value from privileged information. Shin (1991, 1992, 1993) argues that, as a response to this, bookmakers artificially create the FLB to reduce their financial exposure to insider traders. More specifically, bookmakers may shorten the odds offered on longshots, as relatively small amounts bet on these contestants may substantially increase bookmakers' liabilities. Therefore, by adopting a pricing policy of lowering the odds on longshots, bookmakers are able to protect their profits against the estimated proportion of insiders in the market. Furthermore, transaction costs charged by bookmakers have also been linked with supply side explanations of the FLB. Evidence suggests that the variable nature of transaction costs [15] may challenge bettors to effectively learn the underlying true probability of success of low winning probability bets (i.e. longshots). In a laboratory experiment, Andersson and Nilsson (2015) showed that when assessing bets with identical winning probabilities but with different transaction costs, subjects consistently over-estimated the winning probabilities on longshot bets containing higher levels of transaction costs. In fact, it has been widely evidenced that transaction costs in bookmakers markets are positively correlated to levels of FLB (e.g., Vaughan Williams and Paton, 1997). However, the existence of the bias in markets where transaction costs are fixed and final odds are solely determined by the actions of bettors challenges the theory that supply side explanations may be the sole determinants of FLB (Abinzano et al., 2016; Smith et al., 2006). For instance, Schnytzer and Shilony (2003) provide evidence that the FLB cannot be created exclusively from

[15] It is common for transaction costs charged in bookmakers markets to vary from race to race.

bookmakers' attempts to protect themselves against insiders. The authors demonstrate that FLB is created by betting behaviour and bookmakers incorporate such behaviour in final prices. Similarly, Restocchi et al. (2017) show that bookmakers cannot cause the FLB directly, instead their pricing policy and transactions costs charged exacerbate sub-optimal decision behaviour displayed by bettors.

Demand side explanations for the FLB are based on the view that betting behaviour creates the FLB. The mechanisms underlying these relate to bettors' risk profile and cognitive ability. The former is based on the neoclassical utility theory. This theory implies that bettors have, at least locally, risk-preferring utility functions (e.g., Quandt, 1986). As a consequence, rational decision makers who are risk-preferring would seek bets that maximise their expected utility. In this context, bettors would gain utility by betting on the riskiest investments (i.e. bets on low winning probability contestants), which would make them more prone to accept lower returns for these bets; thus causing longshots to be disproportionately over-bet (e.g., Jullien and Salanie, 2000). Alternatively, behavioural theories suggest that FLB is a consequence of a breach of rationality, whereby bettors' tend to systematically make cognitive errors and misperceive probabilities. Such cognitive errors have been associated with bettors overweighting (underweighting) small (large) probabilities (Kahneman and Tversky, 1979), being prone to random misperceptions of winning probabilities (Chadha and Quandt, 1996), using irrelevant information when formulating decisions (Thaler and Ziemba, 1988) and inappropriately discounting expected losses (Henery, 1985). These explanations suggest that an increase in cognitive errors would, *ceteris paribus,* result in the FLB. For example, increasing random errors and/or greater reliance on factors unconnected to a contestant's true winning probability would result in bets being distributed more equally among all contestants than would have been expected from the objective probabilities. Consequently, this would lead to an under-estimation of winning probabilities on favourites concurrently with an over-estimation of the winning probabilities on longshots (Sung et al., 2009). Most of the recent studies have found stronger support for the cognitive ability and misperception of probabilities explanation (e.g., Ottaviani and Soerensen, 2008) cf. the risk-seeking behaviour explanation. Indeed, Snowberg and Wolfers (2010), in an extensive analysis of the origins of FLB, find that a rational agent displaying risk-seeking behaviour under the neoclassical expected utility theory could explain the bias. However, they provide evidence that the FLB is substantially better explained by bettors' cognitive errors when assessing low probability events in the framework of prospect theory.

It is clear from the preceding discussion that by discounting the influence of bookmakers in creating the FLB, it is possible to investigate the extent to which the bias can be attributed to the actions of bettors (i.e., demand side explanations). For instance, it is well accepted that FLB can be explained by bettors' risk preferences and cognitive errors when assessing low probability events. Importantly, psychological and medical literature provide strong evidence that misattribution of mood influences decision making by affecting individuals' risk preferences and cognitive ability. Thus, the manner in which misattribution of mood affects decisions are compatible with demand side explanations of FLB. Consequently, the effects of bettors' mood on decisions should be reflected in the level of FLB present in the market.

4.2.2. Mood and Decision Making

Psychology and neuroscience literature can shed light on explanations for the existence of deviations from fully rational decision making behaviour. Research in these areas, provides evidence that decision anomalies can be caused, at least in part, by individuals' mood. For instance, empirical research have shown that mood experienced at the time a decision is made can lead to behaviour that departs from that expected by the rational decision model. This incongruence in behaviour is more prevalent when a decision about the future involves conditions of risk and/or uncertainty (Loewenstein, 2000; Bechara et al., 1997).

The dual-process theory of decision making and information processing proposes that fully rational and analytical reasoning, as postulated by the rational decision model, can only function effectively if it is guided by mood (Zajonc, 1980; Kahneman and Frederick, 2002; Sloman, 1996). This theoretical underpinning predicates that there are two systems of thinking, the experiential and the analytic. These are argued to operate in parallel and for each to depend on the other for guidance when making decisions. In the analytic system, logic and normative rules prevail. Decision making within this system is normally resource intensive and requires conscious control in the process of making judgments. This system is wired to favour logic, objectivity and skilful cognitive evaluations of context and alternatives (Damasio, 1994).

However, long before probability theory existed and normative rules were still being formulated, individuals had to make choices (e.g. decide whether a particular fruit was edible or to identify which situations could life threating). Such decisions were mainly evaluated by intuition and instinct, which Slovic et al. (2004) labelled as the experiential system of thinking. In the experiential system, mood is an important component driving the decision making process. In most part, decisions from this system are made by the subconscious mind, which enables this system to generate rapid and immediate responses to external conditions. However, decisions made by the experiential system are often more crude assessments than cognitive evaluations performed by the analytic system (Loewenstein et al., 2001). Due to the relatively faster process speed of the experiential system, rapid responses guided by mood are often the first reaction when processing information under conditions of risk and uncertainty. Under these conditions the analytic system's deliberation costs and processing speed to achieve optimal decisions become highly resource intensive and slow. Consequently, the analytic system seeks greater support from the experiential system to achieve sub-optimal, although satisficing, decisions. As a result, in the dual-process theory, the influence of mood on decisions is mainly determined by the interaction and relative importance allocated to each system of thinking.

The risk-as-feelings theory, by Loewenstein et al. (2001), reinforces the conception that decisions are mainly evaluated at the cognitive level, based fundamentally on rational judgments, with the experiential system supporting the decision process. However, under conditions of greater risk, mood caused by transient factors may exert a direct external influence on information-processing and this may lead to sub-optimal decision outcomes. For instance, the theory proposes that individuals may not be aware of the temporal mood that they are experiencing, which may prevent the decision making process achieving an optimal balance between cognitive evaluations and mood. There is also empirical support for the view that in decision settings involving risk and uncertainty, individuals' temporal mood triggered by the decision context and the environmental conditions may lead to a divergence in decision outcomes relative to the same decisions if they were assessed fully by the cognitive system (Loewestein et al., 2001; Sloman, 1996; Ness and Klaas, 1994).

Importantly, the dual-process and risk-as-feeling theories incorporate the view that the degree to which mood influences decisions is dependent on the levels of risk and uncertainty. In particular, both theories propose that in decisions with low levels of risk and uncertainty, the final decision is mainly derived by analytical, rational and logical evaluations of aspects relevant to decision outcomes with mood having little influence.

However, in situations of higher risk and uncertainty, the computational demands required to process information relevant to the decision at hand may cause the analytic system to allow mood to exercise a greater influence.

It becomes evident from the literature presented in this section that mood is an important pillar supporting fully rational decision making under risk and uncertainty. For instance, decision models and rationality are constantly revised and reconstructed with changes in mood (e.g., Slovic et al., 2004). Consequently, behaviour that departs from that expected by the rational decision model may be, in fact, inherent in the fundamental (human) decision making process. This, in turn, motivates inquiry to identify whether, and to what extent, mood influences decision making in naturalistic settings.

4.2.3 Temperature, misattribution of mood and decisions

Transient external stimuli are mainly responsible in causing temporal (i.e. short-lasting) mood disturbances and it has been shown that individuals may not be aware of their short-lasting moods (Loewenstein et al., 2001). Importantly, a large body of literature strongly suggests that temperature has a significant influence on present mood (e.g., Howarth and Hoffman, 1984; Watson, 2000). In a comprehensive study incorporating a large number of weather variables, Rehdanz and Maddison (2005) found that higher average temperatures have the most significant influence on life satisfaction and happiness. In a more recent study, Cunado and De Gracia (2013) investigated the relationship between mood and weather, while controlling for socioeconomic factors that may be associated with mood (e.g. age, income, education, health, marital status, and being unemployed). They found that temperature had a positive influence in mood (i.e. higher temperatures throughout the year were associated with positive moods). Importantly, previous research also suggests that temperature can have an impact on cognition and risk taking, ant that this impact is mediated by the influence of temperature on mood. For example, Howarth and Hoffman (1984) found that temperature had a significant impact on current mood, behaviour and task performance, with temperature influencing mood, and the resulting mood affecting concentration and aggressiveness levels. Furthermore, Sinclair et al. (1994) found that decisions made under better moods (i.e. during higher temperatures) were associated with lower cognition and higher use of heuristics than under poorer moods (i.e. during lower temperatures). Interestingly, Keller et al. (2005) found evidence that the strength of the relationship between temperature and mood (and resulting cognition) was not affected by the amount of time spent indoors.

4.2.4 Misattribution of mood in naturalistic financial markets

The psychology and neuroscience literatures provide strong evidence that (temporal) mood is an important factor in the decision making process as it may influence decision outcomes. For example, decision biases and anomalies have been shown to follow from misattribution of mood, a decision bias whereby individuals allow mood influenced by transient factors (e.g. current temperature) unrelated to the decision at hand to affect decision outcomes (Lucey and Dowling, 2005). Under these conditions the experiential system of thinking becomes more dominant, allowing mood to have a larger direct influence on final decisions (Schwarz and Clore, 1983).

Many researchers have investigated the existence of misattribution of mood, caused by the current weather, on decision making in naturalistic environments and most of these studies have investigated the influence of weather conditions on financial market returns. Some researchers have concluded that weather conditions do influence equity returns, while others find evidence to the contrary (e.g., Goetzmann and Zhu 2005; Lu and Chou, 2012). Shortcomings in previous research may be the foundation of these conflicting results. Generally, previous studies did not account for well-established decision anomalies and relevant economic and underlying factors that may influence market returns (potentially leading to spurious results of the existence of misattribution of mood), there were often large time differences between trades taking place and the weather observations, and there are difficulties associated in establishing an unequivocal measure of the influence of investors' mood on equity returns due to the infinite duration of the assets studied.

Intriguingly, those studies that find evidence of the influence of weather on equity returns, provide no consensus regarding the direction of such influence. A possible reason for this lack of consensus may lie in how mood, influenced by weather, may impact the mechanisms affecting equity returns. For example, some studies have suggested that positive moods caused by good weather conditions, lead to greater risk taking and optimism regarding future performance of the asset being traded. As investors become more optimistic and display higher preference for risks, they become more prone to buy stocks, consequently increasing stock prices, leading to positive equity returns (Denissen et al., 2008; Goetzmann et al., 2015; Kamstra et al., 2003). However, other studies have found that positive moods are related to negative equity returns (Dowling and Lucey, 2005; Hirshleifer and Shumway, 2003). Dowling and Lucey (2005) have argued that that a key factor that may cause positive moods to be associated with negative equity returns is that weather conditions may exert an even greater influence on investors' cognition than on their risk taking and optimism levels. For example, the authors argue that investors in good moods are more prone to engage in less critical thinking and analytical reasoning, consequently becoming more prone to errors when evaluating stocks, leading to negative returns.

The conflicting results of previous studies is highlighted in Jacobsen and Marquering (2008). They examined the influence of temperature on stock market returns from 48 different countries and found that temperature only posed a significant influence on returns in some countries. From the countries where a significant influence was uncovered, the authors found that temperature was positively correlated with returns in some countries, while in others this relationship was reversed. Intriguingly, different authors have also provided conflicting evidence of the direction of the relationship between temperature and equity returns for markets in the same country. For example, when studying equity returns in the UK market, Cao and Wei (2005) find that returns are negatively related with temperature, while Floros (2008) using a different time period, find an inverse relationship for temperature and returns.

Although mood may influence cognition and risk taking levels, clearly their relative importance may lead to polarised conclusions of the existence and direction of misattribution of mood on equity returns. Therefore, it appears evident that this setting may not be appropriate for deriving conclusive evidence of the influence of weather-effects on decision making in a naturalistic environment. The current study is, therefore, aimed at overcoming these limitations.

To achieve this objective, I examine the influence of temperature on decision making in horserace betting markets. This setting, I believe, will provide a solid basis to collect robust evidence concerning the degree to which temperature-induced misattribution of mood affects decision making in naturalistic settings. As discussed in section 4.1, traditional financial markets and betting markets share many similarities. However, assets in horserace betting markets, possess the important advantage of being finite in nature and the final outcomes are unequivocal; which allows all uncertainty to be resolved once a race is finished. This facilitates the investigation of the factors that influence decision making. An additional benefit for studying the effects of temperature-induced misattribution of mood is the existence of the FLB. As indicated in section 4.2.1, this bias can be explained by greater risk taking or cognitive errors displayed by bettors when investing on low-probability contestants (i.e. longshots, which are the riskiest investments (Snowberg and Wolfers, 2010)). The mechanisms by which temperature-induced mood affects decision making are similar for both of these explanations. In particular, temperature associated with good moods have been shown to be related to both greater risk taking and cognitive errors. In addition, it has been suggested that the influence of mood is accentuated under higher risk conditions, such as those experienced in horserace betting. Consequently, the above discussion suggests that there is a very good chance that temperature-induced mood will directly influence the FLB. Therefore, it is proposed that investigating the following hypothesis in horserace markets will contribute to uncover reliable evidence of the influence of misattribution of mood on decision making in naturalistic environments:

H1. Temperatures associated with good (bad) mood states are expected to lead decision makers to become more (less) risk-preferring and more (less) prone to commit cognitive errors when betting, therefore amplifying (diminishing) the magnitude of the FLB in horserace betting markets.

In betting markets, the economic value of bets (i.e. returns) directly reflects the quality of winning probability estimates contained within odds. For instance, if subjective probabilities (implied from betting odds) misrepresent objective probabilities, this will directly translate to reductions in expected returns (Smith and Vaughan Williams, 2010). Consequently, if the FLB exists in the market, returns are expected to be lower on longshots (high odds) cf. to returns on favourites (low odds), as subjective probabilities on low-probability contestants will misrepresent objective winning probabilities at a greater extent.

Therefore, if evidence is found to support H1 (i.e. temperature-induced mood has a significant influence on the level of FLB), the following hypothesis is proposed to investigate the economic consequences of the influence of misattribution of mood on decisions:

H2. Temperatures associated with good (bad) mood states are expected to reduce (improve) returns for bets on low-probability contestants.

4.3. Data

4.3.1. Sources of Data

To test the proposed hypotheses I collected data from the UK bookmaker market concerning horseraces. Importantly, this market offers abundant opportunities for decision makers to learn from outcome feedback, as there are many betting opportunities throughout the year (e.g. more than 5,000 races on average per year). In addition, this market is highly liquid (e.g. the betting volume in the UK bookmaker betting surpassed £600M in 2016 (Statista, 2017)). These characteristics have been shown to facilitate decision calibration and improve the manner in which information is employed by market participants (i.e. market efficiency: Johnson and Bruce, 2001). Furthermore, the UK bookmaker market is composed of a large proportion of well-informed bettors (Bruce and Johnson, 2005). In fact, Bolger and Wright (1994) found that horserace bettors were among a very selective group of decision makers demonstrated to make good judgments. Therefore, if mood misattribution can be shown to affect even the decisions of individuals in this market, who have been shown to be good decision makers, it will suggest that this is a widespread phenomenon in naturalistic environments.

Previous laboratory studies strongly suggest that that temperature can influence mood, cognition and risk preferences[16]. In particular, higher (lower) temperatures have been shown to improve (deteriorate) mood[17] and lead to greater (less) risk taking and more (less) cognitive errors (Watson, 2000; Howarth and Hoffman, 1984). As both greater degrees of risk taking and more cognitive errors have been suggested as causes of greater degrees of the FLB, this presents a good opportunity for definitively identifying the direction of the influence of temperature on decision making in a naturalistic setting (which the settings of previous naturalistic studies have failed to provide).

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[16] It is important to note that this chapter is not explicitly measuring the effects of temperature on mood and, consequently, on decision making. For instance, mood is a multifaceted phenomenon that cannot be objectively measured (i.e., it can only be subjectively assessed by 'scoring' methodologies that approximate one's mood using various physiological and/or behavioural factors) (for example, see: Mehrabian and Russel, 1974; Forgas, 1995). Hence, deriving from the large body of psychological and medical evidence, as discussed in sections 4.1 and 4.2, that temperature can affect mood (e.g., Watson, 2000), and that temperature-induced mood can affect decision making (e.g., Keller et al., 2005), mood is used throughout this paper as the theoretical framework underpinning the effects that temperature may cause on decision making.

[17] Weather variables, other than temperature, have also been shown to influence mood (Eagles, 1994). However, the literature only provides evidence for temperature-induced mood having a direct effect on both cognition and risk taking. Therefore, this motivates the use of temperature to investigate the influence of mood on the FLB.

The horseracing dataset used in this research was supplied by Raceform Ltd. The following data related to the 73,457 horses and 2,717 jockeys involved in the 87,402 flat horseraces run across 43 different racetracks in the United Kingdom between 2002 and 2016 inclusive, was collected: starting date and times, and indicator for handicap (0 for non-handicap and 1 for handicap) races, race class, and starting prices (SP). Races occur in all months of the year on different track conditions, with the majority of races occurring between the months of May and September (61.31%) and on good/fast track conditions (79.9%).

The temperature data was supplied by the Met Office Integrated Data Archive System (2002-16). The database contained hourly temperature data from weather stations covering all the United Kingdom. The closest weather stations to each individual racetrack were identified using their respective zip codes and these were used to retrieve the temperature observed prior to each race start time. The descriptive statistics for the horseracing and temperature data are presented in Table 4.1.

Table 4.1 Descriptive statistics for the horserace and temperature variables: Data relates to the 87,402 flat horseraces run across 43 different racetracks in the United Kingdom between 2002 and 2016 inclusive

Variable	Mean	Std. Dev.	Min	Max
Bookmaker transaction costs (*%*)	0.17	0.08	0.01	0.95
No. Runners	10.01	3.56	2	36
Race class	4.59	1.39	1	7
Temperature (*°C*)	14.25	5.68	-4.4	33.2

4.3.2. Deseasonalyzed temperature

Humans have biological mechanisms that provide them with the ability to maintain equilibrium of internal functions despite changes in climatic conditions. This process, known as acclimation, moderates the influence of seasonal weather conditions on behaviour and decision making (Young et al., 1986). In addition, temperature is significantly higher during summer months compared to winter months. This distinctive seasonal pattern, combined with the fact that individuals have the ability to acclimate to seasonal variations in temperature, may obfuscate the true expected influence of temperature on mood, and hence on decision making. To accommodate individuals' ability to acclimate and to ensure that results are driven by temperature effects on mood and decision making rather than by seasonal effects, I followed Lu and Chou (2012) and Hirshleifer and Shumway (2003), and deseasonalyzed temperature. This process involved subtracting the monthly temperature average from the raw temperature observed for a particular race. An important benefit of deseasonalyzing temperature is that improvements (deterioration) in mood should occur if the observed temperature were above (below) the expected temperature for a particular month. Therefore, good and bad mood can be expected to occur all year round and not exclusively in summer or winter months, respectively. In the period studied, 50.3/49.7% of races (i.e. 44,001/43,401 races) occurred when the observed temperature was above/below the month's expected temperature.

4.4. Methods

Previous research investigating FLB has either focussed on (i) the quality of bettors' decisions, by exploring whether bettors' subjective probabilities, as contained within odds, under-/over-estimate the winning probabilities on favourites/longshots (e.g., Bruce and Johnson, 2000); or (ii) assessing whether abnormal returns can be secured on favourites/longshots odds (e.g., Cain et al., 2003). I employ the first of these approaches to test H1,that temperatures associated with good (bad) mood states lead to increases in the FLB, and the second of these approaches to test H2, namely that temperature-induced mood misattribution imposes a significant economic cost on bettors.

In particular, I first, employed conditional logit (hereafter CL) models to investigate the effect of temperature-induced mood on the quality of bettors' estimates contained in odds on favourites and longshots. This methodology will provide a means of assessing the extent to which bettors' subjective judgments of a horses' chances of winning deviate from their actual probability of success. This approach has been widely adopted to test whether cognitive errors displayed by bettors can explain the FLB (e.g., Sung et al., 2009; Bruce and Johnson, 2000). CL models offer the distinctive advantage of accounting for within race competition in assessing the true extent of FLB in odds.

The methodology to assess the economic significance of the influence of temperature-induced mood on the FLB, employs Tobit regression. More specifically, Tobit regression is employed to investigate whether mood has an influence on returns on bets on favourites (low odds) and longshots (high odds). These methodologies are now discussed in more detail.

4.4.1. Temperature-induced mood, probability estimates and the favourite-longshot bias: the conditional logit model

In horserace betting markets, *SP's* (i.e., betting odds) indicate the economic value attached to a specific betting contract. For example, for a bet of \$1 on a particular competitor, an *SP* of 2/1 means that a bettor receives \$2 winnings plus the original stake if the competitor wins and loses the \$1 stake if the competitor loses. Fundamentally, *SP*'s are established to reflect the probability of a particular competitor (i.e., horse-jockey combination) winning the race based on decision makers' aggregate belief concerning the outcome of the race (Franck et al., 2010). Winning probabilities implied from betting odds, commonly referred as bettors' normalised subjective probabilities (p^n_{ij}), can be represented by:

$$p_{ij}^{n} = \left(\frac{1}{(SP_{ij}+1)}\right) \Bigg/ \left(\sum_{i=1}^{n_j} \frac{1}{(SP_{ij}+1)}\right) \tag{4.1}$$

where SP_{ij} is the final odds on competitor i running in race j with n number of runners. Importantly, the CL model is used to assess the extent to which bettors' subjective probabilities of competitors' chances of winning, as derived from betting odds (i.e., p^n_{ij}), deviate from their true or objective probabilities. To estimate the CL model, a 'winningness' index W_{ij} is defined for every competitor i in race j as follows:

$$W_{ij} = \beta \ln\left(p_{ij}^{n}\right) + \varepsilon_{ij} \tag{4.2}$$

where β measures the importance of p^n_{ij} in determining the likelihood of competitor i winning race j, ε_{ij} being an independent error term distributed according to the double exponential distribution.

The competitor that win race j is the one with the highest winningness index in that race. Therefore, the estimated probability of the competitor v winning race j (i.e., p^{φ}_{ij}, which is distinct from the odds implied probability p^n_{ij}) is estimated by:

$$p_{ij}^{\varphi} = Prob(W_{vj} > W_{ij}, i = 1, 2 \ldots n_j, i \neq v) \tag{4.3}$$

Consequently,

$$p_{ij}^{\varphi} = Prob\left(\beta \ln\left(p_{ij}^{\varphi}\right) + \varepsilon_{ij} > \beta \ln\left(p_{ij}^{n}\right) + \varepsilon_{ij}, i = 1, 2, \ldots n_j, i \neq v\right) \tag{4.4}$$

The winningness index W_{ij} cannot be observed directly. However, whether competitor i wins race j can be observed, and a dichotomous win/lose variable t_{ij} can be defined such that:

$$t_{ij} = 1\ if\ W_{ij} = Max\left(W_{1j}, W_{2j}, \ldots W_{n_i j}\right);\ t_{ij} = 0\ otherwise \tag{4.5}$$

The probability of competitor *i* winning race *j* is conditional on the winningness index of all other competitors in the race. Therefore, a conditional winning probability can be derived as follows (i.e. the CL function):

$$p_{ij}^{\varphi} = Prob\left(t_{ij} = 1 | \ln\left(p_{ij}^{n}\right), i = 1,2 \ldots, n_j\right) = \frac{exp\left[\beta \ln\left(p_{ij}^{n}\right)\right]}{\sum_{i=1}^{n_j} exp\left[\beta \ln\left(p_{ij}^{n}\right)\right]} \quad (4.6)$$

Eq. 4.6, enables one to assess the degree to which odds can be used to accurately predict the winning probability of each competitor. However, I also want examine the extent to which mood, trigged by temperature, may influence the quality of subjective probabilities. Consequently, Eq. 4.6 can be expanded to include a term which assess the degree to which mood may affect the predicted winning probabilities, as follows:

$$p_{ij}^{\varphi} = \frac{exp\left[\beta_1 \ln\left(p_{ij}^{n}\right) + \beta_2\left(Mood_j\right)\right]}{\sum_{i=1}^{n_j} exp\left[\beta_1 \ln\left(p_{ij}^{n}\right) + \beta_2\left(Mood_j\right)\right]} \quad (4.7)$$

where β_1 and β_2 are estimated using maximum likelihood procedures, and $Mood_j$ is a variable that captures the expected temperature-induced mood of bettors in race *j*. Based on the findings of previous research presented in section 4.2, bettors are expected to be in a good (bad) mood when the current temperatures are above (below) the expected temperature for a particular month. Consequently, the *Mood* variable is expressed as a dichotomous variable: 1 for 'good' mood conditions, i.e. when deseasonalyzed temperature is positive; 0 for 'bad' mood conditions, i.e. when deseasonalyzed temperature is negative)[18].

The degree of FLB and the influence of temperature-induced mood on the FLB can be discerned from the value and significance of β_1 and β_2. In particular, if bettors' subjective probabilities are perfectly calibrated and are not influenced by temperature-induced mood (i.e. p^{φ}_{ij} equals p^{n}_{ij}), then β_1 would equal 1 and β_2 would equal 0. In particular, the coefficient β_1 will provide a direct means to assess the degree of FLB

[18] To ensure the robustness of the results to different temperature levels influencing the FLB, Eqs. 4.7, 4.8 and 4.11 were re-estimated by replacing the *Mood* term with temperature deseasonalyzed as a continuous variable and results were compared with the ones reported in Tables 4.2, 4.3, 4.4 and 4.6. Summary statistics (i.e., adjusted and pseudo-R^2, sign of coefficients and their respective significance levels) remained consistent with the results reported in Tables 4.2, 4.3, 4.4 and 4.6. Furthermore, to test whether the effect of mood on FLB may be significantly altered at extreme temperatures, Eqs. 4.7, 4.8 and 4.11 were also conducted by including a quadratic term of temperature deseasonalyzed, and the resulting improvements in model fit were assessed. The inclusion of a quadratic term of temperature deseasonalyzed did not significantly improve model fit compared with the results presented in Tables 4.2, 4.3, 4.4 and 4.6. Taken together, these robustness checks suggest that the results presented in Tables 4.2, 4.3, 4.4 and 4.6 are robust to different temperature levels influencing bettors' moods, and that the relationship between mood and FLB is not altered at extreme temperatures.

displayed by odds (i.e. subjective probabilities). If the estimated value of β_1 is significantly greater than 1, this will indicate the degree of FLB; i.e. longshots are over bet. The coefficient β_2 will provide a means of measuring the influence of temperature on the degree of FLB. More specifically, a positive (negative) β_2 will indicate that the degree of FLB is estimated to be larger (lower) under temperatures when bettors' mood is expected to be good.

As discussed in section 4.2.1, the FLB can be caused by a number of supply and demand elements. Consequently, to discount for the possibility of alternative factors affecting the FLB, the following three robustness procedures are proposed to obtain further evidence of the influence of mood on the FLB.

The first robustness procedure is aimed at investigating the influence of temperature-induced mood on FLB, while discounting for the influence of supply and demand factors that have been shown to affect the FLB. This procedure also controls for the possibility of temperature influencing horserace performance. This can be achieved by incorporating two key sets of *k and r* control variables in Eq. 4.7, namely *Racing factors* and *Performance*:

$$p_{ij}^{\varphi} = \frac{exp\left[\beta_1 \ln\left(p_{ij}^{n}\right)+\beta_2\left(Mood_j\right)+\beta_k\left(Racing\ factors_{kj}\right)+\beta_r\left(Performance_{rj}\right)\right]}{\sum_{i=1}^{n_j} exp\left[\beta_1 \ln\left(p_{ij}^{n}\right)+\beta_2\left(Mood_j\right)+\beta_k\left(Racing\ factors_{kj}\right)+\beta_r\left(Performance_{rj}\right)\right]} \qquad (4.8)$$

These control variables are defined, as follows:

Racing factors (k): As discussed in section 4.2.1, the FLB can be explained by supply and demand factors, which previous research show can be affected by the following race specific variables: race class (Gramm and Owens, 2005), the number of contestants in a race (Sung et al., 2009), whether the race is run at the weekend (Sung et al., 2012), the bookmaker transaction costs charged on the race (Shin, 1993), the incidence of insider trading[19] (Shin, 1991, 1992, 1993) and whether the race is a handicap (Williams and Paton, 1997). These factors are included in the regression as control variables, together labelled as 'Racing factors'.

Performance (r): Based on the medical and psychological literature, Costa Sperb et al. (2017) show that weather conditions, such as temperature, may affect the performance of both horses and jockeys. For example, the authors demonstrate that horses and jockeys

[19] The incidence of insider trading in a race will be derived from Eq. A1.2 in appendix 1; this method has been used in previous research to estimate the proportion of insider traders in a race (e.g., see: Cain et al., 2003).

perform better under specific weather conditions for which they display a 'preference'. As a result, Costa Sperb et al. (2017) present a 'preference variable' methodology, which forecasts competitors' (i.e. horse-jockey combinations) winning probabilities based on the preference they have shown in previous races for the current weather conditions.

Previous research has suggested that more readily discernible information is more effectively discounted by decision makers (Johnson et al., 2006). This is believed to be linked to the variation of the preference variable probabilities between competitors in a given race. For example, if a larger variation between competitors' preference variable probability estimates is observed in a given race, then this may suggest that the influence of weather on performance is more easily distinguishable by the betting public. This is likely to lead to better judgments, which in turn suggests that final odds may be better calibrated. Consequently, the *preference variable variance* (which is the variance of preference variable probabilities for the competitors in a given race) is included in the regression in order to control for the influence of temperature on performance.

This robustness procedure accounts for the fact that the performance of horses and jockeys might also be influenced by track under-foot conditions (Johnson et al., 2010) and these conditions may be correlated with temperature. Consequently, to control for the likely influence of temperature, via track conditions, on a competitor's performance, a *good surface* dichotomous variable is included in the regression (1 for good/fast track conditions and 0 otherwise).

The second robustness procedure is aimed at discounting the influence of bookmakers' pricing policy in creating the FLB. As discussed in section 4.2.1, Shin's (1991, 1992, 1993) theoretical model proposes that bookmakers intentionally create the FLB in odds (i.e., they artificially lower the odds on longshots) as a defence mechanism against the incidence of insider traders. Importantly, the effect of bookmakers' pricing policy in creating the FLB can be discounted by reverse-engineering Shin's model. This results in probability estimates (referred to as 'Shin probabilities' hereafter) that reflect betting behaviour (i.e. the actions of bettors) excluding the impact of the bookmaker (e.g., Jullien and Salanie, 1994; Cain et al., 2002; Smith et al., 2009). A concise summary of the procedure for estimating Shin probabilities is provided in the appendix 1. Consequently, to discount the influence of bookmakers' pricing policy in creating the FLB, Eq. 4.7 is re-estimated, replacing subjective probabilities derived from odds (i.e. p^{n}_{ij}) with Shin probabilities (i.e. p^{S}_{ij}). If β_2 (i.e. the coefficient of the mood variable) is a significant factor explaining the FLB in this model, this will provide evidence to support the proposition that the actions of bettors, via temperature-induced misattribution of mood, influences the FLB.

The final robustness procedure is aimed at investigating whether transaction costs charged by bookmakers can act as a potential underlying channel affecting any misattribution of mood detected. As discussed in section 4.2.1, transactions costs have been shown to induce bettors to overestimate winning probabilities on longshot bets (Andersson and Nilsson, 2015). This means that if transaction costs charged by bookmakers are associated with temperature, it is likely that transaction costs may be an important underlying channel influencing any misattribution of mood observed (cf. to bettors' temperature-induced mood being the principal channel causing misattribution of mood). For instance, Goetzmann and Zhu (2005) found that transaction costs charged by market makers in the New York stock exchange were significantly associated with weather conditions, and by discounting for such weather-induced changes in transaction costs, the influence of misattribution of mood detected in the market became insignificant. Consequently, in order to further establish that any misattribution of mood detected is caused by bettors' mood triggered by the prevailing temperature, it is necessary to inspect the extent to which bookmakers' transaction costs are associated with temperature. Shin (1993) proposed a model to explain transaction costs in relation to a set of variables that capture the proportion of insider traders in the market. Importantly, Shin's (1993) model can be extended to account for alternative factors which may also influence transaction costs. For instance, Vaughan-Williams and Paton (1997) showed that once the variables related to the incidence of insider trading are estimated, alternative explanatory factors can be incorporated in the framework of Shin's model. A concise summary of the procedure for estimating the set of variables to capture the incidence of insider trading in the framework of Shin's (1993) model is provided in appendix 2. Hence, the following regression model is estimated to investigate the extent to which temperature can affect transaction costs:

$$\begin{aligned} \mathrm{TC}_j = \alpha + \beta_1 Mood_j + \beta_s Insider\ Trading_j \\ + \beta_k Horseracing\ Factors_j + \beta_r Performance_j + \varepsilon \end{aligned} \tag{4.9}$$

where the variables related to *Insider trading* are derived using Shin's (1993) framework (see: appendix 2, Table A2.1, 'Iteration = 3'), *Racing factors* and *Performance* include the variables defined in the first robustness procedure and *Mood* captures the influence of temperature on transaction costs (i.e., consistent with the previous methods, *Mood* is a dichotomous temperature indicator: '1' when deseasonalyzed temperature is positive; '0' when deseasonalyzed temperature is negative). If *Mood* is estimated to be statistically insignificant (meaning that transactions costs are not significantly associated with temperature), it will indicate that there is no reasonable basis to regard transaction costs as a relevant underlying mechanism affecting any misattribution of mood detected (i.e., it will provide supporting evidence that temperature-induced mood is the channel causing any misattribution of mood detected).

4.4.3. Mood, returns and the favourite-longshot bias: the Tobit regression

To what extent it is possible to make abnormal returns by backing favourites or longshots has been subject to much debate. A common way of assessing this possibility is to group competitors (i.e., horse-jockey combinations) into odds categories and to investigate differences in expected mean returns per odds category (e.g., Cain et al., 2003). In this method, FLB is evidenced by larger differences in expected mean returns between favourites and longshots. However, it has been shown that the procedure of grouping odds can result in measurement error bias (Vaughan Williams and Paton, 1998).

An alternative procedure is to employ regression analysis to study the actual net return to a unit stake on each betting individual competitor. Net returns for competitor *i* in race *j* are calculated as follows:

$$Net\ return_{ij} = \begin{cases} SP\ if\ the\ competitor\ i\ wins \\ -1\ otherwise \end{cases} \tag{4.10}$$

This eliminates the need to group competitors into odds categories, therefore avoiding measurement error bias.

The following model is estimated to establish whether abnormal net returns on favourites and longshots can be attributed to bettors' mood:

$$\begin{aligned} Net\ return_{ij} = \alpha + \beta_1 SP_{ij} + \beta_1 \left(SP_{ij} \cdot Mood_j\right) \\ + \beta_k \left(SP_{ij} \cdot Racing\ factors_{kj}\right) \\ + \beta_r \left(SP_{ij} \cdot Performance_{rj}\right) + \varepsilon \end{aligned} \tag{4.11}$$

where *Mood, Racing factors and Performance* are defined in section 4.4.1, and *Racing factors* and *Performance* are included in the model to control for alternative factors which may influence the FLB (which could affect returns). Clearly, net returns to a unit stake are censored at -1. Consequently, a Tobit estimation is appropriate (Vaughan Williams and Paton, 1998). Furthermore, independence is only assumed across races, therefore observations are clustered within races.

A significant negative value of β_1 will indicate the presence of the FLB, suggesting that returns are systematically lower for higher odds. The coefficient β_2 will measure the effect of mood on the FLB. For instance, a negative (positive) coefficients will indicate that lower (higher) returns on longshots (i.e. higher odds) are associated with temperatures when bettors are expected to be in good mood. Consequently, a statistically significant negative coefficient for the *Mood* variable would suggest that lower returns are expected for larger odds under good mood (cf. bad mood) conditions (i.e. the strength of the FLB is more prevalent under good temperatures), and the magnitude of the *Mood* coefficient (i.e. β_2) will measure the economic consequences of misattribution of mood on decisions (i.e., β_2 will indicate the economic loss expected for every unit increase in odds when bettors are expected to be in good mood (cf. bad mood)).

4.5. Results

This section presents the results related to the tests to detect whether investors' temperature-induced mood has an influence on the degree of FLB present in betting odds.

4.5.1 Favourite-longshot bias and mood: Subjective probabilities analysis

Initially, I investigated whether the horserace betting market displays the FLB. Subsequently, the extent to which temperature-induced mood can influence any FLB present in subjective probabilities is evaluated. To achieve these objectives, two separate CL models, are estimated: a 'benchmark CL', in the form of Eq. 4.6 and 'mood CL', in the form of Eq. 4.7. The results of estimating these two CL models are presented in Table 4.2.

The results of estimating the 'benchmark CL' indicate that the coefficient of odds probabilities is highly significant, suggesting that they are extremely useful for forecasting winning probabilities (z-score of 220.10). This is consistent with the evidence from previous research, that the characteristics of horseracing markets facilitate good calibration and that bettors in horseracing betting markets are among the most sophisticated decision makers (Bruce and Johnson, 2005; Bolger and Wright, 1994). Despite this, the odds probabilities coefficient of 1.15053 indicates that bettors' subjective probabilities are under-/over-estimating the true winning probabilities on favourites/longshots. This coefficient is significantly greater than 1 at the 1% level ($t(1)$=28.80), confirming that the FLB observed in the horseracing market studied is statistically significant. Consequently, in line with previous studies in horseracing markets, I find that the FLB is present.

Table 4.2 Results of estimating the 'benchmark CL' and 'mood CL' for the 87,402 flat races in the United Kingdom run between 2002 and 2016 inclusive

	Benchmark CL			Mood CL		
Variables	Coef.	Std. Error	z-score (p-value)	Coef.	Std. Error	z-score (p-value)
Subjective probabilities	1.15053	0.00523	220.10** (0.000)	1.13845	0.00743	153.15** (0.000)
Mood				0.02379	0.01046	2.28* (0.023)
Log-likelihood	-164096.63			-164093.80		
Pseudo-R^2	0.1615			0.1616		

Note:

**Indicates significant at the 1% level

*Indicates significant at the 5% level

The results of estimating the 'mood CL' indicate that temperature-induced mood has a significant influence on the level of FLB displayed by bettors' subjective probabilities. For example, in the 'mood CL', the coefficient for subjective probabilities (β_1) measures the level of FLB displayed in the market when bettors are expected to experience bad mood (i.e., when *Mood* equals '0'), and the coefficient of the *Mood* variable (β_2) indicates the adjustment to the level of FLB associated with races when bettors are expected to experience good mood (i.e., when *Mood* equals '1', the level of FLB is given by the sum of β_1 and β_2). The results shown in Table 4.2 clearly show that temperatures associated with good mood conditions may lead to higher levels of FLB (coefficients of subjective probabilities 1.16224 and 1.13845 for races when mood is expected to be good and bad, respectively). The z-score of β_2 confirms that this difference in FLB associated with mood is statistically significant at the 5% level (z-score of 2.28).

Taken together, these results indicate that, independently of their moods, bettors' judgments suffer from the FLB. However, the strength of the bias is more pronounced under temperature conditions which are expected to generate good mood. This result is in line with *a priori* expectations. In particular, previous, largely laboratory based research, has shown that good/bad moods are associated with greater/less risk taking and more/less cognitive errors (Isen et al., 1978; Forgas, 1995). In turn, it has been suggested that greater/less risk taking and more/less cognitive errors can lead to greater/less under-/over-estimation of winning probabilities on favourites/longshots (Jullien and Salanie, 2000; Snowberg and Wolfers, 2010). In sum, these findings suggest that although decision makers' mood associated with the prevailing temperature does not fully explain the FLB (as discussed in section 4.2.1, mood is just one of the factors that may explain the FLB), it does exert a significant influence on the level of the bias. The results, therefore support H1.

4.5.2. The influence of temperature-induced mood on the favourite-longshot bias: Robustness procedures

The following results help to explore the robustness of the influence of temperature-induced mood on FLB.

The first robustness procedure investigates the effect of temperature on FLB while discounting for the influence of various supply and demand factors on FLB, as well as controlling for a possible influence of temperature on the performance of horses and jockeys. To achieve this, I estimated Eq. 4.8 and the results are summarized in Table 4.3.

The results presented in Table 4.3 show that three out of the eight control variables are significant, confirming that factors other than mood may influence the FLB. Importantly, after controlling for these variables, temperature-induced mood remains a significant factor influencing the level of FLB displayed in odds (z-score of 2.09, $p < 0.05$). Furthermore, a positive coefficient for mood indicates that a higher level of FLB is associated with temperatures under which bettors are expected to experience good mood. These results are consistent with the findings presented in Table 4.2, therefore providing evidence that the influence of temperature-induced mood on FLB remains significant when discounting for the effect of various supply and demand factors on the FLB, as well as controlling for any influence of temperature on the performance of horses and jockeys.

Table 4.3 Conditional logit results of the influence of mood on FLB with racing factors and performance variables as control variables

	Variables	Coef.	Std. Error	z-score (p-value)
Racing Factors	*Subjective probabilities*	1.1063	0.0217	51.06** (0.000)
	No. runners	0.0098	0.0021	4.76** (0.000)
	Transaction costs	0.0688	0.1009	0.68 (0.497)
	Insider trading proportion (z)	-0.0002	0.0002	-1.27 (0.204)
	Race class	0.0111	0.0040	2.78** (0.005)
	Handicap	-0.0432	0.0106	-4.08** (0.000)
	Weekend	-0.0006	0.0125	-0.05 (0.960)
Performance	*Preference variable variance*	-1.8122	1.9883	-0.91 (0.363)
	Good surface	0.0382	0.0309	1.24 (0.215)
Mood	*Mood*	0.0220	0.0105	2.09* (0.037)
	Log-likelihood	-164054.81		
	Pseudo-R^2	0.1618		

Note:

**Indicates significant at the 1% level

*Indicates significant at the 5% level

The second robustness procedure is aimed at discounting the influence of bookmakers' pricing policy in creating the FLB. This is achieved by re-estimating Eqs. 4.6 and 4.7 by replacing subjective probabilities (i.e. p^n_{ij}) with Shin probabilities (i.e. p^S_{ij}, as shown in appendix A). The results of these estimations are presented in Table 4.4[20].

[20] To further ensure the robustness of these results to alternative factors which have been shown by previous studies to influence the FLB, Eq. 4.8 was also estimated by replacing subjective probabilities (i.e.

Table 4.4 Results of re-estimating the 'benchmark CL' and 'mood CL' using Shin probabilities for the 87,402 flat races in the United Kingdom run between 2002 and 2016 inclusive

	Benchmark Shin CL			Mood Shin CL		
Variable	Coef.	Std. Error	z-score (p-value)	Coef.	Std. Error	z-score (p-value)
Shin probabilities	1.03637	0.00483	214.63** (0.000)	1.02476	0.00686	149.31** (0.000)
Mood				0.02286	0.00966	2.37* (0.018)
Log-likelihood		-164012.94			-164010.14	
Pseudo-R^2		0.1619			0.1620	

Note:

**Indicates significant at the 1% level

*Indicates significant at the 5% level

The results of the 'benchmark Shin CL' model show that by discounting the effect of bookmakers' pricing policy in creating the bias, the FLB observed in the market as a whole is substantially lower (i.e. coefficient of 1.03637 for the 'benchmark Shin CL' cf. to 1.15053 for the 'benchmark CL', as presented in Table 4.2). A *t*-test confirms that the coefficient of 1.03637 in the 'benchmark Shin CL' is significantly greater than 1 at the 1% level (t (1) = 7.53), therefore confirming that the actions of bettors can still cause the FLB. Importantly, the results indicate that mood associated with current temperatures remains a significant factor influencing the level of FLB. In particular, the level of FLB is larger when bettors are expected to experience good mood (coefficients of 1.04763 and 1.02476 for races when mood is good and bad, respectively), and the difference in these coefficients is significant at the 5% level (z-score of 2.37 for the *Mood* coefficient). Consequently, even after discounting the actions of bookmakers' pricing policy in creating the FLB, I find that heightened risk preferences and cognitive errors associated with temperature-induced mood may still significantly affect the level of FLB.

The final robustness procedure is aimed at investigating whether transaction costs charged by bookmakers is a potential channel causing the misattribution of mood

p^{n}_{ij}) with Shin probabilities (i.e. p^{S}_{ij}). The observed coefficient for the *Mood* variable remained positive and retained its statistical significance when discounting for alternative factors which may also influence the FLB, suggesting that the estimated influence of mood on FLB, presented on Table 4.4, is robust.

detected. To achieve this, Eq. 4.9 is estimated to inspect the extent to which temperature is associated with transaction costs. The results of this estimation are presented in Table 4.5.

The results presented in Table 4.5 show that five variables that capture the influence of insider trading in addition to four variables related to *Racing* and *Performance* factors are significantly associated with transaction costs. Importantly, after controlling for these variables, temperature (as measured by the *Mood* variable) is largely insignificant (*t*-value of -1.03, $p > 0.05$), suggesting transaction costs are not influenced by temperature. Consequently, this strongly indicates that there is no reasonable basis to regard transaction costs as a relevant underlying factor affecting the misattribution of mood detected, thus providing further evidence that bettors' mood is the channel underpinning the effects of temperature on decision making.[21]

Taken together, the results presented in sections 4.5.1 and 4.5.2 provide robust evidence to support H1. In particular, the results suggest that temperature-induced mood has a significant influence on FLB, and that this influence retains its statistical significance after controlling for the various factors which have been identified as affecting the FLB. More specifically, from the literature survey, it was hypothesized that temperature conditions associated with good (bad) mood would lead bettors to engage in greater (less) risk taking and commit more (fewer) cognitive errors when making decisions, therefore leading to higher (lower) levels of FLB. The results provide strong evidence to support this hypothesis.

[21] To further establish temperature-induced mood as the channel affecting the results obtained in this research, Eqs. 4.8 and 4.11 were re-estimated by including an interaction term between *Mood* and *Transaction costs*. The resulting coefficients of this interaction term were not significant at any conventional statistical level, and summary statistics (i.e., pseudo R^2s, sign of coefficients for the *Mood* term and its respective significance levels) remained consistent with the results reported in Tables 3 and 6. This results further suggests that bettors' mood (cf. to temperature-induced transaction costs) is the principal channel underlying the results obtained in Tables 3 and 6.

Table 4.5 Regression estimates of the influence of temperature on transaction costs with insider trading (estimated using Shin's (1993) framework, as shown in appendix 2), racing factors and performance variables as control variables

	Variables	Coef.	Std. Err.	*t*-value (p-value)
Insider trading (Shin framework)	*n-1*	0.0131	0.0001	187.12** (0.000)
	*Var(**p**)*	-0.9442	0.0790	-11.96** (0.000)
	*n • Var(**p**)*	0.3220	0.0216	14.87** (0.000)
	n^2 *• Var(**p**)*	0.0027	0.0014	1.94 (0.052)
	*Var(**p**)*^{2}	1.1607	0.8558	1.36 (0.174)
	*n • Var(**p**)*^{2}	0.9318	0.3881	2.40* (0.016)
	n^2 *• Var(**p**)*^{2}	-0.4773	0.0428	-11.15** (0.000)
Racing factors	*Race class*	0.0016	0.0001	15.23** (0.000)
	Handicap	0.0133	0.0003	41.11** (0.000)
	Weekend	0.0077	0.0003	24.04** (0.000)
Performance	*Preference variable variance*	0.0689	0.0519	1.33 (0.184)
	Good surface	-0.0046	0.0002	-24.43** (0.000)
Temperature	*Mood*	-0.0003	0.0003	-1.03 (0.303)
	Constant	0.0324	0.0011	29.49** (0.000)
	Adjusted-R^2	0.6071		

Note:
**Indicates significant at the 1% level
*Indicates significant at the 5% level
Number of runners is included in the model under the variables related to Insider trading, represented by the variable *n-1*, which measures 'number of runners – 1'.

4.5.3. Favourite-longshot bias and mood: Returns analysis

The results of estimating a Tobit regression in the form of Eq. 4.11, to examine the economic consequences of the influence of mood on the FLB, are summarized in Table 4.6. These results show that five out of the eight control factors have a significant effect on returns, suggesting it was important to control for these factors. A technical particularity of the Tobit model is that the linear effect is estimated on the uncensored latent variable (cf. to observed outcomes). Therefore, Tobit coefficients require adjustment before being interpreted as marginal effects. Estimates of the marginal effects are presented under the 'Slope' column in Table 4.6.

Table 4.6 Tobit regression estimates of the influence of mood on net returns to a unit stake on each individual horse and jockey combination (clustered by race) for the 87,402 flat races in the United Kingdom run between 2002 and 2016 inclusive

	Variables	Coef.	Slope	*t*-value (p-value)
	SP	-0.5541	-0.0615	-31.84** (0.000)
	Interactions			
Racing Factors	*No. runners*	0.0175	0.0019	11.90** (0.000)
	Bookmaker commission	-0.9593	-0.1065	-16.27** (0.000)
	Insider trading proportion 'z'	0.0037	0.0004	2.39* (0.017)
	Race class	0.0103	0.0011	3.62** (0.000)
	Handicap	-0.0956	-0.0106	-10.59** (0.000)
	Weekend	-0.0125	-0.0014	-1.26 (0.208)
Performance	*Preference variable variance*	0.1934	0.0215	0.14 (0.889)
	Good surface	-0.0411	-0.0046	-1.75 (0.080)
Mood	*Mood*	-0.0205	-0.0023	-2.41* (0.016)
	Constant	-15.8234		-103.63** (0.000)
	Log-likelihood	-529122.86		
	Pseudo-R^2	0.0351		

Note:
**Indicates significant at the 1% level
*Indicates significant at the 5% level

The *SP* coefficient and the constant are negative and significant at the 1% level (*SP* coefficient: -0.5541 (t = -31.84); *constant:* -15.8234 (t = -103.63)). A negative constant indicates that returns are expected to be negative when betting on any odds, and the negative *SP* coefficient suggests that returns are significantly lower for larger odds (i.e. on longshots). More specifically, a unit increase in *SP* (i.e. final odds) increases the expected loss by 0.062 cents for every $1 bet. Consistent with the results presented in section 4.5.1 (i.e. the 'benchmark CL' providing evidence of the FLB being present in the market as a whole), the negative coefficient of SP further confirms the existence of the traditional FLB.

In the results presented in Table 4.6, the coefficient of the mood variable is negative and significant at the 5% level (-0.0205 (t = -2.41)), indicating a marginal effect of temperature-induced mood on net returns of -0.23. This implies that under temperatures when bettors are expected to experience good mood, a $1 bet would lead to an additional economic loss of 0.23 cents for every unit increase in odds. This suggests that systematically lower returns are expected for larger odds for good mood conditions (i.e. the FLB is stronger when bettors are expected to be in good moods). In fact, the average returns of all bets when bettors are expected to experience bad mood is -23.80%. The corresponding average returns when bettors are expected to experience good mood is -25.58%, representing an overall increase in economic loss of 7.48%[22]. Together, these results are in line with the predicted influence of temperature-induced mood on returns. In particular, that greater/less risk taking and more/less cognitive errors are expected under temperatures associated with good/bad mood conditions, leading to lower/higher returns on longshots. These results therefore support H2.

Clearly, finding a systematic relationship between temperature and the FLB, even after controlling for the influence of *Racing* and *Performance* factors on returns, suggest that the actions of bettors can indeed explain, at least in part, the FLB observed in betting odds. These results therefore provide evidence that weather conditions, via misattribution of mood, may influence decisions in a naturalistic financial market and that it has significant economic consequences.

[22] A t-test confirms that the difference in average returns for races on good and bad mood conditions is significant at the 5% level (t (872678) = 2.55)

4.6. Discussion

The majority of studies on the influence of mood on decision making have been conducted under controlled laboratory experiments. Laboratory settings provide the benefit of allowing the manipulation of conditions in order to identify relationships between the variables at interest. However, such manufactured conditions may risk omitting elements that are often only present in real-world environments. In addition, they may fail to capture behaviour that occurs in real-world settings, since individuals may behave differently when they know they are being observed (Bruce and Johnson, 1997). It has been argued that these problems are exacerbated when exploring decisions in environments that involve high stakes and greater levels of complexity (e.g. in financial decisions); as these conditions are difficult build into laboratory experiments (Johnson et al., 2009). Consequently, it is important that parallel research be conducted in natural decision environments, to provide external validity to phenomena uncovered in laboratory settings.

Therefore, the principal aim of this study was to identify whether, and to what extent, weather-induced mood influences decision making in a naturalistic setting. Specifically, the evidence available from previous research may be insufficient to derive conclusive answers to the questions of whether individuals' mood associated with the prevailing weather conditions may affect decisions in a naturalistic financial market setting, and if such an effect exists, whether it is mood associated with positive or negative weather conditions that damage decision quality.

This study adopts a novel approach to explore decisions in a naturalistic financial market, namely the horserace betting market, which offer an ideal naturalistic setting to investigate the influence of weather-induced mood on decision making. Importantly, the characteristics that make horseracing markets an ideal setting to unearth the influence of mood on decision making are: (i) the relatively short horizon and finite nature of this market, as at the end of the race all uncertainty is resolved thus facilitating the inspection of the factors (e.g., temperature) that influenced decisions; (ii) the influence of temperature-induced mood on decisions being homologous with the explanations of the FLB, meaning that if mood associated with the prevailing temperature affects bettors' decisions it should have a very high chance of affecting the levels of FLB present in the market.

The results of this study provide a compelling insight into how weather effects (i.e. temperature in particular) may affect decision making in a naturalistic decision environment. They suggest that temperature has a significant influence on decisions. By discounting the influence of bookmakers' pricing policy and other factors on the FLB, the results of this research suggest that bettors' temperature-induced mood is capable of explaining at least some of the FLB observed in the market. In particular, the evidence indicates that the FLB is more pronounced under temperature conditions when the general betting public are expected to experience good mood. This was evidenced when investigating the influence of temperature-induced mood on probabilistic judgments (i.e. bettors under-/over-estimated objective probabilities on favourites/longshots), as well as on returns (i.e. good mood conditions were associated with systematically lower returns on longshots). Importantly, the latter provides a tangible representation of the consequences related with the damage in decision quality associated with misattribution of mood. For instance, decisions made under temperatures associated with good mood (cf. bad mood) where responsible in diminishing bettors' economic welfare by 7.48%.

The implications of this research are far reaching. First, the discussion and evidence presented indicates the importance of selecting naturalistic decision environments and approaches which are suitable to investigate phenomena uncovered in laboratory decision settings. Furthermore, although this research mainly focused on UK horserace betting markets, it can be suggested that decision quality in other contexts may also be subject to temporal mood fluctuations. For instance, if temperature-induced mood poses a systematic influence on investment decisions in a context where individuals have been shown to use information appropriately (Bruce and Johnson, 2005) and have strong (economic) incentives to make accurate predictions, it is likely that these effects may be even stronger in other contexts where these conditions may not exist.

The results also help corroborate the theoretical foundation that decision anomalies may be innate to the human decision making process. For example, if human cognition, by design, allows mood to actively participate in the process of achieving decision outcomes, and individuals are often unaware of their current moods (Loewenstein et al., 2001), this may indicate that under certain (mood) conditions we may not be able to attain full rational control over our decisions. In addition, temporal mood can be influenced by factors other than the one factor which is explored here (i.e. temperature), such as feeling hungry or receiving a bonus at work. This suggests that there are many factors which can potentially influence our decisions (via their influence on mood).

4.7. Conclusion

This research provides a solid foundation to help guiding the efforts of future research aimed at investigating the influence of mood (and perhaps other behavioural factors) on decision making. The results reported here provide strong support to the theoretical grounds that mood can influence decision making, and provide evidence of the importance in selecting an appropriate context and approach when investigating the effects of mood in naturalistic decision environments.

The findings of this research are relevant to at least two strands of the decision making literature. First, they offer direct empirical evidence of mood, triggered by the prevailing temperature, influencing decision making. More specifically, the approaches adopted in this research provide a means to substantiate the plausibility of mood as a valid channel underlying the influence of temperature on FLB and, thus, decision making quality. Second, and perhaps more importantly, the results of this research are of particular importance to the body of literature that investigates the influence of weather-induced mood on decision making in naturalistic environments. A comprehensive literature survey indicated that shortcomings in previous research may be the foundation to the conflicting results of the influence of misattribution of mood. This research shows that selecting an appropriate decision context is necessary to provide robust evidence to discipline the debate on the existence of the influence of weather-induced mood in decision making in a naturalistic setting. Hence, it is recommended for future research to carefully consider the decision setting and research approaches employed when investigating the influence of mood on decision making.

Intriguingly, to the best of my knowledge, no psychological and medical research has investigated the relative effect of mood on risk taking and cognition. This has inhibited the methodology employed in this study to make a distinction between the relative influence of risk taking and cognitive errors on the FLB and, therefore, on decision making. Consequently, this demanded the implementation of various robustness procedures to increase the confidence that the relative importance of temperature-induced risk taking and cognitive errors would not lead to conflicting conclusions of the influence of mood on decision making. Clearly, further research is required to untangle the relative importance of these mechanisms, via misattribution of mood, on decision quality. It is recommended future research to attempt to distinguish the relative effects on decision making of these mechanisms. For instance, depending on the decision context, their relative importance may determine whether mood may, or may not damage decision quality.

In conclusion, the results reported in this paper provide support to the theoretical foundations of the influence of mood on decision making, and provide evidence of the importance in selecting an appropriate context when investigating the effects of mood in naturalistic decision environments.

5. Conclusion

This chapter provides a summary of the main findings and discuss the implications of each of the three papers in this thesis. It also discusses the contribution of the thesis as a whole in providing knowledge and understanding of the effects of environmental conditions on decision making in naturalistic environments. Lastly, this section discusses the limitations of this research and provides suggestions for future research.

5.1. Summary of findings

The research in paper 1, to my best knowledge, is the first to incorporate the effects of a myriad of environmental conditions when forecasting sport performance. A methodology is developed to maximise the information which can be discerned regarding the influence of environmental conditions on the performance of horses and jockeys. The results obtained suggest that including these factors when predicting the performance of horses and jockeys, via the estimates from the preference methodology developed, can substantially improve forecasting power and accuracy. Surprisingly, although bettors in the market studied are well-known for the accuracy of their forecasts, they appeared to not fully discount the influence of weather and atmospheric conditions when predicting performance. Furthermore, the evidence in this paper indicates that there are substantial economic gains by fully accounting for the influence of these environmental conditions when forecasting sport performance. In summary, the findings of this study suggest that not fully accounting for environmental conditions when predicting sport performance may lead to sub-optimal forecasts that do not make full use of information which is unequivocally observable and available to all decisions makers.

Paper 2 explored the direct influence of environmental conditions on decision making in a naturalistic financial market context having controlled for the influence of the same environmental conditions on the performance of assets traded. Literature on psychology and neuroscience suggested that the influence of these environmental conditions on decision making are mediated by their influence on individuals' moods, which in turn may cause a decision anomaly called misattribution of mood (i.e., a condition whereby mood, influenced by transient factors unrelated to the decision, impair individuals' ability to effectively process information leading to incorrect judgments). The methodology developed in paper 1 was used in order to control for the influence of the environmental condition on the actual performance of the assets traded. The results for paper 2 further confirmed that bettors in the horseracing market are not fully discounting the influence of environmental conditions on the performance of horses and jockeys. Furthermore, the results suggested that these conditions also influenced decision makers' judgments directly, therefore leading to poorer decisions. It was also demonstrated that better forecasts can be achieved by correcting for misattribution of mood, and that these have substantial economic value. The results therefore illustrate the extent to which this decision anomaly is a predictable component affecting human rationality and information processing.

Paper 3 further investigated the influence of environmental conditions on decision making in a naturalistic setting from a different angle. This paper was motivated by the disagreement in previous research when answering the question of whether mood, influenced by environmental conditions, affects decision making in a naturalistic financial market setting, and whether the impact of positive or negative moods improved or led to a decrease in decision quality and market efficiency. This paper suggested that the methodological approaches and context studied in the previous research may be an important factor causing the apparently contradictory findings of the influence of mood on financial decisions. Therefore, I suggested that studying the influence of environmental conditions on the FLB in horserace betting markets offers an ideal setting to unearth the extent to which mood influences decisions in a naturalistic setting, and to assess the economic impact of mood on decision quality. The results of this paper demonstrated that mood, influenced by temperature, is significantly associated with the level of FLB displayed by bettors. In particular, the results revealed that when decisions makers face environmental conditions expected to induce good mood, the FLB is more pronounced in market prices, and this has a significant effect on expected market returns.

5.2. Implications and contributions to knowledge

This thesis provides compelling insights into the overall impact of a myriad of weather and atmospheric conditions on decision making in naturalistic financial market contexts. The combined results of the three papers suggest that decision makers in the market studied are skilful at making probabilistic predictions of event outcomes. However, under certain environmental circumstances, market prices deviate from rational levels (as defended by normative decision models), thus leading to less accurate probabilistic judgments. More specifically, this thesis show evidence that decision makers do not successfully made full use of environmental conditions when making predictions, and that these very same environmental conditions can affect decision quality via a direct influence on decision making process.

The implications of the findings from paper 1 (e.g., that decision makers do not successfully made full use of truly exogenous, observable, measurable and predictable information available on environmental conditions when making predictions) are not limited to sport performance and financial decisions, as decision makers from a wide variety of domains can benefit by learning how the environment may influence outcomes of their decisions. For example, business managers may be able to improve human capital productivity by designing organisational structures and systems that embrace the influence of the immediate environment on performance of employees. This paper also contributes to the debate of the role that transparency and availability of information play on market efficiency and optimal decision making. As stated in the paper, the environmental conditions used in this research are truly exogenous variables that are regionally unequivocally observable, measurable, and predictable (Bauer et al., 2015). Consequently, this makes them transparent and widely available to all decision makers in the context studied. Therefore, this information cannot be monopolised or regulated. The results of this paper suggest that the ability to use such information for prediction purposes, depends on the cognitive ability of decision makers. In particular, it depends on their understanding and untangling the true underlying relationship of the environmental factors to the performance of living beings. Thus, it can be argued that although transparency and availability of information may be a necessary condition for market efficiency and optimal decision making, they by themselves are not sufficient conditions to achieve such aims. This, in turn, can have significant implications to policy makers concerning regulating the provision of information to the market. For example, in general, it has been suggested that the financial crisis of 2008 was caused by exotic financial instruments impairing market efficiency and investor rationality (Krugman, 2008; Volcker, 2011). Since then, policy makers around the world have focused on enhancing market transparency as a measure to avoid future crises (Acharya and Richardson, 2009). Undoubtedly, transparency can provide strong foundations to support efficient markets. However, as shown in this paper, even when information is fully transparent, decision makers may not fully discount information that is opaque and less readily discernible. To this end, it is suggested that policy makers should also focus on discouraging the creation of exotic, abstruse and highly complex assets to sustain efficient markets. In sum, this paper contributes to the existing literature on normative decision making. The underpinning of the *corpus* of normative models portrays decision makers (collectively) having limitless cognitive ability as the epitome of optimal decisions that fully reflect information which is available. The findings of this paper directly question the real-world veridicality of this theoretical framework. Finding real-world decisions which failed in fully accounting for available information which is opaque and less readily discernible, provides strong empirical evidence of a breach of rationality defended by the theoretical framework of normative decision models, suggesting that limits to the cognitive ability of our brains can impair, at least in part, the extent of fully optimal decisions.

The implications to knowledge of paper 2 are far reaching. The effective use of prediction markets has helped many organisations predict uncertain and complex outcomes, such as hospitals predicting demand for their services, film producers predicting the box office success of movies, and companies predicting a variety of business activities (Cowgill et al., 2009; Soukhoroukova et al., 2012). Therefore, the underlying value of prediction markets to organisations can be greatly improved by identifying, and correcting for conditions in which individuals may make sub-optimal estimations about future states of the world. This paper may also contribute to knowledge in other arenas where mood may influence decision making. For instance, in the era of 'populism politics', voters are bombarded by politicians using rhetorical communication tactics designed to influence the mood and emotions of the population (Groshek and Koc-Michalska, 2017). Importantly, as indicated by Blais and Kilibarda's (2016) survey, on average 60% of voters, post an election, feel regret associated with their electoral choices. One the primary causes identified by voters for their regret is that they allowed mood and emotions (such as anxiety and enthusiasm) to 'cloud' their judgment when selecting their candidates (Marcus and Mackuen, 1993). Therefore, by understanding when their mood and feelings may lead to poor reasoning, individuals may greatly improve the quality of their decisions. In the specific case of voting, this may reduce post-election regret and could result in them electing politicians which reflect the population socioeconomic interests; their decision not being influenced by their mood and emotions at the time votes were cast.

Paper 3 sheds light on the importance of the relationship between research based on laboratory and naturalistic settings to develop knowledge about decision making. Although naturalistic and laboratory-based research differ in their unique advantages and limitations, it is essential for each inform the other in order to guide the scientific efforts of developing theoretical frameworks which accurately represent human rationality and information processing. Therefore, to substantiate our understanding of the true nature of decision making processes, it is important to observe in real-world settings behaviour which is consistent with that of theoretical decision models. To this end, this paper suggests that it is essential for research on decision making in naturalistic contexts, to (carefully) select methodological approaches and decision settings which are suitable to examine phenomena uncovered in laboratory environments. Failing to do so, may risk misguiding our efforts in uncovering the true nature of human rationality and information processing. Importantly, I find this to be an important shortcoming underlying the conflicting conclusions of the influence of mood on decision making in real-world financial markets. Hence, by addressing the shortcomings identified from previous studies conducted in real-world financial markets, the results of this paper provide reliable empirical evidence that a person's mood can influence judgments in a naturalistic decision setting and, coherent with the theoretical expectation of the effect of environmental conditions-induced misattribution of mood on decisions, it is shown that (in horseracing markets) it is environmental conditions associated with good mood which damage decision quality.

Although not the central aim of paper 3, it is worth noting that the findings of this paper may also provide new insights to help guide research to further develop the understanding on the impact of individual behaviour in explaining the FLB. By showing that mood can explain, at least in part, the FLB, this suggests that FLB levels may also be associated with other personal characteristics or circumstances which can influence individuals' risk taking and cognitive errors (e.g., feeling fatigued or aroused).

The combined findings from paper 2 and paper 3 make significant contributions to the knowledge of the effect of behavioural components underlying the decision making process. It is essential for evidence to be retrieved from naturalistic decision environments in order to provide external validity to the theoretical foundations of behaviour unearthed in laboratory settings. The findings in these papers provide an insightful understanding for the extent and nature of biased decision making in naturalistic settings. Importantly, the results of these papers corroborate the theoretical underpinning that decision anomalies may be innate to human decision making process. For example, if human cognition, by design, allows mood to actively participate in the process of achieving decision outcomes, and individuals are often not aware of their current moods (Loewenstein et al., 2001), this may indicate that under certain (mood) conditions we may not be able to attain full rational control of our decisions. As temporal mood can be influenced by factors other than temperature (e.g. feeling hungry or receiving a bonus at work), this suggests that other common and ordinary circumstances in our daily lives could potentially influence the quality of our decisions.

Taken together, the overall findings of this thesis make important contributions to the theoretical framework of decision making under risk and uncertainty. Normative decision models are built on the theoretical foundations of the rationality employed by the *homo economicus* (i.e., individuals rationally and effectively deliberate on all available options prior to making fully rational and optimal decisions). In such narrow development, decision inefficiencies are mainly attributed to irrationality of individuals. Importantly, the decision making theories discussed in this thesis can provide support for the explanations of the existence of decision making inefficiencies. For example, they postulate that behavioural factors, such as mood, are important pillars of decision making processes, suggesting that, at least in part, decision anomalies are innate to human decision making process, as human cognition, by design, allows mood to actively participate in the process of achieving decision outcomes. Consequently, it is argued that normative decision models (e.g., the efficient market hypothesis) could be greatly improved by accommodating for the existence of the influence of mood, and other important behavioural factors in order to make these theories more representative of human cognition and rationality. Perhaps the definition of rationality employed in the 'fictional' *homo economicus* could be revised by incorporating the (predictive) cognitive features of 'real' persons observed in naturalistic decision environments.

5.3. Limitations and future research

The empirical methods employed in this thesis only incorporated general behaviour displayed by individuals. That is, decision behaviour was represented by the aggregate information contained in final market prices (i.e., decision quality was derived from the decisions made by the representative bettor, as contained in the aggregate final odds). By studying individual (cf. aggregate) behaviour, more direct and/or granular relationships of the influence of environmental conditions on decision making could be established. For instance, the utility functions of bettors could be assessed and discounted, consequently increasing the clarity of the factors that may challenge bettors in making informationally efficient judgments[23]. Consequently, it is recommended for future research to investigate individual behaviour, as this could provide additional breadth and depth to the theoretical foundations of the influence of behavioural factors on decision making

Intriguingly, to the best of my knowledge, no psychological and medical research has investigated the relative effect of mood on risk taking and cognition. This has inhibited the methodology employed in this thesis to make a clear distinction between the relative influence of risk taking and cognitive errors on decision quality. Clearly, further research is required to untangle the relative importance of these mechanisms, via misattribution of mood, on decision quality. This is of great importance to the understanding of the influence of mood on decision making. As discussed in paper 3, depending on the decision context, their relative influence may determine whether mood may, or may not damage decision quality. To this end, it is recommended future research to attempt to distinguish the relative effects on decision making of these mechanisms. Moreover, it is recommended future research to investigate the influence on decision making of other factors that can affect mood. For instance, mood can be affected by circumstances other than environmental conditions. Therefore, if mood influenced by environmental conditions can affect decision making, it is logical to assume that mood influenced by other factors may also influence decision making. Lastly, by finding that misattribution of mood could explain at least in part the existence of the FLB, it would be interesting to investigate whether mood can influence the degree of other well established decision making anomalies which may be susceptible to changes in individuals' risk taking and cognition levels (e.g., investigate whether changes in mood exerts an influence on the degree of wishful thinking or the disposition effect).

[23] As discussed in chapter 1, it is important to note that under certain market conditions (e.g., immature and incomplete markets), it might be possible for misinformed bettors to prevail (i.e., they may come to dominate the market) due to systematic differences in utility functions between misinformed and correctly informed traders (Blume and Easley, 1992; Sandroni, 2000). By investigating individual behaviour, utility functions of bettors may be able to be discounted, hence increasing the clarity on the investigation of the factors that may affect (individual) bettors' judgments.

5.4. Concluding remarks

In summary, although empirical evidence was mainly derived from UK horseracing betting markets, it is suggested that the findings of this thesis are equally relevant to different contexts. For instance, many real-world decisions involve settings where despite relevant information being widely and publicly available, such information may be highly (cognitively) challenging to discern and untangle in order to make optimal judgments (e.g., attempting to efficiently price exotic derivative assets). Furthermore, mood is an innate aspect of human nature, and if mood can negatively influence judgments in a context where individuals have large (economic) incentives to make accurate decisions, this suggests that in other contexts the quality of decisions may also suffer from the current moods of decision makers. Consequently, this thesis makes significant contributions towards understanding the extent, and nature, of the influence of weather and other atmospheric conditions on decision making in naturalistic settings. The conclusion that this thesis has arrived is that environmental conditions can influence decision making, and that significantly better judgments can be obtained by recognising and correcting for (predictive) cognitive features which could affect decision rationality.

Appendix

Appendix 1. Shin Probabilities

Shin's (1991, 1992, 1993) theoretical model proposes that bookmakers' pricing policy may create the FLB as a defence mechanism against the incidence of insider traders. Importantly, the actions of bookmakers in creating the FLB can be removed from odds by reverse-engineering Shin's model, resulting in probability estimates (referred as 'Shin probabilities') that reflect betting behaviour. Cain et al. (2002) and Smith et al. (2009) show that Shin probabilities for the horse and jockey pair *i* in race *j* can be expressed as:

$$p_{ij}^{S} = \frac{\sqrt{\left[z_j^2 + 4\frac{\pi_{ij}^2}{\Pi_j}\left(1 - z_j\right)\right]} - z_j}{2\left(1 - z_j\right)} \qquad \text{(A1.1)}$$

where z_j is Shin's measure of incidence of insider trading in race j, π_{ij} is the nominal odds probability for the horse and jockey *i* in race *j*, and Π_j is the sum of π_{ij}. The proportion of insider trading for a particular race (z_j) with *n* runners can be estimated using a fixed-point iteration process starting at $z_m = 0$:

$$z_{j(m+1)} = \frac{\sum_{i=1}^{n} \sqrt{z^2 + 4(1 - z_m)\frac{\pi_i^2}{\Pi_j}} - 2}{n - 2} \qquad \text{(A1.2)}$$

At convergence, the corresponding value of z_j, $0 < z_j < 1$, will satisfy $\sum_{i=1}^{n} p_{ij}^{S} = 1$; that is, the sum of Shin probabilities for a particular race will sum to unity, therefore yielding probability estimates which discount the influence of bookmakers in creating the FLB.

Appendix 2. Shin's (1993) framework of the influence of insider trading on transaction costs

According to Shin'(1993) framework, transaction costs can be explained as a function of the incidence of insider traders such that:

$$TC = z(n-1) + \sum_{\mathrm{m}=0}^{\mathrm{M}} a_m n^m \mathrm{Var}(\mathbf{p}) + \sum_{m=0}^{M} b_m n^m [\mathrm{Var}(\mathbf{p})]^2 \qquad \text{(A2.1)}$$

where m = 0, 1, …, M, and n is the number of runners in a particular race. The coefficients z, a and b are estimated through an iterative least squares method. In the first iteration, the variance of nominal odds probabilities ($\mathrm{Var}(\tilde{\pi})$) act as a proxy for the objective winning probabilities variance (Var(**p**)). After the first iteration, the estimated coefficient z can be used to calculate the objective winning probabilities variance such as:

$$\mathrm{Var}(\mathbf{p}) = \frac{\beta}{1-z}\mathrm{Var}(\tilde{\pi}) + \frac{\beta - 1 - z(n-1)}{n^2(1-z)} \qquad \text{(A2.2)}$$

where β is the sum of odds probabilities. Then, the estimated Var(**p**) is included in Eq. A2.1 and the model is re-estimated. This process is repeated until z in Eq. A2.1 converges. Similarly to Shin, when estimating the model, the polynomials in Eq. A2.1 are expanded to a second order degree (i.e., m = 2) as higher order polynomials did not significantly improve model fit. The iteration process results are presented in Table A2.1. The coefficient z (as measured by the variable '*n-1*') converged at 0.0179 after three iterations. Therefore, the variables which will be used to discount the effect of insider trading on transaction costs in Eq. 4.9, are the ones estimated by the model 'Iteration = 3', as presented in Table A2.1.

Table A2.1 Regression estimates of the influence of insider trading on transaction costs in the framework of Shin's (1993) model after M adjustments, for the 87,402 flat races in the United Kingdom run between 2002 and 2016 inclusive

	Iteration = 1		**Iteration = 2**		**Iteration = 3**	
Variable	Coef	*t*-value (p-value)	Coef	*t*-value (p-value)	Coef	*t*-value (p-value)
n-1	0.0187	584.04** (0.000)	0.0179	554.64** (0.000)	0.0179	547.68** (0.000)
Var(**p**)	-2.1345	-22.24** (0.000)	-1.4921	-18.33** (0.000)	-1.4871	-18.34** (0.000)
n • Var(**p**)	1.2059	50.69** (0.000)	0.8946	45.13** (0.000)	0.8928	45.26** (0.000)
n^2 • Var(**p**)	-0.0770	-51.73** (0.000)	-0.0440	-35.85** (0.000)	-0.0439	-35.90** (0.000)
Var(**p**)^2	27.6232	25.21** (0.000)	15.1048	17.57** (0.000)	-0.0439	17.62** (0.000)
n • Var(**p**)^2	-12.7371	-24.89** (0.000)	-6.6744	-17.50** (0.000)	-6.6898	-17.57** (0.000)
n^2 • Var(**p**)^2	0.5135	8.41** (0.000)	-0.014	-0.31 (0.757)	-0.0097	-0.22 (0.826)

Note:

**Indicates significant at the 1% level

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