Stumped by the Sun, Saved by the Side: How do teams adapt to heat? Evidence on Peer Adaptation*

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March, 2026

Abstract

How do teams respond to temperature when individual productivity declines? A large body of literature documents that heat deteriorates individual performance. However, workers rarely work in isolation. Using high-frequency data from international cricket games, this paper examines how heat affects team production. I first document a decline in individual productivity of about 1.46% - 2.68% for every degree Celsius increase in temperature, consistent with the literature. In contrast, I find that equilibrium output remains unaffected by heat. To understand this puzzle, I decompose equilibrium outcomes into individual, peer, and adversarial components and introduce a temperature-based split-sample variance decomposition to compare these components across hotter and cooler environments. The results show that the importance of peer interactions increases significantly under heat, while adversarial interactions remain unchanged. Further analysis shows that this adaptation operates through complementarity in skills. Back-of-the-envelope calculation finds that complementary peer interaction compensates about 45% of the decline in individual productivity.

JEL Classification: J24, J44, Q54, Q51, Z20

Keywords: team production, heat stress, labor productivity, peer effects, climate adaptation, skill complementarity

*__Current version__: March, 2026; **Corresponding author**: rimjhim.saxena@unige.ch. I am extremely grateful to my advisors Jonathan Hughes, Daniel Kaffine, Taylor Jaworski, and Beia Spiller for their comments and discussions of this paper. This paper has benefitted tremendously from discussions with Anupma Saxena, Siddhant Saxena, Maulik Jagnani, Austin Kennedy, Edmund Bayliss and comments from participants of University of Colorado Environmental and Graduate Student Seminars.

"One thing that was the highlight of our partnership was how content we were to knock the ball around… just fighting through the physical challenges of what we had to experience through the afternoon and evening. The only chat after 50–70 runs of partnership was, 'let's conserve energy, let's not run the twos." — KL Rahul, on his partnership with Virat Kohli vs. Australia, ICC World Cup 2023 (Chennai; max temp 34 °C)

1 Introduction

Heat impairs individual worker performance.[1] A large body of evidence documents that rising temperatures slow reaction times, impair cognition, and increase the likelihood of execution errors.[2] Field evidence reports productivity losses across a wide range of occupations, including manufacturing workers, judges, and knowledge workers.[3] But most workers do not produce output alone. In most workplaces, production occurs in teams or against a competitor, where individual performance interacts with the actions of peers or adversaries. An important but difficult to measure component of worker skill is therefore the ability to work effectively with others and enhance their productivity. This raises a natural question: when individual performance deteriorates under heat, how do interactions among workers change, and what happens to equilibrium output in team settings?

When production occurs in teams, equilibrium output reflects not only individual productivity but also interactions among workers and responses to adversaries. If heat re-

[1] *Under the scorching sun: Heat stress takes a toll on healthcare workers in Chennai* (Shekhar 2024)

[2] Laboratory experiments in ergonomics have revealed that when Wet Bulb Globe Temperature (WBGT) exceeds 25 °C, task efficiency declines by 1–2% (Solomon M. Hsiang 2010). A meta-review of office productivity studies (covering tasks such as text processing, simple calculations, and customer service) revealed an average productivity loss of 2% above 25 °C (Seppanen, Fisk, and Lei 2006).

[3] Adhvaryu, Kala, and Nyshadham (2022) found that managers mitigate environmental shocks in garment firms in India. Somanathan et al. (2021) surveyed garment, weaving, and steel mills in India and found that task efficiency declined by 2%-8% at high temperatures. Cachon, Gallino, and Olivares (2012) found similar estimates for automobile firms in the United States. Heyes and Saberian (2019) finds that a 10°F increase in temperature reduces convictions in favor of the applicant by 6.55%, and Craigie, Taraz, and Zapryanova (2023) finds that high temperatures increase the likelihood of convictions. LoPalo (2023) documents a 13.6% decline in productivity among DHS survey interviewers. For a detailed review, see: (Heal and Park 2016).

duces individual performance, equilibrium output could decline if errors propagate across workers, if coordination breaks down, or if adversaries are less impacted by heat stress. However, interactions among workers may also provide opportunities for adaptation. Teammates may adjust effort, redistribute tasks, or rely on complementary skills to offset individual productivity losses. Therefore, it is unclear ex-ante how team production would be affected under heat stress without understanding how peers and adversaries impact equilibrium output under heat.

Despite the central role of team production in labor markets, empirically evaluating these interactions is challenging. Identifying how heat affects team production requires detailed worker-level output data combined with data on interactions among workers. Such data are rarely available. Firm-level surveys can measure overall productivity, but typically do not observe how output is generated within teams or how workers interact with one another. As a result, existing empirical work has largely focused on individual productivity rather than team production.

This paper studies how heat affects team production in a competitive environment where workers interact repeatedly with peers and adversaries. I show that although individual productivity deteriorates under heat, equilibrium output in team production remains unaffected by heat. Decomposing equilibrium output into individual, peer, and adversarial components across cooler and hotter conditions reveals that the contribution of peer interactions increases significantly under heat, while adversarial interactions remain largely unchanged. Further analysis shows that this adaptation operates through partnerships with complementary skill sets: when workers with different skill profiles interact, they are better able to coordinate roles and adjust strategies in response to environmental stress.

To study these interactions, I assemble a novel dataset that contains high-frequency production outcomes from men's international cricket games combined with detailed weather data. Sports settings provide several advantages for studying economic behavior because they offer clean measurement of performance, participants operating under strong incentives, and strategic interactions that are directly observable. In this sense, sports data offer the best of lab and field features (Palacios-Huerta 2025). Cricket provides several advantages for studying team production under environmental stress. First, cricket is a competitive team sport. Second, output is observed at both the level of individual actions and team-level equilibrium outcomes. Third, workers interact repeatedly with identifiable peers and adversaries, and finally, the production environment is highly competitive with strong incentives to perform. These features allow me to observe how workers adjust their behavior in response to temperature.

The workers studied in this paper are high-skill and high-income professionals operating in small, relatively homogeneous teams with strong incentives to perform. These features resemble many real-world production environments where production depends on coordination among highly skilled workers, such as surgical teams, financial trading desks, military units, consulting teams, and research groups. In such settings, workers repeatedly interact with the same peers and respond strategically to the actions of competitors. While the institutional details differ across contexts, the mechanisms studied here, peer complementarities, strategic interaction, and adaptation to heat stress are common to many forms of team production. The results, therefore, shed light on how organizations may adjust internally to mitigate the productivity effects of rising temperatures.

I document four main empirical findings in this paper. First, higher temperatures reduce individual's productivity. The measures of execution failure that depend on cognitive function and precise motor coordination show an increase in failure as temperature rises. Second, despite this decline in individual performance, equilibrium output in team production remains largely unchanged. In other words, measures of output that depend jointly on the actions of individuals, peers, and adversaries do not decline with temperature. Third, decomposing equilibrium output into individual, peer, and adversarial components shows that peer interactions become significantly more important in hotter conditions, while adversarial interactions remain largely unchanged. Fourth, I examine the mechanisms underlying this adaptation. The results show that partnerships composed of workers with complementary skill sets perform better under heat stress.

In this paper, I make contributions to three strands of literature. First, I contribute to the literature on temperature and labor productivity. A large body of work documents that exposure to high temperatures reduces individual productivity across a wide range of occupations (LoPalo 2023; R. J. Park et al. 2020; Zivin et al. 2020; Zivin, Hsiang, and Neidell 2018; Somanathan et al. 2021; Adhvaryu, Kala, and Nyshadham 2020; X. Cai, Lu, and Wang 2018). Similar patterns have been documented in professional sports settings where performance depends on physical and cognitive execution (Burke et al. 2023; Sexton, Wang, and Mullins 2022). However, this literature has largely focused on how heat affects individual productivity, with little attention paid to how temperature affects interactions among workers in team production. A related strand of research shows that higher temperatures intensify negative social interactions, including violent behavior and crime (Burke et al. 2009; Solomon M. Hsiang, Burke, and Miguel 2013; Ranson 2014; Heilmann, Kahn, and Tang 2021; Baylis 2020). These studies suggest that environmental stress can alter interactions between individuals, but they do not examine how such interactions affect productive outcomes in team settings. For example, Adhvaryu, Kala, and Nyshadham (2022) show that managers mitigate the productivity effects of air pollution in Indian garment factories through task reallocation across workers. More recently, Garg, Jagnani, and Lyons (2025) (henceforth referred to as GJL) study how heat diminishes team coordination in a controlled lab experiment in Bangladesh. In contrast, this paper provides the first empirical estimates of how peer interactions improve equilibrium outcomes (outcomes jointly influenced by individual, peer, and adversary) under heat in a real-world production environment with repeated interactions where individuals can adjust performance in response to incentives.

Second, I contribute to the literature on peer effects and team production. A large empirical literature documents that worker productivity depends on interactions with coworkers and that peer characteristics can influence performance (Mas and Moretti 2009; Falk and Ichino 2006; Card et al. 2018). Closely related work estimates the contribution of individual agents and their peers to performance using variance decomposition methods applied to high-dimensional panel data, including studies of teacher value-added (Chetty, Friedman, and Rockoff 2014; Mansfield 2015; Bau and Das 2020), physician teams (Silver 2021; Chan 2016), and the effectiveness of bureaucrats (Dahis, Schiavon, and Scot 2023; Best, Hjort, and Szakonyi 2023). This paper makes a methodological contribution by using a split sample design to study how variance components change across different temperature regimes. By estimating variance components separately in cooler and hotter conditions, this approach allows me to quantify how the relative importance of peer and adversary change when workers are exposed to heat stress. In essence, this methodology allows me to not only test whether peers and adversaries matter in equilibrium output, but also test whether peers and adversaries matter more when temperatures rise. To the best of my knowledge, this is the first paper to study how peer and adversarial interactions shape productivity under heat stress and to test whether the importance of peers and adversaries changes in equilibrium output under hotter conditions.

Finally, I contribute to the literature on economic adaptation to climate change. A growing body of work examines how firms and workers respond to temperature through individual-level margins such as migration (Deschenes and Moretti 2009), labor reallocation (J. Park 2016; Ponticelli, Xu, and Zeume 2024; Colmer 2021; Saxena 2024), and investments in defensive systems (Barreca et al. 2016). Other papers in climate adaptation literature have studied firm-level adaptation, such as Somanathan et al. (2021) find that Indian firms with climate control mitigate individual productivity losses due to heat. J. Park (2016) find that increases in temperatures decline county-level payroll in the USA, but hotter places are better able to adapt. Berg et al. (2025) study how regulations and unsafe conditions increase adaptation costs for firms. A common feature of this literature is that adaptation is studied primarily at the level of individuals or firms. In contrast, much less attention has been paid to how the organization of production within firms may adjust to environmental stress. In particular, how teams are composed and how workers interact within teams may itself be an important margin of adaptation. This paper identifies such a margin by showing that complementarities between peers allow teams to adjust coordination and sustain output even when individual productivity deteriorates under heat stress. To the best of my knowledge, this paper provides the first empirical evidence that complementarities between workers can serve as a margin of adaptation to heat stress.

The rest of the paper is organized as follows, Section 2 presents a conceptual framework that explains how equilibrium output in team production is affected by individual, peer, and adversary. Section 3 describes the institutional setting of cricket relevant to this paper and details about the dataset, variables, and sample construction. Section 4 presents empirical estimates of the effect of temperature on individual and equilibrium output. Section 5 describes variance decomposition and split-sample analysis and reports the estimates from using these methodologies. Section 6 explores the mechanism underlying the increased importance of peer interactions under heat stress. Section 7 puts the methodology used in this paper through multiple robustness checks, and finally Section 8 concludes the paper.

2 Conceptual Framework

To fix ideas, consider production in a team setting where an individual worker's output is generated through the actions of an individual worker i, a coworker/peer p, and an opposing force/adversary a. Let T denote the temperature under which the worker, the peer, and the adversary are working. Therefore, the production function of the individual's output is a function of temperature T, the peer interaction with the individual, $\phi_{i,p}$, and the adversary interaction, $\nu_{i,a}$. It can therefore be written as -

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

The functional form of Y_i, also referred to as the equilibrium output, is linear in its components and can be written as -

$$Y_i(T, \phi_{i,p}, \nu_{i,a}) = \bar{Y}_i - C_i(T) + \phi_{i,p}(T) - nu_{i,a}(T)$$

where, $\bar{Y}_i$ is the baseline level of individual's output. $C_i(T)$ is the cost of experiencing temperature T that the individual experiences. It is the physiological experience of heat. The literature has estimated a U-shaped curve for this cost (Seppanen et al. 2006; Heal, Park, and Zhong 2017; X. Cai, Lu, and Wang 2018). The temperature can therefore improve productivity at pleasant temperatures or reduce productivity at extreme temperatures. I am agnostic about the sign of this cost function. $\phi_{i,p}(T)$ is the *peer effect* on individual i of working alongside peer p at temperature T. Similarly, $\nu_{i,a}(T)$ is the *adversary effect* on individual i for working against the adversary at the same temperature.

Comparative Statics: To understand how temperature affects equilibrium output, I examine the marginal effect of temperature on Y_i.

$$\frac{\partial Y_i}{\partial T} = - \underbrace{C_i(T)'}_{\text{individual effect}} + \underbrace{\phi_{i,p}(T)'}_{\text{peer effect}} - \underbrace{\nu_{i,a}(T)'}_{\text{adversary effect}} \tag{1}$$

Above expression decomposes the marginal effect of temperature on output into three distinct channels:

1. $C_i(T)'$ is the direct physiological cost of a one unit increase in temperature on an

individual's productivity, also referred to as *individual effect*. As discussed above, $C_i(T)$ takes a U-shape. Therefore, $C_i(T)^{'} < 0$ at low temperature, $C_i(T)^{'} = 0$ at comfortable middle temperature, and $C_i(T)^{'} > 0$ at high temperature.

2. $\phi_{i,p}(T)^{'}$ is the marginal contribution of *peer effect* on individual's productivity after a one unit increase in temperature. Little research is available on how peer effects interact with individual productivity at high temperatures. This is the central focus of this paper. We do not know ex-ante if $\phi_{i,p}(T)^{'} > 0$ or < 0. It is possible that as temperature increases, peer coordination abilities break (cite maulik's paper) and result in $\phi_{i,p}(T)^{'} < 0$. However, the peer effect could also help adapt to the negative effect of heat on individual productivity through coordination and communication. In such a case, $\phi_{i,p}(T)^{'} > 0$.

3. $\nu_{i,a}(T)^{'}$ is the marginal contribution of *adversary effect* on individual's productivity after a one unit increase in temperature. By definition, the adversary works to reduce an individual's productivity. Therefore, adversary effect is always $\nu_{i,a}(T)^{'} > 0$. The temperature however, changes the magnitude of the marginal adversary effect.

Proposition 1 (Flat equilibrium): *Suppose* $C_i(T)^{'} > 0$. If marginal peer effect increases sufficiently such that $\phi_{i,p}(T)^{'} \geq C_i(T)^{'} + \nu_{i,a}(T)^{'}$, then $\frac{\partial Y_i}{\partial T} \geq 0$ resulting into a zero or positive marginal effect of temperature on overall output (equilibrium).

Assuming that $C_i(T)^{'} > 0$ is not a farfetched assumption. As discussed above, due to the U-shape of the physiological cost function, the marginal temperature cost is positive at high temperatures. Therefore, revisiting Equation 1 shows that the overall effect on temperature on equilibrium output becomes a horse race between the marginal peer effect vs. the marginal adversary effect and marginal physiological cost.

$$\frac{\partial Y_i}{\partial T} = \underbrace{-C_i(T)'}_{<0} + \phi_{i,p}(T)' \underbrace{-\nu_{i,a}(T)'}_{<0}$$

If we examine the flat marginal equilibrium output case, i.e. $\frac{\partial Y_i}{\partial T} = 0$. This would only hold true if, $\phi_{i,p}(T)^{'} = C_i(T)^{'} + \nu_{i,a}(T)^{'}$. This is a situation where the marginal peer effect compensates for the negative effects of marginal physiological cost on individual productivity and the marginal adversary effect on overall output.

The overall sign and the statistical significance level of $\frac{\partial Y_i}{\partial T}$ at high temperature therefore tells us if the marginal peer effect helps in adapting to negative physiological effect of temperature and adversary effect or if the coordination breaks down under heat and peer effect further decreases the effect of temperature on equilibrium output. I test this proposition through data in Section 4 and further reflect on the peer effect under heat in Section 5.

3 Background and Data

Ideally, identifying the causal effect of heat on individual productivity and in a team setting would require a controlled experiment. In such an experiment, individuals would be randomly assigned to room temperature vs. high temperature environments, and their productivity would be measured. To identify the role of peer interaction, individuals would then be randomly assigned to coworkers, and then each pair would be randomly allocated to a comfortable room temperature or a high temperature environment.

In practice, such randomization is rarely feasible. Conducting experiments such as the one detailed above is costly, and even when feasible, experimental settings fail to capture the real-world incentives and strategic interactions that shape individual and equilibrium output. Instead, I leverage high-frequency data, exogenous variation in temperature, and quasi-random variation in peer exposure provided by the institutional structure of professional cricket.

3.1 Institutional Setting: Team Production under Heat

Cricket is a team sport. Two teams of eleven players each play against each other. The core of the sport is to score the most runs while conserving your resources (time and workers). Matches are played outdoors, and players are exposed to weather conditions. Therefore, matches are only played during the driest season of the year in each country to avoid canceling matches due to the rain.

Cricket provides a useful setting to study productivity under heat in a team production environment. Output is generated by two workers at a time, requiring continuous coordination, while an opposing team actively seeks to disrupt production. The sport generates high-frequency, task-level data on output, cognition, and failures. This allows me to disentangle individual, peer, and adversary productivity under heat.

I observe a rich set of performance metrics that capture different margins of production. Table 1 summarizes the metrics used in the analysis and the production margins they primarily reflect[4]. This paper focuses only on the batting side of the play[5]. The goal of each batsman is to maximize run production while avoiding failure (dismissal). A run is produced through joint action. An individual batsman initiates production by striking the ball, then coordinates movement with the peer batsman to complete the exchange. This happens while the opposing team (the adversary) actively seeks to disrupt production. Successful output, therefore, reflects individual execution, peer coordination, and adversary pressure. The positions of the individual batsman, the peer, and the adversary in relation to each other are represented in Figure A1.

Common worker adaptation strategies of switching jobs (J. Park 2016; Colmer 2021; Albert, Bustos, and Ponticelli 2021), migration (Deschenes and Moretti 2009; R. Cai et al.

[4]Cricket is a team sport, and most metrics involve being influenced by your peers and adversaries. I categorize cricket metrics into individual and equilibrium metrics depending on the active decision maker in each of the metric.

[5]A typical cricket game consists of two opposing sides that alternate between batting and bowling.

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 provides an interesting setting to study which dimension of adaptation these high-skilled and high-paid workers adopt[6][7].

Table 2 compares an individual's heat production in watts/minute for different economic sectors. The table shows that heat production for an international cricket batsman during an indoor net session, when the temperature was $15^{\circ}C$ (relatively comfortable temperature), is equivalent to the heat production of workers in the agriculture and manufacturing sectors, with the higher end of the heat distribution in cricket reaching that of workers in the construction industry. Even though worker skill and income are not comparable across these sectors, the physiological impact of heat in cricket is comparable to other economic sectors.

3.2 Cricket data

Cricket data is primarily sourced from the `cricketdata` R package (Hyndman et al. 2023). The package sources the data from (a) ESPNcricinfo (2023) and (b) Rushe (2023). The benefit of using this package is that it provides the data in a consistent format for each game at a ball-by-ball level (play-by-play level). The data covers the universe of cricket matches played between 2001 and the present. I extract a subset of data from the universe of cricket matches data to have consistent players, peers, and adversaries.

I supplemented this data with the home locations of each player, which I obtained from Wikipedia and the ESPNCricinfo page of each player. Additionally, I also got salaries of players from Cricmetric (2023) and rankings from ICC player rankings (ICC (2023)) as of

[6] Cricket is not commonly known as a significantly active sport, such as soccer or rugby. However, an international batsman produces heat at an equivalent rate to an individual running at 8kmph(5mph). Estimates from a University of Portsmouth study suggest that a day spent at the crease by a batsman is equivalent to running a marathon with a helmet, gloves, and pads on (Tipton et al. 2019).

[7] Another lab study revealed that batsmen experience higher increases in core temperature as compared to bowlers and fielders (Stay et al. 2018).

January 1, 2021, which is the pre-period for this study. This is done to remove bias caused by changes in rankings, as heat affects a player's performance.

The `cricketdata` package provides the venue of each game. I then used geocode for Google Sheets to retrieve the latitude and longitude of each game venue to match each location with climate data.

3.3 Weather data

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

3.4 Sample

The final sample for analysis on the effect of temperature on individual and equilibrium productivity is aggregated up the batsman-game level (worker-day level output). The sample statistics are detailed in Figure A5. The extracted sample consists of men's international cricket games spanning four seasons of the sport from 2021 to 2023. It includes data for 407 matches among 16 countries [8]. The data covers the performance of 460 batsmen.

The second part of the analysis hinges on variation within an individual's performance with different peers and adversaries under heat. For this part of the analysis, I create a panel of batsman-peer-match level data (worker-peer-day level output) and batsman-

[8] These matches are played between 16 national teams: Afghanistan, Australia, Bangladesh, England, India, Ireland, Namibia, Netherlands, New Zealand, Pakistan, Scotland, South Africa, Sri Lanka, United Arab Emirates, West Indies, Zimbabwe. All international matches among these teams during the sample period are included in the sample.

opponent-game level data (worker-adversary-day level output). I have 2304 unique batman-peer matches that identify peer variance and 1713 unique batsman-adversary matches that identify adversary variance in an individual's productivity.

4 Individual vs. Equilibrium Effects

In this section, I detail the description of the strategy I used to estimate the effect of temperature on an individual's productivity and equilibrium productivity. I describe equilibrium productivity as the metric of productivity where the decision maker is not only an individual, but they are joint decisions of the individual, peer, and adversary.

I estimate the following high dimension panel fixed effect model:

$$y_{ima} = \sum_j \beta_j T_m + X'_{im}\gamma + \alpha_i + \alpha_t + \alpha_a + \alpha_n + \alpha_f + \epsilon_{ima} \tag{2}$$

where y_{ima} is a batting metric for individual i playing against opponent team a on match-day m. The batting metric can be individual or equilibrium, the details about the decision maker for each batting metric are listed in Table 1. Individual productivity metrics are LBW and Bowled, while the rest of them are equilibrium productivity metrics. β_j is the parameter of interest here. The estimate of β_j shows the effect of the game day temperature when it lands in temperature bin j on productivity as compared to productivity in the reference temperature bin [25°C - 30°C). I estimate the impact for four temperature bins relative to the reference bin: ($-\infty$,15°C), [15°C-20°C), [20°C- 25°C), and [30°C, $+\infty$).

X'_{im} is a vector of controls, which includes weather variables such as precipitation, wind-speed, and dew on game day. Physiological variables like the rest days between matches for each individual i. Institutional variables such as the batting order of each individual batsman. The order in which the individual batsmen get a chance to bat dictates the amount of time they spend in the ambient temperature.

α_i is individual fixed effect that controls for time-invariant striker specific measures (e.g., batsman's skill). α_t is a team-fixed effect that accounts for the peer effect. α_a is the fixed effect for opposition team, this is the adversary's fixed effect. α_n is an inning fixed effect; cricket games have two innings. An individual batting in the second inning has spent time out on the field for all of the first inning and therefore will be differently affected by temperature while spending more time at the temperature in the second inning as compared to an individual working in the first inning. α_f is a format-fixed effect. The two formats of cricket that this paper focuses on are ODI and T20. They are not just different in the number of overs played in each format, but also in the strategy that each individual employs to deal with each format. Therefore, a format fixed-effect only compares the within format differences. Therefore, the only variation in a cricketer's productivity comes from within cricketer variation in temperature realization.

4.1 Individual

Two common modes of dismissal or task failure in cricket are "bowled" and "leg before wicket" (LBW)[9]. An individual is bowled when the delivered ball from the player from the opposite team strikes the wicket[10] directly, and LBW occurs when the ball would have struck the wicket but instead hits the individual batsman's body. In both cases, production ends immediately, and the individual exits the task.

From a production perspective, both bowled and LBW out reflect failures in individual execution in a competitive environment. Avoiding these dismissal types requires the worker to correctly perceive the incoming task demand, process timing and trajectory information correctly, and execute a precise response under time pressure. While the opposing

[9]The distribution of different types of task failures in my sample is plotted in Figure A4.

[10]A wicket in cricket is the set of three vertical wooden stumps topped by two small bales. The goal of each individual batsman is to protect the wicket. Striking or dislodging it results in the individual batsman being dismissed and production ending. The position of the wicket is shown in Figure A3.

worker (the bowler) has an influence on task difficulty, the main cause of failure is a cognitive error by the individual worker. Therefore, these outcomes are informative about how heat affects individual performance.

I estimate a logistic regression with Equation 2 where the outcome is the probability of getting bowled or LBW out. The results of this estimation for the linear effect of temperature are presented in Table 3, and the non-linear effect of temperature is presented in Figure 1. The linear effect of temperature on the individual outcomes shows an increase in the probability of task-failure through a decline in the cognition of an individual batsman. On average, a 1°C increase in temperature results in 2.68% increase in the probability of getting LBW out and 1.46% increase in the probability of getting bowled out.

It is important to note that individual outcomes, such as bowled and LBW dismissals, are jointly determined by the individual batsman's execution and the opposing bowler's performance. As a result, an increase in the probability of these dismissals under higher temperatures could, in principle, reflect improved performance of the bowler rather than a decline in individual batsman's productivity. If bowlers performed better in hotter conditions, we would expect to see that in other metrics of bowlers' performance. To assess this possibility, I test for bowlers' performance with respect to the increase in temperature. The results are reported in Table A1, and show no significant effect of temperature on bowlers' productivity. Therefore, we can rule out the theory that the increase in the probability of getting bowled out or LBW out is due to bowlers becoming more productive at higher temperatures.

Figure 1 illustrates the nonlinear relationship between temperature and an individual's productivity. The coefficients are estimated relative to the reference temperature bin $[25, 30)$, so each point should be interpreted as the effect of playing a game in a given temperature bin compared to playing under $[25, 30)$.

Panel A shows that productivity declines at higher temperatures. In particular, the probability of LBW out is higher when matches are played at $[30, \infty)$ as compared to the matches played at temperature $[25, 30)$. Panel B indicates that while the effects of extreme temperatures are not statistically significant at high temperatures, they are different from the effects observed at cooler temperatures. In other words, the probability of getting bowled out is lower when the game is played at a lower temperature bin $[-\infty, 15)$.

Taken together, these results provide clear evidence that individual productivity deteriorates under heat stress. This is consistent with a large literature documenting negative impacts of high temperature on worker performance (Seppanen, Fisk, and Faulkner 2003; Sexton, Wang, and Mullins 2022; X. Cai, Lu, and Wang 2018; LoPalo 2023).

4.2 Equilibrium

As discussed earlier, cricket is a team sport. Therefore, most cricket performance metrics are jointly determined by the individual batsman, peer, and the adversary. I refer to these metrics as equilibrium outcomes, since they reflect the net result of individual effort, peer coordination, and adversarial pressure under a given temperature environment. In this section, I discuss how equilibrium productivity responds to heat. The results for the linear effect of temperature on equilibrium outcomes are presented in Table 4, and the non-linear effect of temperature is presented in Figure 2.

The description of each equilibrium outcome and its real-life analog is given in Table 1. The results in Table 4 show no significant effect of heat on equilibrium outcomes except for a significant decline of 1.78% in the probability of getting caught out. Therefore, a decline in the probability of getting caught-out is an improvement in productivity as temperature rises by a unit. A caught-out dismissal occurs when an individual batsman makes a risky shot, but it is intercepted by the opposing team before the ball hits the ground, and therefore results in a terminal failure. This terminal failure is produced jointly by individual execution and adversarial response. The decline in the probability of caught-out dismissals as temperature increases implies either a change in an individual's batting strategy away from taking risks or a decrease in the adversary's productivity in response to temperature. As we have established above, there is no significant change in the adversary's productivity. This result, therefore, is consistent with adaptive behavioral response through a change in individual's strategy.

The statistically insignificant effect of heat on equilibrium productivity implies that we are in the "flat-equilibrium" situation as described in *Proposition 1* in Section 2.

4.3 Contrast

The empirical results show a clear contrast between individual and equilibrium productivity under heat. I find a decline in individual productivity along with the absence of a change in equilibrium productivity. This is consistent with the "flat-equilibrium" case described in *Proposition 1*, which states that at sufficiently high temperatures, if marginal peer effect increases sufficiently, it could result in zero or positive marginal effect of temperature on equilibrium output.*

These results suggest that team production environments might facilitate adjustment mechanisms through peer coordination or strategic adaptation. In the next section, I tease out if peer effect does compensate for decline in individual productivity in the next section.

5 Peer and Adversarial Effects under heat

A key methodological innovation of this paper lies in modeling peer and adversarial effects as *match effects* rather than through observable average peer-group characteristics. Traditional approaches in peer effects literature typically regress individual outcomes on observable attributes of peers.[11] While this approach identifies how observable peer characteristics correlate with individual outcomes, it is limited in some important ways that are crucial in this context. It cannot capture the implicit and unobservable dimensions through which peers affect individual outcomes.

In contrast, the match-effects methodology (Silver 2021), which I employ in this estimation, introduces a fixed effect for each individual-peer pair. In this paper, I also employ a fixed effect for each individual-adversary pairing. These fixed effects capture the total extent of influence of peer over individual's outcomes. This approach allows for peer effects that operate not only through observable attributes but also through unobserved channels such as tacit coordination, interpersonal chemistry, strategic complementarity, motivation, or fatigue spillovers. Importantly, these effects can be heterogeneous, allowing the response of each player to differ across pairings and environmental conditions such as temperature.

By assigning a unique match effect to each player-peer dyad, I capture the full heterogeneity of interpersonal dynamics. This is particularly important in high-frequency, team-based tasks like cricket, where outcomes emerge from split-second coordination between peer pairs rather than from static group averages.

Unlike settings where peer groups are endogenous, this paper's context involves quasi-random pairings that vary across cricket games and across exogenously realized temperature shocks. The match effects framework, therefore, isolates the within-dyad, within-adversary variation caused by contemporaneous environmental conditions.

Although the estimated match effects are agnostic about the underlying mechanisms, they can be readily related back to observable peer attributes ex post. This enables a two-step analytical framework that I undertake in this paper. First, estimate the true empirical relevance of peer effects without restrictive structural assumptions, and second, use the

[11] (Mas and Moretti 2009; Arcidiacono, Kinsler, and Price 2017; Card et al. 2018)

estimated effects to explain which observable attributes, such as skill complementarity, ability, or experience, account for variation in those effects. This decomposition is especially powerful for assessing adaptation mechanisms under temperature stress.

5.1 Match-Effect Decomposition

Motivated by the discussion in Section 2 and following the match-effect methodology in Silver (2021), I model equilibrium performance as arising from a data generating process in which individual, peer, and adversary each contribute to the variation in outcome. Specifically, I assume a linear production function of runs scored by batsman i in match m in the presence of peer p against adversarial team a, conditional on a rich set of observable match-level covariates X'_m. While the individual i is performing, he is influenced by the actions of his peer p, and the actions of his adversary a.

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

In earlier specifications, the unit of observation was at the individual-game level. To examine peer and adversary specific interactios within matches, I restructure the data such that the observations are at a more detailed individual-peer-game level. Each observation now corresponds to outcomes that were observed during peer-individual interaction at different games.

In the above specification, outcome represents the log runs made by striker i during instances when peer p occupied the non-striker's end in match m versus team a. Because each batsman partners with multiple peers across matches and faces multiple adversaries across seasons, the panel allows me to estimate how much of performance variation is attributable to (a) the individual's own ability, (b) specific peer pairings, and (c) particular adversarial encounters.

Here, α_i captures the individual's intrinsic ability, $\phi_{i,p}$ represents the peer match effect which captures the influence of peer p on individual i, and $\nu_{i,a}$ represents the adversary match effect which captures the influence of adversary a on individual i.

While Silver (2021) applied this method to estimate the peer effect on physicians' case speed among emergency department physicians, I extend the framework to a competitive team setting and link it to exogenous environmental shock. This extension requires two sets of fixed effects, one for the peer and one for the adversary, to capture how productivity is jointly determined by cooperation and competition.

To quantify the relative contribution of individual, peer, and adversarial factors to overall performance, I perform a variance decomposition of Equation 3. Direct estimation with all dyads included would overfit the model because many pairings appear infrequently. To address this, I separately estimate two nested specifications that focus alternately on peer and adversarial match effects:

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

$$log(Runs)_{impa} = \beta_1 T + X'_{im}\beta_2 + \alpha_i + \theta_p + \nu_{i,a} + \epsilon_{impa} \tag{5}$$

where θ_a and θ_p are adversary and peer fixed effects, respectively. From these regressions, I decompose the variance in log runs into portions attributable to each component: the individual effect $Var(\alpha_i)$, the peer match effect $Var(\phi_{i,p})$, and the adversarial effect $Var(\nu_{i,a})$.

As in Silver (2021), peer-match and adversarial-match effects are normalized to have mean zero within each individual, such that each variance term captures the within-individual heterogeneity in outcomes arising from differences across peers or opponents. Identification of peer and adversarial variances, therefore, relies on within-dyad variation across matches under different temperatures, which are exogenously realized at the match level. I have provided the details of the variance decomposition in Section 5.1.

Table 5 column 1 reports the variance decomposition for the full sample. I find that peer variance is 0.34 in log runs. This result implies that a one standard deviation better peer helps the individual make 58.6% more runs (~8.96 runs). I also find adversary variance to be 0.32, which implies that a one standard deviation better adversary reduces individual's runs by 56.4% (~8.62 runs). These results show that both peers and adversary play a significant role in individual's total performance. Next, I conduct a split-sample analysis to examine whether variance components differ systematically between matches played at low versus high temperatures.

5.2 Split-Sample Analysis

The central question of this paper is whether peer and adversarial effects themselves change at higher temperatures. While the variance decomposition in column 1 of Table 5 shows that the contributions of individual, peer, and adversarial effects on total productivity, it does not reveal whether these components differ systematically between low and high temperatures. The above section asked the question, do peers and adversaries matter in equilibrium productivity? This section asks a different question: does the variance attributable to peer and adversary interactions differ systematically between cooler and hotter matches?

Split-sample approach is widely used in empirical value-added and peer-effects research. In many applications, authors estimate high-dimensional fixed-effects and then decompose the variance of components. A known issue in this estimation is that the variance of estimated fixed effects could be biased when shocks are correlated. Split-sample approach addresses this by estimating effects separately on two independent subsamples and using cross-sample covariances, $Cov(\phi^1, \phi^2)$ to remove estimation noise and recover unbiased variance components. This logic underlies the split-sample corrections used by Chetty, Friedman, and Rockoff (2014) to estimate bias in teacher fixed-effect estimation, Silver (2021) uses this technique to get unbiased estimates for physician-group match effects, Dahis, Schiavon, and Scot (2023) use it to correct bias in judge-court effect estimation, and Best, Hjort, and Szakonyi (2023) use it to correct for bias in their bureaucrat-organization effect estimation. Formally, if $\hat{\phi}^{(1)} = \phi + \varepsilon^{(1)}, \quad \hat{\phi}^{(2)} = \phi + \varepsilon^{(2)}$, then $\text{Cov}(\hat{\phi}^{(1)}, \hat{\phi}^{(2)}) = \text{Var}(\phi)$ under independece of estimation errors across partitions by design. In this literature, the split-sample approach is used for bias-correction.

In contrast, I use split-sample analysis to measure how the magnitude of peer and adversarial effects differs across temperature regimes, specifically below and above 25°C. Temperature is an exogenous, contemporaneous shock affecting the individual, peer, and adversary within each game. I leverage temperature variation to examine how the variance of the components changes under different temperature regimes. To do so, I divide the data into two partitions, all matches played at temperatures <=25$^{\circ}C$ and all the matches played at temperatures >25$^{\circ}C$. Since realized game temperature is exogenous, this results in the random allocation of matches in each partition. I test for other cut-off values of temperature for this analysis. The results of that are discussed in Section 7.

I compute the same variance decomposition in the <=25$^{\circ}C$ (partition A) and >25$^{\circ}C$ (partition B) subsamples. Let $\hat{\phi}^A_{i,p}$ and $\hat{\phi}^B_{i,p}$ denote the estimated peer effects in the cool and hot regimes, respectively. These estimates capture regime-specific structural objects $\phi^A_{i,p}$ and $\phi^B_{i,p}$. The question of interest is therefore whether:

$$Var(\phi^A_{i,p}) = Var(\phi^B_{i,p})$$

That is, whether the variance component attributable to peers changes under different temperature regimes. I formally test the equality of variances using an F-test.

Columns 2 and 3 of Table 5 report the results from above estimation such that column 2 has estimates of variance decomposition for partition A (below 25°C matches) while column 3 has estimates for partition B (above 25°C matches). Column 4 reports the F-test results for the two samples. I find that at games played below 25°C, a one standard deviation better individual player makes 74.3% more runs (~11.36 runs). Similarly, a one standard deviation better peer helps the individual make 69.3% more runs (~10.59 runs). However, a one standard deviation better adversary reduces individual's runs by 59.2% (~9.05 runs).

In contrast, at games played above 25°C, a one standard deviation better individual player makes 91.4% more runs (~13.97 runs). A one standard deviation better peer helps the individual make 76.9% more runs (~11.76 runs). While, a one standard deviation better adversary reduces individual's runs by 59.7% runs (~9.13 runs).

I test for statistically significant differences in variance components between games below 25°C and above 25°C games. The results are in column 4, and they reveal striking differences in how individual, peer, and adversary effects vart with temperature. Individual variances increase significantly from 0.56 at below 25°C games to 0.84 at above 25°C games. This indicates that individual skill differences become more pronounced under heat stress.

More importantly for the central hypothesis, peer variance increases substantially from 0.48 at below 25°C games to 0.59 at above 25°C games (F-test p-value <0.001). A one standard deviation better peer-match allows the individual to score 11% more runs (~ 1.17 runs). This statistically significant increase demonstrates that peer effects become significantly more valuable as an adaptation mechanism when temperature increases.

In contrast, adversary's variance shows no statistically significant difference between the games below and above 25°C. This finding is crucial because it rules out the alternative explanation that equilibrium outcome remain stable due to a decline in adversarial pressure as temperature increases. Instead, this confirms that the stable equilibrium outcome that we observe comes from increased peer effect compensating for individual performance decline.

These results support *Proposition 1* demonstrating that marginal peer effects increase sufficiently at high temperatures such that $\phi_{i,p}(T)' \geq C_i(T)' + \nu_{i,a}(T)'$, resulting in the flat equilibrium outcomes we observed in Section 4.2. Next, I discuss the mechanism through which the peer effect could compensate for the negative individual productivity decline.

These findings differ from GJL, who document a decline in team performance in a randomized programming experiment. In their setting, teams working in warmer rooms perform worse than in cooler rooms, even though individual programmers show no decline in performance. They find that the effect was more pronounced in mixed-gender teams. The setting studied in this paper differs along several important dimensions that may explain the contrasting results. First, the men's national cricket teams studied in this paper are relatively homogeneous, unlike the mixed-gender teams in GJL. Second, workers interact repeatedly with the same peers in multiple games as well as during training sessions, allowing for coordination and tacit understanding to develop over time, whereas the experimental teams studied in GJL collaborate only briefly. Third, production in my setting involves substantial physical effort in addition to cognitive execution. Finally, workers operate under a competitive environment with strong intrinsic motivation to perform against an adversary. Taken together, these differences suggest that the impact of heat on team performance may depend on how teams are structured and how workers interact within them.

6 Mechanism

This paper has so far presented two central findings. First, individual performance deteriorates at high temperatures. Second, equilibrium productivity remains stable, driven by an increase in peer variance under heat. This raises a natural question, what mechanisms govern peer effects, or what are the determinants of peer effects that help compensate for individual productivity decline under heat?

Since peer interactions operate at the individual-peer level (dyad), I use the more detailed sample of data at the individual-peer-game level and exploit within-dyad temperature variation to examine whether the same partnership performs differently under hotter conditions.

The key empirical question that I ask in this section is whether the temperature-productivity gradient varies with observable characteristics of the peer that proxy for coordination capacity and complementarities.

I estimate the model of equilibrium performance that allows temperature to vary with pre-determined peer characteristics.

$$log(y_{impa}) = \beta_1 T + \beta_2 Z_{ip} + \beta_3 T * Z_{ip} + X'_{im}\beta_4 + \alpha_d + \alpha_a + \epsilon_{impa} \tag{6}$$

The coefficient of interest in the interaction between temperature and peer characteristics, β_3. This term captures whether the marginal effect of temperature on productivity differs across peer characteristics. β_3 measures how the temperature elasticity of output changes with the peer characteristic Z_{ip}. If $\beta_3 > 0$, higher values of Z_{ip} attenuate the negative marginal effect of temperature on equilibrium productivity.

Z_{ip} is a measure of peer p's characteristic that stands as a proxy for peer's ability to coordinate with individual i. These measures are a pre-determined level of peer's characteristics measured from before the time period of my sample. α_d are dyad fixed effects, which absorb all time-invariant attributes of the individual-peer match, such as baseline compatibility. α_a is the opposing team's fixed effect. Identification comes from within-dyad variation in temperature across games.

Individual players differ in their playing styles. Some adopt an aggressive strategy, scoring runs quickly through riskier boundary shots, while others follow a more defensive approach, and accumulate runs through rotation of strike and scoring less risky singles or doubles. Anecdotal evidence in cricket suggests that partnerships that combine complementary styles, such that one aggressive and one defensive player play as peers, are often more effective than peers with similar strategies.

To capture strategic complementarity, I measure each individual player's historical strike-rate[12] over four seasons of the sport, preceding the sample period, and create a measure of difference in strike-rate between the individual and the peer. I then convert this difference into absolute value and into a percentile rank (0-100) within the sample. A high percentile indicates a greater dissimilarity between individual and the peer.

Column 1 of Table 6 shows that the interaction between temperature and distance in strategy is positive and statistically significant for runs. This indicates that as temperature increases, partnerships with more dissimilar playing styles experience a smaller decline (or even an increase) in runs (equilibrium productivity) relative to homogeneous partnerships.

The results show that complementarity in skill-set between the individual and peer mitigates the impact of heat on equilibrium productivity. Specifically, a 10 percentile difference in peer's strategy results in 0.12% higher runs as temperature increases by 1°C. The estimates also imply a threshold at approximately 32°C, above which the marginal effect of temperature on equilibrium productivity is positive, as the negative effect gets compensated by peer complementarity. The results also suggest that peer complementarity only becomes beneficial at sufficiently high temperatures.

[12] Strike-Rate is the ratio of runs scored to the balls taken to score those runs. Strike Rate can be thought of as the productivity per unit resource of an individual. Players with a high strike-rate are considered aggressive while, those with a lower strike-rate are considered defensive players. See Table 1 for more details about strike-rate.

I find similar results for other equilibrium productivity measures, such as balls, dot balls, and the share of runs scored through boundaries.[13] A 10-percentile increase in strategic dissimilarity between peer and individual increases the number of balls faced by the individual player by about 0.09%, dot balls by 0.10%, and the share of boundary runs by 0.032 percentage points for each additional degree Celsius.

Taken together, these results indicate that peers with complementarity in skill-set help individual players respond to heat by stabilizing the batting spell and choosing scoring opportunities more selectively. Partnerships with greater differences in skill-set face more deliveries and absorb more non-scoring balls, while also converting a slightly larger share of scoring opportunities through boundaries. This pattern suggests that complementary peers allow players to manage heat stress by coordinating roles within the partnership and maintaining equilibrium productivity despite declining individual execution.

Peer effect could operate through multiple dimensions. Peers could help adapt through differences in baseline ability, accumulated experience of playing in multiple settings, or through differences in playing styles to work as complements. To evaluate these alternative channels, I estimate the above model for each characteristic. Estimates for other characteristics, such as ability is presented in Table A2, and experience in Table A3. While both characteristics are positively associated with the performance of the individual, they do not help mitigate the temperature effect. This suggests that adaptation operates through complementary roles within partnerships rather than through accumulated experience or ability.

Peer compensation: To gauge the economic magnitude of this mechanism, I conduct a simpleback-of-the-envelope calculation using the estimates in Table 6. The interaction coefficient implies that a 10 percentile increase in skill dissimilarity (complementarity)

[13] Balls are the number of balls faced by the individual player during their tenure on the field. Dot balls are the number of balls faced that did not turn into any runs scored. Share of Boundary runs is the runs scored through taking risky shots that return higher runs.

between partners increases equilibrium output by about 0.12% for each one degree Celsius increase in temperature. If I assume a fully complementary partnership, i.e., a 100 percentile dissimilar peer would increase output by about 1.2% per degree.

Assuming that equilibrium productivity decline would have been similar to individual productivity decline in the absence of peers, a one degree Celsius increase in temperature would result in approximately 2.68% decline in productivity (Table 3). Taken together, these magnitudes suggest that complementary partnerships recover on the order of 45 percent of individual productivity loss attributable to one degree celsius increase in temperature.

Importantly, this calculation only captures the observable component of peer's effect on equilibrium performance. The variance decomposition presented earlier showed the full extent of peer's effect, including the unobserved elements of peer coordination. The total contribution of peer compensation to adaptation may therefore be larger than 45%.

7 Robustness Checks

In this section, I evaluate the robustness of my results along various dimensions. First, I examine the sensitivity of the results in Section 5.2 to alternative temperature thresholds beyond the baseline cutoff of 25°C. Second, I verify that the estimated match effects reported in Section 5.1 are consistent across other equilibrium productivity measures than runs, and inconsistent with individual productivity measures. Third, I test whether the estimated peer and adversarial match effects are sensitive to the inclusion of additional environmental and match-specific controls. Finally, I address the potential concerns that differences in game characteristics across temperature could drive the observed results.

A potential concern with results in Section 5.2 could be that the results are dependent on the specific temperature threshold that is used to partition games into hot and cool subsamples. The analysis used the threshold of 25°C, but one could be worried that an alternate threshold could yield results different from the peer component compensating for individual productivity decline. To evaluate this possibility, I repeat the split-sample variance decomposition with different temperature cutoff values ranging from 20°C to 32°C.

Figure 3 reports the ratio of variance components estimates in hot and cool subsamples across alternative thresholds. Each point represents the ratio of hot to cool variance, while the error bars are 95% confidence interval obtained from an F-test of equality of variances. A value of one corresponds to equal variance across hot and cold games. The results show that peer variance increases consistently across a wide range of temperature cutoffs, while adversarial variance remains mostly unchanged. Adversarial variance increases sharply at high temperature values, there are very few games that are played at temperatures > 29°C (1036 observations), and even fewer as temperature increases to 32°C (335 observations). The larger variance at the extreme temperature threshold, therefore, reflects the high variance within a small number of observations in the hot subsample as compared to the cold.

One might be concerned that the estimated peer and adversarial match effects reported in Section 5.1 might be specific to the equilibrium productive measure I tested. In other words, the peer and adversarial match effects are only observed for total runs made in the partnership, and specific interaction between the individual, peer, and the adversary in jointly producing runs is driving the results. If this were the case, then the estimated match effects would be inconsistent with other measures of equilibrium output.

If instead, the estimated match effects genuinely capture individual, peer, and adversary interactions, then the estimated match effects would be consistent across other equilibrium outcomes, such as balls faced, and runs scored through boundaries, and inconsistent with individual outcomes such as LBW and Bowled Out. A peer match that increases the individual player's runs should also allow the striker to face more balls and score more boundaries. Conversely, an adversarial match that reduces the runs made by the individual player should also reduce the number of balls faced by the individual and the boundaries scored.

To examine this, I compare the peer and adversarial match effects estimated from the run model (ϕ_{RUNS}) with those obtained from alternative equilibrium productivity models such as balls faced (ϕ_{BALLS}) and runs scored through boundaries ($\phi_{BOUNDARIES}$). If the match effects capture meaningful equilibrium interactions, the estimated peer and adversarial variance should be positively correlated across these outcomes.

The results are presented in Figure A6 and Figure A7. Panel (A) of Figure A6 shows that peer matches that increase an individual player's runs also increase the number of balls faced by the individual, with a correlation of 0.88. Panel (B) shows a similar pattern for adversarial matches, such that adversaries that reduce runs also reduce the number of balls faced by the individual, with a correlation of 0.83.

A similar pattern emerges for runs scored through boundaries. Peer effects estimated from runs are positively correlated with peer effects estimated from boundary runs (β = 0.64), while adversarial effects show a comparable relationship ($□ = 0.60). These correlations indicate that the estimated match effects operate consistently across multiple equilibrium productivity measures.

I test for the inconsistency of equilibrium match effects with individual match effects. These results are presented in Figure A8 and Figure A9. Panel (A) of Figure A8 shows that the correlation of runs peer-match and peer-match effect for the probability of an individual getting LBW out is -0.25. Panel (B) shows a similar pattern for the correlation of runs adversarial-match effect and adversarial-match effect for LBW is -0.21. Similarly, correlation between ϕ_{RUNS} and ϕ_{BOWLED} is 0.09, and ν_{RUNS} and ν_{BOWLED} is -0.13. The explanatory power of each of these models is precisely zero. These results show that peer and adversarial match effects for equilibrium outcomes are inconsistent with match effects for individual outcomes. This distinction reinforces the interpretation that the estimated peer and adversarial match effects capture team production interactions rather than individual productivity shocks.

Another potential concern could be that the estimates of match-effect decomposition, presented in Section 5.1 are sensitive to including certain individual player and game specific covariates. Table A4 contains the sensitivity of estimates to the exclusion of game specific covariates. I found that my estimates were stable across multiple models. The correlation between peer variance in my baseline model and those in models where I removed important covariates one at a time was not less than 0.9946. Similarly, the correlation between adversarial effects in my baseline model to those in other models was not less than 0.9888. These results indicate that the estimated peer and adversarial variances are highly stable across specifications and are not driven by particular observable game characteristics.

A reader could be concerned that the observed increase in peer effects at higher temperatures may reflect systematic differences in the nature of games played under hotter conditions rather than adaptation within team settings. For example, if games played at higher temperatures are less competitive or more one-sided than between well-matched teams, the observed increase in peer effects could also reflect differences in game dynamics rather than changes in team production.

To examine this possibility, I analyze whether the win margin for games varies across temperature. Figure A10, panel (A) plots the relationship between temperature and the win margin of the game. The estimates are noisy and show no consistent relationship between temperature and margin of victory in the games. This suggests that games played at higher temperatures are not systematically different from games at colder temperatures.

Another potential concern is that team captains may respond to heat by strategically reallocating individual players during matches. For instance, team captains may adjust batting order to shield certain players from heat exposure or fatigue. These adjustments could attribute adaptation to peer coordination, while instead it might be strategic adaptation.

I examine whether batting order becomes more variable at higher temperatures. If teams strategically adapt to higher temperatures by reshuffling the batting order of individual players, then we would expect greater dispersion in batting order in matches played at higher temperatures. Figure A10, panel (B) plots the standard deviation of batting order with temperature. The plot shows no significant increase in batting order variation at higher temperatures. This pattern suggests that teams do not strategically adjust player roles or batting order in response to heat exposure.

Finally, one potential concern is that the observed increase in peer effects at higher temperatures could reflect changes in how players are paired during matches rather than adaptation within partnerships. In cricket, a new partnership is formed when the previous one ends with an execution failure by one player (individual). Therefore, the number of partnerships should not vary with temperature if partnerships are exogenous to temperature. To evaluate this, I examine whether the number of partnerships varies with temperature. Figure A11, which shows that the number of partnerships formed within a game remains stable across the temperature distribution. This indicates that hotter matches do not involve more frequent turnover of partnerships.

Additionally, revisiting Figure A10, panel (B), shows that there is no strategic shuffling of batting order of players in hotter matches. Taken together, the two plots show that a) the number of partnerships formed in a game is independent of temperature, and b) there is no shuffling of partners along the batting order in a game in response to temperature. This evidence supports the assumption that partnerships are quasi-random with respect to temperature and that the increase in peer effects observed in hotter conditions reflects changes in the value of peer interactions rather than strategic reassignment of players.

8 Discussion

Workers bring many skills to their jobs. One unobserved skill that often goes overlooked is the ability to work well with peers. At the same time, a growing body of evidence shows that heat impairs worker performance, slows reaction times, clouds judgment, and degrades the precise motor execution that many skilled tasks require. This raises a natural question: what happens to team production when individual performance deteriorates under heat?

Using detailed high-frequency data from international cricket games combined with exogenous variation in temperature, I show that although individual productivity declines under heat, equilibrium output remains unchanged because peer interactions help offset the individual productivity losses caused by heat.

I document four central empirical findings in this paper. First, individual productivity deteriorates under heat stress. Higher temperatures increase the probability of execution failures that require cognition and motor coordination. Second, despite this decline in individual productivity, equilibrium output remains largely unchanged. This contrast between declining individual performance and stable equilibrium output suggests adjustments in team production under heat.

Third, I introduce a temperature-based split-sample variance decomposition that allows me to estimate individual, peer, and adversarial variance components separately at hotter and cooler temperatures, and test whether they change across temperature regimes. The results show that peer interactions become significantly more important in hotter conditions while adversarial interactions remain unchanged.

Finally, I examine the mechanisms through which peers compensate for declining individual productivity. The results show that adaptation occurs through pairing with peers with complementary skill sets. When workers with complementary skills interact, they are better able to cope with heat stress as complementarities allow for coordination of roles within the peer group and adjustments in strategy in response to environmental conditions.

In this paper, I provide the first evidence of adaptation to heat through peer coordination in homogeneous team production settings with repeated interactions and strong intrinsic incentives to perform against an adversary. As climate change shifts the temperature distribution rightward across the global labor markets, understanding the full portfolio of adaptation margins available to workers and firms becomes increasingly consequential. The results of this paper suggest that one such margin may lie not in individual behavior, but in the organization of teams. How teams are composed, how roles are assigned, and whether partnerships are stable enough to develop the tacit coordination that complementarities require. The evidence presented in this paper shows that these organizational choices matter for productivity under heat.

The workers studied in this paper are high-skilled and high-income individuals with strong intrinsic motivation and extensive experience of working alongside their peers. Whether peer complementarities operate with equal force among lower-skill workers, workers with less established peer networks, or workers in settings without adversarial interaction is outside the scope of this paper. Future research examining peer adaptation in team production should explore these margins in other settings, such as, factory floors, construction sites, and agricultural work.

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Figures and Tables

Table 1: Mapping Cricket metrics to Production outcomes

Cricket Metric	Measures	Decision Maker	Real Life Analog
LBW	Reaction time, perceptual judgement	I	Cognitive error, Timing delay
Bowled	Motor execution, precision	I	Execution failure (eg: misoperating machine)
Runs	Total output	I+P+A	Units produced in team-based production with competition
Balls	Exposure, endurance, time on task	I+P+A	Time spent on task before exit or failure
Boundary	Risk taking, output variance	I+A	High-risk, High-reward task (eg: court proceeding, political debate)
Strike Rate	Productivity per unit time	I+P+A	Output per hour, Pieces per minute
Out	Terminal failure	I+P+A	Task termination, worker exit, process breakdown
Caught	Failure induced by adversary	I+A	Mistake due to external scrutiny (eg: failing audits, inspection)
Run Out	Coordination failure	I+P+A	Miscommunication in team task

Note: *The table details cricket metrics used in this paper, defines who the decision maker is and maps each cricket metric to a real life analog in a production factory. I stands for Individual, P for Peer, and A for Adversary.*

Table 2: 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

Note: *The table compares heat production in economic sectors with that of cricket batsmen during indoor practice at 15°C. (Poulianiti, Havenith, and Flouris 2019; Tipton et al. 2019)*

Table 3: Individual Outcomes

	LBW	Bowled
T	0.0268**	0.0146*
	(0.0133)	(0.0086)
Observations	5414	6442
R^2	0.09	0.08
Average Probability	0.08	0.16
Observations	5,414	6,442
Individual FE	x	x
Peer FE	x	x
Adversary FE	x	x
Format FE	x	x
Innings FE	x	x

Note: *This table presents the estimates of linear effect of temperature on individual outcomes of batsmen. Both columns present estimates of logistic regression. Each regression includes controls for precipitation, windspeed, dew, rest days, and batting order. Errors are clustered at game level.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

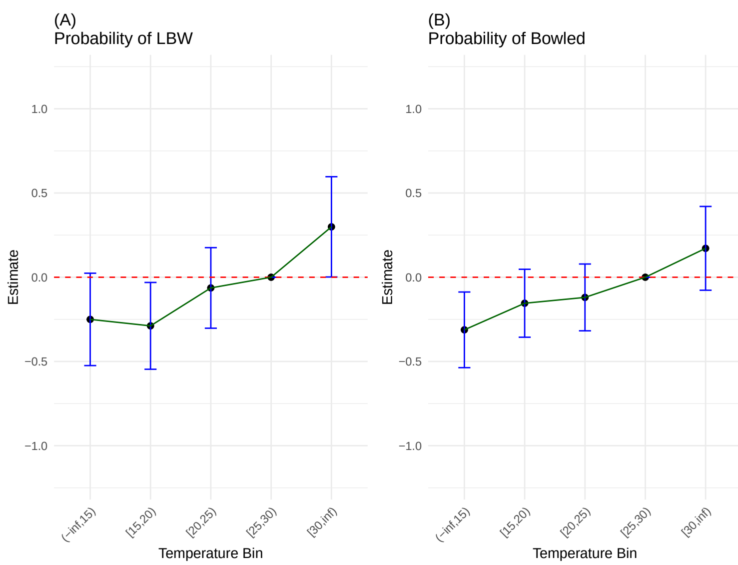

Figure 1: Individual Outcomes

The figure shows the estimated nonlinear effect of temperature on batsmen's performance by temperature bin, relative to the [25,30)°C bin. Regressions control for weather (precipitation, wind, dew), rest days, and batting order. Errors are clustered at the game level.

Table 4: Equilibrium Outcomes

	Runs	Balls	Boundary	Strike-Rate	Out	Caught	Run-Out
T	0.0041	0.0028	0.0007	0.0027	-0.0116	-0.0178**	-0.0311
	(0.0035)	(0.0025)	(0.0032)	(0.0024)	(0.0092)	(0.0070)	(0.0192)
Observations	6256	6911	4599	6256	6417	6758	3510
R^2	0.25	0.32	0.20	0.23	0.16	0.08	0.13
Average	21.26	21.92	2.5	89.58	0.79	0.48	0.03
Observations	6,256	6,911	4,599	6,256	6,417	6,758	3,510
Individual FE	x	x	x	x	x	x	x
Peer FE	x	x	x	x	x	x	x
Adversary FE	x	x	x	x	x	x	x
Format FE	x	x	x	x	x	x	x
Innings FE	x	x	x	x	x	x	x

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, and batting order.Errors are clustered at game level.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

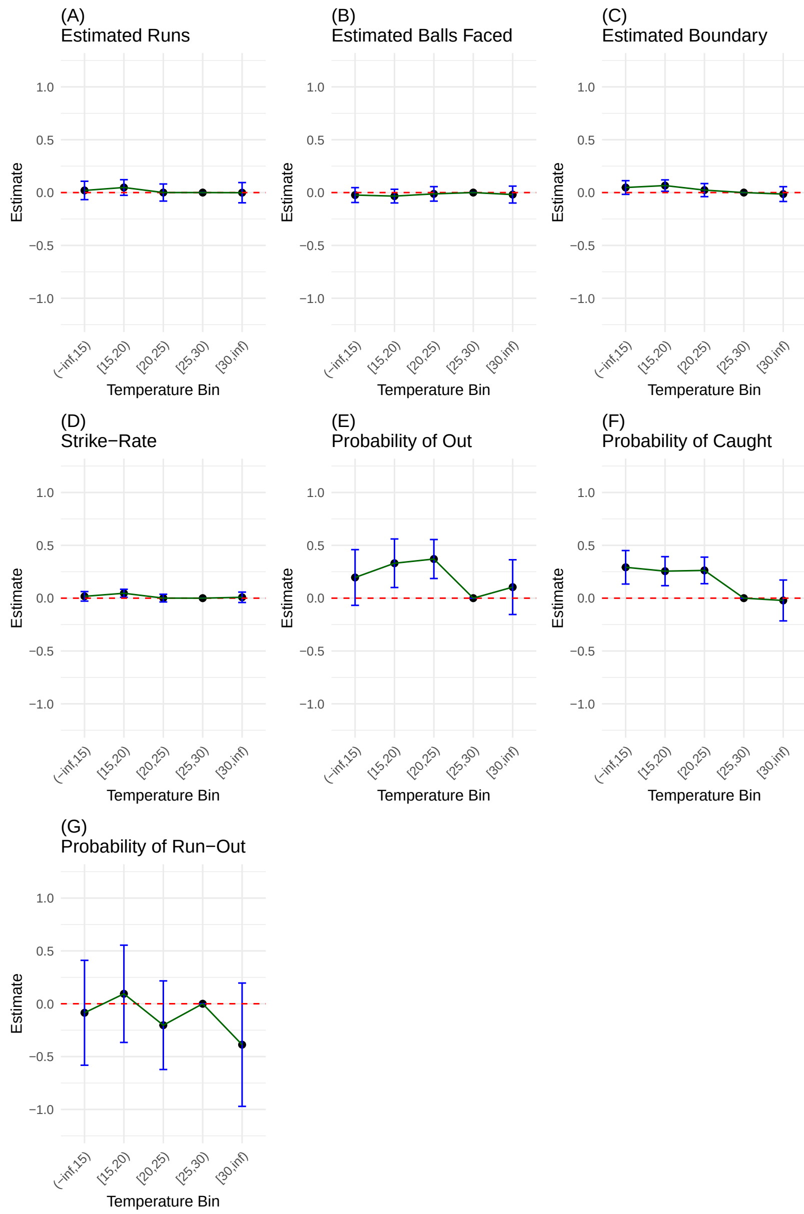

Figure 2: Equilibrium Outcomes

Note: *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, and batting order.Errors are clustered at game level.*

Table 5: Variance Decomposition

	Full Sample (1)	<=25 $^{\circ}C$ (2)	>25 $^{\circ}C$ (3)	F-test (4)
Individual	0.4715	0.5588	0.8356	0.6546***
$Var(\alpha_i, \theta_a)$	[0.687]	[0.743]	[0.914]	(0.0005)
Peer	0.3431	0.4775	0.5943	0.8035***
$Var(\phi_{i,p})$	[0.586]	[0.693]	[0.769]	(0.0001)
Adversarial	0.3178	0.4349	0.3987	1.0910
$Var(\nu_{i,a})$	[0.564]	[0.592]	[0.597]	(0.2066)
Total	1.3200	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$^{\circ}C$* 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 5.1 * p < 0.1, ** p < 0.05, *** p < 0.01

Table 6: Peer Effect through Complementarity in Skill-Set

	Runs	Balls	Dot Balls	Share Boundary
T	0.0005	-0.0003	-0.0030	-0.0000
	(0.0047)	(0.0037)	(0.0029)	(0.0014)
Dissimilarity	-0.3807***	-0.2950**	-0.2766**	-0.0634
	(0.1407)	(0.1234)	(0.1065)	(0.0425)
T x Dissimilarity	0.0118*	0.0094*	0.0103**	0.0032*
	(0.0065)	(0.0054)	(0.0042)	(0.0018)
Observations	8754	8754	7957	8754
R2	0.10	0.21	0.28	0.06
Adjusted R2	0.09	0.20	0.27	0.05
Average	14.17	14	6.67	0.39
Dyad FE	x	x	x	x
Adversary FE	x	x	x	x
Innings FE	x	x	x	x

Note: *This table reports the estimates of the temperature and dissimilarity in the batting strategy of peers. Peer dissimilarity is measured as the difference in the strike rate of individual and peer calculated over the four seasons of cricket prior to the sample period. Then turned into percentile rank. All specifications include dyad fixed effects (individual-peer), adversary, format, and innings fixed effects, along with controls for precipitation, wind speed, dew point, and rest days. Standard errors are clustered at the game level.* p < 0.1, ** p < 0.05, *** p < 0.01*

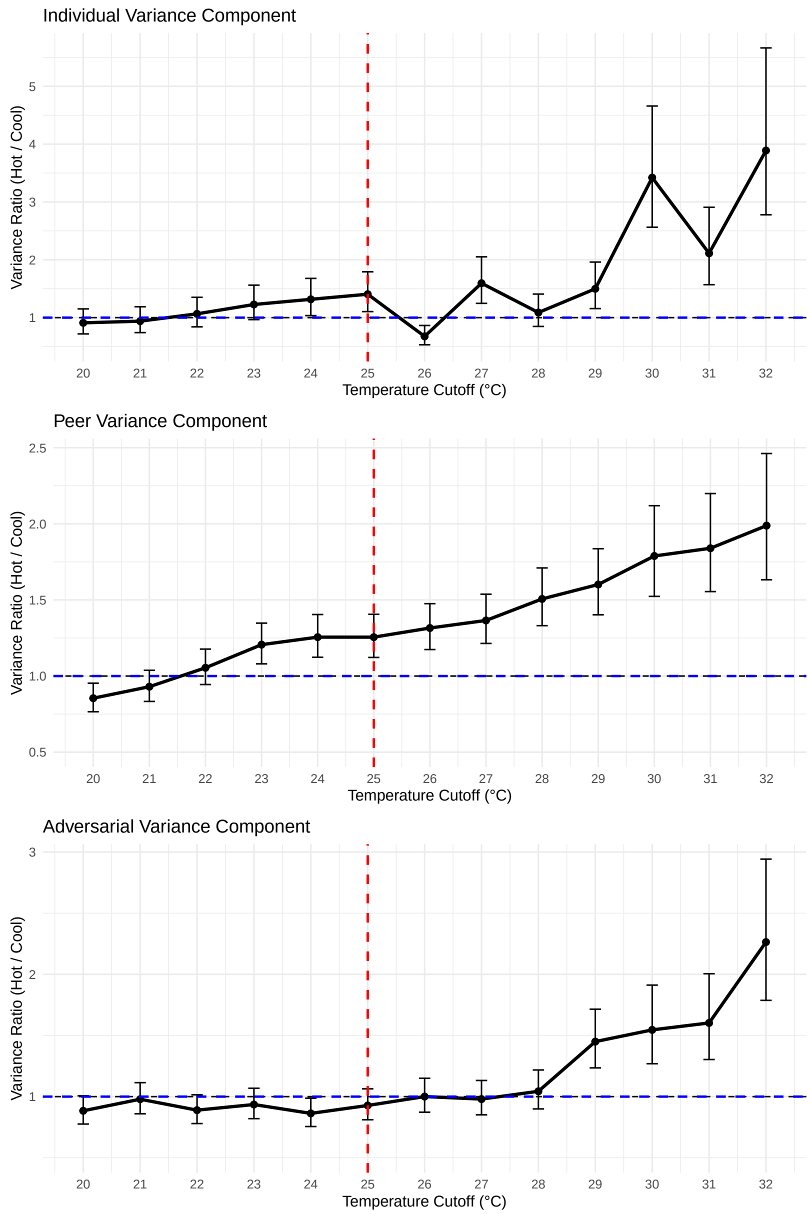

Figure 3: Split-Sample Variance Decomposition at multiple Temperature cutoffs

Above figure shows the variance decomposition of individual, peer, and adversary components in equilibrium outcome (runs). The plot reports variance ratios between hot and cool matches across alternative temperature thresholds. Error bars show 95% confidence interval. The hot sample decreases from 4,161 observations at 20°C cutoff to 335 observations at 32°C cutoff.

A Appendix

A.1 Background and Data Appendix

A.1.1 What is Cricket?

Cricket is a two-sided game played by opposing teams, each consisting of 11 players. Cricket is always played outdoors, on uncovered pitches and play can be stopped 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 meters) pitch in the middle with a wicket on each end (Figure A3). A wicket is made of three stumps with two bails balanced on top. A toss takes place at the start of the game between the captains of the two teams; the captain who wins the toss decides whether to bat or bowl first. Therefore, deciding which team bats or bowls 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 10 wickets. Because batsmen come out to play in pairs, 11 players make up 10 pairs; therefore, a team has 10 wickets. The goal for the bowling team is to limit the runs scored by the batting team and take as many wickets as possible. The goal for the team that bats second (the team that bowled first) is to chase the runs scored by the team that batted first.

The 11 players in each team can be categorized into (a) batsmen, (b) bowlers, and (c) all rounders (players who can bat as well as bowl). While a team is batting, batsmen take turns batting according to their batting order, which is decided by the team captain. 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 fewer overs[14]. 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 run by coming out in pairs to bat; therefore, they are 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 A1. The 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." A batsman can get out in ten different ways, most common are presented in Figure A4. International cricketers travel across the globe to play at different temperatures (Figure A2), which allows me to observe worker productivity at different temperatures.

A.1.2 Cricket Format

In cricket, different formats of the sport are played at the international level. Test match is the oldest format of the game, which lasts for up to 5 days and is not limited by the number of overs bowled during the match. Other formats have limited over matches—one day international (ODI), and

[14] An over consists of six legal deliveries (balls) bowled by a single bowler from one end of the pitch. The number of overs in a game is fixed (e.g., 50 in One Day Internationals), so earlier batsmen have the opportunity to face more deliveries if they remain not out.

twenty 20 (T20). In this paper, I only focus on ODI and T20 games due to data limitations for test match. An ODI match is a match with two innings, each played by one team. Each inning consists of 50 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-minute break. Two drink breaks per session are permitted with each break taken at least 1 hour 10 minutes apart.

In comparison, T20 is a different format of limited over games. The desire 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 2.5 hours, with two innings of 70 minutes each separated by a 10-minute break. A recent change in T20 allows optional drinks break of 2 minutes and 30 seconds that can be taken at the midpoint (at the 10-over mark) of each inning. Bliss et al. (2021) found that greater physical energy per minute was spent by players in T20 games as compared to ODI games. Therefore, a T20 game is more physically intense for each player, albeit for a shorter time.

B Additional Figures and Tables

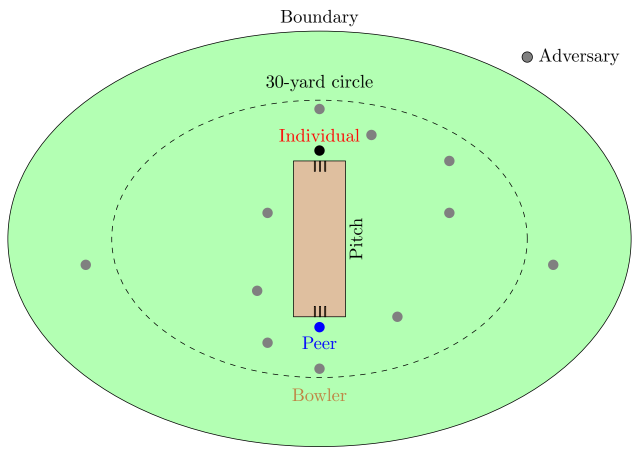

Figure A1: Cricket Ground

Note: *Above is an illustration of cricket ground. This figure illustrates relative positions of individual, peer, and the adversary on the cricket ground.*

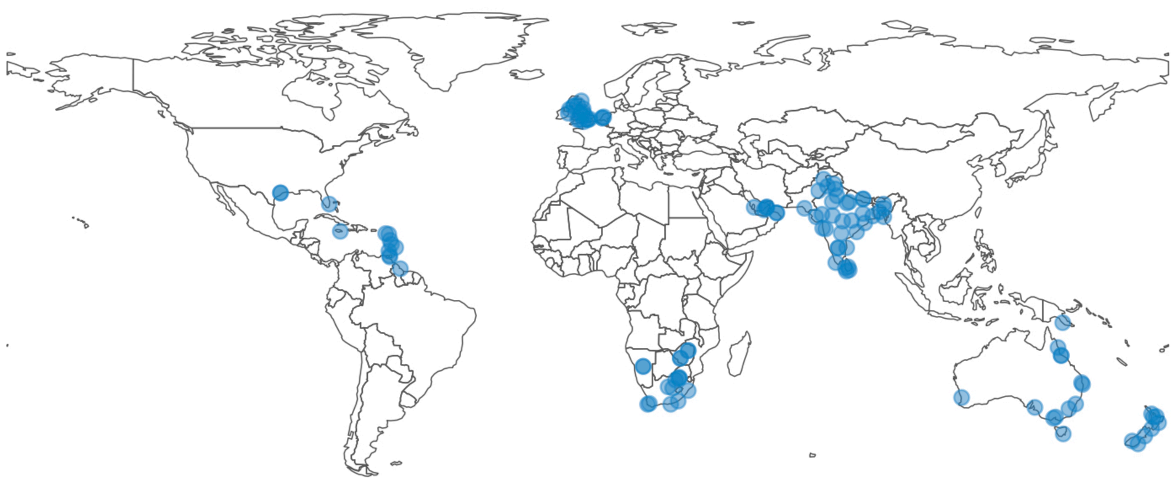

Figure A2: Locations of Cricket Matches

Note: *Map shows the location of cricket matches during 4 seasons of cricket from 2021 to 2023 across the world. This makes up the sample period studied in the paper. The blue dots show the locations.*

Figure A3: Illustration of Cricket Pitch

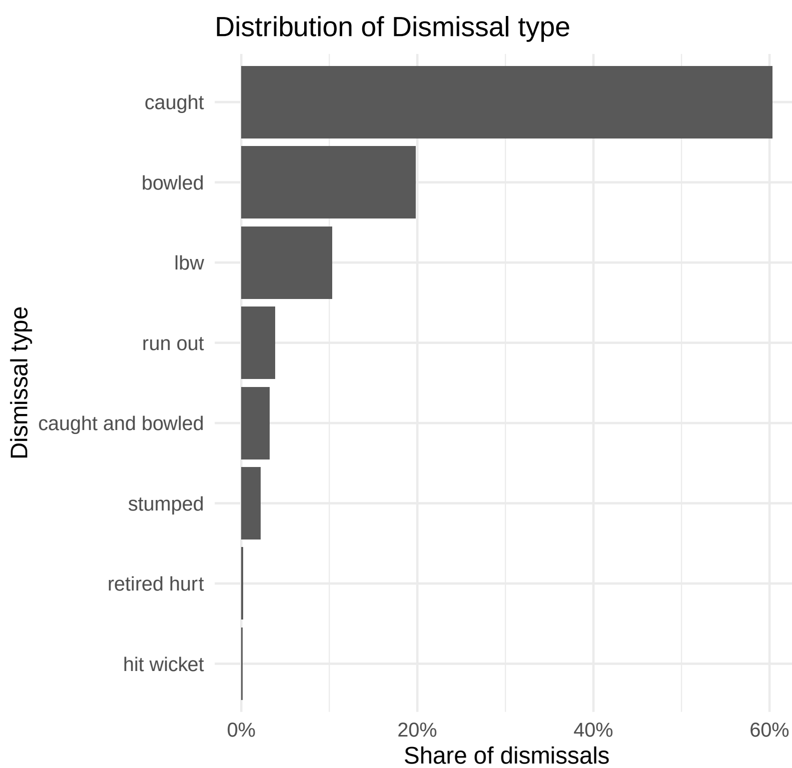

Figure A4: Distribution of Dismissal Type

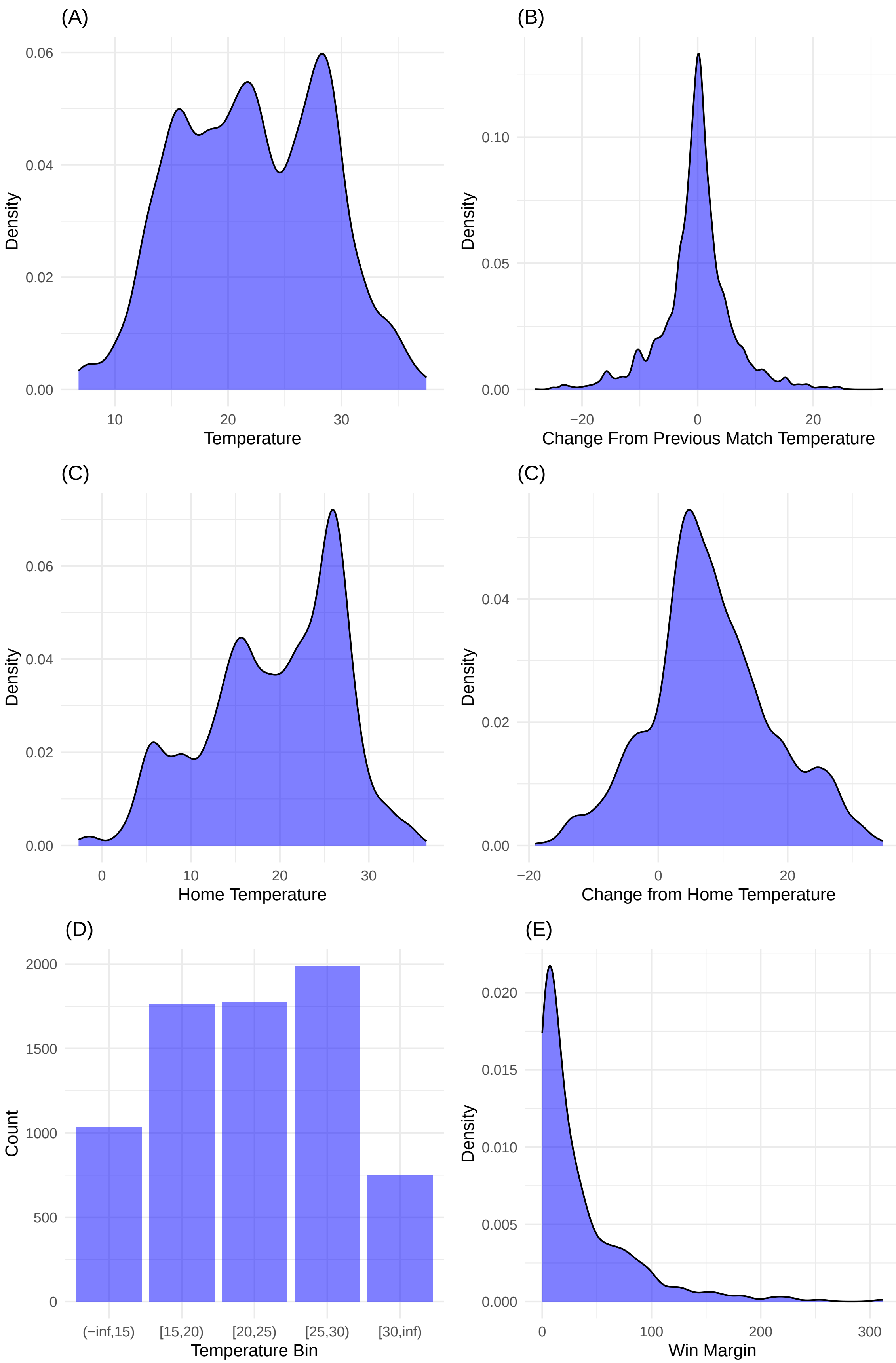

Figure A5: Summary Statistics

Table A1: Bowler's productivity (Adversary)

	Wides	No-Ball	Extras	Balls	Wicket	Bowling Avg	Economy
T	0.0016	-0.0082	-0.0001	0.0003	0.0011	-0.0023	0.0002
	(0.0033)	(0.0069)	(0.0033)	(0.0020)	(0.0021)	(0.0041)	(0.0019)
Observations	2469	377	3259	5102	3286	3282	5093
R^2	0.19	0.56	0.18	0.61	0.13	0.21	0.33
Average	1	0.09	1.73	30.26	1.15	21.3	6.36
Observations	2,469	377	3,259	5,102	3,286	3,282	5,093
Individual FE	x	x	x	x	x	x	x
Peer FE	x	x	x	x	x	x	x
Adversary FE	x	x	x	x	x	x	x
Format FE	x	x	x	x	x	x	x
Innings FE	x	x	x	x	x	x	x

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 game level.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Peer Effect through Ability of Peers

	Runs	Balls	Dot Balls	Share Boundary
T	0.0122**	0.0078**	0.0032	0.0047***
	(0.0048)	(0.0037)	(0.0037)	(0.0014)
Ability	0.4647**	0.2724*	0.1274	0.1927***
	(0.1865)	(0.1574)	(0.1457)	(0.0471)
T x Ability	-0.0110	-0.0043	-0.0002	-0.0074***
	(0.0071)	(0.0060)	(0.0061)	(0.0019)
Observations	7120	7120	6503	7120
R2	0.11	0.22	0.29	0.06
Adjusted R2	0.09	0.20	0.27	0.05
Average	14.17	14	6.67	0.39
Dyad FE	x	x	x	x
Adversary FE	x	x	x	x
Innings FE	x	x	x	x

Note: *This table reports the estimates of the temperature and ability of peers. Peer ability is measured using peer's average score over four seasons of cricket prior to the sample period, then turned into percentile rank. All specifications include dyad fixed effects (individual-peer), adversary, format, and innings fixed effects, along with controls for precipitation, wind speed, dew point, and rest days. Standard errors are clustered at the game level.* p < 0.1, ** p < 0.05, *** p < 0.01*

Table A3: Peer Effect through Experience of Peers

	Runs	Balls	Dot Balls	Share Boundary
T	0.0159***	0.0102***	0.0049	0.0041***
	(0.0050)	(0.0037)	(0.0034)	(0.0014)
Experience	0.4560***	0.2467**	0.1071	0.1485***
	(0.1362)	(0.1092)	(0.1161)	(0.0439)
T x Experience	-0.0183***	-0.0093*	-0.0035	-0.0060***
	(0.0061)	(0.0049)	(0.0050)	(0.0020)
Observations	7594	7594	6911	7594
R2	0.11	0.22	0.28	0.06
Adjusted R2	0.09	0.20	0.27	0.05
Average	14.17	14	6.67	0.39
Dyad FE	x	x	x	x
Adversary FE	x	x	x	x
Innings FE	x	x	x	x

Note: *This table reports the estimates of the temperature and experience of peers. Peer experience is measured using number of matches played by the peer over four seasons of cricket prior to the sample period, then turned into percentile rank. All specifications include dyad fixed effects (individual-peer), adversary, format, and innings fixed effects, along with controls for precipitation, wind speed, dew point, and rest days. Standard errors are clustered at the game level.* p < 0.1, ** p < 0.05, *** p < 0.01*

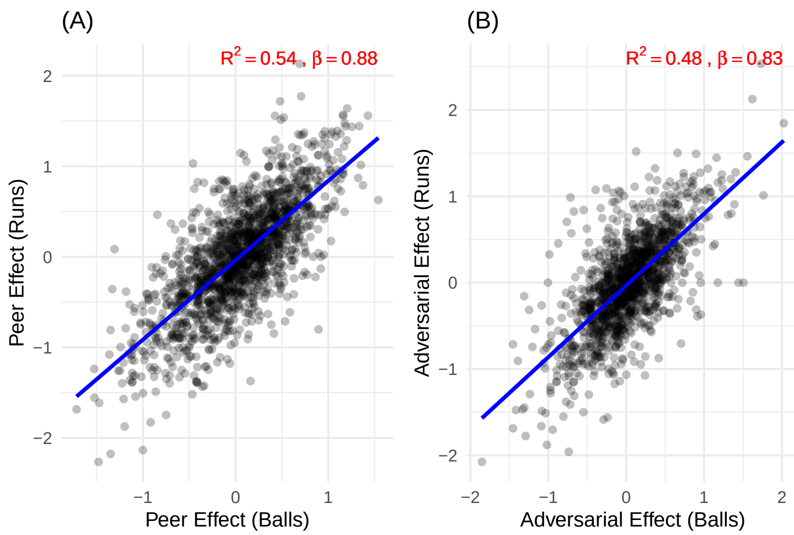

Figure A6: Runs vs Balls

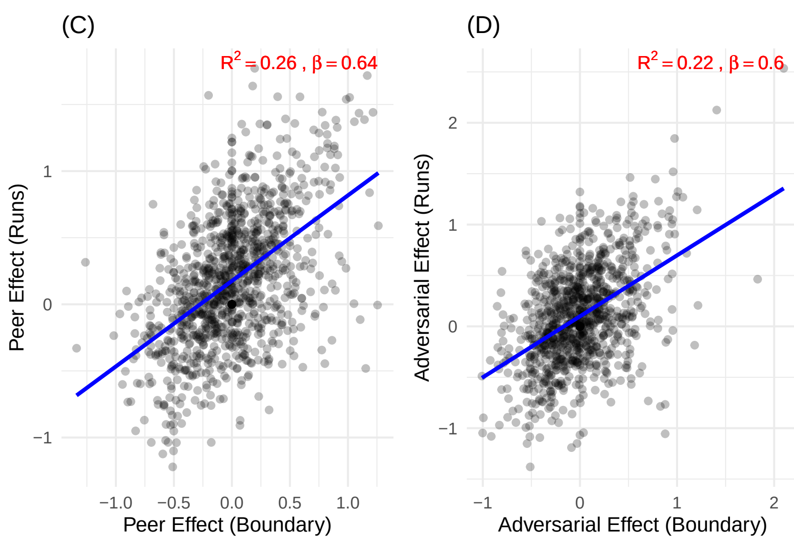

Figure A7: Runs vs Boundary

These scatterplots illustrate the relationships between estimated peer and adversarial effects in various outcomes: log of runs scored with log of balls faced and log of runs scored through hitting boundaries. To construct quantities in each panel, I estimate Equation 4 for peer effect and Equation 5 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.*

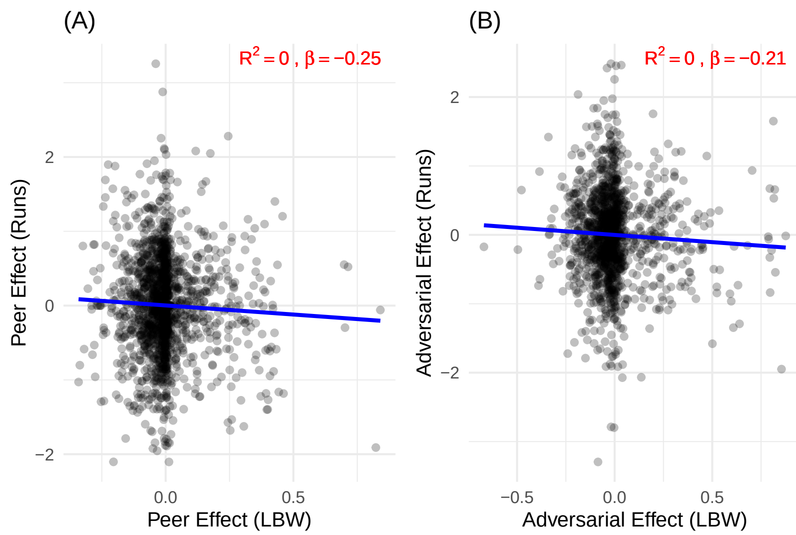

Figure A8: Runs vs LBW

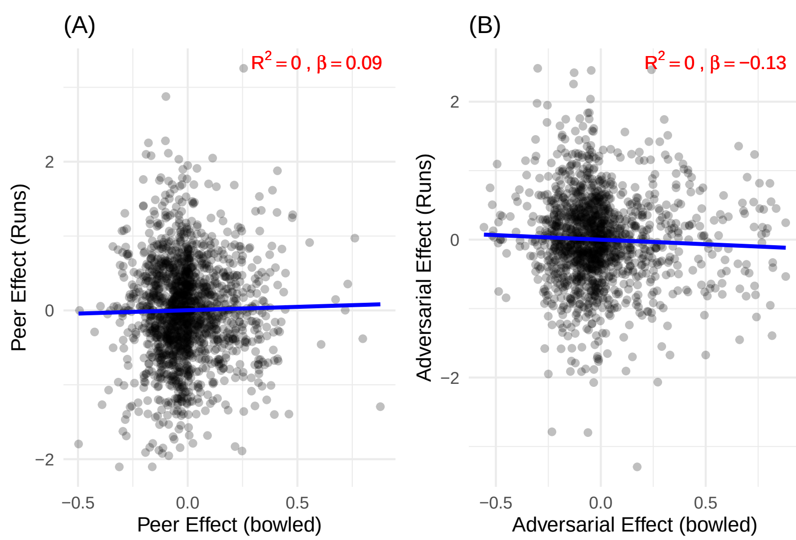

Figure A9: Runs vs Bowled

These scatterplots illustrate the relationships between estimated peer and adversarial effects in various outcomes: log of runs scored with probability of lbw and run out. To construct quantities in each panel, I estimate Equation 4 for peer effect and Equation 5 for adversarial effect to recover ϕ_{RUNS},ϕ_{LBW},ϕ_{BOWLED} *and* ν_{RUNS},ν_{LBW},ν_{BOWLED}.*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 A4: Sensitivity Analysis (Correlations)

	Baseline	-Precip	-Rest Days	-Batting Order
Peer	1.0000	0.9998	0.9995	0.9946
Adversarial	1.0000	0.9991	0.9997	0.9888

Note: *Above table reports result of Sensitivity analysis. The baseline estimates are calculated by estimating Equation 4 for peer effect and Equation 5 for adversarial effect. Each covariate is removed in subsequent iteration and correlation of estimates with baseline estimates are reported in table above.*

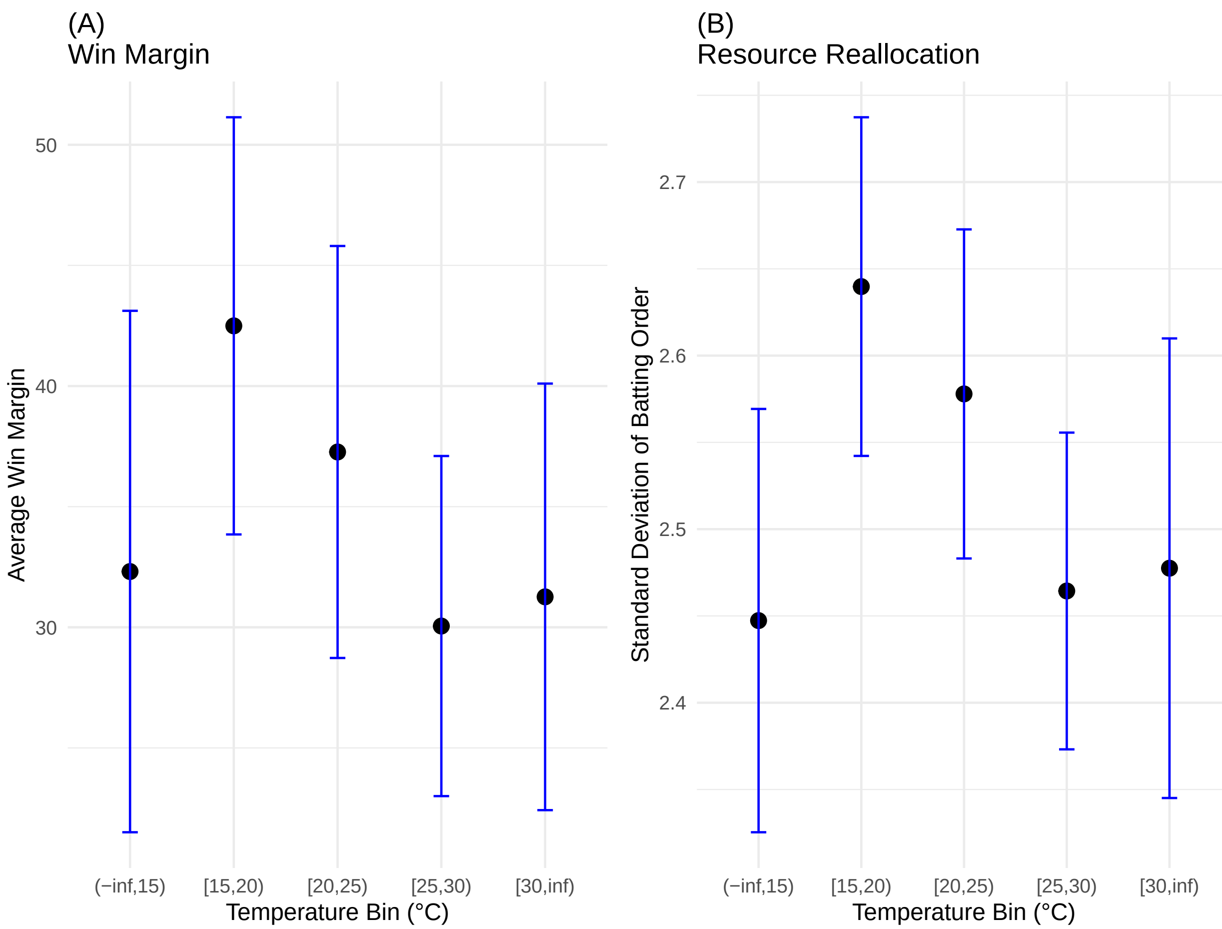

Figure A10: Robustness Checks

Panel A plots the average match win margin across temperature bins. Panel B reports the standard deviation in batting order positions within a team's innings across temperature bins. Points represent bin means and error bars are 95% confidence intervals.

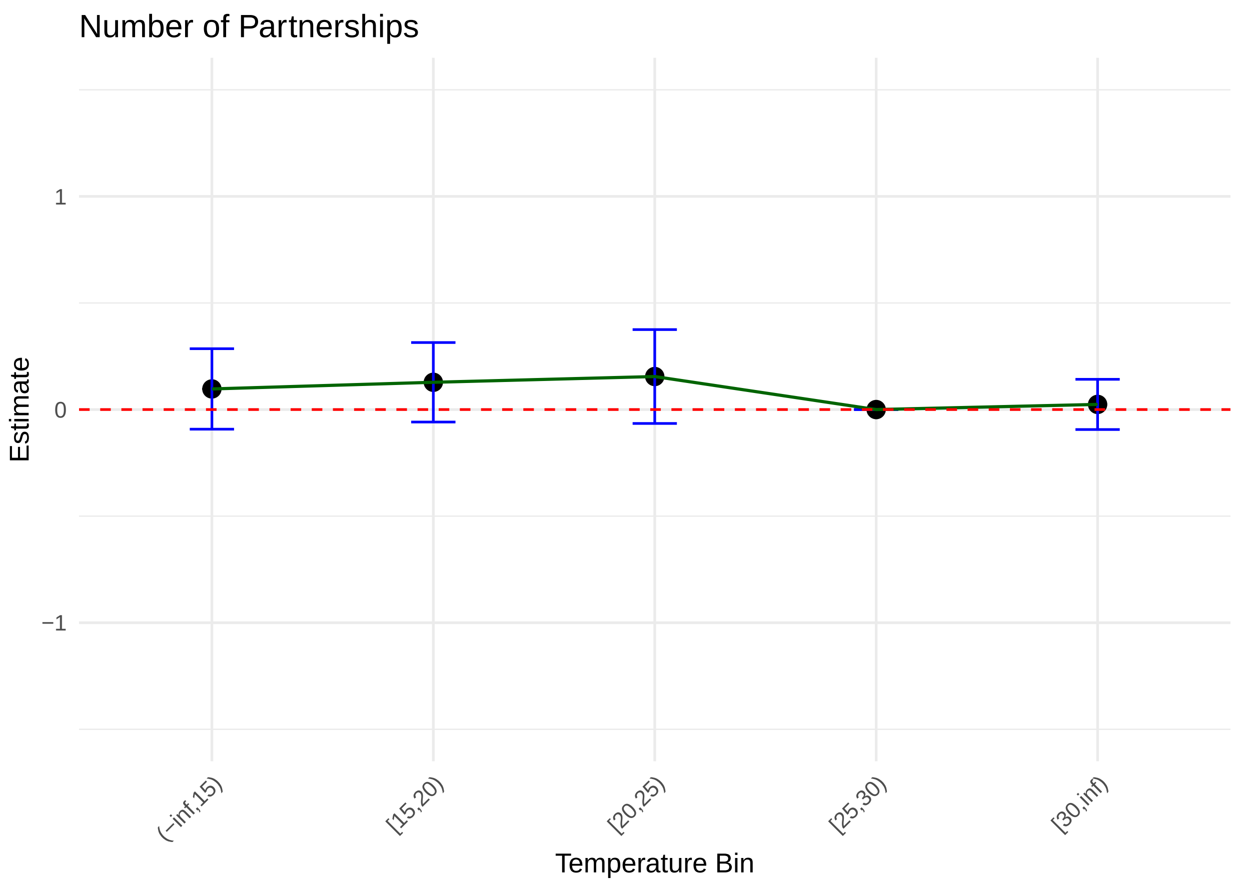

Figure A11: Partnerships and Temperature

Above figure plots the estimates from a fixed effects regression of log of number of partnerships to game-day temeprature as it falls in temperature bins. Points represent bin means and error bars are 95% confidence intervals.

C Variance Decomposition

Here I first layout Equation 4, Equation 5 and decompose the variance into parts.

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

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

Decomposing Equation 4 :

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

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 5 :

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

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:

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