

Turning the heat on financial decisions: Examining the role temperature plays in the incidence of bias in a time-limited financial market.

Abstract

Many laboratory-based studies provide evidence that temperature can influence how people make decisions, by affecting their risk preferences and propensity to make cognitive errors. However, the role of temperature on the quality of decisions made in real-world settings it is not well-understood. A strand of literature in financial markets has attempted to explore this, but the results have been inconclusive: some studies suggest that temperature does not affect financial decisions, whilst others reach contrasting conclusions – some suggesting that higher, and others that lower temperatures, reduce the quality and economic value of financial decisions. We design an empirical experiment to overcome the limitations of previous studies in order to shed new light on the role of temperature in financial decisions. The study employs data from a time-limited market for state-contingent assets, namely an event-driven prediction market. We assess the extent to which prediction market participants' subjective judgments of event probabilities deviate from the actual probability of the event occurring, as a result of temperature-induced cognitive errors and risk-taking. The results demonstrate that higher temperatures are associated with lower decision quality. We also found that temperature differentially influences the decisions of those with different decision profiles, with the largest influence observed on individuals whose decisions are based on logic, objectivity and skilful cognitive evaluations of alternatives.

1. Introduction

Global warming, the gradual rising of Earth's temperatures, was identified by the World Economic Forum as one of the most pertinent global risks in 2020 in terms of potential impacts (World Economic Forum, 2020). For example, rising world temperatures are estimated to cause labour productivity losses equivalent to 80 million full-time jobs by 2030 (International Labour Organisation, 2020). Although the impacts of rising temperatures have been widely investigated in macroeconomic terms, such as in aggregate output and productivity losses (e.g., Desmet and Rossi-Hansberg, 2015), not much is known about its potential impacts on economic decision making.

Over recent years, a large number of medical and psychology studies have found that temperature can affect how people make decisions. For instance, it is well-evidenced that temperature can impact consumer behaviour (Cheema and Patrick, 2012). However, there is little conclusive evidence of the role and impact of temperature on financial decisions (Jacobsen and Marquering, 2008). Motivated by the importance of financial-related decisions to the world economy (e.g., it is estimated that the value of global financial assets surpassed 172.5 trillion euros in 2018, (Allianz, 2019)), we develop an empirical experiment which will overcome the limitations of previous enquiries in order to shed reliable new light on the role of temperature in financial decisions.

The psychology and neuroscience literatures provide evidence that the decision-making process is associated with two distinct, but interdependent, domains of thinking: System 1, referred as the

experiential domain of thinking, is fast, preconscious, associated with intuition and is automatically activated through interaction with the environment. System 2, referred as the rational system, is slow, conscious, effortful, and draws on logical justification (Pacini and Epstein, 1999; Kahneman and Tversky, 1979). Importantly, individuals differ in their capacity (ability) and proclivity for using one or both of these domains when processing information (Slovic et al., 2004).

Several laboratory-based studies have shown that temperature is an important exogenous element in the decision-making process, as it influences the functioning of the experiential and rational domains of thinking. The main conclusion to emerge from studies exploring the effects of temperature on decisions is that decisions made under higher/lower temperatures are more/less susceptible to cognitive errors (as individuals are more prone to engage in lower cognitive effort and deliberation under higher temperatures) and to engage in greater/lesser degrees of risk-taking behaviour (as individuals become more optimistic and assign higher probabilities to events they see as favourable under higher temperatures) (Sellaro et al., 2015). Therefore, the impact of temperature on decision may be affected by the context of a decision (i.e. whether logic or intuition are favoured to reach an adequate decision) and on an individual's proclivity and ability to engage with the different information processing domains.

The main strand of empirical research which has investigated the influence of temperature on real-world decision-making has explored the decisions of investors in financial markets (Hirshleifer and Shumway, 2003). However, this literature fails to account for an individual's information processing characteristics. This is an important limitation, as it has the potential to yield conflicting conclusions regarding the existence and nature of the influence of temperature on financial market returns. In particular, individuals may prefer and/or engage with different domains of thinking (i.e., the experiential and rational) when making decisions, and temperature may affect the function of these two domains in different ways. Consequently, the effects of temperature on decision makers may impact market returns in different ways (e.g., Hancock and Vasmatzidis, 2003). This issue is well illustrated by the fact that some studies find that temperature affects financial market returns (e.g., Cao and Wei, 2005), while others find it does not (e.g., Jacobsen and Marquering, 2008). Furthermore, of the studies that find evidence that temperature does affect market returns, some found that higher temperatures are positively related to financial market returns and argue that this may be because higher temperatures resulted in greater risk-taking (Goetzmann et al., 2015; Denissen et al., 2008; Kamstra et al., 2003). Other studies found that higher temperatures led to lower returns and argued that this resulted from higher temperatures leading to more cognitive errors on the part of investors (Dowling and Lucey, 2005; Hirshleifer and Shumway, 2003). This conflicting evidence illustrates a potential inadequacy of employing financial market returns to measure the effects of temperature on financial decisions. For example, if higher (lower) temperatures are associated with greater (less) risk taking and cognitive errors, and greater (less) risk taking and cognitive errors have opposite effects on financial market returns (greater risks taking leading to higher returns, while more cognitive errors leading to lower

returns), then these effects may cancel each other out, leading to the spurious conclusion reached in some studies that temperature does not affect financial decision-making.

In summary, the conflicting nature of the conclusions reached in previous empirical studies suggest the importance of accounting for individual decision-making styles when assessing the influence of temperature on financial decision-making. In addition, the market settings employed in previous empirical enquiries may not be appropriate for reaching conclusive evidence regarding the impact of temperature on financial decisions. In particular, it is difficult to develop an unequivocal measure of the influence of temperature on market prices due to the infinitely lived nature of the assets being studied (e.g., stocks). This means that at no point in time can the true effects of temperature on real asset values be revealed with certainty.

To obtain reliable empirical evidence concerning the role of temperature on financial decisions, we investigate decisions made in a setting where the limitations of previous studies can be overcome. In particular, we explore the effects of temperature on decisions made in a time-limited market for state-contingent assets, an event-driven prediction market. In recent years, prediction markets have been “heralded as effective mechanisms for harnessing the wisdom of the crowd” (Restocchi et al., 2018) in order to make accurate forecasts. These markets range from ‘political futures’ markets (based on election outcomes) traded on the Iowa Electronic Markets, to in-house company markets designed to forecast sales or the likely success of a product, to event-driven markets offered by bookmakers and betting exchanges (based on sports events, economic events (e.g., tax or interest rate changes) and political events).

Traditional financial markets, such as stock markets, and event-driven prediction markets, such as horserace betting markets, share many similarities: assets can be easily traded due to their high liquidity, information about performance is widely available and future outcomes are uncertain. Consequently, in seeking to obtain reliable information concerning the role of temperature on financial decisions, we investigate decisions made in horserace betting markets because these offer the following important advantages over decisions made in traditional financial markets: they involve a relatively short time horizon, they are finite in nature and the final outcome is unequivocal (a winner is determined) and all uncertainty is resolved once the race is over (Thaler and Ziemba, 1988). This facilitates the inspection of factors that may cause detected decision bias. In particular, the influence of temperature on decisions and, consequently, on returns, can be revealed once a race is finished. In addition, the quality of bettors’ decisions can be measured by the forecasting accuracy of betting odds, which are the result of the combined decisions of all bettors in the market. It has been shown that these are more accurate at certain times, where the proportion of skilled/informed bettors in the market is expected to be higher (see: Sung et al., 2019, 2012). This provides us with the opportunity to investigate how temperature may affect the decisions of different groups of decision makers.

The results of our research demonstrate that temperature has a significant influence on the level of decision bias displayed by bettors. In particular, we find that higher temperatures damage decision

quality. In addition, we find that those individuals whose decisions are most likely to be affected by temperature are those who tend to adopt the rational (cf. experiential) approach to decision-making. By addressing the challenges identified from previous financial market studies, this research provides strong evidence to establish temperature as a credible exogenous factor affecting financial decision-making.

The remainder of the paper is organised as follows. Section 2 discusses previous literature in an attempt to identify the influence that temperature may have on decision-making. This discussion is used to develop the research hypotheses to be tested. In section 3, the data used in this research is introduced. Section 4 describes the methodology employed to test the proposed hypotheses. The empirical results are reported and discussed in section 5. Section 6 presents a discussion of the findings, and in section 7 conclusions are drawn and the implications of this research are discussed.

2. Decision-making and temperature

2.1. Decision-making process

Normative decision models postulate that individuals effectively assess the likelihood of the possible decision outcomes, and unimportant factors and psychological features experienced at the time do not affect the decision-making process (Loewenstein et al., 2001). Under this paradigm, logic drives the deliberation process, and individuals make effective use of normative rules while employing fully-reasoned information processing mechanisms. However, this paradigm fails to appropriately explain well-evidenced systematic decision biases and errors (Kahneman and Tversky, 1979). For example, investors can change risk preferences (and consequently reach different decisions) when financial decisions with identical pay-offs are framed differently (i.e., framed in the domain of losses or gains (Fraser-Mackenzie et al., 2014)). Evaluating this phenomenon under normative decision models, the different frames would be classified as irrelevant decision inputs, as they have no impact on the economic value of the decision, and the cognitive effort demanded to reach a decision is identical in both frames (Slovic et al., 2004).

Notably, research in psychology and neuroscience suggests that the decision-making process can be influenced by the context of the decision and by individuals' proficiency in, and preference for, engaging in rational or experiential information processing (Slovic et al., 2004). Under this premise, decision-making is supported by two systems of thinking, the experiential and the analytic. These are argued to operate in parallel, with each depending on the other for guidance when making decisions. In the analytic system, logic and normative rules prevail. Decision-making within this system is resource intensive, effortful and requires conscious control in the process of making judgments. This system favours logic, objectivity and skilful cognitive evaluations of alternatives (Kahneman, 2011).

In the experiential system, associations with past experiences drive the decision-making process. Decisions using 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 cruder assessments than cognitive evaluations performed by the analytic system

(Loewenstein et al., 2001). Importantly, under conditions of risk and uncertainty, the analytic system's deliberation and processing procedures to achieve optimal decisions become highly resource intensive and slow. Consequently, the reactions formed by the experiential system provide initial guidance and support to the analytic system. It is then the role of the analytic system to determine whether to allow the guidance of the experiential system to affect decision outcomes (Slovic et al., 2004). Furthermore, Loewenstein et al. (2001) show that under conditions where there are clear incentives or rewards to make optimal decisions, decisions are mainly evaluated at the cognitive level, based fundamentally on rational judgments (i.e., the analytic becomes the determinant system of thinking). By contrast, in contexts where there are no clear incentives or rewards to make optimal decisions, the decision-making process increases its reliance on the experiential system to achieve suboptimal, although satisficing, decisions. As a result, decision outcomes are mainly determined by the relative importance allocated to each system of thinking.

Decision outcomes have also been shown to differ in relation to an individual's proficiency in, and preference for, one or both of the systems of thinking. This factor in turn modulates the relative contribution of each system when making a decision (Pacini and Epstein, 1999). In particular, some people may favour the experiential domain, while others rely more on the analytic system. Importantly, an individual's proficiency and preference for engaging the two systems of thinking have been shown to be associated with particular decision outcomes (e.g., Fletcher et al., 2012; Norris and Epstein, 2011; Pacini and Epstein, 1999; Shiloh et al., 2002; Toyosawa and Karasawa, 2004). In particular, those who display an experientially dominant thinking style have been shown to make less accurate probabilistic judgments, as they tend to ignore basic statistical conventions (e.g., neglecting base rates), to employ more heuristics, to be more susceptible to cognitive biases and to rely more on their risk preferences to determine decisions. On the other hand, those who display a rationally dominant thinking style have been shown to make more accurate probabilistic judgements, as they exhibit a lower susceptibility to cognitive biases, employ superior reasoning and information processing skills, seek lower support from heuristics and achieve decisions in a risk neutral manner.

The literature discussed in this section makes it clear that information processing is maintained by two systems of thinking, the analytic and the experiential. The general consensus is that the relative contribution of each system of thinking when processing information depends on the nature of decisions (i.e., the decision context) and individuals' proclivity towards engaging each of these systems (i.e., their decision-making profile).

2.2 The influence of temperature on mood and cognitive performance

The influence of temperature on decisions can take place via its effect on an individual's mood or through an influence on the resources made available to maintain the operations of the analytic system.

It has been shown that one's mood can influence decisions via misattribution of mood. In particular, 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) and become more prone to use irrelevant information (Forgas, 1995; Sinclair and Mark, 1995). By contrast, individuals in bad mood states are prone to become more pessimistic about future states of the world, to become more risk-averse (Isen et al., 1978), and to react more efficiently to relevant news (Sinclair and Mark, 1995).

Importantly, a large body of literature strongly indicates that external stimuli associated with temperature have a significant influence on present mood (e.g., Howarth and Hoffman, 1984; Watson, 2000). For example, 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 temperatures above the monthly average throughout the year were associated with positive moods. Previous research also suggests that, *ceteris paribus*, participants under good mood states were likely to process information in a similar fashion to that which is expected from individuals who display experientially dominant decision-making style, whereas bad moods lead individuals to process information in a similar manner to that which would be expected from rationally dominant decision makers (Sinclair et al., 1994). Keller et al. (2005), manipulated participants' time spent outdoors to measure whether this would moderate the relationship of temperature and decisions. They found that the strength of the relationship between temperature and mood (and resulting decisions) was not affected by the amount of time subjects spent outdoors.

The relationship between temperature and decisions can also occur via energy depletion. In particular, decreases in acclimated temperature¹ trigger the thermoregulatory system to expand its thermogenesis and vasoconstriction activities to elevate body temperature, whereas increases in temperature result in the body responding by increasing vasodilatation and perspiration to dissipate excess heat (Gonzalez-Alonso et al., 1999). Importantly, the speed and amount of energy allocated to dissipate temperature is substantially higher relative to the energy required to increase body temperature (Mekjavic and Eiken, 2006). Given the limited availability of the body's energy resources, the energy expenditures demanded to maintain thermal balance deplete the resources made available to sustain the functioning of the information processing systems (Mekjavic and Eiken, 2006). Since the analytic system is substantially more resource intensive than the experiential system, the activities of the former are impacted more heavily by the reallocation of energy to maintain thermal balance caused by changes in temperature. As a consequence, a reduction in resources available to sustain the analytic system may weaken cognitive performance (Hancock, 1986). For example, in line with the resource depletion explanation, studies have shown that the temperature effect on decisions only appeared on cognitively-demanding tasks (e.g., Hancock and Vasmatazidis, 2003; Sellaro et al., 2015).

¹ The human organism can adjust and adapt to current temperature, to allow it to maintain the stability of its functions.

Evidence concerning the impact of temperature on decision-making quality in real-world settings has received little attention in the literature. This may be due to the difficulty in identifying an appropriate naturalistic setting, one where a large number of decisions are available and where the effects of temperature on risk-taking and cognitive errors can be observed. As discussed in the introduction, a strand of literature exploring decisions in financial markets has attempted to fill this gap. However, it is difficult to obtain an unequivocal measure of the influence of temperature on decisions due to the infinitely lived nature of financial market prices. For example, some studies have suggested that higher temperatures 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, leading to stock prices that are higher compared to their true value (i.e., a stock's fundamental value; Denissen et al., 2008; Goetzmann et al., 2015; Kamstra et al., 2003). However, other studies have found that higher temperatures are related to lower market returns (Dowling and Lucey, 2005; Hirshleifer and Shumway, 2003). Dowling and Lucey (2005) have argued that this may occur because temperature may exert an even greater influence on investors' cognition than on their risk taking and optimism levels. The authors suggest that when experiencing higher temperatures, investors are more prone to engage in less critical thinking and analytical reasoning, causing them to make more errors when evaluating stocks, thus leading to lower market returns relative to their true value. Since higher (lower) temperatures are associated with greater (less) risk taking *and* lower (higher) cognition, and because these two factors lead to opposite effects on financial market returns, it appears evident that a stock market setting may not be appropriate for deriving conclusive evidence of the influence of temperature-effects on financial decision-making. As a result, the true impact of temperature on financial decisions in real-world settings has yet to be unearthed.

Based on the foregoing literature review, we suspect that higher (lower) temperatures will lead to better (worse) moods and, thus, greater (less) reliance on the experiential decision-making system and greater (less) risk taking. In addition, that higher (lower) temperatures will result in greater (less) resource depletion and, as a result, less (greater) use of the analytical decision-making system, leading to more (less) cognitive errors. Both these factors suggest that higher (lower) temperatures will result in prices which are less (more) in line with their true value (see Figure 1 for a summary of the hypothesized relationships).

To shed light on this issue, we identify an appropriate real-world financial setting where the limitations of previous real-world enquiries can be overcome, in which we can test the following hypothesis:

H1. Higher (lower) temperatures lead to market prices that are more out of (in) line compared to their true value.

In testing this hypothesis and interpreting the results, we needed to consider the literature which suggests that 'extreme' higher (lower) temperatures may cause lower (higher) risk taking (i.e., apathy dominates aggressiveness under extreme higher temperatures, and individuals may become more

aggressive at extreme colder temperatures (e.g., Schneider et al., 1980; Bell, 1981; Cunningham, 1979). For example, Cao and Wei, 2005 found that extreme low temperatures led to more aggressive risk taking that caused higher stock returns, while extreme high temperatures led to a prevalence of apathy that reduced risk taking, leading to lower returns. However, we use data from the UK to test the hypotheses, and temperatures in the UK very rarely reach extreme (high/low) temperatures. Consequently, it is unlikely that such a reverse relationship will appear in our study setting. This is further supported by the findings in Cao and Wei (2005), where they found that the impact of extreme temperatures on British financial markets was insignificant, suggesting that the role of temperature is not significantly inversed under extreme temperatures in this setting. Interestingly, there is also evidence that apathy influenced by extremely high temperatures may only be evident in tropical countries due to the high temperatures observed in such locations (Bandyopadhyaya, 1978).

Despite, the likelihood that this reversal of the role of temperature on risk taking will not be observed in data drawn from the UK, we do conduct robustness checks to cater for this possibility.

Previous studies in laboratory settings provide compelling evidence that the relative contribution of different systems of thinking when processing information, depends on the decision context and an individual's proclivity towards engaging the analytic and experiential systems when making decisions (i.e., one's decision-making profile) (Fletcher et al., 2012; Slovic et al., 2004). This suggests that, holding the decision context equal, the decision-making profile may be an important factor affecting the influence of temperature on the quality of decisions. For example, when studying the UK market over the period from 1989 to 1999, Cao and Wei (2005) found that returns are negatively related with temperature, while Floros (2008) using the period from 1995 to 2006, found that returns are positively related with temperature. Notably, the effects of temperature on market returns obtained in both studies should be in the same direction (i.e., either positively or negatively related to returns) as the decision context (UK market) is equal. Based on the evidence that the composition of investor profiles and preferences may change over time (Malmendier et al., 2020), the conflicting results from Cao and Wei (2005) and Floros (2008) suggest that temperature-effects may have some correlation with the decision-making profiles of the particular groups of investors that composed the market in the different periods. To our best knowledge, this proposition has not been investigated in real-world decision settings. Consequently, we test the following related hypothesis:

H2: The strength of the relationship specified in H1 is affected by an individual's decision-making profile.

As indicated above, individuals may prefer to, or be more adept in engaging with different domains of thinking (i.e., the experiential and rational) when making decisions. Furthermore, temperature may affect the function of these two domains of thinking in different ways: by increasing the number of cognitive errors via energy depletion or by affecting risk preference via an influence on mood. Thus, if decision making profiles do not modulate the influence of temperature on financial decisions, it is expected that the relationship specified in H1 will be equally present in the two groups of decision

makers (i.e., the experiential and rational decision makers). However, if we find that temperature has a greater influence on financial decisions made by those that adopt the rational approach, this will indicate that temperature has a greater influence on the cognitive effort of decision makers, via energy depletion. Alternatively, if we find that temperature has a greater influence on financial decisions in the group of decision makers that adopt the experiential approach, this will indicate that temperature has a greater influence on the risk preferences of decision makers via its effect on an individual's mood.

3. Data

3.1 Horserace markets and the favourite-longshot bias

To achieve our research objectives, we chose to examine the influence of temperature on financial decision-making in the horserace betting markets. This market setting was selected as it provides an ideal naturalistic setting to collect robust evidence concerning the degree to which temperature affects financial decisions. 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.

We focus our investigation on the UK bookmaker market concerning horseraces. Market prices, which in this setting are known as betting odds, are established in a manner to reflect decision makers' estimates of the true (i.e., objective) winning probabilities of assets (i.e., each competitor in a race) (e.g., Johnson et al., 2006). 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 annual turnover of off-course horserace betting in Great Britain surpassed £4.2 billion in 2019 (Statista, 2020)). These characteristics have been shown to facilitate decision calibration and improve the manner in which information is employed by market participants (e.g., Johnson and Bruce, 2001; O'Leary, 2017). 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 temperature can be shown to affect the financial 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 other financial markets.

An important reason for using the UK horserace market to study the effects of temperature on decisions is the existence the favourite-longshot bias (FLB). This widely observed bias in event-driven prediction markets, arises from bettors under/over-estimating the winning probabilities of high/low-probability contestants (favourites/longshots), resulting in systematically lower returns to bets on longshots (cf. favourites). The FLB has been widely documented in different horseracing markets across a variety of countries (Sung et al., 2009) and in other prediction markets (see Wolfers and Zitzewitz, 2004), including, for example, in S&P500 and FTSE100 index futures options (Hodges et al., 2003).

The impact of temperature on the degree of FLB displayed in a market offers a useful way of assessing the degree to which temperature impacts decision-making. Previous research suggests that the FLB can be caused by supply and demand side factors. In bookmaker 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. Bettors can either bet or not at the quoted prices. If bettors with superior skills and access to privileged information are able to exploit mispricing on the part of the bookmaker, they can secure the odds when bets are placed, therefore guaranteeing they obtain the expected value from superior decisions. This, exposes bookmakers to substantial risk (i.e., the payout to winners would be disproportionately larger than that which would be expected from posted odds). Shin (1993) argues that, in response to this, bookmakers artificially create the FLB to reduce their financial exposure to these bettors. In particular, bookmakers may shorten the odds offered on longshots, as relatively small amounts bet on these contestants can substantially increase bookmakers' liabilities. In this way bookmakers are able to protect their profits against bettors who have access to inside information or who possess superior skills.

However, the existence of the bias in markets where odds are solely determined by the actions of bettors, challenges the theory that supply-side explanations are the sole determinants of FLB (Smith et al., 2006). Demand side explanations for the FLB are based on the view that bettors' risk profiles and limited cognitive ability result in betting behaviour which leads to the bias. It has been evidenced that people may make financial choices with the aim to produce maximum utility (Johnstone, 2011). In particular, neoclassical utility theory suggests that bettors have, at least locally, risk-preferring utility functions (e.g., Quandt, 1986). Hence, 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; causing longshots to be disproportionately over-bet (e.g., Jullien and Salanie, 2000). Alternatively, behavioural theories suggest that FLB is a direct consequence of bettors' tendency to systematically make cognitive errors, such as 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. This would lead to an under/over-estimation of winning probabilities on favourites/longshots. (Feess et al., 2016; Vaughan-Williams et al., 2018).

It is clear from the preceding discussion that by controlling for the influence of bookmakers on the FLB (as proposed in Shin's (1993) methodology), it is possible to investigate the extent to which the bias can be attributed to the actions of bettors (i.e., demand side explanations). Importantly, in the

context of the aim of our paper, psychological and medical studies provide strong evidence that higher (lower) temperatures induce better (worse) mood, which leads to greater (less) risk taking. In addition, higher (lower) temperatures lead to greater (less) resource depletion, which in turn results in more (less) cognitive errors. Risk taking and cognitive errors are the two important demand-side factors linked to the FLB (e.g., Fees et al., 2016; Jullien and Salanie, 2000). In addition, it has been suggested that the influence of temperature is accentuated in cognitively demanding tasks, such as those experienced in horserace betting. This implies that the effects of temperature on bettors' decisions should be reflected in the level of FLB present in the market. Consequently, we believe that investigating our hypotheses using data from horserace markets will enable us to uncover reliable evidence of the influence of temperature on decision-making in a financial market context. The specific relationships between temperature and the level of FLB displayed in the market studied, which are expected to result in the proposition outlined in H1, are displayed in Figure 1.

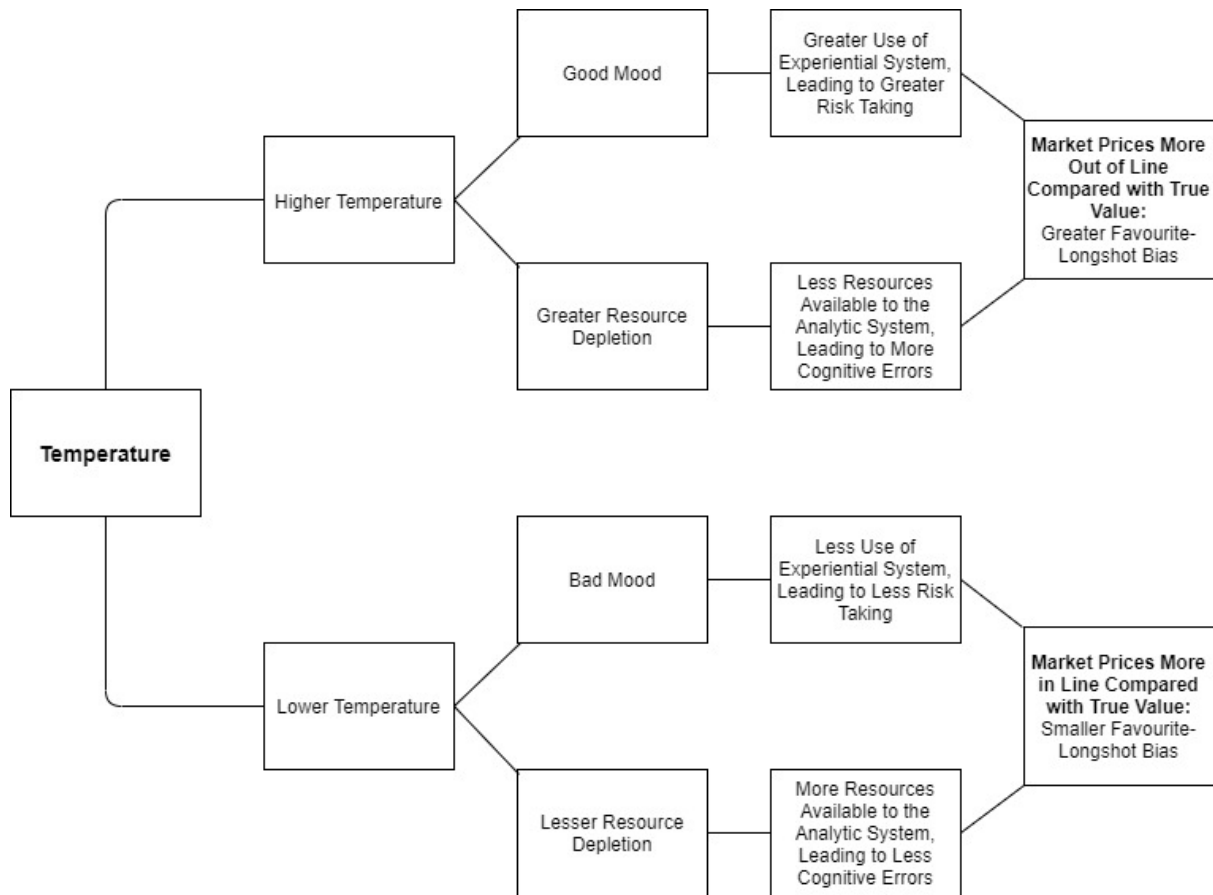


Figure 1 The influence of temperature on the favourite-longshot bias.

3.2 Sources of data

The horseracing dataset employed in this research was supplied by Raceform Ltd. The 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: The data included date and time of each race, starting prices (odds: SP) for each runner, an indicator for the race class (quality of runners) and an indicator for the type of race (1 for non-handicap and 0 for handicap). Races occur during 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 postal codes and these were used to retrieve the temperature observed immediately prior to each race start time.

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 temperature 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, may obfuscate the true expected influence of temperature on decision-making. To accommodate individuals' ability to acclimate and to ensure that results are driven by temperature effects on decision-making rather than by seasonal effects, we followed Hirshleifer and Shumway (2003), and deseasonalized temperature. This process involved subtracting the monthly temperature average from the raw temperature observed for a particular race. Another important benefit of using deseasonalized temperature is that improvements/deterioration in mood and cognitive ability should occur if the observed temperature were above/below the expected temperature for a particular month. Therefore, deseasonalization makes the measurement consistent with observed human nature, as the influence of temperature on decisions can be expected to occur all year round and not exclusively in summer or winter months. 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.

The descriptive statistics for the horseracing and temperature data are presented in Table 1.

Table 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.

Variable	Mean	Std. Dev.	Min	Max
<i>Bookmaker transaction costs (%)</i>	0.17	0.08	0.01	0.95
<i>No. runners</i>	10.01	3.56	2	36
<i>Race class (1: highest grade; 7: lowest grade)</i>	4.59	1.39	1	7
<i>Deseasonalized temperature (°C)</i>	0.03	3.20	-9.31	14.23

4. Methods

In order to explore the impact of temperature on the degree of FLB observed in horserace betting markets, we control for factors unrelated to temperature, which have been shown to affect the level of

FLB. In particular, the level of FLB has been shown to increase in non-handicap races (Vaughan-Williams and Paton, 1997), in races that attract lower quality runners (Gramm and Owens, 2005), and in races run during the weekends (Sung et al., 2012). Hence, we incorporate the following variables to control for these factors: race class, whether the race is a handicap and if the race takes place on the weekend. Furthermore, we discuss in section 4.1 the method we use to discount the influence of bookmakers on the FLB, thus ensuring that we capture the impact of *bettors' decisions* on the bias. In section 4.1, we also explain how we control for the influence of temperature on the racing performance of competitors and the influence of temperature on the racetrack surface conditions.

Conditional logit (hereafter CL) models are employed to investigate the effect of temperature on the quality of bettors' winning probability estimates contained in odds. 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 (i.e., whether betting odds under-/over-estimate the winning probabilities on favourites/longshots). This approach has been widely adopted to test the factors impacting the magnitude of the FLB in horserace betting markets (see: Lessmann et al., 2012; Ma et al., 2016; Sung et al., 2009).

4.1 Exploring the influence of temperature on bettors' financial decisions

In horserace betting markets, SPs (i.e., betting odds at the time the race commences) indicate the economic value attached to a specific betting contract. For example, a bet of \$1 on a particular competitor with an SP of 2/1 results in a profit of \$2 if the competitor wins and a loss of \$1 if the competitor loses. Fundamentally, SPs are established which reflect the probability of a particular competitor (i.e., horse-jockey combination) winning the race based on bettors' aggregate beliefs concerning the outcome of the race (Franck et al., 2010). Winning probabilities implied from betting odds, commonly referred to as subjective winning probabilities (p_{ij}^n), can be represented by:

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

where SP_{ij} is the market odds at the time the race commences on competitor i running in race j with number of runners, n_j . As indicated in section 3.1, market makers may intentionally create the FLB (i.e., by artificially lowering the odds on longshots) as a defence mechanism (Shin, 1993). To control for the effect of such a pricing policy, we reverse-engineer the odds using a model proposed by Shin (1993). This results in probability estimates (referred to as 'Shin probabilities' hereafter) that reflect investors' behaviour (i.e., the actions of bettors) excluding the impact of the bookmaker (e.g., Cain et al., 2002; Smith et al., 2009). A concise summary of the procedure for estimating Shin probabilities is provided in Appendix A. Consequently, to remove the influence of bookmakers' pricing policy (i.e., supply factors) in creating the FLB, we employ Shin probabilities (i.e., p_{ij}^s) in our subsequent methods as the measure of subjective winning probabilities.

The CL model is used to assess the extent to which bettors' subjective winning probability estimates, as derived from betting odds (i.e., p_{ij}^s), 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:

$$W_{ij} = \beta \ln(p_{ij}^s) + \varepsilon_{ij} \quad (2)$$

where β measures the importance of p_{ij}^s 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 wins 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_{ij}^ϕ , which is distinct from the odds implied probability p_{ij}^s) is estimated by:

$$p_{ij}^\phi = \text{Prob}(W_{vj} > W_{ij}, i = 1, 2 \dots n_j, i \neq v) \quad (3)$$

Consequently,

$$p_{ij}^\phi = \text{Prob}(\beta \ln(p_{ij}^\phi) + \varepsilon_{ij} > \beta \ln(p_{ij}^s) + \varepsilon_{ij}, i = 1, 2, \dots n_j, i \neq v) \quad (4)$$

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:

$$t_{ij} = 1 \text{ if } W_{ij} = \text{Max}(W_{1j}, W_{2j}, \dots W_{n_jj}); t_{ij} = 0 \text{ otherwise} \quad (5)$$

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):

$$p_{ij}^\phi = \text{Prob}(t_{ij} = 1 | \ln(p_{ij}^s), i = 1, 2 \dots, n_j) = \frac{\exp[\beta \ln(p_{ij}^s)]}{\sum_{i=1}^{n_j} \exp[\beta \ln(p_{ij}^s)]} = \frac{(p_{ij}^s)^\beta}{\sum_{i=1}^{n_j} (p_{ij}^s)^\beta}, \quad (6)$$

Eq. (6), enables us to assess the degree to which bettors' subjective probabilities of competitors' chances of winning, as derived from betting odds (i.e., p_{ij}^s), deviate from their true or objective probabilities as observed from realised racing outcomes. Specifically, if the estimated value of β is 1, this indicates that bettors' subjective probabilities are equal to the true probabilities (i.e., $p_{ij}^s = p_{ij}^\phi$). If β is estimated to be greater than 1, this indicates that the FLB is present. The greater the value of β , the greater the FLB. Consequently, β measures the degree to which betting odds under-/over-estimate the winning probabilities on favourites/longshots (Sung et al., 2019). To test whether β is statistically greater than 1, the standard normal test statistic is calculated:

$$z = (\beta - 1) / S.E. (\beta) \quad (7)$$

where S.E. measures the standard error of coefficient β .

In order to assess the influence of temperature on the quality of bettors' subjective probabilities, we examine the extent to which temperature affects the magnitude of the FLB. Based on the findings of previous research outlined in section 2, bettors are expected to engage in higher (lower) risk taking and display more (less) cognitive errors when the current temperatures are above (below) that expected for a particular month; suggesting higher (lower) levels of FLB under these conditions. Consequently, the

Temp variable, expressed as a dichotomous variable: 1 when deseasonalized temperature is positive and 0 when deseasonalized temperature is negative², is included in Eq. (6) and this is expanded to include a term which assesses the degree to which temperature may affect the FLB present in bettors' subjective winning probabilities, as follows:

$$p_{ij}^{\varphi} = \frac{\exp[\beta_1 \ln(p_{ij}^s) + \beta_2 (Temp_j \cdot \ln(p_{ij}^s))]}{\sum_{i=1}^{n_j} \exp[\beta_1 \ln(p_{ij}^s) + \beta_2 (Temp_j \cdot \ln(p_{ij}^s))]} = \frac{(p_{ij}^s)^{\beta_1} + (Temp_j \cdot p_{ij}^s)^{\beta_2}}{\sum_{i=1}^{n_j} (p_{ij}^s)^{\beta_1} + (Temp_j \cdot p_{ij}^s)^{\beta_2}} \quad (8)$$

where β_1 and β_2 are estimated using maximum likelihood procedures, and $Temp_j$ is a variable that captures the expected influence of temperature on bettors' decisions in race j .

The degree of the influence of temperature on the FLB can be discerned from the value and significance of β_1 and β_2 in Eq. (8). In particular, the coefficient β_1 will measure the degree of FLB when $Temp_j$ is 0 (i.e., when deseasonalized temperature is negative: the temperature conditions when bettors are expected to engage in less risk taking and make less cognitive errors). A positive (negative) β_2 will indicate that the degree of FLB is estimated to be larger (smaller) under higher temperatures, which is when bettors are expected to engage in greater risk taking and commit more cognitive errors. Specifically, the value of β_1 will measure the degree of the FLB when deseasonalized temperatures are negative, and the sum β_1 and β_2 will measure the degree of the FLB when deseasonalized temperatures are positive.

H1, will be supported if the degree of FLB is shown to be significantly greater in races when the deseasonalized temperatures are positive (i.e., when β_2 is significantly greater than zero).

To increase the robustness of Eq. (8) in measuring the influence of temperature on the degree of FLB, we incorporate two sets of k and r observable control variables in Eq. (9), namely *Racing factors* and *Performance factors*, as follows:

$$p_{ij}^{\varphi} = \frac{\exp[\beta_1 \ln(p_{ij}^s) + \beta_2 (Temp_j \cdot \ln(p_{ij}^s)) + \beta_k (Racing\ factors_{kj} \cdot \ln(p_{ij}^s)) + \beta_r (Performance_{rj} \cdot \ln(p_{ij}^s))]}{\sum_{i=1}^{n_j} \exp[\beta_1 \ln(p_{ij}^s) + \beta_2 (Temp_j \cdot \ln(p_{ij}^s)) + \beta_k (Racing\ factors_{kj} \cdot \ln(p_{ij}^s)) + \beta_r (Performance_{rj} \cdot \ln(p_{ij}^s))]} \quad (9)$$

² To ensure the robustness of the results to different temperature levels influencing the FLB, the results from Eqs. 8 and 9 were re-estimated by replacing the *Temp* term with deseasonalized temperature as a continuous variable and results were compared with the ones reported in Tables 4, 5 and 6. Summary statistics (i.e., sign of coefficients and their respective significance levels) remained consistent with the results reported in Tables 4, 5 and 6. Furthermore, Cao and Wei (2005) suggest that under extreme temperatures the association between temperature and risk taking may be reversed cf. to the relationship presented in Figure 1. In particular, Cao and Wei (2005) propose that extreme high (low) temperatures may induce individuals to decrease (increase) risk taking. This would lead to higher (lower) temperatures decreasing (increasing) the level of FLB displayed by bettors. To test whether the effect of temperature on FLB may be significantly altered at extreme temperatures, Eqs. 8 and 9 including a quadratic term for deseasonalized temperature were re-estimated. The resulting improvements in model fit were assessed. The inclusion of a quadratic term did not significantly improve model fit compared with the results presented in Tables 4, 5 and 6. We also re-estimated Eqs. 6, 8 and 9 with standard errors clustered by race calendar year in order to control for any variation related to different racing calendar years. The interpretation of significance levels of covariates remained consistent with the results reported in Tables 4, 5 and 6. Taken together, these robustness checks suggest that the results presented in Tables 4, 5 and 6 are robust to variations related to different calendar years, and that the relationship between temperature and FLB is not significantly altered at extreme temperatures experienced in the UK.

These control variables are defined, as follows:

Racing factors (k): Previous research shows that the FLB increases in lower-class races (i.e., Gramm and Owens, 2005), in non-handicap races (Vaughan-Williams and Paton, 1997) and when the race is run at the weekend (Sung et al., 2012). To control for the influence of these factors on the FLB, the following are included in the regression as control variables, together labelled as ‘Racing factors’: *race class* (1: highest grade; 7: lowest grade); *non-handicap* (1 when a race is non-handicap and 0 otherwise) and *weekend* (1 when the race is run during the weekend and 0 otherwise).

Performance (r): Costa Sperb et al. (2017) show that temperature may affect the performance of both horses and jockeys. For example, they demonstrate that horses and jockeys perform better under temperatures 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 temperature conditions. [More specifically, rolling regressions for each competitor \$i\$ are estimated using historical performance information \(i.e., finishing positions\) and the observed temperatures on those races, up to race \$j-1\$. The resulting regression coefficients are then paired with the observed temperature of race \$j\$, which then captures the forecast performance for \(each\) competitor \$i\$ in race \$j\$ given the temperature observed at race \$j\$. Further details of this methodology are provided in Costa Sperb et al. \(2017\).](#)

Previous research has suggested that readily discernible information is more effectively discounted by bettors, leading to odds which are more in line with true winning probabilities (i.e., lower FLB levels; Johnson et al., 2006). Discernibility of information 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, it is likely that bettors will more readily distinguish the relative impact of temperature on each of the competitors, leading to odds which better reflect true winning probabilities, and, hence, lower FLB. Consequently, the *preference variable variance* (the variance of preference variable probabilities for the competitors in a given race) is included in the CL in order to control for the influence on the FLB of the bettors’ ability to discern the effect of temperature on performance. Lastly, a horse’s performance might also be influenced by racetrack 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). If β_2 remains significantly greater than zero after the inclusion of racing and performance control factors, this will provide further support to H1, that higher temperatures are associated with greater levels of FLB.

In Table 2 we present a matrix of correlations³ which illustrate the very limited degree of association between deseasonalized temperature and the control variables.

Table 2: Correlations between deseasonalized temperature and control variables

	Deseasonalized temperature	Race class	Non-handicap	Weekend	Preference variable variance	Good surface
Deseasonalized temperature	1.00					
Race class	-0.11	1.00				
Non-handicap	0.05	-0.01	1.00			
Weekend	0.02	-0.22	0.01	1.00		
Preference variable variance	0.03	-0.08	0.04	0.01	1.00	
Good surface	0.06	0.03	0.01	0.01	0.02	1.00

4.3 Exploring the influence of temperature on bettors with different decision-making profiles

Temperature may affect the operation of the experiential and analytic systems in distinct ways. For example, changes in temperature may lead the experiential system to alter the risk preference employed, the extent to which heuristics are employed, the degree to which decision biases are displayed and the analytic system’s susceptibility to making cognitive errors (e.g., Loewenstein et al., 2001; Pacini and Epstein, 1999).

Importantly, individuals may display a proclivity towards engaging either the analytic or the experiential systems when making decisions (Fletcher et al., 2012). Given the distinct decision-making mechanisms underlying each system (i.e., cognitive evaluations dictating decisions in the analytic system, and risk taking in the experiential system), we believe that these changes of preference of one system over the other are likely to influence the relationship between temperature and the FLB displayed. To examine this proposition, we investigate the influence of temperature on the FLB for races likely to attract greater proportions of bettors with different decision-making profiles.

To achieve this, it is first necessary to classify bettors’ decision-making profiles. [We classify these profiles](#) in relation to an individual’s inclination towards engaging in rationality (the analytic system) and experientiality (the experiential system) when making decisions: rationally dominant (high rationality/low experientiality) and experientially dominant (low rationality/high experientiality).

We did not have access to information concerning individual decisions. However, it has been widely reported that certain race characteristics attract greater proportions of bettors with different profiles.

³ Pearson correlation coefficients are used to indicate the degree of association between all variables except racing class, for which we report Spearman coefficients (as the variable is ordinal).

This allows us to consider the aggregate decisions of bettors in particular types of race as those of a representative bettor with a particular decision-making profile (e.g., Sung et al., 2012).

Shin (1993) provides support for the proposition that races with particular characteristics (e.g., those with a large number of competitors) are likely to attract a higher proportion of bettors who possess superior information and/or skill in predicting winners. Bettors who have access to superior information and skills are characterised as being risk neutral, staking their bets in proportion to the expected monetary value of their information and predictions; characteristics which are analogous to individuals who engage in rational thinking when making decisions (Sobel and Raines, 2003). Importantly, Shin's (1993) model allows us to distinguish the proportion of informed and skilled bettors in any given race.

Based on the characteristics discussed above, it becomes evident that bettors' decision profiles may vary in relation to the proportion of informed and skilled bettors being present. In races which we expect to attract bets from a larger (lower) proportion of informed and skilled individuals, bettors are more (less) likely to make skilful decisions, making full use of the expected value of the information they hold. These decisions are likely to display a large (low) degree of rationality.

We split the dataset of races into subsets which are likely to involve bets from greater proportions of bettors with specific decision-making profiles. In particular, we identify bets on races which attract the largest proportions of informed/skilled bettors as those most likely to have been made using a *rationally dominant* (i.e., high rationality/low experientiality) decision-making profile. Those bets placed on races attracting the largest proportions of less informed/skilled bettors are regarded as those most likely to have been made using an *experientially dominant* (i.e., low rationality/high experientiality) decision-making profile.

Shin (1993) developed a means of assessing the proportion of informed and skilled individuals who bet on a given race, referred to as the Shin z value (see Appendix A for details). [We identify races with the largest proportions of more and less informed and skilled bettors as those with above- and below-median Shin \$z\$ values, respectively.](#)

To test H2, we re-estimate Eq. (8) separately on the [two](#) subsets of races identified above as those most likely to attract greater proportions of bettors with specific decision-making profiles. To determine whether the effect of temperature on decision biases (FLB) differs for decisions made by those with the [two](#) decision-making profiles, we inspect the coefficients of the temperature variable and their statistical significance for each subset of races. If the strength of the impact of temperature on FLB is unaffected by decision profiles, we would expect the temperature coefficient (β_2 in Eq. (8)) to be equally significant across races attracting different subsets of bettors. Thus, if we observe the significance of the temperature coefficient to differ across decision profiles, this will provide evidence to support H2.

[The descriptive statistics for the temperature, performance and racing factors data for subsets of bets placed on races regarded as those most likely to have been made using rationally dominant and experientially dominant decision-making profiles are presented in Table 3.](#)

A potential confound to the results may occur if there is an association between temperature and the presence of casual bettors (as this group of bettors is likely to perceive betting as a leisure activity). Clearly, weather may well affect the proportion of casual bettors attending the racetrack. However, in the UK market, the vast majority (>90%) of betting takes place in off-course betting offices or via the internet. Consequently, we suspect that there will be little association between temperature and the proportion of casual bettors. In addition, throughout the analyses we use hourly deseasonalised temperature and we believe that it is unlikely that hourly variations in temperature from that expected will change the participation in betting from casual bettors from one race to another. Although there is literature suggesting that inexpensive ‘consumption’ acts might be influenced by temperature (e.g. ice cream sales increasing when temperatures are high (Murray et al., 2010)), we believe that, due to the greater planning and logistics required to participate in betting at a racetrack (cf. to inexpensive consumption acts), the presence of casual bettors at the racetrack may be more influenced by long-term weather conditions (e.g., climate, season of the year, good weather forecast, etc) as opposed to whether the temperature at the time of a particular race is higher or lower than expected.

We explored this issue by calculating the correlation between Shin z and deseasonalised temperature and found it to be -0.001, indicating no strong association between these factors. This result is in line with our suspicions. In particular, based on the proposition that Shin z is associated with bettors with different decision profiles (i.e., informed/skilled individuals are regarded as rationally dominant and less informed/skilled individuals are experientially dominant), the low association between temperature and Shin z gives us further confidence that any observed impact of temperature on FLB is caused by the influence temperature has on decision making (cf. to simply increasing the number of casual bettors participating in betting).

Table 3: Descriptive statistics for the temperature and control variables for subsets of races regarded as rationally dominant and experientially dominant decision-making profiles.

Variable	Rationally Dominant				Experientially Dominant			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Race class (1: highest grade; 7: lowest grade)	4.60	1.32	1	7	4.56	1.44	1	7
Preference variable variance	0.01	0.003	0.00	0.16	0.03	0.002	0.00	0.11
Non-handicap ⁺ (1: non-handicap; 0: handicap)	0.45				0.35			
Weekend ⁺ (1: weekend ; 0: weekday)	0.26				0.24			
Good surface ⁺ (1: good/fast going; 0: otherwise)	0.81				0.78			
Temp ⁺ (1: positive deseasonalized temperature; 0: otherwise)	0.50				0.50			

*Non-handicap, Weekend, Good surface and Temp are dichotomous variables. Consequently, only the mean (which measures the proportions of races for each subset that display such characteristics) is reported for these variables.

5. Results

5.1 The impact of temperature on the favourite-longshot bias

We investigated the extent to which temperature influences FLB present in subjective winning probabilities (i.e., p_{ij}^S) by estimating CL models in the form of Eq. (6). (Model I, with odds probabilities as covariate) and Eq. (8) (Model II, with odds probabilities and temperature as covariates). The results are presented in Table 4.

Table 4: Results of estimating conditional logit models (Eq. 6 and 8) using bettors' subjective probabilities (p_{ij}^S) for the 87,402 flat races in the United Kingdom run between 2002 and 2016 inclusive.

Variables	Model I			Model II		
	Coef.	Std. Error	Z-score	Coef.	Std. Error	Z-score
Odds probabilities	1.0364	0.0048	214.63** (0.000)	1.0248	0.0069	149.31** (0.000)
Temp				0.0229	0.0097	2.37* (0.018)
Pseudo-R ²		0.1619			0.1620	
Log-likelihood		-164012.94			-164010.14	
LLR test						5.6*

Note:

**Indicates significant at the 1% level

*Indicates significant at the 5% level

The results indicate that the coefficient of odds probabilities is highly significant, suggesting that they are extremely useful for forecasting winning probabilities (z-score of 214.63). 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 (Bolger and Wright, 1994; Bruce and Johnson, 2005). Despite this, the odds probabilities coefficient of 1.03637 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 ($z(1)=7.53$), confirming that the FLB observed is statistically significant. Notably, since Shin probabilities (p_{ij}^S) discount the actions of bookmakers in creating the FLB, the results support the proposition that the FLB arises from bettors' behaviour. Consequently, in line with previous studies in horseracing markets, we find that the FLB is present and results from the actions of bettors.

The results presented in Table 4, also indicate that temperature has a significant influence on the level of FLB displayed in bettors' subjective probabilities. For example, the coefficient for odds probabilities (β_1) measures the level of FLB displayed in the market when bettors are expected to engage in less risk taking and to make less cognitive errors (i.e., when *Temp* equals '0'), and the coefficient of the *Temp* variable (β_2) indicates the adjustment to the level of FLB associated with races when bettors are expected to engage in greater risk taking and to make most cognitive errors (i.e., when *Temp* equals '1', the level of FLB is given by the sum of β_1 and β_2). The results in Table 4 clearly show that increases in temperature are associated with higher levels of FLB (coefficients of subjective probabilities 1.0476 and 1.0248 for races when deseasonalized temperature is positive and negative, respectively). The z-score of β_2 confirms that the difference in FLB associated with the different temperature conditions is statistically significant at the 5% level (z-score of 2.37). Lastly, the model that includes the *Temp* variable better explains the results of races (pseudo- R^2 of 0.1619 and 0.1620 for Model I and Model II, respectively). This suggests that winning probabilities derived from betting odds can be improved by correcting for the influence that temperature may have on bettors' decisions. This is confirmed by conducting a log-likelihood ratio test (LLR) to analyse whether the improvement in explanatory power observed by incorporating the *Temp* variable in Model II is statistically significant. In particular, we calculated $LLR = 2[LL_{Model II} - LL_{Model I}]$, where $LL_{Model II}$ and $LL_{Model I}$ are the log-likelihoods of Model II and Model I, respectively (see Green et al., 2019). We found that $LLR = 5.6$ ($\chi^2_1[0.05] = 3.841$). The significance of this result suggests that temperature influences bettors' decisions.

Overall, the results shown in Table 4 indicate that, independent of temperature conditions, bettors' judgments suffer from the FLB. However, the strength of the bias is more pronounced under higher deseasonalized temperatures, the conditions when decision makers are expected to engage in greater risk taking and to display lower cognitive performance.

As discussed in section 3.1, the strength of the FLB can vary in relation to factors associated with the types of race, with technical factors related to racing and as a result of the impact of temperature on horses' performance. Consequently, we estimate a CL model in the form of Eq. (9) in order to control for the influence of these factors when examining the influence of temperature on bettors' decisions. The results of this estimation are shown in Table 5. These results show that two out of the five control variables are significant and the signs of the coefficients are in line with *a priori* expectations (that the FLB is greater in lower-grade races and in non-handicap races). We find that the FLB is present, despite discounting the influence of various factors on FLB, and after controlling for a possible influence of temperature on the performance of horses.

Table 5: Results of re-estimating the conditional logit model (Eq. (9)) controlling for race and performance factors, using odds probabilities (p^s_{ij}) for the 87,402 flat races in the United Kingdom run between 2002 and 2016.

Variables	Coef.	Std. Error	z-score (p-value)
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	<i>Odds probabilities</i>	1.0018	0.0199	50.10** (0.000)
Racing Factors	<i>Race class</i>	0.0077	0.0037	2.10* (0.036)
	<i>Non-handicap</i>	0.0256	0.0097	2.64** (0.008)
	<i>Weekend</i>	-0.0001	0.0115	-0.001 (0.992)
Performance	<i>Preference variable variance</i>	-2.624	1.771	-1.48 (0.139)
	<i>Good surface</i>	0.0327	0.0287	1.14 (0.253)
Temperature	<i>Temp</i>	0.0236	0.0097	2.42* (0.015)
	Log-likelihood	-164002.96		
	Pseudo-R ²	0.1620		

Note:

**Indicates significant at the 1% level

*Indicates significant at the 5% level

Importantly, the results presented in Table 5 indicate that temperature remains a significant factor influencing the level of FLB displayed by bettors' subjective probabilities. The results clearly show that higher temperatures (those expected to increase risk taking and cognitive errors) are associated with greater FLB. In particular, the coefficient of the *Temp* variable indicates that the level of FLB displayed in bettors' subjective probabilities increases by 0.024 for races when deseasonalized temperatures are positive (cf. to races when deseasonalized temperatures are negative). The z-score of the *Temp* variable confirms that this difference in FLB associated with temperature is statistically significant at the 5% level (z-score of 2.42). Consequently, even after controlling for the effect of bookmakers' pricing policies and racing and performance factors on the bias, we find that temperature significantly affects the level of FLB.

Taken together, the results presented in Tables 4 and 5 provide robust evidence to support H1. In particular, the results suggest that temperature exerts a significant influence on FLB, even after controlling for the various racing, technical and bookmaker-related factors which have been identified as affecting the FLB. In particular, previous, largely laboratory-based research has shown that higher/lower temperatures are associated with greater/less risk taking and more/less cognitive errors (e.g., Forgas, 1995). These factors have, in turn, been shown to lead to under-/over-estimation of winning probabilities on favourites/longshots (Jullien and Salanie, 2000; Snowberg and Wolfers, 2010). Consequently, the findings presented in this section suggest that temperature exerts a significant influence on the level of the FLB. The results, therefore, provide strong evidence in support of H1.

5.2 The influence of temperature on bettors with different decision-making profiles

In order to test H2, namely, that the impact of temperature on decisions is affected by an individual's decision-making profile, we explore whether the impact of temperature on the FLB differs in subsets of races most likely to attract bettors that exhibit rationally dominant and experientially dominant decision-making profiles. We achieve this by re-estimating CLs in the form of Eq. (6) (Model I, with odds probabilities as covariate) and Eq. (8) (Model II, with odds probabilities and temperature as covariates) for each of these subsets of races and inspect the coefficient of temperature⁴. The results are presented in Table 6⁵.

The results related to Model I show that the estimated subjective probability coefficients for races likely to attract (a) rationally dominant and (b) experientially dominant bettor profiles are significantly greater than 1 at the 1% confidence level (coefficients of 1.0231 and 1.0538 and $\beta_1 > 1$ z-scores of 3.01 and 3.67, for races likely to attract rationally dominant and experientially dominant bettors, respectively). Taken together, these results confirm that bettors who are likely to display rationally dominant and **those who are likely to display** experientially dominant decision profiles, **both** exhibit the FLB.

Table 6: Results of re-estimating the conditional logit models (Eq. (6): Model I and Eq. (8): Model II) employing bettors' subjective probabilities (p_{ij}^s) for the different subsets of races most likely to attract bettors that exhibit the four decision-making profiles, for the 87,402 flat races in the United Kingdom run between 2002 and 2016.

Rationally dominant						
Parameter	Model I			Model II		
	Coef.	Std. Error	z-score (p-value)	Coef.	Std. Error	z-score (p-value)
<i>Odds probabilities</i>	1.0211	0.0066	154.33** (0.000)	1.0060	0.0094	107.23** (0.000)
<i>Temp</i>				0.0300	0.0132	2.27* (0.023)
Pseudo-R ²		0.1825			0.1826	

⁴ To ensure the robustness of the results to alternative factors that may influence the FLB, we also estimated Eq. (9) on each of the subsets of races representing the different decision-making profiles. Summary statistics (i.e., sign of coefficients and their respective significance levels) remained consistent with the results reported in Table 6. This suggests that the results presented in Table 6 are robust to alternative factors that may influence the FLB.

⁵ Using Shin z to define decision making groups may add a potential source of endogeneity to our analyses due to the relationship between Shin z and odds probabilities. To correct for this possible source of endogeneity and to increase the reliability of results reported in Table 6, we conducted an additional test based on the two-stage method proposed by Mavruk (2021). The first stage of the methodology involves using a set of instruments to predict Shin z (denoted as Shin \hat{z}). The instruments selected were bookmakers' transaction costs (TC), number of runners in a race (NR) and the race's prize money (i.e., the 'purse': PM). This first-stage regression is derived as follows: $Shin z_j = \alpha + \beta_1 TC_j + \beta_2 NR_j + \beta_3 PM_j$. Subsequently, in the second stage of the methodology, Shin \hat{z} was used to define the rationally dominant and experientially dominant decision-making profiles, and CLs in the form of Eq. (6) and Eq. (8) were estimated on these subsets of races. The results (displayed in Appendix B) are qualitatively identical to the ones reported in Table 6 (notably, the variable *Temp* was only significantly associated with higher FLB levels in the rationally dominant group), thus, increasing our confidence in the reliability of results reported in Table 6.

Log-likelihood		-75055.34				-75052.77
LLR test				5.13*		
<hr/>						
Experientially dominant						
		Model I			Model II	
Parameter	Coef.	Std. Error	z-score (p-value)	Coef.	Std. Error	z-score (p-value)
<i>Odds probabilities</i>	1.0534	0.0071	149.37** (0.000)	1.0460	0.0101	104.07** (0.000)
<i>Temp</i>				0.0147	0.0141	1.04 (0.299)
Pseudo-R ²		0.1438			0.1438	
Log-likelihood		-88952.02			-88951.48	
LLR test				1.08		

Note:

**Indicates significant at the 1% level

* Indicates significant at the 5% level

The results displayed for Model II in Table 6, indicate that the coefficient for temperature estimated using subsets of races likely to attract rationally dominant (races with high Shin z) and experientially dominant (races with low Shin z) bettors are positive (0.03, 0.0147, respectively), but only the first of these is significantly different from zero at the 5% level (z-scores of 2.27 and 1.04, respectively). The positive coefficients for the temperature variable are consistent with the expectation that increases in temperature would be associated with higher levels of FLB.

When assessing the pseudo-R² from Table 6, we found that the winning probabilities derived from betting odds for the rationally dominant group can be significantly improved by including the *Temp* variable (pseudo-R² of 0.1825 and 0.1826 for Model I and Model II, respectively; $LLR = 5.13$ ($\chi^2_1[0.05] = 3.841$)). Conversely, the *Temp* variable does not improve the winning probabilities derived from betting odds for the experientially dominant group (pseudo-R² of 0.1438 and 0.1438 for Model I and Model II respectively; $LLR = 1.08$ ($\chi^2_1[0.05] = 3.841$)).

If decision profiles were not an important factor underlying decisions, we would expect that all decision profiles exhibit the FLB and for the level of the bias to be equally influenced by temperature. However, taken together, the results presented in Table 6 provide strong support to H2. In particular, the results suggest that decision profiles exert a significant influence on the degree of decision bias displayed by bettors. More specifically, we find that temperature only exhibited a significant influence on the level of FLB on rationally dominant bettors.

6. Discussion

The results suggest that temperature has a significant influence on decisions made by bettors. In particular, we find that the bias displayed by bettors for over-/under-betting longshots/favourites is more pronounced in higher temperatures. Previous, largely laboratory-based research has shown that higher temperatures can lead to greater risk taking and a decreased level of cognitive processing of information,

and both these behaviours have been advocated as causes of the FLB (Jullien and Salanie, 2000; Sung et al., 2009).

The impact of temperature on bettors' decisions was evidenced by the fact that higher temperatures were associated with greater FLB displayed in winning probabilities contained in betting odds. Given that the subjective probabilities we employ discount the influence of bookmakers in creating the bias, these results strongly suggest that the impact of temperature on FLB stems from the fact that bettors' decisions are affected by temperature.

We also observed that **the FLB is present** in races when the representative bettor is characterised as **having either a** rationally dominant or experientially dominant decision profile. However, temperature only imposed a significant influence on the FLB in races where bettors are characterised as rationally dominant. These findings have a number of important implications: First, it demonstrates the importance of accounting for decision-making profiles when investigating the influence of exogenous and psychological factors on decisions. For example, it has been shown that such factors may affect the operations of the analytic and experiential systems in distinct manners, and that individuals differ in their preference for engaging with these two systems when making decisions (e.g., Fletcher et al., 2012). This implies that in order to uncover reliable evidence concerning the influence of psychological factors on decision outcomes, it is important to account for individual differences in decision-making profiles.

Second, it demonstrates the importance of the contributions of the two systems of thinking when making decisions under risk and uncertainty. Under these conditions, the analytic system's deliberation and information processing become highly resource intensive and slow (Slovic et al., 2004). Consequently, the analytic system becomes more prone to consult the experiential system given the fast speed and low mental resource demand nature of the inputs provided by the latter system. In particular, the experiential system contains positive and negative memories and associations formed from previous experiences related to the current decision. This, in turn, provides readily accessible experiential 'cues' to support the information processing operations of the analytic system. Put simply, the inputs from the experiential system may serve as orienting mechanisms for the analytic system to maintain its information processing functions in complex, uncertain and risky decision conditions (Zajonc, 1980). Therefore, fully rational decisions under such conditions require appropriate integration and effectiveness of the two systems of thinking (Slovic et al., 2004). That is, under conditions of risk and uncertainty, such as in decisions made in betting markets, superior decisions should be expected from individuals who can engage and are proficient in using both systems of thinking.

Third, the results suggest that temperature posed a greater influence on the operations of the analytic system of bettors (cf. to their experiential system). As discussed in section 2.2, temperature may affect the analytic and the experiential systems in distinct manners. In particular, changes in temperature may influence the resources made available for the operations of the analytic system or by influencing the risk preference displayed by the experiential system (e.g., Isen et al., 1978; Mekjavic and Eiken, 2006). The evidence that temperature only impacted FLB displayed by bettors who are prone to be risk neutral

and to engage more in the analytic decision-making system (i.e., on races where the representative bettor has a rationally dominant profile), suggests that temperature posed a stronger influence on the cognitive performance of individuals (i.e., via energy depletion) rather than on their experiential system (i.e., via changes in mood and, consequently, in risk preference). In particular, the analytic system demands substantial energy resources to function optimally, whereas the experiential system does not (Hancock, 1986). Hence, reductions in energy available to support the functioning of the analytic system may cause individuals to make more cognitive errors when assessing winning probabilities, thus inflicting a significant influence on the FLB. For example, although rationally dominant individuals are characterised as making risk neutral decisions, it does not necessarily indicate that they do not possess either a positive or negative risk appetite. Rather, their final decisions are risk neutral because the analytic system is able to override the influence of subjective aspects of their decisions (Slovic et al., 2004). Therefore, even if the influence of temperature on the FLB displayed by rationally dominant bettors were a result of the impact of temperature on their risk preferences, this would only be possible if the analytic system allowed this to occur. Consequently, this suggests that temperature influenced the performance of the analytic system of bettors rather than directly influencing their risk preferences. Assuming a linear relationship between temperature and risk taking, this view is further supported by the fact that the impact of temperature on the FLB is insignificant in races where bettors' decisions are mainly impacted by their risk preferences (i.e., in races which largely attract bettors with experiential dominant decision profile). This view also holds if a non-linear relationship exists between temperature and risk taking. Under this framework, higher temperatures are expected to have a proportionally larger influence on the risk taken by bettors who are naturally risk averse (i.e. those who start from a low risk-taking level) compared to bettors who naturally display higher risk preference (who are likely to start from a higher risk-taking level). However, independently of the level of risk taken by an individual, increases in temperature would still lead to increases in risk taking, albeit at different magnitudes, depending upon the individual's risk preference. Nevertheless, if temperature had a significant influence on their decisions, we would expect this to be reflected in the FLB level displayed in the group of bettors where the rational system is less likely to override changes in risk preferences dictating final decisions. However, we find that temperature only affects those bettors who use the analytic system to reach their decisions. To this end, finding that temperature only affected the FLB in races when individuals engage more in the analytic decision-making system, supports the proposition that temperature may influence financial decisions by increasing the number of cognitive errors.

A potential limitation of this proposition arises if the relationship between prices and risk taking is non-linear (e.g., logarithmic). Under this construct, the influence of temperature on the level of risk taken by bettors may be less likely to be reflected in prices in races when, ceteris paribus, prices are already greatly influenced by a high level of risk taking. In this case, increments in the level of temperature-induced risk taking would only have a marginal effect on prices and, consequently, on the FLB. To the best of our knowledge, no literature identifies the specific proportion of bettors with a

particular risk preference profile that populate the market, nor that indicates whether there are characteristics of certain races that attract more or less risk taking. In light of this, when interpreting our findings, we could only assume that betting markets may be composed of bettors with different risk preferences and that the relationship between prices and risk taking (in whatever form) is likely to be similar across the rationally dominant and experientially dominant groups of decision makers.

Fourth, our findings help shed light on the results of previous research conducted in financial markets. As outlined in section 2.2, the impact of temperature on decisions has a theoretically sound basis and has been demonstrated in laboratory-based studies (Sellaro et al., 2015). However, empirical evidence for the existence of the phenomenon in financial markets is inconclusive as some financial market studies show no effect of temperature on decisions of investors, while those that do show an effect, report conflicting results (see: Jacobsen and Marquering, 2008). For example, some studies suggest that lower temperatures reduce decision quality (e.g., Goetzmann et al., 2015), while others suggest that better decisions are made under lower temperatures (e.g., Dowling and Lucey, 2005).

By showing that temperature influenced decisions in our setting, we provide evidence in support to the proposition that temperature may have the potential to influence decisions in financial market settings. Furthermore, our results show that the temperature differentially influences the decisions of those with different decision-making profiles, with the most significant impact being observed on rationally dominant decision makers via the cognitive errors proposition. This suggests that to further our understanding of the effects of temperature on decisions in financial markets, future studies should focus on developing research designs that are able to account for the different decision-making profiles of investors and to measure the impact of temperature-induced cognitive errors on market prices.

7. Conclusion

Previous research has been unable to determine conclusively whether temperature affects decisions in financial markets. Consequently, the principal aim of this study was to identify whether, and to what extent, temperature influences decisions in a financial market setting. To achieve this aim, we examine decisions made in an ideal market setting for shedding light on this phenomenon. In particular, we examine decisions made in 87,402 separate horserace betting markets, each of which is a time limited prediction market, at the end of which all uncertainty is resolved. This provides the opportunity to unequivocally assess the quality of decisions made by participants in each market under different temperature conditions.

The results reported here provide strong support for the view established from theoretical grounds and from laboratory studies that temperature can influence decisions. In particular, we demonstrate that temperature can affect financial decisions in a real-world context. Importantly, the results clearly demonstrate that to uncover genuine temperature effects in financial markets it is important to select an appropriate context and to account for decision-making profiles. Furthermore, they offer direct empirical evidence that exogenous factors unrelated to the decision (i.e., the prevailing temperature)

influence the decision-making process; more specifically, that temperature impacts the decision-making process, which in turn influences the quality of financial decisions.

The results of this research are of particular importance in helping to better understand the body of literature that investigates the influence of temperature and other environmental factors on decision-making in financial markets. A comprehensive literature survey indicated that limitations of previous studies may be the cause of the conflicting results concerning the influence of temperature on financial market returns. Our study demonstrates that selecting an appropriate setting is necessary to provide robust evidence to inform the debate concerning the influence of temperature (and perhaps other behavioural and exogenous factors) on decisions in financial markets. We also demonstrated that the effects of temperature on decisions may be influenced by the decision-making profiles of individuals. This suggests that future studies need to carefully consider the setting, the research approaches employed and the decision profiles of individuals when investigating the influence of environmental factors on decisions.

It appears that human information processing systems allow exogenous factors unrelated to a decision to actively influence decision outcomes, and it has been found that individuals are often unaware of this influence (Loewenstein et al., 2001). This suggests that, under certain conditions, we may not be able to attain full rational control over our decisions. Notably, decisions can be influenced by many exogenous factors in addition to temperature, such as feeling hungry (Fisher and Rangel, 2014). This suggests that there are many factors which can potentially influence decision outcomes, via their influence on our rational and experiential systems of thinking.

Lastly, our results show the diverse contexts in which global warming may impact humans. The negative effects that global warming have on natural ecosystems, on social development and on the real economy have been clearly demonstrated (e.g., World Economic Forum, 2020). However, finding that (higher) temperatures may negatively impact financial decisions, and that this has the potential to impose substantial economic penalties to decision makers, sheds light on an alternative means by which rising global temperatures may impact our lives.

We have shown that temperature systematically influences investment decisions in a context where individuals have been shown to generally use information appropriately (Bruce and Johnson, 2005) and have strong (economic) incentives to make accurate predictions. Consequently, it is likely that these effects may be even stronger in many contexts where these conditions do not exist.

Appendix A. Shin Probabilities

Shin (1993) developed a price-setting model for bookmaker markets. The proposed model assumes that market prices (i.e., odds) are the result of an economic game between bookmakers and bettors. As part of the game, bookmakers face a number of ‘insider traders’, who are bettors that possess superior knowledge and/or skills to pick winners, the proportion and identity of whom are unknown to bookmakers (i.e., adverse selection). Since bookmakers are not perfectly informed, they purposely lower odds on longshot contestants relative to favourites to minimise losses to better

skilled/knowledgeable bettors. Put simply, Shin's (1993) model is based on the notion that bookmakers' pricing policies may create the FLB in betting odds 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 winning probability estimates (referred as 'Shin probabilities') that reflect the decisions of the betting public. Following Cain et al. (2002) and Smith et al. (2009), Shin probabilities for the horse and jockey pair i in race j can be expressed as:

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

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 and/or bettors with superior skills for a particular race (z_j ,) with n runners can be estimated using a fixed-point iteration process starting at $z_m, = 0$:

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

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, thereby yielding probability estimates which discount the influence of bookmakers in creating the FLB.

Appendix B. Endogeneity Robustness Test

This Appendix contains the estimates of the two-stage robustness test of the influence of temperature on bettors with different decision-making profiles. The results of the first-stage and second-stage estimates are displayed in Tables B1 and B2, respectively.

Table B1: Stage-1 Shin z regression.

Variables	Coef.	Std. Error	t -score (p-value)
TC	0.1191	0.00120	98.55** (0.000)
NR	-0.0026	0.00002	-119.2** (0.000)
PM	0.0001	0.00003	4.51** (0.000)
constant	-0.0920	0.00126	-72.97** (0.000)
Adjusted-R ²	0.1424		

Note:

**Indicates significant at the 1% level

Table B2: Results of re-estimating the conditional logit models (Table 6) by using Shin \hat{z} to categorise rationally dominant and experientially dominant groups of decision makers.

Rationally dominant

Parameter	Model I			Model II		
	Coef.	Std. Error	z-score (p-value)	Coef.	Std. Error	z-score (p-value)
<i>Odds probabilities</i>	1.0148	0.0068	148.50** (0.000)	0.9985	0.0097	103.30** (0.000)
<i>Temp</i>				0.0325	0.0137	2.38* (0.017)
Pseudo-R ²		0.1690			0.1691	
Log-likelihood		-74720.70			-74717.88	
LLR test				5.65*		
Experientially dominant						
Parameter	Model I			Model II		
	Coef.	Std. Error	z-score (p-value)	Coef.	Std. Error	z-score (p-value)
<i>Odds probabilities</i>	1.0574	0.0068	155.07** (0.000)	1.0508	.0097	107.89** (0.000)
<i>Temp</i>				0.0128	0.0136	0.94 (0.347)
Pseudo-R ²		0.1560			0.1560	
Log-likelihood		-89282.50			-89282.06	
LLR test				0.88		

Note:

**Indicates significant at the 1% level

* Indicates significant at the 5% level

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