Stumped by the Sun, Saved by the Side: Estimating the role of peer and adversarial effects in adaptation to heat*

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Abstract

Literature has conclusively established that temperature has negative impact on individual's labor productivity. However we rarely work in isolation, most jobs require working with peers or against an adversary. This paper provides first estimates of the magnitude of peer and adversarial effect on individual's productivity under heat. Utilizing rich data, institutional details, and team dynamics of the sport of cricket, I find that even though temperature affects individual's productivity negatively, it doesn't have any effect on equilibrium outcomes that are affected by peers and adversaries. There could only be two explanations for this: increased peer effect under heat or a decreased adversarial effect. A further analysis reveals that peer effect increases significantly at temperature above 25°C while adversarial effect has no significant difference between games played below 25°C and above 25°C temperature. These peer effects accrue through complementarity of skill-set among peers which creates opportunity for learning at higher temperature. This finding shows that even when workers are individually affected negatively by temperature, they can adapt in team settings through positive peer effect given complementary skills exist among peers.

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"One thing that for me was the highlight of our partnership was how content we were to knock the ball around. Not necessarily looking at the number of balls we had played and the runs we had got. Just fighting through the physical challenges of what we had to experience through the afternoon and coming into the evening. The pressure obviously makes you feel more tense and you start getting more fatigued than you actually are. Just knocking the ball around and then bringing the total down 10-15 runs at a time. That for me I felt like was something that really helped build that partnership. I am tired, I won't lie. You know how it was. The only chat after I think 50-70 runs of partnership was let's conserve energy, let's not run the twos…" - KL Rahul, Indian Batsman (On his match winning partnership of 165 runs with Virat Kohli vs. Australia in World Cup match on Oct 8, 2023 played in Chennai, India at maximum temperature of 34$^{\circ}C$ (93.2$^{\circ}F$))

1 Introduction

How does temperature affect labor productivity? A large body of literature exists that estimates the effect of heat on individual's labor productivity. Lab experiments conducted in ergonomic studies show that as Wet Bulb Globe Temperature (WBGT)[1] rises above 25$^{\circ}C$, task efficiency declines by 1%-2% (Solomon M. Hsiang (2010)). A meta review of studies focused on productivity in office work (eg: text processing, simple calculations, length of telephone customer service time, call handling time) finds an average productivity loss of 2% from temperature above 25$^{\circ}C$ (Seppanen, Fisk, and Lei (2006)). Lab experiments however do not emulate real world, where workers can alter behavioral response as a function of incentive system. Causal studies of individual productivity require worker level output and demographic data which is usually not available. Firm surveys can be conducted but are expensive to do so.[2] While utlilizing firm level output to estimate productivity impacts misses worker level interaction.[3] Humans rarely ever work in isolation. They usually work in peer groups or against an adversary and the literature so far has not estimated how peers and adversaries might affect individual productivity under heat.

In this paper, I provide the first estimates of the role of peers and adversaries in adaptation to heat. I estimate the impact of temperature on labor productivity - both at an individual level and within the dynamics of peer and adversarial interactions. These inter-worker interactions are important to study to understand dimensions of adaptation to higher temperature. Moreover, most jobs, including legal teams, diplomatic missions, consulting firms, military action, academic setting, political campaigns, stockbrokers, require work-

[1] Wet bulb temperature is defined as the lowest temperature that can be reached by evaporating water into the air at a constant pressure, typically measured by using a wet bulb thermometer. It is an important parameter in meteorology since it considers the impact of humidity on weather conditions.

[2] Adhvaryu, Kala, and Nyshadham (2022) find that managers mitigate environmental shocks in garment firms in India. Somanathan et al. (2021) survey garment, weaving, and steel mills in India and find that task efficiency declines by 2%-8% with high temperature. Cachon, Gallino, and Olivares (2012) finds similar estimates for automobile firms in US. For a detailed review see: Heal and Park (2016)

[3] J. Park (2016); Dell, Jones, and Olken (2009); Heal and Park (2013); Zhang et al. (2018); Adhvaryu, Kala, and Nyshadham (2020)

ing in teams and against an adversary. The analysis centers around two questions: First, are individual productive outcomes affected differently with temperature than equilibrium productive outcomes that are affected by individual, peers, and adversaries? Second, what causes these differences - peer effect or adversarial effect? Having found the evidence that equilibrium outcomes are not affected by temperature while individual outcomes are, I find that it is the increase in peer effect that causes this adaptation to heat rather than a decline in adversarial effect. I then investigate the mechanism that could lead to adaptation through peer effect: ability, experience or complimentarity of skill-set.

I address the data issues mentioned above in estimating individual and inter-worker interactions by utlizing rich data and team dynamics of the sport of international cricket. I exploit the structure of cricket game as a workplace to estimate individual worker productivity and equilibirum productivity (affected by peer and adversaries).

In the first part of the analysis, I estimate the impact of temperature on individual measures of productivity that are not affected by the peer or the adversary. By utilizing panel data of individual outcomes, variation in temperature at games and controlling for effect of heat on opposition, I find a negative effect of temperature on measures of productivity for batsman which are unaffected by peer or adversary, ranging between 1.73 to 2.71$\%$ for every $1^{\circ}C$ increase in temperature. While estimating the imapct of temperature on equilibrium measures of productivity for an individual i.e. the productive measures for an individual that are affected by the individual, the peer, and the adversary, I find no effect of temperature on productivity. Considering the fact that individual worker is negatively affected, the null effect of heat on equilibrium outcomes posits two explanations: either positive *peer effect* compensates for the negative effect of temperature on individual as temperature increases and allows individual workers to adapt or that the *adversarial effect* declines more than individual productivity decline, therefore causing a null effect of heat on equilibrium outcomes. I explore this question further.

I find that adversaries' productive outcomes are not differently affected with temperature. This implies that the second explanation of adversarial effect declining is not true. Therefore, the first explanation of positive peer effect at higher temperature has to be true. To test this hypothesis, I utilize generalized approach of variance decomposition from Silver (2021) to estimate the magnitude of peer and adversarial effect under heat. In this section, I estimate the magnitude of each. A split sample analysis has been used in the literature to show that there are no correlated effect, however I utilize a comparative split sample analysis to show the magnitude of the correlated effect of heat on games played under $25^{\circ}C$ to games above $25^{\circ}C$. I find that above $25^{\circ}C$ peer variance exhibits statistically significant increase as compared to games played below $25^{\circ}C$. A one standard deviation above peer-match increases about 1.15 runs for a batsman. While, I find no statistical difference between adversarial variance between two samples. This finding supports the above hypothesis that workers adapt to higher temperature through peer effect.

Testing for the mechanism of peer effect reveals that when workers are paired with peers with complementary skill set to theirs, these peers help them adapt to negative effect of temperature. As temperature increases, workers are more productive with peers who have different skill-set. I also find that batsmen change their batting strategy as temperature increases, instead of scoring runs through hitting boundaries (aggressive strategy), they resort to scoring runs by exchanging positions with their non-striker peer (defensive strategy). Therefore, peers with complementary skill-set help workers adapt to higher temperatures more effectively. If peers have substitutable skills, the opportunity for learning and adaptation is minimized.

In this paper, I make three main contributions: First, this paper provides the first estimates of peer effect under heat and underlines the role of peers in adaptation to heat. As detailed above, many papers in the literature have estimated individual productivity decline with temperature (LoPalo (2023); R. J. Park et al. (2020); Zivin, Hsiang, and Neidell (2018); Zivin et al. (2020)) including papers utilizing dynamics of sports (M. Burke et al. (2023); Sexton, Wang, and Mullins (2022)). However, the literature so far has missed out on the role of inter-worker interactions in labor productivity under heat. The only exception to this would be papers that find positive relationship between temperature and violence (M. B. Burke et al. (2009); Solomon M. Hsiang, Burke, and Miguel (2013); Ranson (2014); Heilmann, Kahn, and Tang (2021); Baylis (2020)) and posits that negative inter-worker interactions might increase with temperature or Adhvaryu, Kala, and Nyshadham (2022) which surveys India's ready-made garment firms to find that managers are able to mitigate negative impact of air pollution on labor productivity through task reallocation. Whereas, this paper utilizes readily available and rich cricket data, its institutional details and team dynamics to find the magnitude of peer and adversarial effect on individual's productivity under heat and finds that peers can help adapt to temperature.

Second, I leverage methodology used in teacher value added (Chetty, Friedman, and Rockoff (2014); Mansfield (2015); Bau and Das (2020)), physician-hospital care (Silver (2021); Chan (2016)), effectiveness of bureaucrats (Dahis, Schiavon, and Scot (2023); Best, Hjort, and Szakonyi (2023)), peer effect in cashier speed and wages (Mas and Moretti (2009); Card et al. (2018)) and productivity spillovers in basketball (Arcidiacono, Kinsler, and Price (2017)) to this paper. This literature utilizes variance decomposition of data generating process of an individual's outcome to estimate the contribution of teachers, physicians, peer groups, bureaucrats to the outcome. I exploit high frequency, quasi-random allocation of worker (striker) to peer (non-striker) in cricket and high frequency allocation of worker to adversary at different match-level temperature to estimate individual, peer, and adversary effect on individual outcome. The literature has used split sample technique to account for the effect of correlated shocks. However in this paper, since my setting certainly has correlated temperature shock that affects individual, peer, and adversary, a split sample analysis allows me to compare the magnitude of the correlated shock between two partitions of below 25°C games and above 25°C games. It allows me to find the difference in individual, peer, and adversarial effect due to this correlated shock below and above 25°C. To my knowledge, this is the first paper in heat and labor productivity literature to employ this technique. Guryan, Kroft, and Notowidigdo (2009) posit an interesting challenge, utilizing random assignment of peers in golf tournaments they find that no evidence of peer effect in workers in high skilled occupation. My results contradict this finding and demonstrate that even in high skilled occupation at high temperature, peer effect can play a significant role in improving individual's productivity and therefore helping adapt to temperature.

Finally, Multiple different segments of economics literature have shown that coordination mitigates negative outcomes. Development literature finds that kinship networks share the risk in absence of formal markets (Kinnan and Townsend (2012); Chiappori et al. (2014); Cox and Fafchamps (2007); Munshi (2014); Mobarak and Rosenzweig (2013)). Another strand of literature finds that certain peers can - improve people's views on caste (Lowe (2021)), reduce racial prejudice (Corno, La Ferrara, and Burns (2022)), increase diversity in hiring (Battaglini, Harris, and Patacchini (2023)), alter gender attitudes (Dahl, Kotsadam, and Rooth (2021)), reduce cannibalism in historical China (Chen, Lin, and Zhang (2024)), and can foster nation building (Bazzi et al. (2019)). The main finding of this paper which states that when faced with a temperature shock workers adapt through peer effect adds to the literature's understanding of the role peers can play in mitigating negative outcome due to environmental stressors.

The rest of paper proceeds as follows. Section 2 discusses institutional details of cricket, the data sources and provides descriptive statistics. In Section 3, I present conceptual framework to link individual's equilibrium outcomes with peer and adversarial effect. In Section 4, I discuss my empirical methods to estimate productivity impacts of temperature on individual outcomes and equilibrium outcomes as well as the results. Section 5 focuses on the main goal of the paper: to estimate peer and adversarial effect under heat. I also deal with threats to identification in this section. In Section 7, I conduct robustness checks on my estimates and Section 8 concludes the paper.

2 Background and Data

2.1 What is Cricket?

Cricket is a two sided game played among opposing teams, with each team consisting of eleven players. Cricket is always played outdoors, on uncovered pitches and the play can stop due to rain. Therefore, cricket is played during the driest season of the year in each country. The game is played on an oval shaped ground, with a 22 yard (20 metres) pitch in the middle with a wicket on each end (Figure A1). A wicket is made of three stumps with 2 bails balanced on top. A toss takes place at the start of the game between the captains of the two team, the captain who wins the toss decides whether to bat or bowl first. Therefore, which team gets to bat or bowl first is a random assignment. If the team bats first, their goal is to score as many runs as possible within the limited overs (or time) without losing all their ten wickets. Since batsmen come out to play in pairs eleven players make up ten pairs and therefore a team has ten wickets. The goal for bowling team is to limit the runs scored by batting team and take as many wickets as possible. The goal for team that bats second (the team that bowled first) is to chase the runs scored by the team that batted first.

The eleven players in each team can be categorized into - batsmen, bowlers, and all rounders (players who can bat as well as bowl). While a team is batting, batsmen take turns batting according to their batting order decided by the captain of the team, substitutes are generally not allowed. Ideally, the batsman who bats first has the opportunity to bat through the whole game if they do not lose their wicket, subsequent batsmen face fewers overs.[4] At the start of the game, two batsmen take their positions on either end of the pitch. A run is scored by striking the ball bowled by the bowler of the opposing team and then exchanging the positions with the batsmen on the other end. Batsmen in cricket score runs by coming out in pairs to bat, therefore being continuously affected by whichever peer batsman on the non-striker end they bat with. The two peers battle against the opposing team (adversary) to score runs. These peer and adversarial interactions are illustrated in Figure 2. Partnership between batsmen is a crucial way for a team to score runs. The fielders from the opposing team try to prevent a successful run score by getting to the ball before it leaves the oval field boundary and getting it to the fielder at either end of the wicket (wicket keeper or active bowler). If a player from the fielding team removes bails of the wicket with the ball before a batsman completes a run (reaches the crease of the 22 yard pitch), that batsman is considered dismissed or “out”. There are a total of ten ways in which a batsman can get out (details in Section A.1 Table A1). International cricketers travel across the globe to play at different temperature (Figure 1), which allows me to observe worker productivity at different temperature.

[4] an over consists of 6 balls bowled by one bowler

Common worker adaptation strategies of switching jobs (J. Park (2016); Colmer (2021); Albert, Bustos, and Ponticelli (2021)), migration (Deschenes and Moretti (2009); Cai et al. (2016); Benonnier, Millock, and Taraz (2019); Mueller et al. (2020)), changing clothing, altering work hours (Graff Zivin and Neidell (2014)) or absenteeism (Somanathan et al. (2021)) are not available to international cricketers. This allows for an interesting setting to study which dimension of adaptation do these high skilled, high paid, cricketers adopt. Cricket is not commonly known as a significantly active sport like soccer or rugby. However an international batsman produces heat equivalent to an individual running at 8kmph (5mph). Estimates from a University of Portsmouth study suggests that a day spent at the crease by a batsman is equivalent to running a marathon with helmet, gloves, and pads on (Tipton et al. (2019)). Another lab study finds that batsmen face higher increase in core temperature as compared to bowlers and fielders (Stay et al. (2018)).

Table 1 compares heat production in watts/minute for different economic sectors.The table shows that heat production for a international cricket batsman during an indoor net session, when the temperature was $15^{\circ}C$ is equivalent to heat production in agriculture and manufacturing sectors with higher end of heat distribution in cricket reaching heat production in construction. Even though worker skill and income is not comparable across these sectors, physiological impact of heat in cricket is comparable to other economic sectors.

2.2 Cricket Format

Within the sport of cricket there are different formats of the sport that are played at the international level: Test match is the oldest format of the game which lasts for upto 5 days and is not limited by the number of overs bowled during the match. Other formats have limited over matches - one day international, and twenty 20. In this paper, I focus only on one day international (ODI) and twenty 20 (T20) games in this paper due to data limitations for test match. A one day international match is a match with two innings, each played by one team. Each innning consists of fifty overs (or 300 balls) played at the maximum. The matches are scheduled to be finished within a day. A typical ODI lasts for about 8 hours : with two innings of 3.5 hours each separated by a 45 minutes break. Two drinks breaks per session are permitted with each break at least 1 hour 10 minutes apart.

T20 is a different format of limited over games. The want to improve the popularity of the game among english youth led to the creation of a shortened, fast paced, game in 2003. T20 much like ODI has two innings but each inning is limited to 20 overs. An average T20 match is completed in two and a half hours : with two innings of 70 minutes each separated by a 10 minute break. A recent change in T20 allows for optional drinks break of two minutes and thirty seconds that can be taken at the mid point (at 10 over mark) of each innings. Bliss et al. (2021) find that greater physical energy per minute was spent by players in T20 game as compared to a ODI game. Therefore, making T20 game more physically intense for each player, albeit for a shorter time.

2.3 Cricket Data

Cricket data primarily comes from `cricketdata` R package (Hyndman et al. (2023)) which provides cricket data in a consistent format. The sources for data on `cricketdata` R package are: ESPNcricinfo (2023) and Rushe (2023) . The data consists of men's international cricket games spanning four seasons of the sport from 2021 to 2023. It includes data for 238 ODI matches and 277 T20 matches among 16 countries[5]. The data covers performance of 463 batsmen and 338 bowlers across multiple countries. From the ball to ball data acquired from `cricketdata` package, I construct a panel of each player's performance in a match against a team.

I supplement this data with home locations of each player which I get from Wikipedia and ESPNCricinfo page of each player, salaries of players from Cricmetric (2023) and rankings from ICC player rankings (ICC (2023)) as of January 1, 2021, which is pre-period for this study. This is done so to remove bias caused by change in rankings as heat affects player's performance. I do the same for player's salaries.

The `cricketdata` package provides venue of each game, I then use geocode for google sheets to retrieve latitude and longitude of each game venue to match location with climate data.

2.4 Climate Data

I get climate variable for game venues from Visual Crossing Corporation (2023). Visual crossing sources data from Integrated Surface Database from NOAA (National Oceanic and Atmospheric Administration). It then uses multiple weather stations to triangulate the exact latitude, longitude pair and interpolates the results. I get daily maximum temperature, precipitation and dewpoint data from this source.

3 Conceptual Framework

To fix ideas, Consider a scenario where batsman i's aims to maximize runs while contending with the physiological and psychological costs of playing in different temperatures while playing with peer p against team a. The performance function of batsman i is modeled as:

[5] Afghanistan, Australia, Bangladesh, England, India, Ireland, Namibia, Netherlands, New Zealand, Pakistan, Scotland, South Africa, Sri Lanka, United Arab Emirates, West Indies, Zimbabwe

$$maxR_i(T, \phi_{i,p}, \nu_{i,a})$$

where T is the contemporaneous temperature faced by players i, p and team a. The batsman derives benefit from making runs R_i for their team, these benfits could accrue as higher salary, longer tenure in the team, or non monetary benefits such as altruistic pleasure of contributing to the team's victory. The runs made by the batsman are a function of temperature T experienced while on the pitch. $\phi_{i,p}$ is the peer effect of peer p which can mitigate the negative impact of temperature and increase runs for batsman i. $\nu_{i,a}$ is the adversarial effect of team a which can exacerbate the impact of temperature on batsman i.

The functional form of R_i can be defined as:

$$R_i(T, \phi_{i,p}, \nu_{i,a}) = R_i(T) + Q_i(T, \phi_{i,p}) - O_a(T, \nu_{i,a}) - C_i(T)$$

where $R_i(T)$ is the base runs expected from batsman i under normal conditions. The term $Q_i(T, \phi_{i,p})$ reflects positive *peer effect* of playing with player p which can be scaled with temperature and can be written as $T\phi_{i,p}$ as the peers are alos affected by contemporaneous temperature. Since partnerships between the batsmen who are on the pitch at the same time are crucial factor in a team's score and ultimately its victory. The communication between the players is important in making more runs together by running to rotate strike or comparing notes on a particular bowler they are batting against. The term $O_a(T, \nu_{i,a})$ is the *adversarial effect* of playing against team a that can also be scaled with temperature, $T\nu_{i,a}$. $C_i(T)$ captures the physiological and psychological costs associated with playing in temperature T on batsman i. The optimization problem is to maximize the adjusted runs accounting for these factors:

$$max_T R_i(T) - C_i(T) + T\phi_{i,p} - T\nu_{i,a}$$

This results in first order condition $\frac{dR_i}{dT} - \frac{dC}{dT} + \phi_{i,p} - \nu_{i,a} = 0$ or equivalently,

$$\mu_i = \frac{dC}{dT} - \phi_{i,p} + \nu_{i,a}$$

where μ is the shadow value of temperature, which can also be thought as the marginal cost of temperature on batsman on making a run. Above equation highlights three effects on batsman's performance under heat. a) $\frac{dC}{dT}$ which is the *temperature effect*. The paper later shows, that temperature has an inverted U-shape effect on an individual's productivity, at extremes of temperature low or high an individual's productivity is negatively affected and therefore shadow value follows a U-shaped curve with temperature. b) $\phi_{i,p}$ is the positive *peer effect* on the batsman on strike by playing with batsman p. The better the peer effect, lower the shadow value will be. Therefore, the impact of peer on the runs made by a batsman can be considered adaptation to conditions. c) $\nu_{i,a}$ is the negative *adversarial effect* on batsman on strike by playing against team a. The higher the adversarial effect, higher the shadow value will be.

The tension between the opposing forces of peer and adversarial effect on the shadow value of temperature can be seen in Figure 3 at a fixed average temperature. The figure shows that shadow value peaks when there is no peer effect but strong adversarial effect. Figure 4 shows that at a fixed adversarial effect, the shadow value follows a U-shaped path with respect to temperature but the U-shaped surface is also slanted downwards with increasing peer effect, highlighting that a strong peer effect can be a path to adaptation, theoretically at every temperature level. Realistically different level of temperature can have varying effect on peer & adversarial effect and therefore the outcome runs will tell us if peer or adversarial effect dominates.

This framework guides my empirical analysis, I first identify the effect of temperature on a worker's productivity on individual outcomes and equilibrium outcomes, impacted by peer and adversary. I then utilize the above framework for batsmen to estimate individual, peer and adversarial effect. The main contribution of this analysis is a variance decomposition that compares magnitudes of peer and adversarial effect under low and high temperature to estimate the level of adaptation among batsmen. I then investigate the mechanisms for peer effect.

4 Identifying impact of temperature on labor productivity

4.1 Empirical strategy

This section describes the estimation strategy used to estimate the effect of temperature on individual's productive outcomes that affected only by the individual (individual outcomes) and ones that are affected by the individual, the peer, and the adversary (equilibrium outcomes). I estimate the following panel fixed effects regression, with one observation per individual striker for a game:

$$y_{ima} = \sum_{j} \beta_j T_m + X'_{im}\gamma + \alpha_i + \alpha_t + \alpha_a + \alpha_n + \alpha_f + \epsilon_{ima} \tag{1}$$

where y_{ima} is a batting metric for striker i playing against team a in innings n in format f on match-day

m. I divide batting metrics into two: individual and equilbrium outcomes. Individual outcomes are the batting metrics that are affected only by the individual striker's productivity. Equilbrium outcomes are influenced by striker, non-striker, as well as the opposing team. This allows me to estimate how individual's productivity is affected by temperature as well as how their productivity is affected by temperature when they work with a peer as well as against an adversary. Individual batting metrics[6] are the type of dismissal that happen when the striker misjudges the line of ball: bowled out and lbw (leg before wicket). Equilibrium outcomes[7] used in the analysis are: runs, balls faced, boundaries scored, strike-rate. I also estimate probability of dismissal of a striker and type of dismissal that involves peer and adversaries: caught-out and run-out. β_j is the parameter of interest and shows the effect of match day temperature in temperature bin j on batting productivity as compared to batting productivity in temperature bin 25°C - 30°C. I estimate the impact for 4 temperature bins relative to the reference bin: <15°C, 15°C-20°C, 20°C- 25°C, and >30°C. The distribution of temperature bins is shown in Figure A2 panel D.

$X_{im}^{'}$ is a vector of controls which includes precipitation, windspeed, dew on the game day, the rest days between matches for each batsman i, the batting order of each batsman, and the predicted effect of temperature on no-balls bowled by the bowlers who bowled in match m. Contemporaneous temperature of match day impacts the player, the peer and the adversary. This accounts for the impact of match day temperature on the bowlers. Generally a bowler's performance is also highly contingent on his team and the adversary (batsman). For a bowler to not give away too many runs, his team needs to field well. Similary for him to be able to take a wicket, the rest of the team's cooperation is needed. However, since the bowler only bowls one over at a time, can not bowl two consecutive overs and has an upper limit on number of overs bowled in each innings[8], bowlers are not as affected by temperature as batsmen are, the batsmen as long as they are on the crease have to continuously perform.

α_i is striker fixed effect that controls for time invariant striker specific measures eg: batsman's skill. α_t is team fixed effect which accounts for peer effect. α_a is the fixed effect for the team striker i is batting against, this is adversary's fixed effect. α_n is innings fixed effect, both ODI and T20 games have two innings, a batsman batting is second inning has spent time out on the field for all of first innings fielding and therefore will be differently affected by temperature while spending more time on the pitch in second innings as compared to a batsman batting in first innings. α_f is format fixed effect, the two formats of cricket that this paper concerns with - ODI and T20 are not just different in the number of overs played in each format but also in the strategy that each batsman employs to deal with each format therefore a format fixed effect only

[6]details in Table A1

[7]details in Section A.2

[8]A bowler can bowl a maximum of 10 overs in ODI and 4 overs in a T20 game.

compares the within format differences. This approach focuses on within striker, within opposition variation in temperature. Therefore the only variation in a cricketer's productivity comes from within cricketer variation in temperature realization.

4.2 Results

Since individual outcomes measured in this analysis are types of dismissal which takes on values of 0 or 1, I utilize logistic regression to estimate the linear effect of temperature on individual's productivity, the results of which are presented in Table 2. The outcome estimated in Columns 1 and 2 are the probability of a batsman being dismissed by being bowled or LBW (leg before wicket) out, both of which happen due to failure of the batsman to accurately judge the trajectory of the ball. Controlling for bowler's productivity change due to match day temperature, the results show a significant negative effect of heat on batsman's individual productivity. The probability of being LBW out increases by 2.71$\%$ and probability of LBW out increases by 1.73$\%$ as temperature increases by 1$^{\circ}C$, indicating a diminished ability of batsman to judge the line and length of the ball at higher temperatures. Figure 5 illustrates the nonlinear effect of temperature on individual productivity. Panel A of the figure shows that as compared to a match played at temperature bin [25,30), a match played at higher temperature affects batsman's individual productivity negatively. Panel B of the figure does not find a statistically different effect of temperature of 30$^{\circ}C$ and above from temperature in 25$^{\circ}C$ - 30$^{\circ}C$, however the impact is significantly different from that at lower temperatures. These results indicate that individual worker's productivity is negatively affected by higher temperature. This result is expected, similar results have been found by other papers .

I also estimate the impact of temperature on equilibrium productive outcomes of a batsman, these are metrics of productivity that are not individually affected by the striker but rather impacted by their peer and also adversary (even after controlling for bowlers' productivity under heat). The results of which are presented in Table 3. Columns 1-4 are continuous outcomes estimated by using a fixed effect OLS regression, while estimates in columns 5-7 are binary outcomes estimated by a logistic regression. The table shows that the increase in temperature has no significant effect on equilibrium estimates of productivity for a batsman. In fact, some equilibrium outcomes improve as temperature increases. Probability of dismissal through getting caught-out decreases by 1.51$\%$ and the probability of getting run-out decreases by 4.03$\%$. As discussed in Section 3 postitive peer effect can decrease the marginal effect of temperature on productivity. If peer effect increases more that adversarial effect at higher temperature, then the effect of temperature on equilibrium productivity can be positive. Figure 6 illustrates the non-linear effect of temperature on equilibrium outcomes of productivity and the figures show that there is no significant impact on equilibrium productivity at temperature higher than 30°C as compared to temperature bin 25°C - 30°C for any equilibrium productivity measure.

Taken together, these results show that even though individual workers are affected by temperature negatively. Their productivity measures which are dependent on their peers and their adversary are not affected, indicating adaptation at higher temperature either through increased peer effect or decreased adversarial effect. This result demands further exposition of peer and adversarial effect at higher temperature.

5 Identifying Peer and Adversarial Effect

This section is motivated by the discussion in Section 3. I assume that the data generating process of runs made by a striker in a match is linear in temperature and a rich set of striker and match covariates X'_{im}. A striker i is sent out to bat in a batting order but the depending on which of the two batsmen gets out, I am able to observe multiple quasi-random pairings of stiker and non striker $\phi_{i,p}$ in my data. I also observe a striker playing against multiple adversaries over the seasons $\nu_{i,a}$. The model for $log(Runs)_{impa}$ takes the following form:

$$log(Runs)_{impa} = \beta_1 T + X'_{im}\beta_2 + \alpha_i + \phi_{i,p} + \nu_{i,a} + \epsilon_{impa} \tag{2}$$

where the outcome is the runs made by batsman i as a striker in the presence of batsman p at non-striker's end in match m against team a. To note here, these are not the total runs made by batsman i in match m but rather the total runs made by batsman i in presence of batsman p at non striker end in match m. I observe multiple such pairs for a batsman i. T is match day temperature. X'_{im} includes following covariates - precipitation on the game day, the rest days between matches for each batsman i, the batting order of each batsman, and the effect of temperature on bowlers, determined by the predicted effect of temperature on no-balls bowled by bowlers in match m.

θ_i is a stiker-specific effect, it captures the runs that a striker would make because of their skill level. Since individual strikers do not get to choose which matches they want to play, as long as they are available for a series, the decision to choose them depends on the cricket board of their respective countries and the captain of the team. Therefore there is no sorting among strikers.

The peer effect $\phi_{i,p}$ captures the influence on runs that striker i makes due to non-striker peer p's presence on the other end. This effect should capture how well a pair of batsmen work together, either due to unobserved social understanding, skill complimentarity or communication between the two.

The adversarial effect $\nu_{i,a}$ captures the influence on runs that a striker i makes against team a. This effect captures how a batsman plays against an adversary. I utilize Silver (2021) methodology to estimate peer and adversarial effects.

Previous work in estimating the effect of a peer has focused on peer group characteristics included as regressors of interest. These studies capture observable dimension of peer effect. While in my paper, by utilizing peer pair effect, I am able to capture unobservable dimension of working with a peer and against an adversary.

5.1 Variance Decomposition

I observe 1719 unique peer matches and 1540 unique adversarial matches. Estimating Equation 2 will lead to overfitting issues. Ideally to identify the peer effect, I want to observe unique pair matches observed on multiple instances, playing against different adversaries. To identify adversarial effect, I want to observe a striker-adversary match multiple times in the presence of different peers. Therefore I estimate two separate equations:

$$log(Runs)_{impa} = \beta_1 T + X'_{im}\beta_2 + \alpha_i + \phi_{i,p} + \theta_a + \epsilon_{impa} \tag{3}$$

$$log(Runs)_{impa} = \beta_1 T + X'_{im}\beta_2 + \alpha_i + \theta_p + \nu_{i,a} + \epsilon_{impa} \tag{4}$$

where θ_a is opposition fixed effect and θ_p is non striker fixed effect. I present variance decomposition estimates based on Equation 6 and Equation 7 in Table 5. I decompose variance in log runs into parts attributable to the individual striker $var(\alpha_i)$, to peer-match $var(\phi_{i,p})$, and to adversary-match $var(\nu_{i,a})$

The peer-match effects ϕ are normalized to be mean zero for each individual striker, so that $var(\phi_{i,p})$ is the within-individual variance in peer effects. Similarly, adversary-match effects ν are normalized to be mean zero for individual striker as well, therefore $var(\nu_{i,a})$ is within-individual variance in adversary effect. I can not identitfy individual variance because individual strikers might be selected keeping in mind the adversary. However, the mean zero restriction on individual striker for peer and adversarial variance, and the quasi-random pairing of peer allows me to identify peer and adversarial variance. I layout details of variance decomposition in Section A.3.

Table 5 column 1 reports variance decomposition for the full sample. It shows individual variance of 0.48 for individual striker for log runs. This implies that a one standard deviation above skill striker makes 68.9% more runs (~about 10 more runs).

Peer match effects have a variance of 0.34, this suggests that a one standard deviation above peer-match helps striker make 58.4% more runs (~ about 9 more runs). Adversary match effects have a variance of 0.33 which suggests that one standard deviation above adversary reduces runs made by striker by 54.8% (~ about 8 runs).

5.2 Split Sample

The literature uses the split sample technique to account for correlated shocks in estimation of peer effect. In my paper however, I am aware that temperature is a correlated shock for individual, peer and the adversary and I employ split sample technique to find if the correlated shock is different at lower temperature as compared to higher temperature for individual, peer and the adversary. I divide my sample into two groups (A, B), where sample A is sample for matches that happened at temperature <=25$^{\circ}C$ and sample B is for matches that happened at temperature >25$^{\circ}C$. This is random allocation of sample as temperarture realization on match day are exogenous. I estimate Equation 6 and Equation 7 separately for each partition and it yields, two estimates for individual effect $(\widehat{\alpha_i^A}, \widehat{\alpha_i^B})$, peer effect $(\widehat{\phi_{i,p}^A}, \widehat{\phi_{i,p}^B})$ and adversarial effect $(\widehat{\nu_{i,a}^A}, \widehat{\nu_{i,a}^B})$.

Revisiting peer-match effect:

$$\widehat{\phi_{i,p}^A} = \phi_{i,p} + e_A$$

where e_A is partition specific error. Estimating the variance of each partition yields:

$$\begin{aligned} var(\widehat{\phi_{i,p}^A}) &= var(\phi_{i,p} + e_A) \\ &= var(\phi_{i,p}) + var(e_A) + 2cov(\phi_{i,p}, e_A) \end{aligned}$$

estimating variance for each partition yields above equation. Therefore difference between variance of two partition, helps identify impact of temperature shock (partition error). A variance F-test of two partitions would yield following equation:

$$\frac{Var(\phi^A_{i,p})}{Var(\phi^B_{i,p})} = \frac{var(\phi_{i,p}) + var(e_A) + 2cov(\phi_{i,p}, e_A)}{var(\phi_{i,p}) + var(e_B) + 2cov(\phi_{i,p}, e_B)}$$

Columns 3 & 4 from Table 5 reports estimates for both partitions. A F-test of the variances in Column 7 shows that there is a statistically significant difference in individual and peer variance at below and above 25$^{\circ}C$ temperature. However, there is no statistical difference in the variance between adversarial effect in two partitions. This result provides support for the results discussed in Section 4.2. This result shows that peer and individual effect both increase at higher temperature, reconciling with the framework discussed in Section 3, an increase in peer effect would decrease shadow value of temperature, particularly reducing the impact of heat on productivity if peer effect increases relative to adversarial effect. The results in Table 5 align with the conceptual framework, establishing that at higher temperature through increased peer effect, productivity of striker is maintained and therefore adaptation happens. In the next section of the paper I explore the mechanism through which peer effect accrues.

6 Mechanism of Peer effect

Hypothesis for mechanism through which peer effect accrues as temperature increases include that as temperature increases the peers with higher ability, experience or a complementary skill set would help an individual adapt to the negative effect of temperature on individual productivity. In this section, I test for each of these using peer characteristics in each dyad. I use the following estimating equation:

$$logy_{impa} = \beta_1 T + \beta_2 Z_{ip} + \beta_3 T * Z_{ip} + X'_{im}\beta_4 + \alpha_d + \alpha_a + \epsilon_{impa} \tag{5}$$

where y_{impa} is equilibrium productive outcome that is measured for batsman i in presence of peer p against adversary a in match m. Z_{ip} is a peer characteristic for peer i and p. β_3 is the coefficient of interest that captures the interactive effect of temperature and peer characteristic. X'_{im} is a vector of controls which includes precipitation, windspeed, dewpoint, predicted effect of temperature on bowlers through no-balls, total rest of both peers, ability of individual striker, ability of peer, innings, and format. α_d is batting order dyad fixed effect for example, fixed effect for batting order dyad (1,2) where individual plays at order 1 and peer plays at batting order 2 and α_a is opposition team fixed effect.

Distance in Strategy: Cricket batsmen pairs (peers) are known to perform better when one batsman has a aggressive batting strategy and another has defensive strategy, as the complementarity of their skills improves outcomes for each of them. I use strike-rate of each player in the preceeding four seasons of my sample as a proxy for their strategy. A batsman with high strike-rate is considered to have attacking strategy, while low strike-rate batsman is considered defensive. The distance in strategy is a metric that takes the absolute value of the difference between the strike rates of the two peers. Therefore, the distance between the strategy matters but not which one is defensive and which one is attacking.

Table 6 tests the mechanism of peer effect at high temperature through distance in strategy between peers. The table reports the effect of temperature, distance in strategy, and the interaction of two on equilibrium productive outcomes. The marginal effect of temperature is a function in distance in strategy which increases runs for the individual striker as distance in strategy increases. The results show that as soon as the temperature rises above 28°C with 1 unit increase in strike rate of batsman and peer, increases runs for batsman by 0.012$\%$. Average distance in strike rate for peers is 42.76, as temperature rises above 28°C an average peer will increase runs for individual striker by about 7.27 runs.

This effect through distance in strategy only arises above a specific temperature, this could be due to mulitple reasons. a) The negative effect of high temperature demands alteration in batting strategy as witnessed by results in column 4 of Table 6, which shows that as temperature increases, runs made through running between the wickets (nonboundary runs) also increases. This indicates a switch from attack focused batting strategy of making runs by hitting boundaries to defense focused strategy of making runs by taking singles or doubles. If individual striker has a peer with a different batting strategy, that would help striker alter their strategy and the complementary skills inspires learning between peers as temperature increases. b) Similarly, The need for collaboration between peers to adapt to negative effect of high temperature only arises at a certain temperature, below which certain conditions might favor individual performances. c) Adversaries are also individually affected by heat therefore having batting peers with different batting strategies might keep bowling team guessing, with bowlers unsure of how to bowl and the captain of opposing team unsure of how to set the fielding team for both attacking and defensive batsmen. This result shows that at high temperature having peers with complementary skills rather than subsitutable skills, helps individual striker adapt to negative effect of heat on their individual productivity.

Ability: Peer effect could also accrue at high temperature, if individual batsmen are paired with high ability peers as temperature increases. This could be because high ability peers are better able to adapt to temperature and therefore the quasi-random dyads that are formed in cricket might not be random if peers with better skill (higher batting order) are differently affected by temperature than lower skill batsmen (lower batting order). I estimate Equation 1 with interaction of temperature with batting order for individual outcomes - probability of lbw and bowled and equilibrium outcome of probability of getting out. The estimates are presented in Figure 7. The estimates show no significant difference in the effect of temperature at different batting orders as compared to batting order #1. This implies that all individual batsmen are equally affected by temperature. Therefore, we can reject the hypothesis that better batsmen are paired up with better ability peers ar high temperature.

I also test if higher ability peers do improve individual outcomes at higher temperature. In this test, I create a measure of ability by calculating the number of runs made by each batsman in four seasons preceeding my sample. I then find the average runs made by each batsman, which is calculated as a ratio of total runs made in previous four seasons and total matches played in that time period. Using this average, I find the distance in ability between the two peer batsmen and create an indicator for more able peer. I estimate Equation 5 using an indicator for being paired with more able peer as peer characteristic. The results are reported in Table 7. The results show no significant difference in individual striker's outcome as temperature increases when playing in the presence of more able peer for any of the outcomes.

Experience: Another measure through which peer effects could acrrue are through being paired up with peers with more experience. More experienced peer batsmen have worked in multiple scenarios and therefore could help striker adapt to high temperature. I test this hypothesis by estimating Equation 5 using an indicator for being paired with more experienced peer as peer characteristic within the dyad of batting peers. Experience metric is created by finding the number of cricket matches each batsman has played in each format since 2001. Distance in experience is a simple difference between the striker's experience and peer non striker's experience and then an indicator is created for more experienced peer when distance is negative. The results are presented in Table 8, the results show no significant difference in individual striker's outcome as temperature increases when playing in the presence of more experienced peer for any of the outcomes.

The above exposition of the mechanisms through which peer effects acrrue conclusively shows that it is the complementarity of skills between striker and the peer that improves outcomes at high temperature.

6.1 Threats to Identification

Identification of peer and adversarial match effects require that the error term ϵ_{impa} be uncorrelated with the identity of peer and adversary.

6.1.1 Sorting

As long as a player is available to play (i.e. uninjured and available), the team administration, country's cricket board and the team captain pick a player to play in a match series. In practice, a core team of about 4-5 players stays the same across multiple seasons of cricket and other players are given opportunities to debut. Specialists for a specific adversaries are rarely chosen.

Sensitivity In Table 9, I assess the sensitivity of estimates to inclusion or exclusion of match specific covariates. In this analysis, I ask how sensitive my estimates are to particular choices of striker and match specific covariates. If there was truly random assignment of strikers to adversaries or strikers to peers on observables then my estimates of peer effect and adversarial effect would be insensitive to including or excluding these covariates. This exercise is similar to tests of student-teacher sorting in education literature (Chetty, Friedman, and Rockoff (2014)) and physician-patient sorting in hospital literature (Silver (2021)).

I find that my estimates are stable across a multiple models. The correlation of peer effects in my baseline model to models where I remove important covariates one at a time is no less than 0.9946. Similarly, correlation of adversarial effect in baseline model to other models is no less than 0.9897. These results strongly suggest absence of sorting.

6.2 Are peer and adversarial effects consistent?

In Section 4, I find evidence of adaptation at higher temperature in equilibrium outcomes and in Section 5.2 I find that at higher temperature peer effect significantly increases. Therefore, a striker who plays with a higher peer-match and scores more runs, the same peer-match should also help the striker face more balls (spend more time on the pitch), and increase other observable measures of productvity. This implies, a positive correlation between peer-induced changed in runs and changes in balls and boundaries. To estimate this effect, I relate my estimates of peer effect on runs (ϕ_{RUNS}) to those from alternative peer and adversarial match effect models: log balls (ϕ_{BALLS}) and log runs scored through boundaries ($\phi_{BOUNDARIES}$). Since peer effect reduces the shadow value of temperature, the estimates of peer effect from alternative models should have positive correlation with peer effect on runs, similarly adversarial effect on runs should have positive correlation with peer effect from alternative models.

The results of this exercise are illustrated in Figure 8 and Figure 9. Figure 8 panel (A) shows that peer matches that increase striker's runs also increase balls faced by striker. These match-effects are highly correlated (corr=0.88). Similar results are estimated for adversary-matches in panel (B), suggesting that a adversary-match that reduces runs for striker also reduces the balls faced by the striker with a correlation of 0.83. I find same results for runs scored by hitting boundaries by the striker in Figure 9 with correlation of 0.64 for peer effect and 0.60 for adversarial effect between runs and boundaries.

These findings provide robust evidence that peer effects significantly enhance a striker's performance across multiple productivity metrics, while adversarial effects consistently diminish it.

7 Robustness Checks

7.1 Are games at hotter temperature different from games at colder temperature?

A potential concern is that the observed increase in peer effects at higher temperatures may be due to inherent differences in the nature of games played at higher versus lower temperatures. High temperatures affect both teams, and if these effects are symmetric, one might expect games played at higher temperatures to exhibit smaller win margins. To investigate this hypothesis, I analyzed the relationship between temperature and win margins, as presented in Figure Figure 10, panel (A). The results show noisy estimates of win margins across different temperature bins, indicating no clear relationship between temperature and win margin. This suggests that the nature of games, in terms of competitiveness and win margins, does not systematically differ between hotter and colder temperatures.

7.2 Is there resource reallocation during the game at higher temperature?

Another possibility is that team captains might adjust their strategies and reallocate resources, such as altering the batting order, in response to increased temperatures and player fatigue. This could influence the observed peer effects. To test this hypothesis, I examined the standard deviation in batting order as a function of temperature, shown in Figure Figure 10, panel (B). The analysis reveals that the standard deviation in batting order does not significantly change with temperature. Interestingly, the standard deviation is slightly higher at lower temperatures (below 20°C) and then stabilizes. This pattern suggests that resource reallocation in response to temperature is minimal. Instead, it appears that team captains are more likely to experiment with batting order at lower temperatures, possibly due to lower fatigue levels, rather than making strategic adjustments at higher temperatures. Thus, the lack of reallocation at higher temperatures reinforces the robustness of the observed peer effects.

8 Conclusion

Workers possess multiple skills. One important *unobservable* skill that is often overlooked in the literature is the skill to work well with other workers and improve their productivity. This paper explores how peers affect individual's productivity under temperature stress.

Using high frequency cricket data along with institutional details of the game, I document two sets of empirical evidence estimating a high dimensional fixed effect model. First, I find that individual productivity decreases by 1.73$\%$ to 2.71$\%$ for every 1$^{\circ}C$ increase in temperature. Second, this impact of temperature on productivity dissipates on measures of productivity that are impacted by individual, peer, and the adversary (equilibrium outcomes). This finding suggests that individual productivity decline is either being compensated by increase in peer effect or decline in adversarial effect.

Second, I estimate the adversarial team outcomes controlling for opposition batsman's productivity and I do not find any significant difference in adversarial productivity with temperature. I conduct a variance decomposition exercise on runs as outcome for each batsman, and explore how peers and adversaries contribute to variation in runs for a striker. I conduct a split-sample analysis which is often used in the literature by randomly dividing sample into two, this is done to show that there are no correlated shocks biasing the outcome. In my paper, there is a correlated temperature shock that affects individual, peers, and the adversary. Therefore by splitting sample into two partitions of below 25$^{\circ}C$ and above 25$^{\circ}C$, I am able to estimate the magnitude of the peer and adversarial effect with temperature. I find that individual and peer variance is significantly different between two samples, while there is no statistically significant difference in adversarial effect. The two findings from empirical results and variance decomposition, taken together, imply that peer effect increases significantly at temperature above 25$^{\circ}C$ (also reflected in F-test). The results show that a one standard deviation better peer-match improves individual strikers runs by about 1.15 runs when playing at temperature above 25$^{\circ}C$ as compared to below 25$^{\circ}C$.

I investigate the mechanisms through which these peer effects accrue at higher temperature. I hypothesize that peer effect increases at high temperature if a worker is paired with either more able peers, more experienced peers, or peers with complementary skills. I first show that workers are not differently affected to heat by their ability, therefore the peer pairings are quasi-random and we can refute the hypothesis that more able peer pairings are made as temperature increases. I then show that having more able or more experienced peers don't improve individual's outcomes as temperature increases. However, having peers with complementary skill-set improve productive outcomes for individual workers. I posit that this could be because increased temperature which causes decline in individual productivity demands altering work strategy by the worker, having a peer with a different skill-set creates an opportunity for individual worker to learn. In adversarial settings, having peers with different skill-set could keep adversary on their toes and unable to create an effective opposition strategy because adversaries are also individually affected by the environmental stressor.

As individuals rarely work in isolation but rather in teams of peers and/or against an adversary, this paper highlights the potential for collaborative dynamics to mitigate the negative effects of environmental stressors. This paper opens further questions for future research in the inter-play of peer effect and environmental stressors. This paper estimates these peer effects in high-skilled, high-income workforce, how do these effects under temperature stress vary by observables such as skill, income, gender, age are open questions for further research.

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Figures and Tables

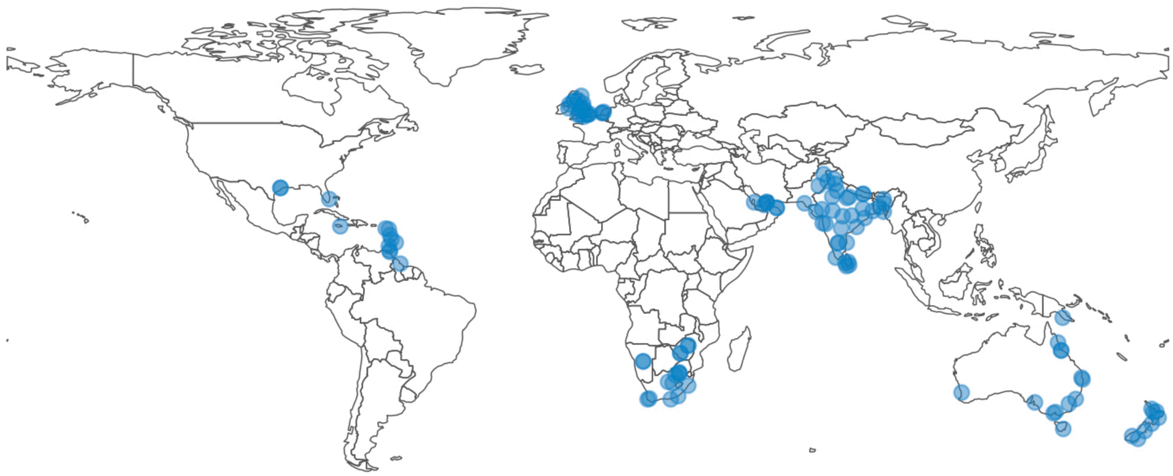

Figure 1: Locations of Cricket Matches

Above map shows the location of cricket matches during 4 seasons of the sport from 2021 to 2023 across the world. The blue dots show the locations.

Table 1: Estimated Heat Production by Sectors

Sector	Estimated Heat Production (Watts/min)
Tourism	134 - 218
Agriculture	200 - 420
Construction	345
Manufacturing	122 - 443
Transportation	129 - 286
Cricket	216 - 387

Source: Poulianiti, Havenith, and Flouris (2019) and Tipton et al. (2019). The above table shows the range of estimated heat production in different economic sectors as compared to heat production among batsmen in cricket during practice session at indoor nets at 15°C temperature.

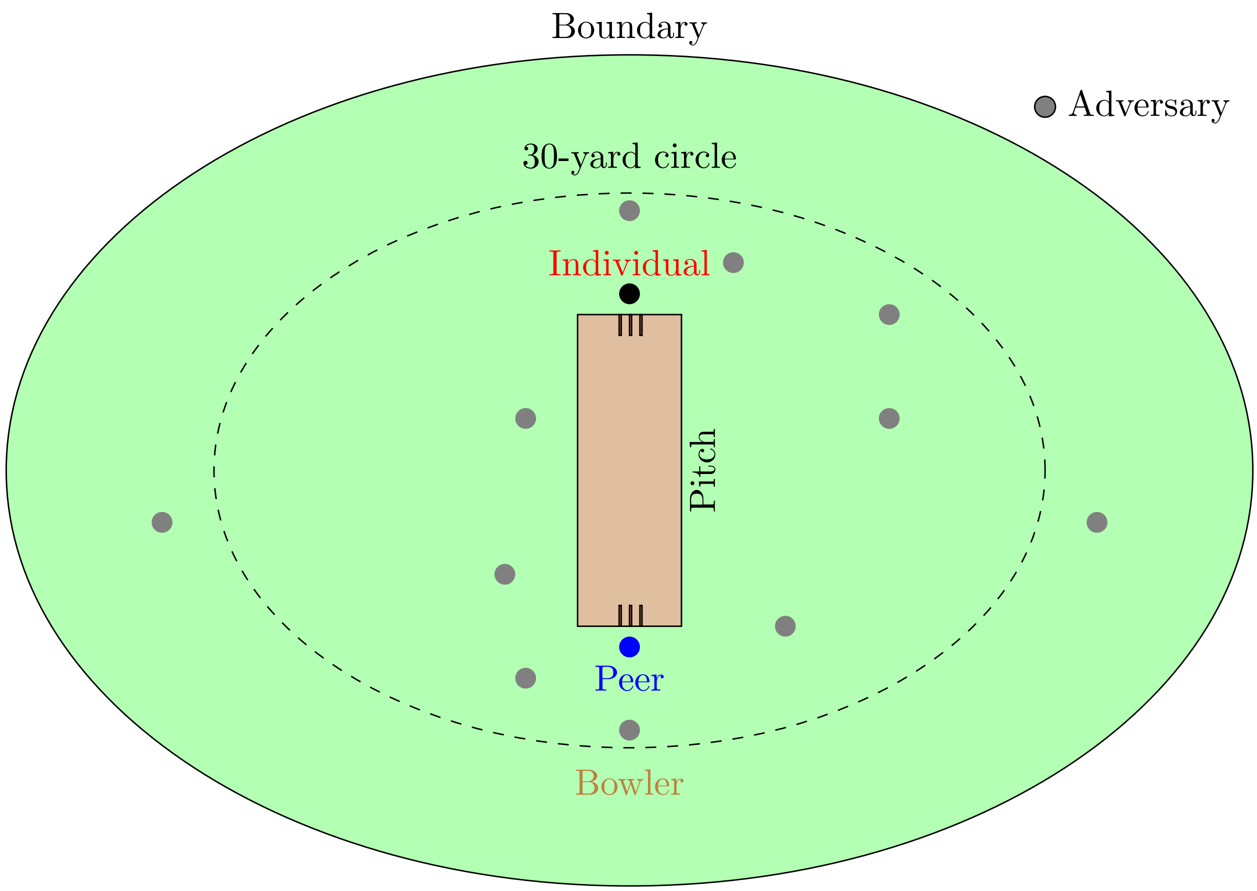

Figure 2: Cricket Ground

Above figure is an illustration of cricket ground. Analysis in this paper relies on the collaborative interaction between the individual striker and peer non striker on each end of the pitch and the adversarial interaction between the individual and the opposing bowling team consisting of the bowler and the fielders. This figure illustrates relative positions of individual, peer, and the adversary on the cricket ground.

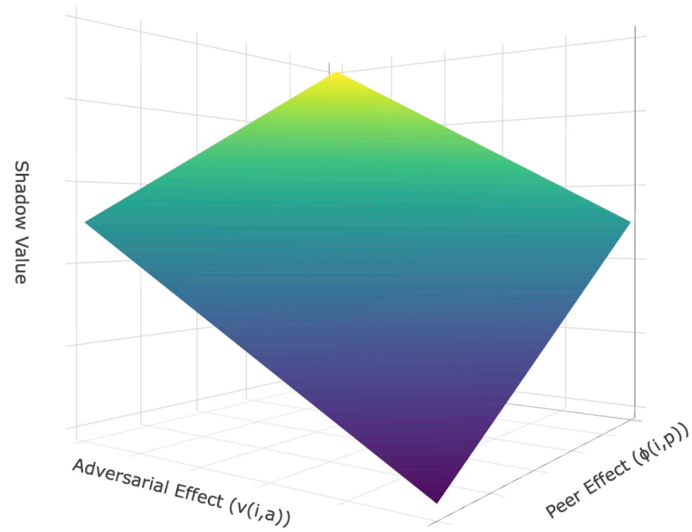

Figure 3: Peer vs. Adversarial Effect

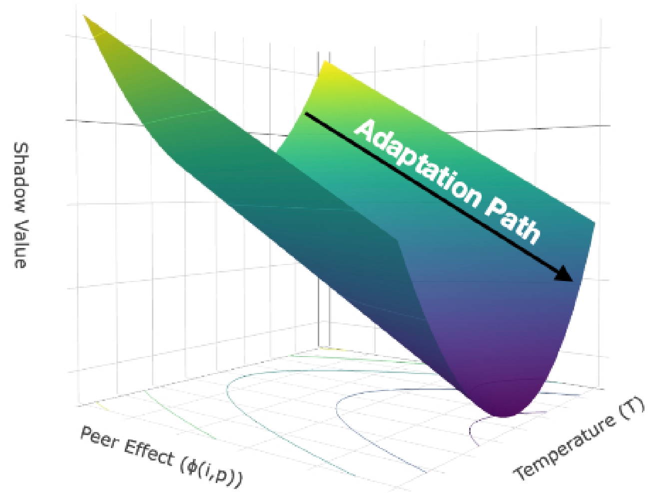

Figure 4: Adaptation Path

Figure 4, illustrates the plane of possible combinations of peer and adversarial effect and the resulting shadow value of temperature when temperature is fixed, it shows the tension between peer and adversarial effect on shadow value as shown in conceptual framework. Figure 3, assumes a fixed adversarial effect to show the resulting form of shadow value of temperature when it is affected by temperature and peer effect. It shows a decrease in shadow value at every temperature level due to positive peer effect, illustrating the adaptation path for a batsman.

Table 2: Individual Outcomes

	LBW	Bowled
	(1)	(2)
T	0.0271*	0.0173*
	(0.0157)	(0.0098)
Observations	4681	5642
R^2	0.09	0.08
Average	0.08	0.15
Striker FE	Y	Y
Opposition FE	Y	Y
Peer FE	Y	Y
Format FE	Y	Y
Innings FE	Y	Y

Note: *This table presents the estimates of linear effect of temperature on individual productive outcomes of batsmen. Both columns present estimates of logistic regression. Each regression includes controls for precipitation, windspeed, dew, rest days, batting order, predicted effect of temperature on no-balls delivered by adversary's bowling unit.Errors are clustered at match level.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

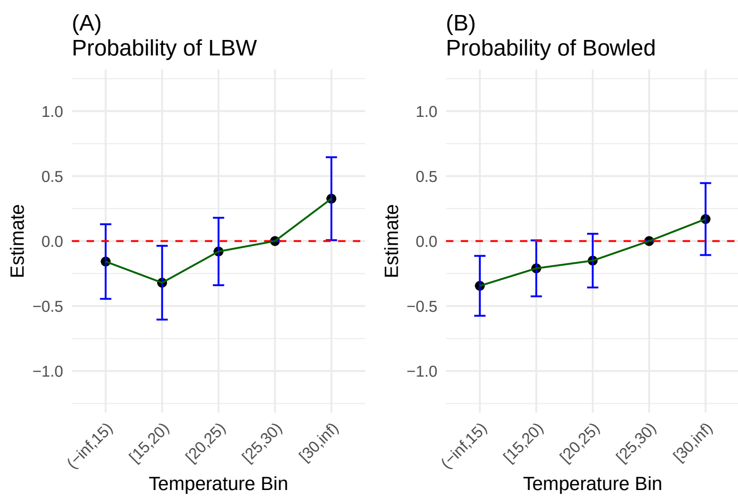

Figure 5: Individual Outcomes

Above figure shows the estimated nonlinear effect of temperature on individual productive outcomes of batsmen in each temperature bin as compared to the effect in temperature bin [25,30). Each regression includes controls for precipitation, windspeed, dew, rest days, batting order, predicted effect of temperature on no-balls delivered by adversary's bowling unit.Errors are clustered at match level.

Table 3: Equilibrium Outcomes

	Runs	Balls	Boundary	Strike-Rate	Out	Caught	Run-Out
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T	0.0036	0.0021	0.0002	0.0013	-0.0068	-0.0151**	-0.0403*
	(0.0040)	(0.0028)	(0.0038)	(0.0026)	(0.0101)	(0.0076)	(0.0215)
Observations	5548	6134	4077	5548	5598	5962	2755
R2	0.26	0.33	0.21	0.22	0.16	0.08	0.13
Adjusted R2	0.19	0.27	0.12	0.15	0.04	-0.01	-0.14
Average	20.98	21.26	2.48	90.48	0.21	0.48	0.03
Striker FE	Y	Y	Y	Y	Y	Y	Y
Opposition FE	Y	Y	Y	Y	Y	Y	Y
Peer FE	Y	Y	Y	Y	Y	Y	Y
Format FE	Y	Y	Y	Y	Y	Y	Y
Innings FE	Y	Y	Y	Y	Y	Y	Y

Note: *This table presents the estimates of the linear effect of temperature on equilibrium productive outcomes of individual batsmen. Outcome variables in Columns 1-4 are logged and therefore estimates are from high dimensional panel fixed effect model. Outcome variables estimated in Columns 5-7 are binary and estimates are using a logistic regression. Each regression includes controls for precipitation, windspeed, dew, rest days, batting order, predicted effect of temperature on no-balls delivered by adversary's bowling unit.Errors are clustered at match level.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

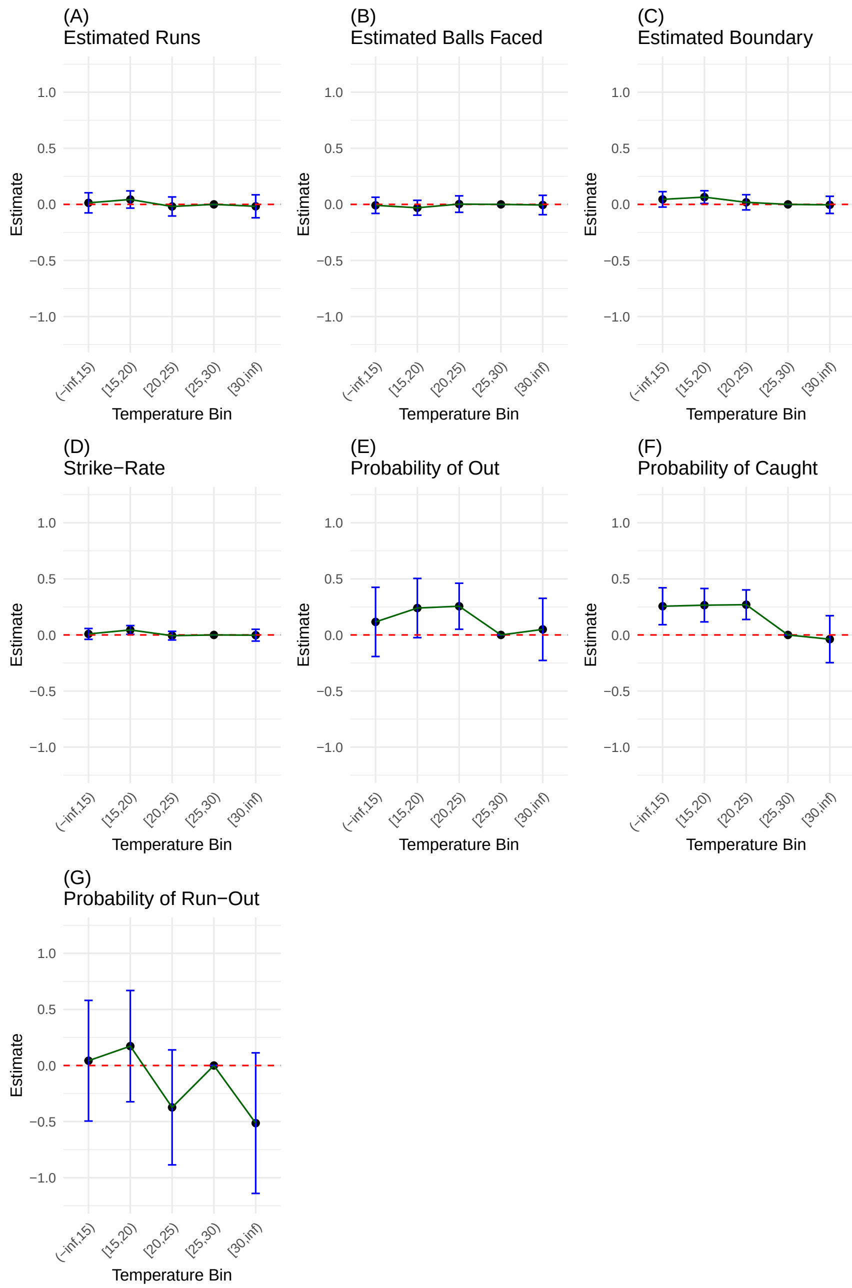

Figure 6: Equilibrium Outcomes

Above figure shows the estimated nonlinear effect of temperature on equilibrium productive outcomes of individual batsmen. Panel A-D estimates are from estimating high dimensional panel fixed effect model on log outcomes. Panel E - G are from estimating logistic regression. Each regression includes controls for precipitation, windspeed, dew, rest days, batting order, predicted effect of temperature on no-balls delivered by adversary's bowling unit.Errors are clustered at match level.

Table 4: Adversary's productivity

	Extras	Balls	Wickets
	(1)	(2)	(3)
T	0.0055	0.0018	-0.0006
	(0.0048)	(0.0024)	(0.0040)
Observations	804	809	797
R2	0.22	0.71	0.18
Adjusted R2	0.18	0.70	0.14
Average	10.23	178.69	6.8
Team FE	Y	Y	Y
Opposition FE	Y	Y	Y
Format FE	Y	Y	Y
Innings FE	Y	Y	Y

Note: *This table presents the estimates of the linear effect of temperature on productive outcomes of adversarial team (bowling team). Outcome variables are logged and therefore estimates are from high dimensional panel fixed effect model. Each regression includes controls for precipitation, windspeed, dew, rest days, batting order, ability of batsmen the team is bowling against. Errors are clustered at match level.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Variance Decomposition

	Full Sample	<=25 $^\circ C$	>25 $^\circ C$	F-test
	(1)	(2)	(3)	(4)
Individual	0.4762	0.5588	0.8356	0.6546***
$Var(\alpha_i, \theta_a)$	[0.689]	[0.743]	[0.914]	(0.0005)
Peer	0.3415	0.4775	0.5943	0.8035***
$Var(\phi_{i,p})$	[0.584]	[0.693]	[0.769]	(0.0001)
Adversarial	0.3267	0.4349	0.3987	1.0910
$Var(\nu_{i,a})$	[0.538]	[0.592]	[0.597]	(0.2066)
Total	1.3199	1.3245	1.3110	1.0103
	[1.149]	[1.151]	[1.145]	(0.7720)
Observations	7114	4573	2541	-

Note: *Above table shows the result of Variance Decomposition analysis. Column 1 reports variance of full sample, while columns 2 & 3 report variances from split sample analysis of below and above 25°C partition. Square brackets in Columns 1-3 report standard deviation. Column 4 contains results of F-test conducted on variance of estimated effects from analysis in Column 2 & 3. Round brackets in Column 4 reports p-value of F-test. Details of Variance Decomposition are in Section A.3* * p < 0.1, ** p < 0.05, *** p < 0.01

Table 6: Distance in Strategy

	runs	balls	dot balls	nonboundary runs
	(1)	(2)	(3)	(4)
T	0.00203	0.00272	0.00127	0.00488*
	(0.00403)	(0.00295)	(0.00289)	(0.00284)
Distance Strategy	-0.00336**	-0.00263**	-0.00241*	-0.00276**
	(0.00144)	(0.00122)	(0.00131)	(0.00117)
T x Distance Strategy	0.00012**	0.00009*	0.00009*	0.00008
	(0.00006)	(0.00005)	(0.00005)	(0.00005)
Observations	6706	6706	6100	6456
R2	0.11	0.22	0.29	0.13
Average	14.17	14	6.67	6.63
Dyad FE	Y	Y	Y	Y
Opposition FE	Y	Y	Y	Y

Note: *This table presents the estimates of the interactive effect of temperature and distance in strategy of peers on productive outcomes of striker. Outcome variables are logged and estimates are from high dimensional panel fixed effect model. Each regression includes controls for precipitation, windspeed, dew, total rest days for both peers, predicted effect of temperature on no-balls delivered by adversary's bowling unit order, experience of both peers.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

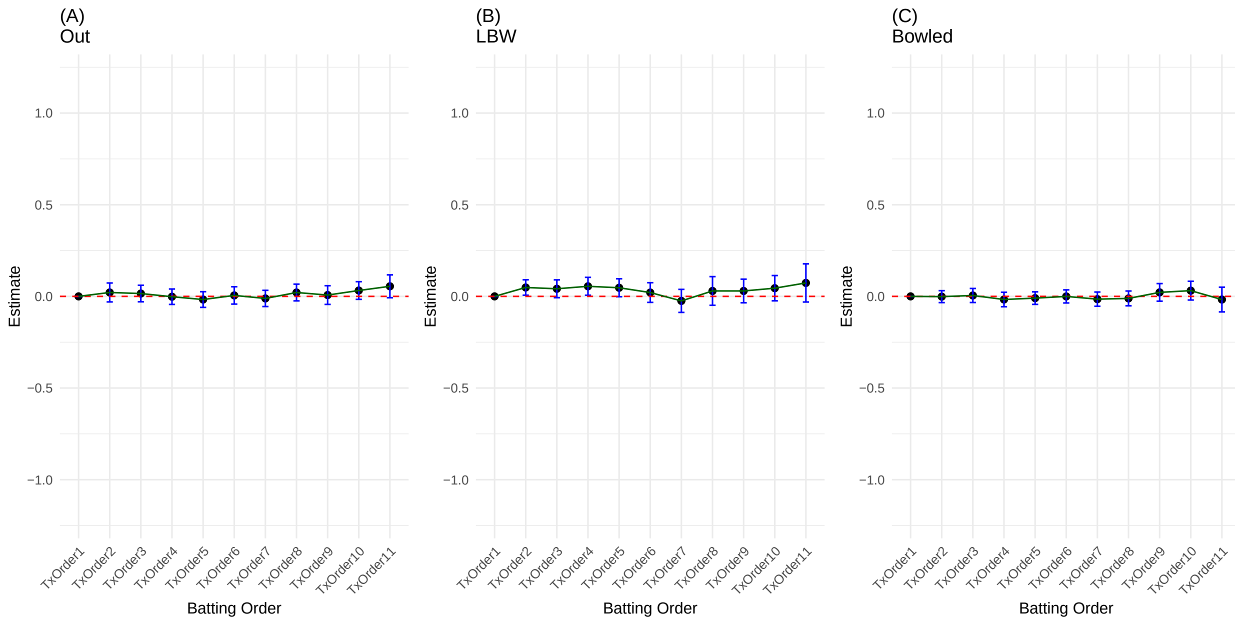

Figure 7: Heterogenous effect of Temperature with Ability

Above figure shows the estimates for the heterogenous effect of temperature with the ability of the batsman. Here I use the batting order of the batsman as a proxy for ability. The estimates are in comparison to first batting order. The estimates are from a logistic regression where each regression includes controls for precipitation, windspeed, dew, rest days, predicted effect of temperature on no-balls delivered by adversary's bowling unit, innings, and format. Each regression is estimated with peer and adversary fixed effect. All errors are clustered at match level.

Table 7: Ability

	runs	balls	dot balls	nonboundary runs
	(1)	(2)	(3)	(4)
T	0.00426	0.00472	0.00365	0.00716**
	(0.00433)	(0.00316)	(0.00290)	(0.00332)
Ability	-0.07497	-0.06094	-0.05824	-0.00927
	(0.09679)	(0.07876)	(0.08338)	(0.08585)
T x Ability	0.00249	0.00122	0.00047	0.00029
	(0.00373)	(0.00307)	(0.00334)	(0.00320)
Observations	6706	6706	6100	6456
R2	0.11	0.22	0.29	0.13
Average	14.17	14	6.67	6.63
Dyad FE	Y	Y	Y	Y
Opposition FE	Y	Y	Y	Y

Note: *This table presents the estimates of the interactive effect of temperature and if striker is paired with more able peer on productive outcomes of striker. Outcome variables are logged and estimates are from high dimensional panel fixed effect model. Each regression includes controls for precipitation, windspeed, dew, total rest days for both peers, predicted effect of temperature on no-balls delivered by adversary's bowling unit order, experience of both peers.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Experience

	runs	balls	dot balls	nonboundary runs
	(1)	(2)	(3)	(4)
T	0.00341	0.00464	0.00340	0.00593*
	(0.00444)	(0.00321)	(0.00273)	(0.00336)
Experience	-0.10203	-0.07089	-0.06038	-0.09320
	(0.08290)	(0.07281)	(0.07538)	(0.07592)
T x Exp	0.00433	0.00143	0.00105	0.00279
	(0.00337)	(0.00279)	(0.00302)	(0.00331)
Observations	6706	6706	6100	6456
R2	0.11	0.22	0.29	0.13
Average	14.17	14	6.67	6.63
Dyad FE	Y	Y	Y	Y
Opposition FE	Y	Y	Y	Y

Note: *This table presents the estimates of the interactive effect of temperature and if striker is paired with more experienced peer on productive outcomes of striker. Outcome variables are logged and estimates are from high dimensional panel fixed effect model. Each regression includes controls for precipitation, windspeed, dew, total rest days for both peers, predicted effect of temperature on no-balls delivered by adversary's bowling unit order, experience of both peers.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

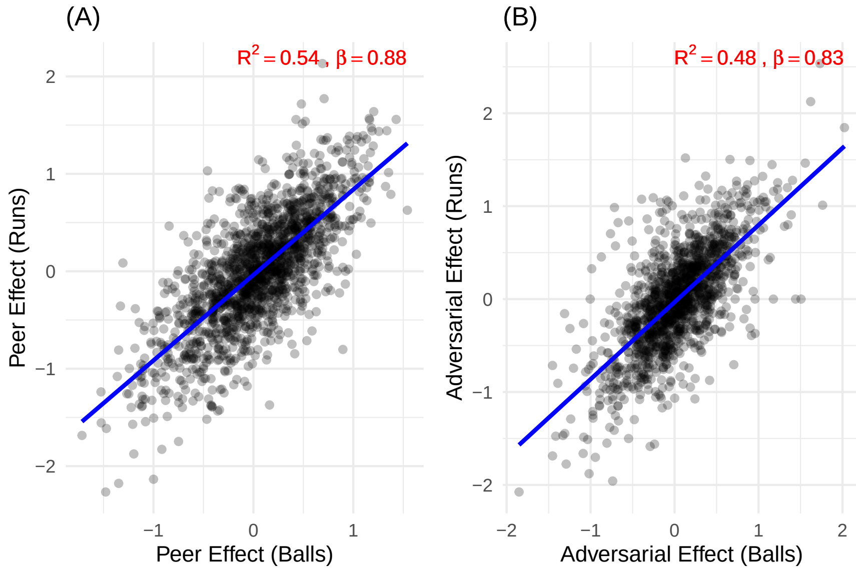

Figure 8: Runs vs Balls

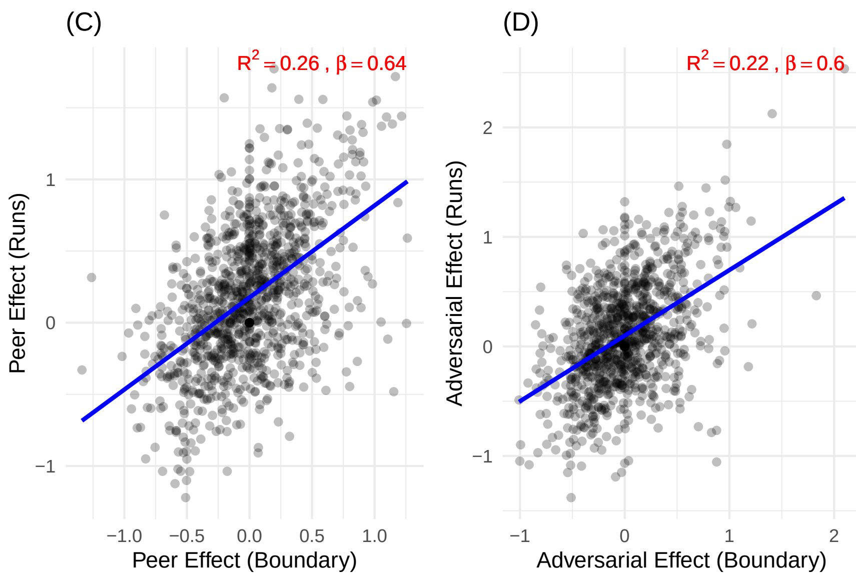

Figure 9: Runs vs Boundary

These scatterplots illustrate the relationships between estimated peer and adversarial effects in various outcomes: log of runs scored, log of balls faced, log of runs scored through hitting boundaries. To construct quantities in each panel, I estimate Equation 6 for peer effect and Equation 7 for adversarial effect to recover $\phi_{RUNS}, \phi_{BALLS}, \phi_{BOUNDARIES}$ *and* $\nu_{RUNS}, \nu_{BALLS}, \nu_{BOUNDARIES}$*.These match effects for each dependent variable are normalized to mean zero for each striker. The displayed regression coefficient and* R^2 *are from bivariate regressions*

Table 9: Sensitivity Analysis (Correlations)

	Baseline	-Precip	-Rest Days	-No-Ball	-BattingOrder
Peer	1.0000	0.9999	0.9997	0.9992	0.9946
Adversarial	1.0000	0.9993	0.9999	0.9983	0.9897

Note: *Above table reports result of Sensitivity analysis. The baseline estimates are calculated by estimating Equation 6 for peer effect and Equation 7 for adversarial effect. Each covariate is removed in subsequent iteration and correlation of estimates with baseline estimates are reported in table above.*

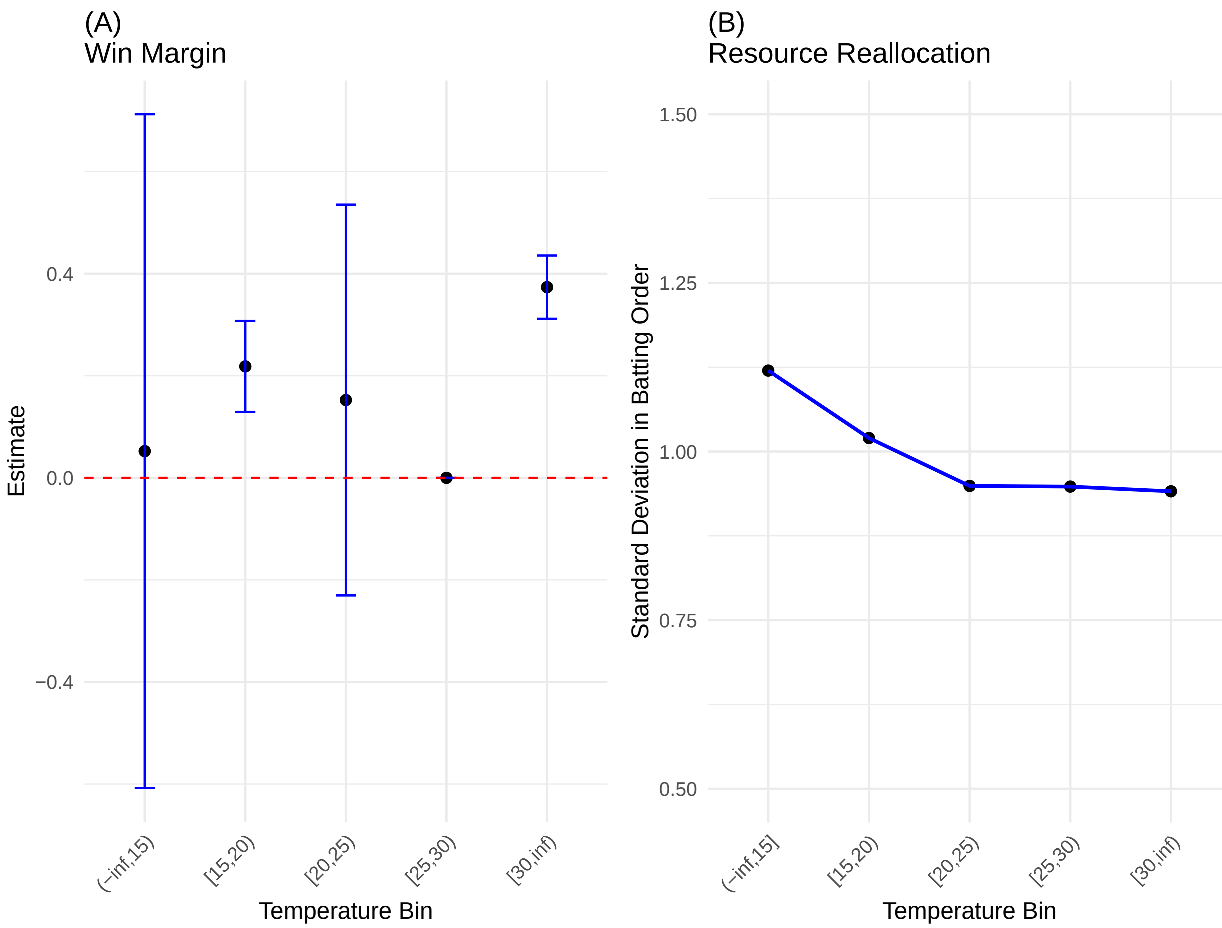

Figure 10: Robustness Checks

Panel A shows estimates of non-linear impact of temperature on win margin, estimated from Equation 1 . Panel B shows a simple plot of standard deviation in batsman's batting order with temperature.

A Appendix

A.1 Additional Figures and Tables

Figure A1: Illustration of Cricket Pitch

Table A1: Dismissals in Cricket

Dismissal	Explanation
Bowled Out	If a bowler's ball (not a no-ball) hits the wicket of striker
Caught	If the striker hits the ball and ball is caught by bowler or fielder before it hits the ground
LBW (Leg Before Wicket)	If the ball would have hit the wicket but hits part of striker's body without touching the bat
Run Out	While the ball is in play, the wicket is put down using the ball by the opposing side while no part of batsman's bat or body is grounded behind the popping crease
Stumped	Striker leaves popping crease to play a ball but misses the ball such that wicket keeper is able to put down the wicket with the ball
Retired	Batsman leaves the field of play without umpire's consent for any reason other than injury or incapacity
Hit the ball twice	If the striker hits the ball twice
Hit Wicket	If the batsman dislodges their own stumps with their body or bat
Obstructing the field	If the batsman obstructs or distracts the fielding side by their action or with their words
Timed Out	An incoming batsman is timed out if they take more than three minutes to be ready to face the next ball.

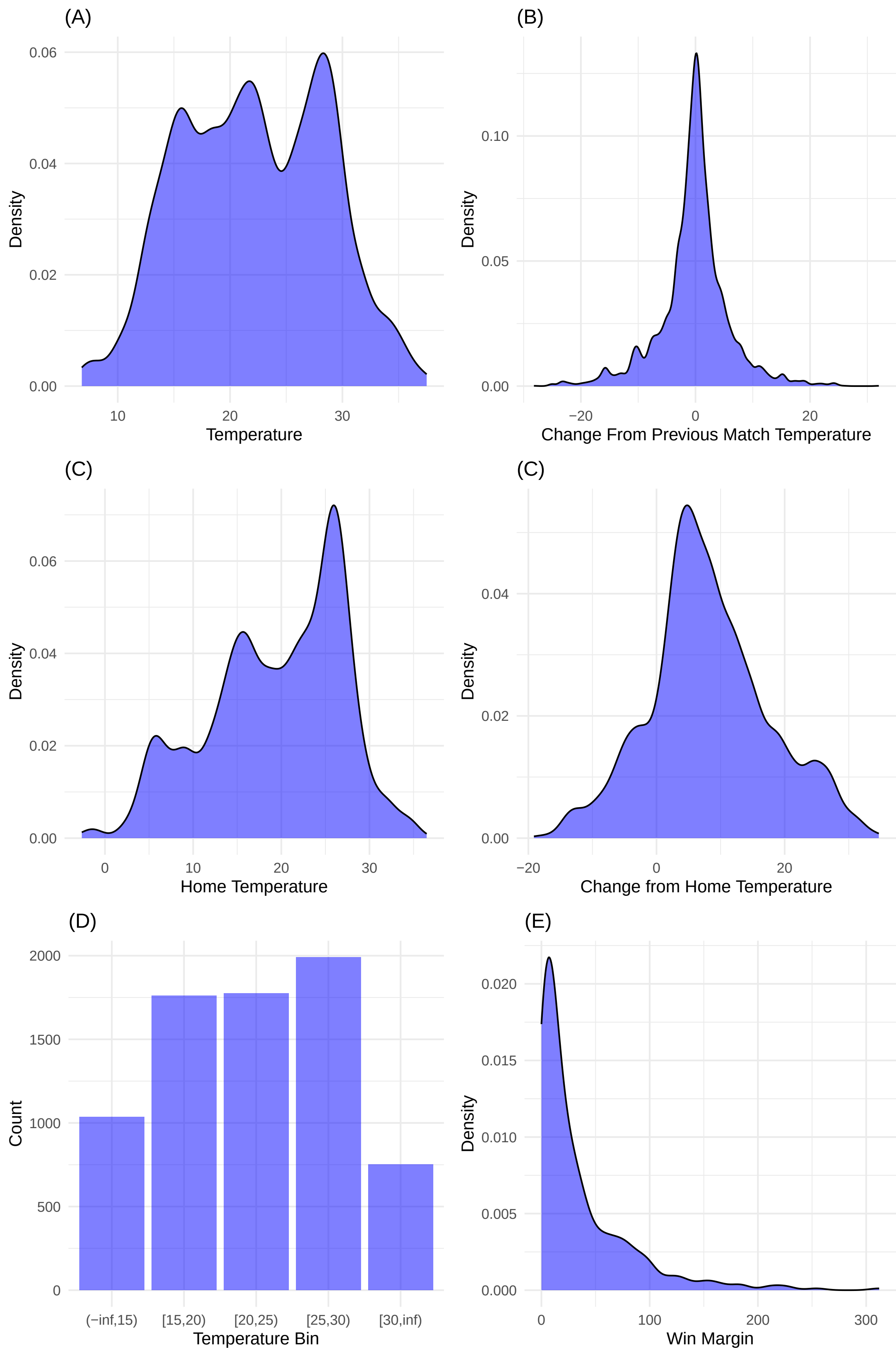

Figure A2: Summary Statistics

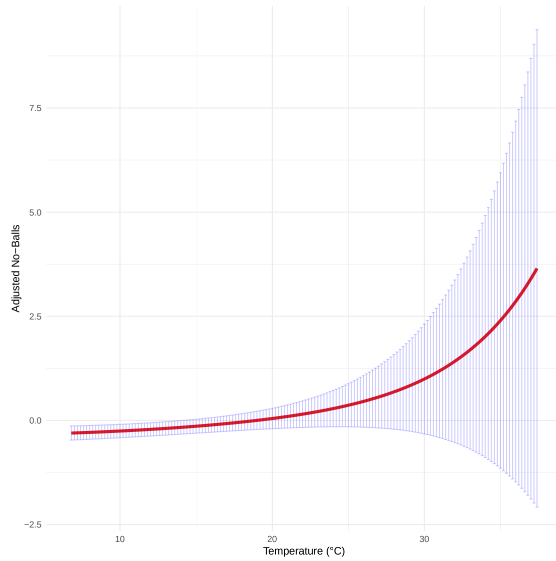

Figure A3: Estimated effect of temperature on No-balls

Note: *This image shows the estimated non linear effect of temperature on no-balls as compared to 25°C.*

A.2 Batting Metrics

1. *Runs*: Two batsmen on each side of the pitch (see: Figure A1) run to exchange positions to complete one run after the striker has struck the ball. Team with more number of runs at the end of the game, wins the match.
2. *Balls Faced*: More number of balls bowled by bowlers that are faced by batsman correlates with the amount of time spent on the pitch by the batsman
3. *Boundaries*: Another way for a batsman to make runs is to score a boundary. A boundary is scored when the ball reaches the boundary of the stadium before it is stopped by a fielder of the opposing team. If the ball reaches the boundary without touching the ground that results in a score of 6 runs, else it is results in a score of 4 runs. A batsman who scores more runs through hitting boundaries is considered an aggressive player. The threat in hitting boundaries is of mistiming the ball and getting caught out.
4. *Strike-Rate*: The ratio of $\frac{\text{Runs}}{\text{Balls}} * 100$ is strike rate, it tells us how fast the batsman scored in an inning.
5. *No-ball*: A no-ball is a illegal delivery in cricket. It occurs when a bowler oversteps the popping crease (see: Figure A1) on his end of the pitch when delivering the ball to the striker on the other end of the pitch. It results in the opposing team gaining a run, and the bowler has to bowl again to compensate for a no-ball bowled earlier. On this compensatory ball, the striker gains a "free hit", and the striker can not be dismissed on this ball (other than getting run out, hitting the ball twice, and obstructing the field). A no-ball is a good measure of a bowler's performance because it is unaffected by bowler's team and the opposing batsman. It is purely a mistake made on bowler's behalf.

A.3 Variance Decomposition

Here I first layout Equation 6, Equation 7 and decompose the variance into parts.

$$log(Runs)_{impa} = \beta_1 T + X'_{im}\beta_2 + \alpha_i + \phi_{i,p} + \theta_a + \epsilon_{impa} \tag{6}$$

$$log(Runs)_{impa} = \beta_1 T + X'_{im}\beta_2 + \alpha_i + \theta_p + \nu_{i,a} + \epsilon_{impa} \tag{7}$$

Decomposing Equation 6 :

$$\begin{aligned} Var(log(Runs)_{impa}) &= Var(\alpha_i) + Var(\phi_{i,p}) + Var(\theta_a) \\ &\quad + \underbrace{2Cov(\alpha_i, \phi_{i,p}))}_{=0} + 2Cov(\alpha_i, \theta_a) + \underbrace{2Cov(\phi_{i,p}, \theta_a)}_{=0} \end{aligned}$$

Since, additional restrictions are imposed that both individual and peer fixed effects are mean zero for each striker. Therefore they are estimated to be within striker variance, so we can assume $Cov(\alpha_i, \phi_{i,p}))$ to be zero. Since peer matches are made quasi-randomly depending on the order in which opposing team is able to take wickets, we can assume $Cov(\phi_{i,p}, \theta_a)$ to also be zero. Therefore variance decomposition becomes:

$$Var(log(Runs)_{impa}) = Var(\alpha_i, \theta_a) + Var(\phi_{i,p})$$

Similarily, Decomposing Equation 7 :

$$\begin{aligned} Var(log(Runs)_{impa}) &= Var(\alpha_i) + Var(\theta_p) + Var(\nu_{i,a}) \\ &\quad + 2Cov(\alpha_i, \theta_p) + \underbrace{2Cov(\alpha_i, \nu_{i,a})}_{=0} + \underbrace{2Cov(\theta_p, \nu_{i,a})}_{=0} \end{aligned}$$

Same as above, the quasi random nature of peer matches leads to $Cov(\theta_p, \nu_{i,a})$ to be zero and the restriction of adversarial effect being mean zero for each striker and therefore identified as within striker adversarial effect, leads to $Cov(\alpha_i, \nu_{i,a})$ to be zero. This gives following variance:

$$Var(log(Runs)_{impa}) = Var(\alpha_i, \theta_p) + Var(\nu_{i,a})$$

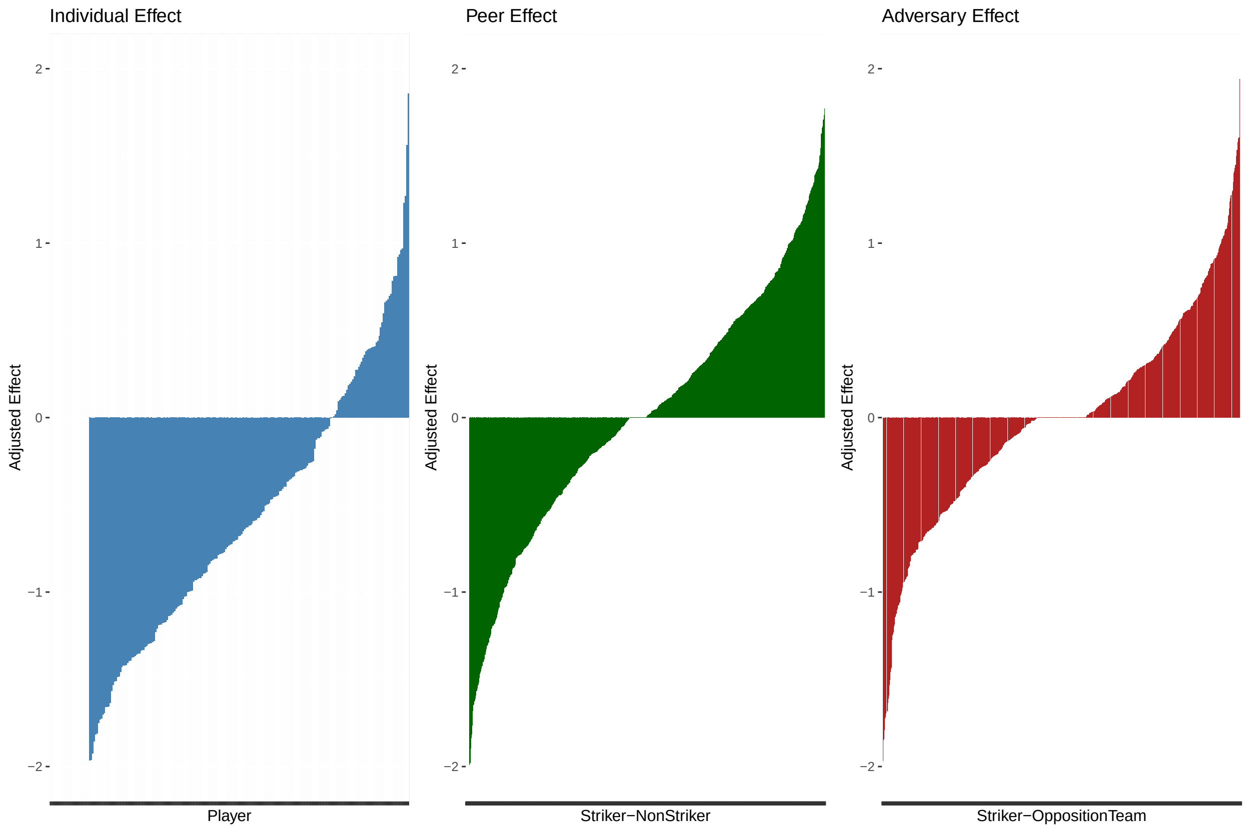

Figure A4: Effect

Note: *This image illustrates the individual, peer, and adversarial effect calculated from split sample analysis of above 25°C sample.*