NBER WORKING PAPER SERIES

GAME, SWEAT, MATCH:
TEMPERATURE AND ELITE WORKER PRODUCTIVITY

Marshall Burke
Vincent Tanutama
Sam Heft-Neal
Miyuki Hino
David Lobell

Working Paper 31650
http://www.nber.org/papers/w31650

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2023

We thank seminar participants at AERE Annual Meeting and Stanford University for helpful comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Game, Sweat, Match: Temperature and Elite Worker Productivity
Marshall Burke, Vincent Tanutama, Sam Heft-Neal, Miyuki Hino, and David Lobell
NBER Working Paper No. 31650
August 2023
JEL No. Q50

ABSTRACT

The effect of hot temperatures on labor productivity is thought to be a key channel through which a warming climate will impact the economy, and these impacts could help explain broader observed relationships between temperature and economic output. Yet for many workers and jobs, especially the high-wage service-economy work that constitutes a large share of total economic output in wealthy nations, productivity is hard to measure and thus climate impacts hard to quantify. We study a high-wage job where individual productivity is readily observable: professional tennis. Using 15 years of data on 177 thousand tennis matches merged to hourly temperature data, we study the effects of temperature on tennis performance in contemporaneous and future matches. Variation in player birthplace and residence allows us to study whether players adapt to heat, and data from betting markets allows us to evaluate whether markets price climate risk. We find that hot temperatures increase contemporaneous errors and retirements, and reduce win probability in the subsequent match. In percentage terms, estimated effects on earnings are smaller than lower-wage settings studied in existing literature. By most measures, top players are less affected by hot temperatures. Most tennis betting markets appear to accurately price climate risk, and temperature impacts do not appear to offer profitable arbitrage opportunities.

Marshall Burke
Doerr School of Sustainability
Stanford University
Stanford, CA 94305
and NBER
mburke@stanford.edu

Vincent Tanutama
Independent Researcher
vincent.tanutama@gmail.com

Sam Heft-Neal
Center on Food Security and
the Environment
Stanford University
473 Via Ortega
Stanford, CA 94305
sheftneal@stanford.edu

Miyuki Hino
University of North Carolina
at Chapel Hill
mhino@unc.edu

David Lobell
Stanford University
Department of Environmental
Earth System Science
Y2E2 Bldg - MC4205,
473 Via Ortega, room 367
Stanford, CA 94305
dlobell@stanford.edu

"*I was dizzy from the middle of the first set and then I saw Snoopy and I thought, 'Wow Snoopy, that's weird*"'. – Tennis player Frank Dancevic, after playing a match in $>40°C$ heat in the 2014 Australian Open.

"*We evolved on the high plains of Africa chasing antelope for eight hours under these conditions. There will be some players who complain and no-one is saying it is terribly comfortable to play out there, but, from a medical perspective, we know that man is well adapted to exercising in the heat.*" – Dr. Tim Wood, the chief medical officer for the 2014 Australian Open.

1 Introduction

Work in both laboratory and observational settings has shown that hot temperatures appear to make workers less productive, raising concerns that future warming could lead to large reductions in productivity and output.[1–3] However, for multiple reasons, linkages between temperature, productivity, and output remain incompletely understood in the existing literature. First, the large majority of observational studies on temperature and labor productivity focus on lower-wage settings where productivity is easily observable (e.g. piece-rate wages in agricultural or factory work; Fig 1). This leaves open the question whether high-wage workers, and particularly those in the service economy who contribute a large proportion of total output in many economies, are similarly affected. This question has remained largely unanswered given the difficulty in observing individual-level productivity or output in most high-wage jobs.

Second, with few exceptions,[2,4,5] past studies on labor productivity have not grappled with questions of how workers – and the markets that employ and support them – might anticipate and adapt to changing temperatures, which is a key component in understanding potential future damages under climate change. One form of potential adaptation is based on repeated exposure, wherein individuals accustomed to hot temperatures are less harmed by a given temperature increase. Existing literature on outcomes other than labor productivity finds evidence of such adaptation in some sectors[6] but not others,[7] while labor productivity studies find evidence that heat acclimation can reduce impacts of heat on performance.[4,5] Another form of adaptation is when markets appropriately price climate risk and thus encourage behavior among market participants that is consistent with these risks. Evidence in the literature is again inconsistent regarding this market-led adaptation, with evidence of underpricing of climate risk in various asset markets[8–10] but appropriate pricing of temperature risk in derivatives markets.[11] Finally, few studies have examined how individual characteristics influence vulnerability to heat effects on labor productivity. For instance, impacts could vary as a function of worker skill, gender, or other factors in ways that remain relatively unexplored in existing literature but that could have implications for the magnitude and distributional impacts of future warming.

Here we study the impacts of temperature on productivity in a high-wage service economy job where individual productivity is relatively straightforward to observe: professional tennis. Tennis offers several unique benefits for understanding how temperature might affect high-wage worker productivity. First, average incomes for professional tennis athletes are substantially higher than in past studies for which meaningful quantitative estimates of the effect of temperature on productivity are available (Fig 1; Methods). Compared to average incomes in sectors and settings in which existing temperature/productivity studies have been conducted, average salaries in professional tennis are many times higher than the highest existing estimate and an order of magnitude higher than the average across these studies. For most participants, professional tennis is very high wage work.

Second, unlike most high-wage settings, individual output in tennis is readily observed and measured. Incredibly detailed information is collected on player performance and movement in each match, and these data have already been compiled into comprehensive point-by-point datasets spanning hundreds of thousands of matches. Third, there are multiple sources of variation with which to study heterogeneous effects and possible adaptations among these high-wage workers. Specifically, we can examine whether the effects of temperature on productivity are either rank- or gender-biased, and evaluate whether individuals who are more accustomed to hotter temperatures are less affected by temperature increases. Finally, because betting markets for tennis are active and robust (tennis is the 3rd most bet upon sport in the world), tennis offers a unique opportunity to understand whether markets correctly anticipate the economic impacts of a changing climate and thus send the right "signals" to market participants (e.g. investors).

We match data on over 177 thousand men's and women's professional tennis matches played over 15 years around the world, to temperature exposure during the hours of each match was played. An empirical challenge in using these data to understand the effect of temperature on labor productivity is the adversarial nature of tennis: opposing players in a given match are exposed to the same temperature. To overcome this challenge, we exploit rich data on within-match performance outcomes, including errors committed by players, serve speed, distance run, and the likelihood of a player retiring from a match (i.e. quitting). Because changes in some of these outcomes in response to temperature (e.g serve speed or distance run) could reflect changes in in-game strategy rather than changes in productivity, we exploit the fact that two players playing under the same current-match temperatures frequently experienced substantially different temperatures in their prior matches, and we model in-match win probability for a given player as a function of differential previous match temperature relative to his or her opponent.

Using a panel fixed-effects regression framework, we model each outcome as a flexible function of temperature and individual player characteristics (Methods). Inclusion of both player and tournament-by-year fixed effects helps to isolate temperature variation from a large set of potential confounding variables, including average differences in outcomes or temperatures experienced between players, or differences in performance or temperature between tournaments. Our approach, for example, asks how playing a match during a hot day at the 2018 US Open increased the number of double faults by Roger Federer relative to his normal number of double faults in a match, after accounting for the average number of double faults across all players in the 2018 US Open; we can additionally control for other match-specific characteristics, such as number of games played.

To explore heterogeneous effects and potential adaptation, we obtain data on players' locations of birth as well as current residence, and examine whether players more accustomed to warmer temperatures are less affected by hotter match temperature. We also examine differences in temperature sensitivity by player rank, to measure whether climate effects differ across the skills distirbution, as well as by gender. Finally, to study whether markets correctly anticipate the effect of temperature on productivity, we combine extensive data on match-specific betting odds from nine online betting portals with our finding that differential previous match temperature affects competitors' performances in the current match.

2 Data and methods

Literature Review To assess existing evidence, we collected data from 6 pioneering studies[12–17] which repeatedly appeared in the meta-analysis of productivity-temperature relationship,[3] as well as 16 published and working papers in economics and climate science since 2000[2,18–32] through references on Google Scholar or in meta-analysis studies. We included the paper if it investigated the labor productivity response to temperature. As such, we excluded numerous papers in economics which studied labor productivity without specific response to temperature variation. Characteristics of included studies are listed in Table S1. We obtained the paper's reported non-linear specifications to chart the marginal responses at different baseline temperatures. In particular, we mapped temperature bin response relative to an omitted bin and interpreted the response as changes in output when moving from the omitted bin's median temperature to the reported bin's median temperature at that temperature. When only linear response was provided, we reported only one marginal response and computed the average baseline temperature based on that experienced by the study's sample.

Measurements of labor productivity range from manual labor in agriculture and manufacturing to mental performance of judges and workers. To maintain a coherent unit, measurements of labor productivity across all the included papers were normalized to percentage changes in output. The unit in our figure reads how many percentage points output changes per unit of labor in response to 1°C increase in temperature, at varying baseline temperatures or baseline earnings. We obtained baseline earnings directly if the included study reported average earnings of sample workers. Otherwise, we obtained the baseline earnings for the reported samples through available statistics on average incomes in the location of study. All earnings were converted to USD in 2017.

Tennis data Our tennis data primarily come from author and sports data aggregator Jeff Sackmann,[33] who assembled match and point statistics from both men's and women's tennis governing bodies, Association of Tennis Professionals (ATP) and Women's Tennis Association (WTA). We constructed a list of where each tournament is played, scraped match start times from a sports betting website,[34] and merged these location and time information with the tennis statistics data. Match statistics for main ATP and WTA tournaments are available since 1991, those for challengers and futures tournaments since 2008, and those for main tournaments' qualifying rounds since 2011. Match start times are available for all tournaments and qualifying rounds since 2002.

These data include record match-level observations for all tennis tournaments that are published on the website of men's tennis governing body (Association of Tennis Professionals (ATP)) and on that of the women's counterpart (Women's Tennis Association (WTA)), which include four major tournaments called Grand Slams (Australian Open, French Open, Wimbledon and US Open), ATP/WTA Tour Series, ATP Challengers/WTA 125K Series and ATP/WTA Futures Tournaments. These observations include oft-cited aggregated statistics of each player during a match, such as number of double faults commited by each player, breakpoints faced or saved, number of aces as well as statistics of the match such as match score and length of match. Our dataset excludes doubles tournaments.

Match locations were derived from Tournament names, which are often include the city of the tournament, or filled in manually where tournament names did not indicate the city. We excluded tournaments whose locations are not fixed every year, such as the Summer Olympics, and tournaments happening in multiple cities, such as Rogers Cup (Canadian Open) in Toronto and Montreal. We then used Google Maps API to get the latitude and longitude of our match locations.

To mitigate concerns about indoor temperature control biasing the main results, we obtained list of indoor tennis tournaments from Wikipedia[35] and removed matches that happen indoor. As a result of excluding indoor matches, merging location and match start times, and singling singles, our final dataset contains 177,874 match-level observations in 6,223 tournament-years.

We further scraped the Wikipedia pages of each player in our dataset to obtain where they were born and currently reside to investigate the role of adaptation in tennis performance. 2,494 and 1,700 players out of 8,889 total players in our dataset have their birthplace and residence information listed on Wikipedia. Where birthplace location is not available but residence temperature is, we assign player's country of origin to her birthplace. As a result, 257,303 and 220,956 out of 355,748 player-match-level observations are included in the analyses which study the adaptation effects.

Finally, the tennis data[33] also include more detailed statistics at the point- and player-point-level, such as serve speed, total distance run, and forced/unforced error, for a subset of Grand Slams matches since 2011 due to Hawk-Eye technology. We merge each point and player-point observations to the main match-level dataset. In total, 916 and 1,429 matches out of the main dataset have information on distance run and serving speed per player in each point, resulting in 298,326 and 233,348 player-point observations. 3,473 matches have ball rally count per point, resulting in 1,154,392 point-level observations.

Temperature Data Data used to estimate match temperature come from NOAA's Global Surface Summary of the Day (GSOD)[36] which record daily meteorological information from more than 9,000 weather stations. We assigned temperature data from the nearest station to each match, used the daily meteorological information to interpolate temperatures throughout the day of the match (see Supplement for details), and finally calculated the average temperature at which the match is played. Our main specification uses dry-bulb match temperature. However, we incorporate humidity into our alternative temperature measures by calculating wet-bulb globe temperature and heat indices (Supplement).

Birthplace and residence temperatures were obtained by matching their location centroid coordinates with the average temperature values from the raster cells of WorldClim2.0 at 10 minute resolution,[37] averaged across all the twelve months provided in the data.

Analysis Data The analysis samples for all of our outcomes are summarized in Table S2. The largest merged dataset contains 177,868 mens' and womens' matches (47%/53%) from 1,109 tournaments from January 2002 to June 2017. As two players play in each match, our unit of observation is the player-match for outcomes that can be individually determined (such as double faults, win/loss), and the match for those that cannot (match duration, match retirement). Furthermore, beginning in 2011 Grand Slams tournaments have started to use a Hawk-Eye camera system to record details of a tennis match down to the point-level. Our dataset contains 4,285 of those matches from 46 Grand Slams tournaments. These data generate 1,419,944 point-level observations on serve speed. Distance run and rally length only became available in 2015 and so we observe 229,866 point-level observations for rally length and (due to missing observations) 173,473 point-level observations for distance run.

Empirical Strategy Our analysis can be divided into four main categories based on whether the outcome is reported at the point or match level and whether the outcome is determined jointly or is attributable to a specific player. Namely, the four categories are: jointly determined-match-level outcomes (match duration), player specific match-level outcomes (total double faults, match retirement, win probability), jointly determined point-level outcomes (rally length), and player specific point-level outcomes (distance run, serve speed). While our general empirical approach remains the same, the level of observation and thus the estimation equation varies across structures.

For match duration (jointly determined at the match-level) our estimation strategy takes the following form:

$$y_{ijmkt} = \alpha_i + \alpha_j + \mu_{kt} + f(T_{ijmkt}) + X'_{ijmkt}\gamma + \epsilon_{ijmkt} \tag{1}$$

where y_{ijmkt} is a tennis outcome of match m between player i and player j at tournament k and year t, T_{ijmkt} is the temperature at which player i plays against player j in match m. Vectors α_i and α_j are player fixed effects for each player that control for any average differences between players, and the vector

μ_{jt} is tournament-year fixed effects which account for all differences between tournament-years – e.g., oft-cited tournament features such as court surface or any differences between Wimbledon in 2015 and Wimbledon in 2016 in average temperatures or average match duration. $f(T_{ijmkt})$ captures the functional form of average match temperature. Our main functional form assumes a quadratic function of temperature, $\beta_1 T_{ijmkt} + \beta_2 T^2_{ijmkt}$ where β_1 and β_2 capture the non-linear effects of temperature. X_{ijmkt} is a control vector including the number of games within a match. In essence, this approach compares match durations between matches in a given tournament (Wimbledon 2016) and asks whether hotter matches have shorter duration, after accounting for average duration that each player in that match normally plays for. Our causal identification relies on the assumption that short-run temperature fluctuations across approximately fourteen days of a tournament is random. We cluster our standard errors at the tournament-year level because the residuals are likely correlated within a given tournament.

For double faults (total in the match) and retirements (player specific outcomes reported at the match level), our estimation strategy takes the distinct but analogous following form:

$$y_{imkt} = \alpha_i + \mu_{kt} + \beta f(T_{imkt}) + X'_{imkt}\gamma + \epsilon_{imkt} \tag{2}$$

where y_{imkt} is a tennis outcome of player i in match m at tournament k and year t, T_{imkt} is the temperature at which player i plays in match m, α_i is player fixed effects and μ_{kt} are tournament-year fixed effects. In the main specification where $f(\cdot)$ is assumed to be a quadratic, β_1 and β_2 again capture the non-linear effects of temperature.

For rally-length (jointly determined and reported at the point-level) we include additional fixed effects for each player and for the match-game and our estimation strategy becomes:

$$y_{ijpgmkt} = \alpha_i + \alpha_j + \nu_{gm} + \mu_{kt} + \beta f(T_{ijmkt}) + \epsilon_{ijpgmkt} \tag{3}$$

where $y_{ijpgmkt}$ is a tennis outcome at point p in game g in match m between player i and player j at tournament k and year t. ν_{gm} is a fixed-effect for game number in the match to ensure that later games in a match do not bias the β_1 and β_2 coefficients, similar to the effect of number of games control in Equations 1 and 2

For distance run and serve speed (player-specific outcomes reported at the point-level), we drop the second player fixed effect but include the game-of-match fixed effect and our estimating equation becomes:

$$y_{ipgmkt} = \alpha_i + \nu_{gm} + \mu_{kt} + \beta f(T_{ipgmkt}) + \epsilon_{ipgmkt} \tag{4}$$

where p indicates a single point played by player i in game g of match m at tournament k and year t. Because point-level data are only available for Grand Slam Tournaments and only since 2011, our analysis of point-level outcomes relies a more limited sample than our match level outcomes.

Finally, to estimate the impact of temperature on win probability, we model a player's in-match win probability using two separate approaches. First, we model win probability as a function of the difference between temperatures in the previous matches played by the two players. This estimation equation becomes:

$$y_{imkt} = \alpha_i + \mu_{kt} + \beta_1 \Delta T_{imkt-1} + X'_{imkt}\gamma + \epsilon_{imkt} \tag{5}$$

where y_{imkt} is the win/loss outcome for player i in match m at tournament k in year t. ΔT_{imkt-1} is the difference between previous match temperature of player i and that of his opponent. The parameter β_1 captures the effect of playing hotter than opponent's previous match temperature on the probability that player i wins a match. X_{imkt} includes number of games in the match, number of days elapsed since the previous match, player i's rank, and his opponent's rank. We replace y_{imkt} with the probability of player i's winning the game as predicted from betting market odds when we study if the betting market captures the effect of heat in its prediction of players' performance. Results from this regression are plotted in Fig 2g.

Second, we model win probability as a function of an individual's temperature in the previous match. This estimation equation becomes:

$$y_{imkt} = \alpha_i + \mu_{kt} + \beta_1 f(T^{prev}_{imkt-1}) + X'_{imkt}\gamma + \epsilon_{imkt} \tag{6}$$

where y_{imkt} is the win/loss outcome for player i in match m at tournament k in year t and T^{prev}_{imkt-1} is the temperature during player i's previous match. The parameter β_1 captures the lagged effect of previous match temperature on the probability that player i wins a match. X_{imkt} includes number of games in the match, number of days elapsed since the previous match, player i's rank, and his opponent's rank. To plot the marginal effect of temperature on win probability shown in Fig 3 we estimate $f(T^{prev}_{imkt-1})$ as quadratic and plot the derivative of Eq (6) as a function of temperature. In both cases, to calculate confidence intervals we bootstrap each estimation equation 1,000 times and plot the inner 95% of estimates.

Estimating heterogeneous impacts To test the differential response functions by gender, players' temperatures of origin, or rank, we linearly interact the temperature terms in the above estimation equations with the variable of interest: dummy for male, dummy for top-10 player, and demeaned birthplace or residence temperature. The former two categories are binary outcomes while the latter two are continuous. For example, in the player-match-level regressions, we estimate:

$$y_{imkt} = \beta_1 T_{imkt} + \beta_2 T_{imkt} \cdot C_i + X'_{imkt}\gamma + \alpha_i + \mu_{kt} + \epsilon_{imkt} \tag{7}$$

where C_i is the player-specific interaction variable of interest. For parsimony, and because most temperature responses in the uninteracted models appeared roughly linear, we model temperature linearly in these estimations.

3 Results

We find clear evidence that heat reduces labor productivity in tennis. When temperatures are hot, matches consist of more double faults, more frequent retirement, shorter rallies, and less total distance run (Figure 2, Table S3). Results are highly consistent across different temperature measures, including wet bulb temperature or heat index measures that incorporate humidity (Fig S1).

Double faults are perhaps the easiest measure of player performance to interpret, given that a player's serve is relatively unaffected by their adversary. The negative impact of warming on double faults was significant across the entire temperature distribution, robust to alternate measures of heat exposure, and resulted in more than 10% more double faults for a match played at at 35 °C as compared to 15 °C. Negative impacts materialize at relatively moderate temperatures, suggesting that the higher rate of double faults is not due to strategic, riskier serving. Taken as an overall measure of productivity, we observe a roughly -0.5% decline in productivity per °C, which is about half of the roughly -1.0%/C pooled estimate we see in lower-wage settings across the labor productivity literature (Fig 3).

The other measures of player performance that commence after a point begins are more difficult to interpret as direct measures of labor productivity, since both players are exposed to the same in-match conditions. For instance, errors may increase with warming because one or both players are hitting harder or because both are moving less well. Similarly, we found that match duration exhibited no response to temperature, despite significant declines in rally length and distance run and increases in chance of retirement. A likely explanation is increased time taken between points during hot matches, as all matches in this study were played before the implementation of a serve clock. For instance, amateur players were found to take 10s more between points when playing at 34°C vs. 19°C.[38]

An additional concern with looking at temperature's effect on in-match outcomes is that although they measure aspects of performance, they do not directly assess the ultimate measure of productivity - whether a player wins the match. For example, players could be strategically altering play in response to hot temperatures (making riskier serves, running less) in ways that actually boost probability of winning the match. Yet since in-match temperature exposures are identical between players, the impact of contemporaneous temperatures on winning cannot be identified. Instead, we consider the impact of differential temperature exposure in the previous match on current-match win probabilities. Matches are played at different times during the day, generating large variation in previous match temperature for two players in a current match; for instance, the 10th-90th percentile in previous match temperature differential ranges from -3.6C to 3.6C (histogram in Fig

2g).

We find significant negative effects on win probability when players experienced a higher temperature in their previous match than their opponent (Fig 2g). We also find comparable negative effects of own previous match temperature exposure (rather than differential exposure) on subsequent win probability. These lagged effects of temperature on win probability – plausibly our closest analog to the labor productivity estimates in the literature – are substantially smaller than effects estimated in lower-wage settings: at sample mean temperatures, estimated productivity effects are -0.1%/C in our data, as compared to -1.0%/C in the pooled estimate from the literature (Fig 3). The lower magnitude of our estimates are perhaps unsurprising given that they only capture residual effects of temperatures in the previous match, which typically occurs a median two (mean three) days before the current match. The role of lagged temperatures has not generally been considered in most prior studies of worker productivity (the exception is ref,[2] which finds lagged impacts on some productivity measures but not others), and thus reconciling our estimate with other studies based on contemporaneous exposure is difficult.

Heterogeneity in heat effects We examine heterogeneity by gender, player rank, and previous exposure to warmer average temperatures. We find limited evidence that females are more or less affected by males. Men double fault significantly more when temperatures rise, perhaps retire at a higher rate (although differences are not statistically significant), but none of our other outcomes show meaningful differences (Fig 4, first column).

We do find evidence that the impacts of temperature on productivity in our setting are ”skills-biased”: players ranked in the top 10 are less likely to double fault and run more relative to lower ranked players when temperatures increase (Fig 4, second column), and the serve speed of top-10 players increases with hotter temperatures, while lower-ranked players see no effect. Point estimates also indicate that statistically significant negative effects of previous match temperature on current match win probability are only observable for lower ranked players, although the difference between top- and lower-ranked players is itself not statistically significant given large error bars for estimates for top players.

Finally, to shed light on adaptation, we quantify whether consistent previous exposure to warm temperatures, as proxied by the average temperature of the birth place or of the current residence of each player, helps reduce the effect of temperature on productivity (Fig 4, right columns). We find limited evidence consistent with exposure-driven adaptation: players born or residing in locations with hotter temperatures do not appear substantially less affected by hot match temperatures. If anything, such players appear to run less and retire more when it is hot.

Mechanisms Multiple mechanisms could link temperature to labor productivity in our setting, including physiological effects, psychological effects, or interactions between labor and capital (e.g. altered performance of equipment such as grips, strings, or balls). Regarding this latter channel, we note that hotter temperatures reduce air density which could modestly increase ball velocity; we calculate that a change in temperature from 10 ° to 38°C (roughly, the coldest to warmest temperatures in our data) reduces the air density by 10%, which could increase ball speed by up to 5km/h. However, we find no statistically significant effect of hotter temperature on serve speed, and in any case both players would face similar "capital depreciation" during the game, suggesting this equipment channel is not dominant. Similarly, the relationship between previous match temperature and current performance cannot easily be explained by in-game equipment differences.

Nearly every aspect of tennis has both a physical and mental component, making clean separation of physiological and psychological heat effects impossible. Both almost certainly play a role. Outcomes with a clear physical component (e.g. distance run) show significant effects in this study, consistent with evidence from other sports settings showing that temperature negatively affects exercise-related biological function.[39,40] Changes in physical output may also be related to changes in strategy, as players may choose to try to end points faster or conserve energy in certain match contexts to increase their odds of winning.

Regarding psychological factors, tennis is often recognized as a sport where psychology can play an important role in performance.[41,42] One line of evidence is that mental training interventions are often found to improve performance, including on outcomes such as double faults that we find exhibit temperature effects.[43] Consistent with our results, past work in other settings indicates that hotter temperatures can affect related cognitive processes.[44]

Market perceptions of heat effects Although to our knowledge there are no previous studies documenting the effects of heat in prior matches on win probability in subsequent matches, we find that bookmakers on average appear to correctly "price" the impact of temperature on performance (Fig 5a). That is, a player who experiences a hotter previous match temperature than her opponent is correctly predicted by bookmakers to be more likely to lose the current match. This suggests that at least in the context of professional tennis, markets appear to correctly anticipate the impacts of a variable climate on productivity. A subset of bookies appear to actually *overpenalize* the player who experienced a hot previous match. However, a simulated strategy of betting against these bookies over time is not profitable; it is better than random guessing, but given betting fees, costs exceed gains (Fig 5b). This result is consistent with findings in equity markets, where sunny days boost stock prices but trade costs mean that trading on this effect is not generally profitable.[45]

4 Discussion

Professional tennis competition, with its meticulously measured outcomes, provides a useful view into whether and how workers with elite physical and mental skills are affected by temperatures. We find clear evidence of effects on several outcomes, although the adversarial nature of tennis and the fact that opponents experience the same conditions both provide empirical challenges. At the same time, these same features of tennis allow us to cleanly detect lagged effects of temperature exposures on productivity. Given that tennis players typically have access to state-of-the-art recovery facilities and air conditioning (except during matches), these residual effects could be a lower bound on what is experienced in other work settings. Lagged effects of temperature could also help explain observed negative effects of temperature on productivity in settings where productive activity itself is protected from climate (e.g. due to air conditioning),[2,26,46,47] with exposure to temperature outside of the workplace perhaps affecting productivity while subsequently at work.

Our findings provide less evidence of adaptation than past studies. In contrast to studies in other sports settings (e.g. archery[4]), we find that previous longer-term exposure to heat, proxied in our study by warmer birthplaces or residence locations, does not lower the effect of hot temperatures on performance in tennis. Our results are thus more consistent with studies of sleep loss[48] in which the sleep of individuals residing in warmer locations was no less affected by a hot night than individuals in cooler locations, and some studies of manufacturing in which firms in warmer regions were at least as harmed by additional heat exposure than firms in cooler regions.[26] Our study also does not provide clear evidence of short-term acclimatization, in contrast to studies of track and field competitions in which exposure to hotter temperatures in the week preceding the competition was found to reduce the negative effects of hot weather on competition performance,[5] and in contrast to many studies in physiology that demonstrate that workers can acclimate, at least to some extent, to hot working environments.[49] We find that players who play a match in hot temperatures a few days before the current match performed worse than players who played a cooler previous match. One potential explanation for this difference is that heat acclimatization could be more effective during repeated episodes of more restrained effort, as emphasized in most sports heat acclimatization protocols,[50] and that the physiological cost of high output during heat exceeds acclimatization benefits. Additional work is needed to understand short- and (especially) longer-run adaptation in work environments.

Our results on the relatively smaller effect of hot temperatures on the labor productivity of top performers mirror those found in a number of settings, including for marathon runners, where high temperatures led to smaller percentage reductions in finishing times for elite runners,[39] as well as in archery, where hot temperatures had less effect on top players.[4] These findings relate to a recent study of US manufacturing, which found that productivity of larger firms was less affected by hot temperatures as compared to smaller firms.[47] Taken together, these findings imply that warming temperatures could have important, and largely unrecognized, distributional effects at the ”micro” level – i.e. at the level of individuals or firms – mirroring documented distributional impacts at the macro level.[51] Better understanding the magnitude and generalizeability of these differential micro-level effects is an important area for future work.

Finally, our results on betting markets contribute to a growing understanding of whether markets appropriately price climate risk. Standard finance theory argues that asset prices will quickly reflect all relevant public information, and ambient temperatures are easily publicly observed around the world. However, recent empirical work typically does not find that asset prices fully reflect relevant climate risks. Studies of both US and global firms have repeatedly found that analysts and investors often fail to anticipate the negative effect of abnormally hot temperatures or drought on firm performance,[9,10,52] and studies in housing markets similarly find that home prices typically do not fully reflect climate risk.[8,53] A related study of betting markets in the National Football League also found that markets mispriced the negative productivity impacts of temperature on visiting-team performance.[54] In contrast, we find that most tennis betting markets appear relatively efficient, with markets correctly anticipating the lagged effect of heat exposure on subsequent performance in tennis. One explanation for this difference might be the relative salience of heat during tennis competitions, for instance the well-publicized adoption of a "heat rule" during the typically hot Australian Open that restricts play during the hottest periods. While we are cautiously optimistic that markets *can* appropriately price risk, it does appear that the effect of temperature on labor productivity in tennis is better understood by market participants relative to other settings. Providing information on the detrimental effects of heat or other climate stressors appears needed for other markets to function efficiently.

References

[1] Lai, W., Qiu, Y., Tang, Q., Xi, C. & Zhang, P. The effects of temperature on labor productivity. *Annual Review of Resource Economics* **15** (2023).

[2] Somanathan, E., Somanathan, R., Sudarshan, A. & Tewari, M. The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy* **129**, 1797–1827 (2021).

[3] Seppanen, O., Fisk, W. J. & Faulkner, D. Control of temperature for health and productivity in offices (2004).

[4] Qiu, Y. & Zhao, J. Adaptation and the distributional effects of heat: Evidence from professional archery competitions. *Southern Economic Journal* **88**, 1149–1177 (2022).

[5] Sexton, S., Wang, Z. & Mullins, J. T. Heat adaptation and human performance in a warming climate. *Journal of the Association of Environmental and Resource Economists* **9**, 141–163 (2022).

[6] Heutel, G., Miller, N. H. & Molitor, D. Adaptation and the mortality effects of temperature across us climate regions. *The review of economics and statistics* **103**, 740–753 (2021).

[7] Lobell, D. B. *et al.* Greater sensitivity to drought accompanies maize yield increase in the us midwest. *Science* **344**, 516–519 (2014).

[8] Hino, M. & Burke, M. The effect of information about climate risk on property values. *Proceedings of the National Academy of Sciences* **118**, e2003374118 (2021).

[9] Pankratz, N., Bauer, R. & Derwall, J. Climate change, firm performance, and investor surprises. *Management Science* (2023).

[10] Hong, H., Li, F. W. & Xu, J. Climate risks and market efficiency. *Journal of econometrics* **208**, 265–281 (2019).

[11] Schlenker, W. & Taylor, C. A. Market expectations of a warming climate. *Journal of financial economics* **142**, 627–640 (2021).

[12] Pepler, R. D. Temperature and learning, an experiment study. *ASHRAE Trans.* **74**, 211–219 (1968).

[13] Link, J. & Pepler, R. Associated fluctuations in daily temperature, productivity and absenteeism. no 2167 rp-57. *ASHRAE Transactions* **76**, 326–337 (1970).

[14] Johansson, C. R. Mental and perceptual performance in heat (1975).

[15] Allen, M. A. & Fischer, G. J. Ambient temperature effects on paired associate learning. *Ergonomics* **21**, 95–101 (1978).

[16] Wyon, D. P., Andersen, I. & Lundqvist, G. R. The effects of moderate heat stress on mental performance. *Scandinavian journal of work, environment & health* 352–361 (1979).

[17] Berglund, L., Gonzales, R. & Gagge, A. Predicted human performance decrement from thermal discomfort and et*. In *Proceedings of the fifth international conference on indoor air quality and climate*, 215–220 (1990).

[18] Niemelä, R., Railio, J., Hannula, M., Rautio, S. & Reijula, K. Assessing the effect of indoor environment on productivity. In *Clima 2000/Napoli 2001 World Congress, Napoli, Italy, 15-18 September 2001*, 6 (2001).

[19] Niemelä, R., Hannula, M., Rautio, S., Reijula, K. & Railio, J. The effect of air temperature on labour productivity in call centres—a case study. *Energy and buildings* **34**, 759–764 (2002).

[20] Heschong, L. & Mahone, D. Windows and offices: A study of office worker performance and the indoor environment. *California Energy Commission* 1–5 (2003).

[21] Fang, L., Wyon, D. P., Clausen, G. & Fanger, P. O. Impact of indoor air temperature and humidity in an office on perceived air quality, sbs symptoms and performance. *Indoor air* **14**, 74–81 (2004).

[22] Federspiel, C. *et al.* Worker performance and ventilation in a call center: analyses of work performance data for registered nurses. *Indoor air* **14** (2004).

[23] Tham, K. W. Effects of temperature and outdoor air supply rate on the performance of call center operators in the tropics. *Indoor air* **14**, 119–125 (2004).

[24] Hedge, A., Sakr, W. & Agarwal, A. Thermal effects on office productivity. In *Proceedings of the human factors and ergonomics society annual meeting*, vol. 49, 823–827 (SAGE Publications Sage CA: Los Angeles, CA, 2005).

[25] Cai, X., Lu, Y. & Wang, J. The impact of temperature on manufacturing worker productivity: evidence from personnel data. *Journal of Comparative Economics* **46**, 889–905 (2018).

[26] Zhang, P., Deschenes, O., Meng, K. & Zhang, J. Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants. *Journal of Environmental Economics and Management* **88**, 1–17 (2018).

[27] Heyes, A. & Saberian, S. Temperature and decisions: evidence from 207,000 court cases. *American Economic Journal: Applied Economics* **11**, 238–265 (2019).

[28] Stevens, A. Temperature, wages, and agricultural labor productivity. Tech. Rep., UC Berkeley Working Paper, Accessible on UC Berkeley website (2019).

[29] Adhvaryu, A., Kala, N. & Nyshadham, A. The light and the heat: Productivity co-benefits of energy-saving technology. *Review of Economics and Statistics* **102**, 779–792 (2020).

[30] Bao, X. & Fan, Q. The impact of temperature on gaming productivity: evidence from online games. *Empirical Economics* **58**, 835–867 (2020).

[31] LoPalo, M. Temperature, worker productivity, and adaptation: evidence from survey data production. *American Economic Journal: Applied Economics* **15**, 192–229 (2023).

[32] Zhang, W., Ding, N., Han, Y., He, J. & Zhang, N. The impact of temperature on labor productivity–evidence from temperature-sensitive enterprises. *Frontiers in Environmental Science* **10**, 2632 (2023).

[33] Jeff sackmann's tennis github repository. `https://github.com/JeffSackmann`. Accessed: Aug 2017.

[34] Tennis explorer. `https://www.tennisexplorer.com`. Accessed: Aug 2017.

[35] Wikipedia: Indoor tennis tournaments. `https://en.wikipedia.org/wiki/Category:Indoor`$_{t}ennis_{t}ournament$
Aug2017.

[36] Noaa global surface summary of the day. `https://www.ncei.noaa.gov/data/global-summary-of-the-day/acc`
Accessed: Aug 2017.

[37] Fick, S. E. & Hijmans, R. J. Worldclim 2: new 1-km spatial resolution climate surfaces for global land areas. *International journal of climatology* **37**, 4302–4315 (2017).

[38] Périard, J. D. *et al.* Thermal, physiological and perceptual strain mediate alterations in match-play tennis under heat stress. *Br J Sports Med* **48**, i32–i38 (2014).

[39] Ely, M. R., Cheuvront, S. N., Roberts, W. O. & Montain, S. J. Impact of weather on marathon-running performance. *Medicine and science in sports and exercise* **39**, 487–493 (2007).

[40] Tatterson, A. J., Hahn, A. G., Martini, D. T. & Febbraio, M. A. Effects of heat stress on physiological responses and exercise performance in elite cyclists. *Journal of science and medicine in sport* **3**, 186–193 (2000).

[41] Harris, D. J., Vine, S. J., Eysenck, M. W. & Wilson, M. R. Psychological pressure and compounded errors during elite-level tennis. *Psychology of sport and exercise* **56**, 101987 (2021).

[42] Kovalchik, S. & Ingram, M. Hot heads, cool heads, and tacticians: Measuring the mental game in tennis (id: 1464). In *MIT Sloan Sports Analytics Conference* (2016).

[43] Morais, C. & Gomes, A. R. Pre-service routines, mental toughness and performance enhancement of young tennis athletes. *International Journal of Sport Psychology* **50**, i76–i92 (2019).

[44] Park, R. J., Goodman, J., Hurwitz, M. & Smith, J. Heat and learning. *American Economic Journal: Economic Policy* **12**, 306–339 (2020).

[45] Hirshleifer, D. & Shumway, T. Good day sunshine: Stock returns and the weather. *The journal of Finance* **58**, 1009–1032 (2003).

[46] Cachon, G. P., Gallino, S. & Olivares, M. Severe weather and automobile assembly productivity. *Columbia Business School Research Paper* (2012).

[47] Ponticelli, J., Xu, Q. & Zeume, S. Temperature and local industry concentration. Tech. Rep., National Bureau of Economic Research (2023).

[48] Minor, K., Bjerre-Nielsen, A., Jonasdottir, S. S., Lehmann, S. & Obradovich, N. Rising temperatures erode human sleep globally. *One Earth* **5**, 534–549 (2022).

[49] Robinson, S., Turrell, E., Belding, H. & Horvath, S. Rapid acclimatization to work in hot climates. *American Journal of Physiology-Legacy Content* **140**, 168–176 (1943).

[50] Racinais, S. *et al.* Consensus recommendations on training and competing in the heat. *Scandinavian journal of medicine & science in sports* **25**, 6–19 (2015).

[51] Burke, M., Hsiang, S. M. & Miguel, E. Global non-linear effect of temperature on economic production. *Nature* **527**, 235–239 (2015).

[52] Addoum, J. M., Ng, D. T. & Ortiz-Bobea, A. Temperature shocks and industry earnings news. *Journal of Financial Economics* **150**, 1–45 (2023).

[53] Gourevitch, J. D. *et al.* Unpriced climate risk and the potential consequences of overvaluation in us housing markets. *Nature Climate Change* **13**, 250–257 (2023).

[54] Borghesi, R. The home team weather advantage and biases in the nfl betting market. *Journal of Economics and Business* **59**, 340–354 (2007).

Figure 1: **Meta-analysis of the effects of heat on labor productivity**. Marginal effect of temperature on labor productivity against the average annual salary of each study's samples. Rug plots show the distributions of average annual salaries of professional tennis players in our sample. Vertical lines above the rug plots indicate the average salary across our sample for men and women, weighted by the number of matches each individual played, as well as the average earnings of individuals studied in the literature.

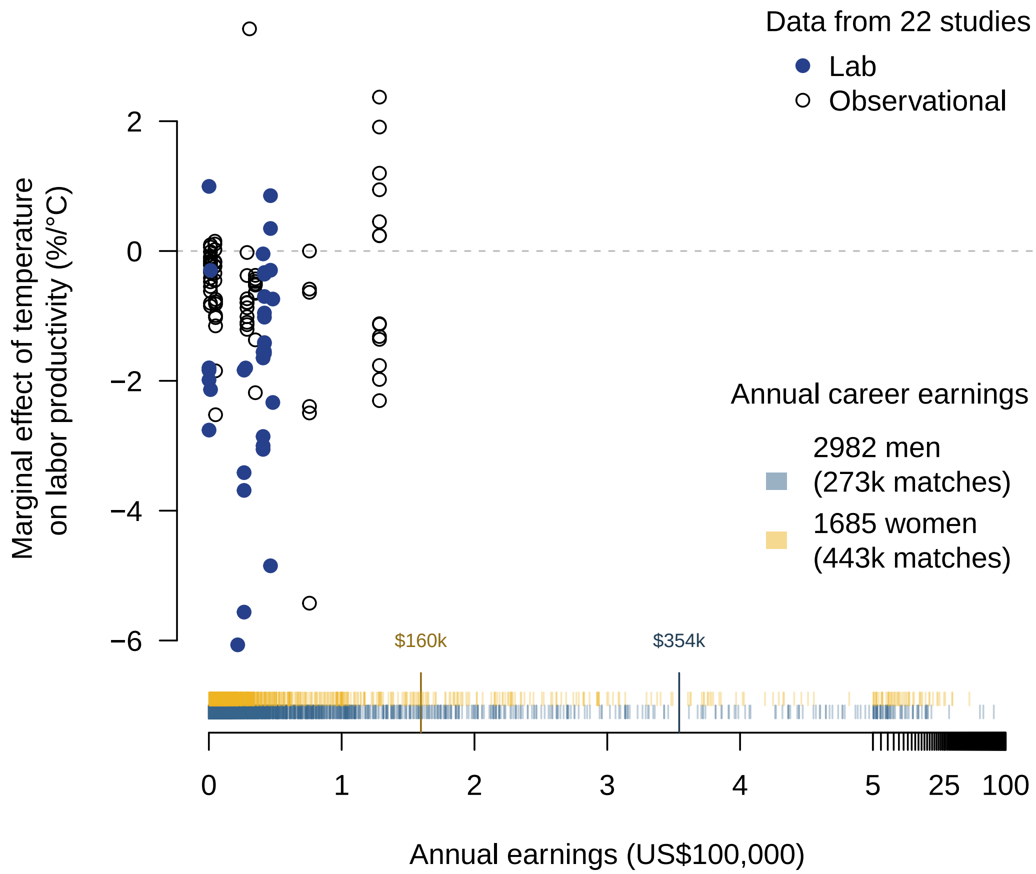


Figure 2: **Effect of temperature on various measure of tennis performance**. **a.** number of double faults, **b.** probability of match retirement, **c.** rally length, **d.** distance run by each player, **e.** serve speed, **f.** match duration, and **g.** change in win probability as a function of difference in previous match temperatures between players. Effects are calculated at percentage changes in the outcome variable, relative to a match played at 25C. Colored segments indicate the significance level at which responses to heat are different from zero, at each point in the temperature distributions (see legend at bottom right). Data for panels c, d, e, and f are only available for Grand Slam tournaments.

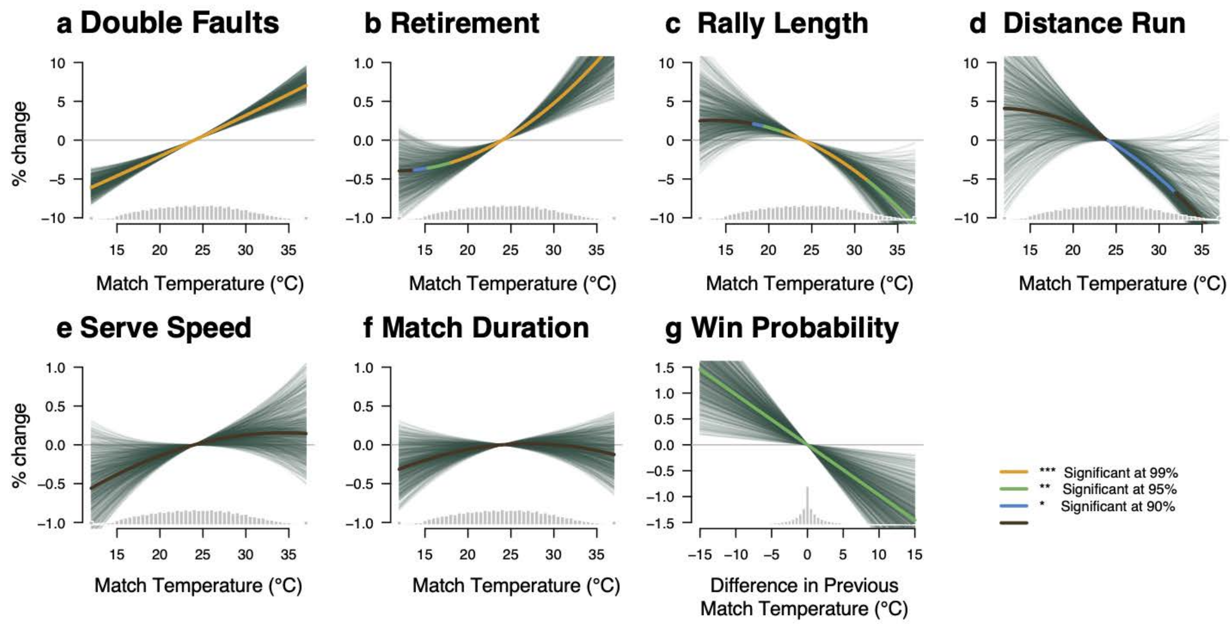


Figure 3: **Effect of temperature on labor productivity from this study vs other existing labor productivity studies**. Orange estimates are estimated effect of previous match temperature on win probability from this study or current match temperature on increase in double faults; blue is the pooled estimates from the literature in Figure 1. Transparent lines are bootstrapped confidence intervals.

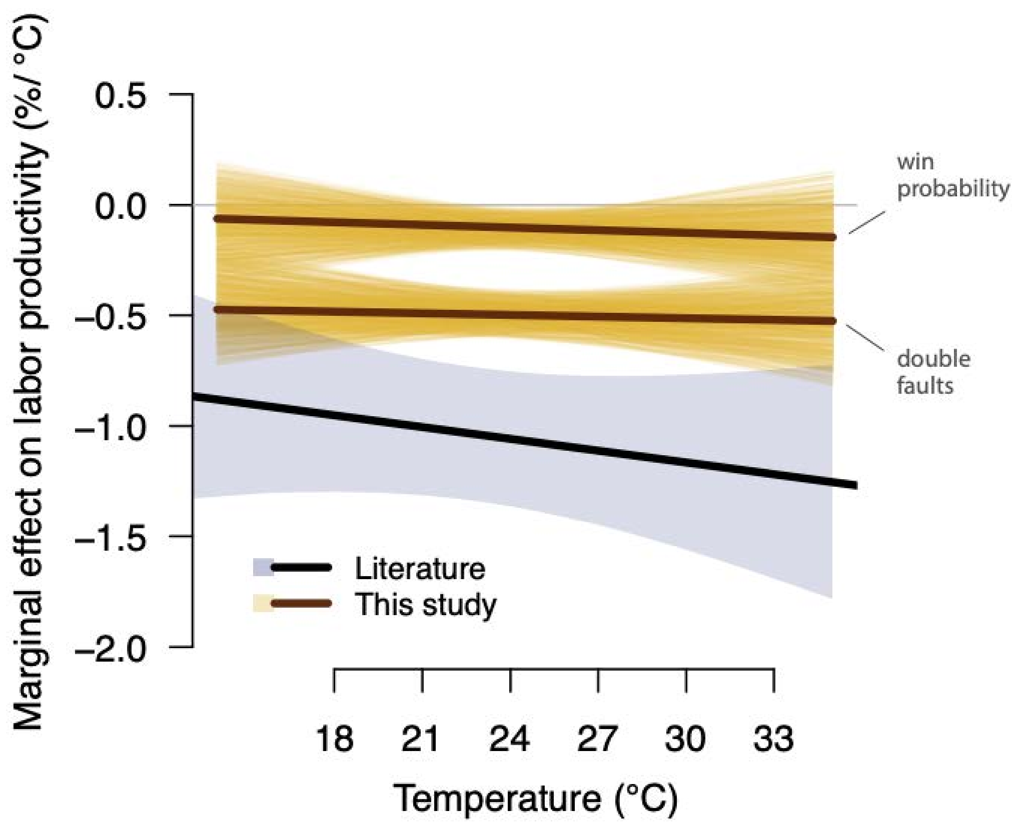


Figure 4: **Heterogeneous effects by gender, skills and adaptation**. Comparison in the marginal effects of temperature on tennis performance, for men versus women, top 10 vs non-top 10 players, players who were born in regions with hotter average temperatures (90th percentile = 18.9C) versus lower average temperature (10th percentile = 6.4C), and players who train in locations with hotter average temperature (90th percentile = 22.2C) and lower average temperature (10th percentile = 7.8C). Performance measured by various outcomes. Estimates measured as marginal effects (% change in each outcome per +1C increase in temperature) from a regression that interacts the measure of heterogeneity with linear temperature (match temperature for the first three outcomes, previous match temperature for win probability). Lines indicate 95% confidence intervals corresponding to the null hypothesis that the respective effect is equal to 0. Stars on the group connecting bars identify significance levels corresponding to the null hypothesis that effects are equal between comparison groups (0.1*, .05**, ,005***).

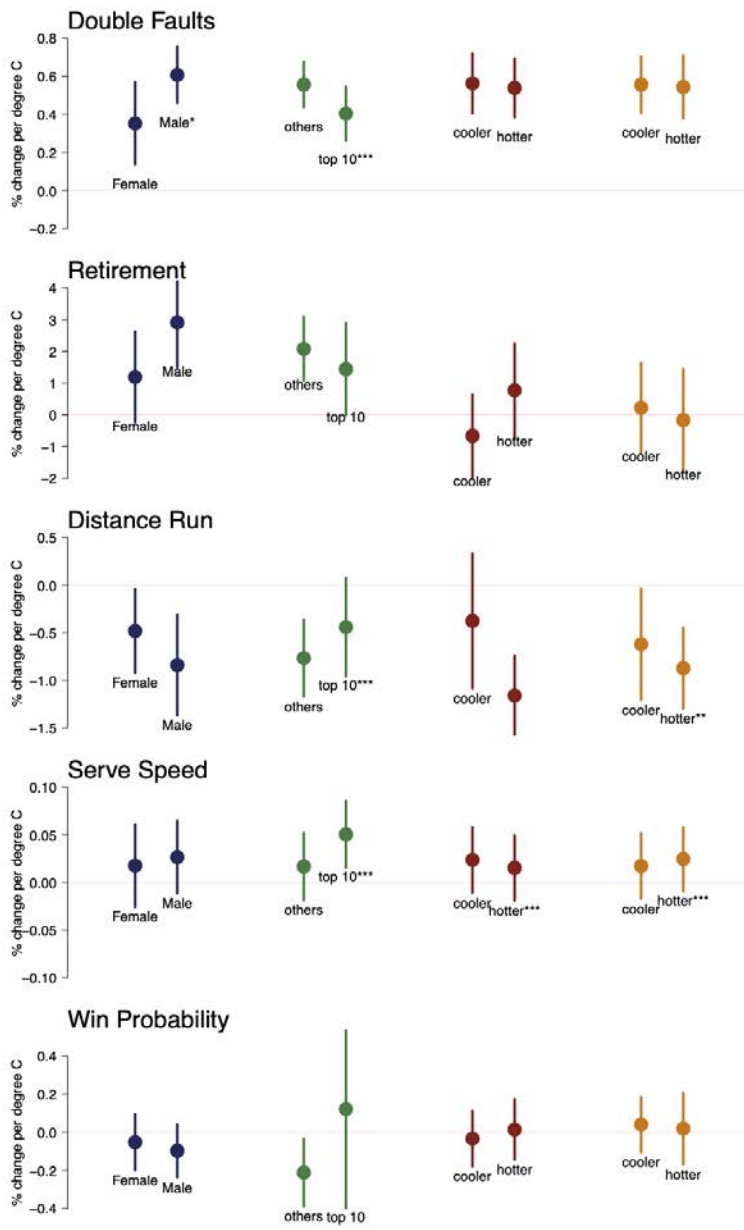
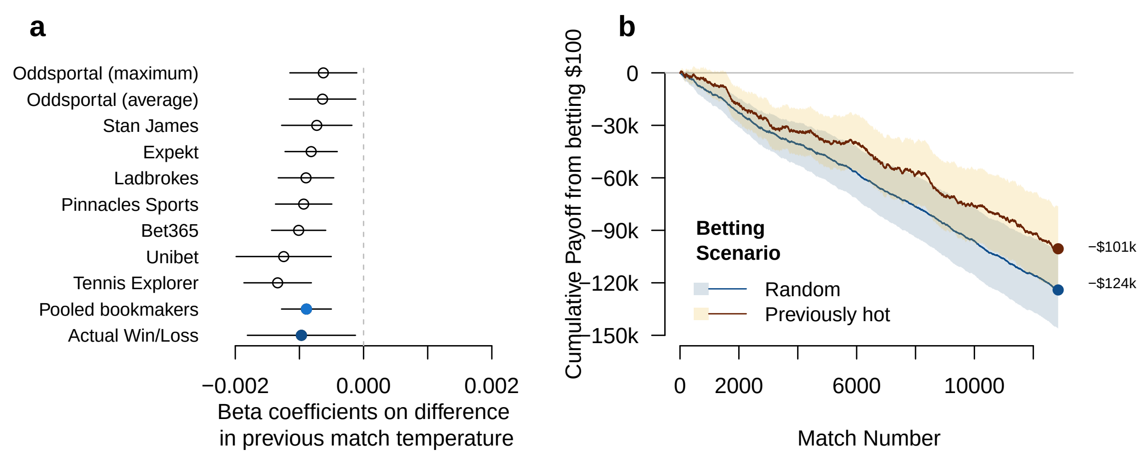


Figure 5: **Bookmakers appear to correctly penalize players from hotter previous matches, although some over-penalize**. **a.** We regress the effect of players' differential in previous match temperatures on actual win/loss outcomes and on implied win probabilities as predicted by various bookmakers. **b.** As some bookmakers (e.g. Tennis Explorer) appear to over-penalize players whose previous match was hotter than their opponent's, we show that betting $100 on players who played in hotter matches previously does better than random betting but still generates losses, given betting fees.



Supplementary Information

Additional Methods

Temperature interpolation Because tennis observations are at sub-daily level, more granular than GSOD daily temperature data, we interpolated the recorded temperatures to obtain the temperature at which tennis matches are played. We use a sinusoidal function to interpolate the hourly temperature bins of each venue-date observation from recorded daily minimum and maximum temperatures

$$T(h) = \frac{1}{2}\big(\text{TMAX} + \text{TMIN}\big) - \frac{1}{2}\big(\text{TMAX} - \text{TMIN}\big)\left(\cos\left(\frac{\pi(h - \text{HMIN})}{\text{HMAX} - \text{HMIN}}\right)\right) \tag{8}$$

where TMAX and TMIN are daily maximum and minimum dry-bulb temperatures reported in GSOD data, HMAX and HMIN are hours $\in [0, 24)$ at which daily maximum and minimum dry-bulb temperatures occur, and h is the hour of the day. Hour of maximum temperature (HMAX) is assumed to occur 1.5 hours after solar noon, while hour of minimum temperature (HMIN) is assumed to occur 3.5 hours before astronomical twilight. These parameters are obtained from the distributions of HMAX and HMIN based on available hourly temperature data for US-based tournament venues. Solar noon and astronomical twilight of locations are obtained using https://sunrise-sunset.org/api.

We computed match average temperature by averaging the hourly temperatures at which match occur, weighted by the minutes spent in each temperature bin.

Our supplementary temperature measures include wet-bulb temperatures (WBGT) and heat indices (HI), which incorporate the effects of humidity. We convert average match temperature into these measures with the following polynomial functional forms:

$$\text{WBGT} = 0.567T + 1.318e^{\left(\frac{17.67T}{243.5+T}\right)}\frac{R}{100} + 3.38 \tag{9}$$

$$\text{HI1} = \alpha_0 + \alpha_1 F + \alpha_2 R + \alpha_3 FR + \alpha_4 F^2 + \alpha_5 R^2 + \alpha_6 F^2 R + \alpha_7 FR^2 + \alpha_8 F^2 R^2 \tag{10}$$

$$\text{HI2} = \alpha_0 + \alpha_1 F + \alpha_2 R + \alpha_3 FR + \alpha_4 F^2 + \alpha_5 R^2 + \alpha_6 F^2 R + \alpha_7 FR^2 \tag{11}$$

$$\begin{aligned}\text{HI3} =& \alpha_0 + \alpha_1 F + \alpha_2 R + \alpha_3 FR + \alpha_4 F^2 + \alpha_5 R^2 + \alpha_6 F^2 R + \alpha_7 FR^2 + \alpha_8 F^2 R^2 \\ & \alpha_9 F^3 + \alpha_{10} R^3 + \alpha_{11} F^3 R + +\alpha_{12} FR^3 + \alpha_{13} F^3 R^2 + \alpha_{14} F^2 R^3 + \alpha_{15} F^3 R^3\end{aligned} \tag{12}$$

where F is average match temperature in °F and R is percentage relative humidity of a given day, calculated as a function of average daily temperature $\bar{T}$ and average daily dewpoint temperature $\bar{D}$ reported from GSOD:

$$\gamma = 17.67\bar{D}/(243.5 + \bar{D}) \tag{13}$$

$$R = 100 \times e^{\left(\gamma - \frac{17.67\bar{T}}{243.5+\bar{T}}\right)} \tag{14}$$

and the parameters:

	α_0	α_1	α_2	α_3	α_4	α_5	α_6	α_7	α_8
HI1	-4.237·10	2.049	1.014·10	-2.248·10^{-1}	-6.834·10^{-3}	-5.482·10^{-2}	1.229·10^{-3}	8.528·10^{-4}	-1.99·10^{-6}
HI2	3.634·10^{-1}	9.886·10^{-1}	4.777	-1.140·10^{-1}	-8.502·10^{-4}	-2.072·10^{-2}	6.877·10^{-4}	2.750·10^{-4}	
HI3	1.692·10	1.852·10	5.379	-1.002·10^{-1}	9.417·10^{-3}	7.289·10^{-3}	3.454·10^{-4}	-8.150·10^{-4}	1.021·10^{-5}
	α_9	α_{10}	α_{11}	α_{12}	α_{13}	α_{14}	α_{15}		
HI3	-3.865·10^{-5}	2.916·10^{-5}	1.427·10^{-6}	1.975·10^{-7}	-2.184·10^{-8}	8.433 ·10^{-10}	-4.820 ·10^{-11}		

Figure S1: **Labor productivity effects of heat** We test our robustness of main results in Figure 2 using different temperature measures, with first columns using dry bulb temperature (main specification), second wet bulb temperature, third-fifth heat index measured in different ways. As heat indices were designed to capture perception of heat, heat index ranges are at the higher temperature range, with temperatures outside the ranges bottom- or top-coded. (See Appendix for how we calculated wet bulb temperatures and heat indices.) Dependent variables are arranged in rows: **a.** double fault, **b.** probability of match retirement, **c.** rally length, **d.** distance run, **e.** serve speed, **f.** match duration, and **g.** probability of winning a match given players' previous temperatures.

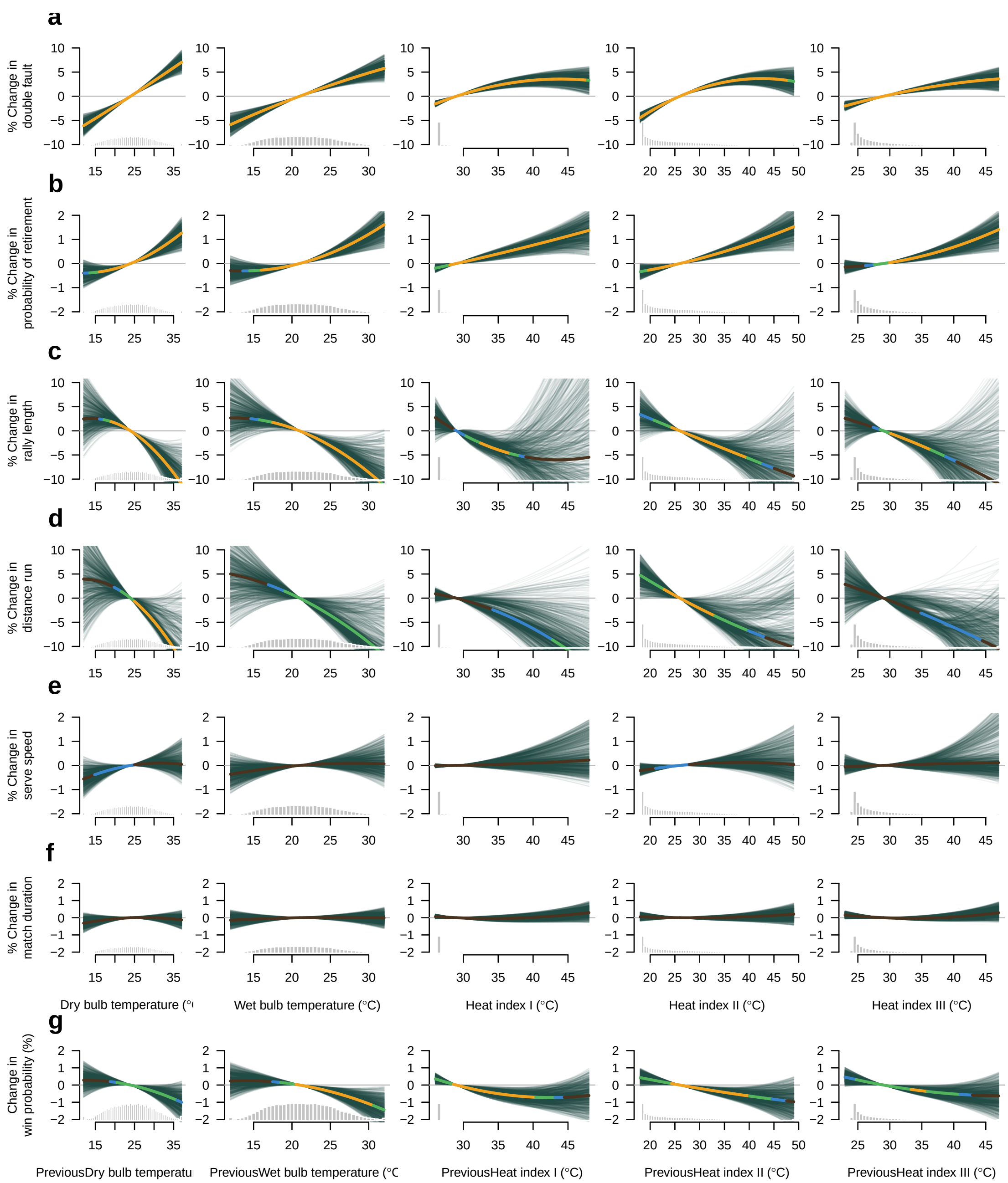


Table S1: Studies included in meta-analysis

Study	Country	Sample Description	Measure of Productivity	Sample Size
Pepler and Warner 1968[12]	US	Students	Assignment correct rate	72
Link and Pepler 1970[13]	US	Sew workers	Absenteeism and tasks completed per hour	-
Johansson 1975[14]	SE	Office work	Mental test performance	-
Allen and Fischer 1978[15]	US	Male psychology students	Acquisition rate of word association	60
Wyon et al 1979[16]	DK	Danish high school students	Cognitive test	76
Berglund et al 1990[17]	SE	Wireless telegraph operator	Perceived energy expenditure	20
Niemela et al 2001[18,19]	FI	Call center workers in Finland	Number of calls/hour	33
Heschong 2003[20]	US	Call center workers in CA	Hourly average handling time	100
Fang et al 2004[21]	DK	Office workers in Denmark	Typing, proofreading, & creative thinking	30
Federspiel et al 2004[22]	US	Call center nurses	Wrap up time	119
Tham 2004[23]	SG	Call center workers	Self-assessed talk time productivity	56
Hedge et al 2005[24]	US	Insurance company workers in FL	Error keys struck/Number of keystrokes	9
Cai et al 2018[25]	CN	Factory machine operators	Over target output ratio	14,128
Zhang et al 2018[26]	CN	Manufacturing plants	Output value	1,833,408
Heyes and Saberian 2019[27]	US	Immigration judge decision	Asylum grant rate	206,924
Peng et al 2018[26]	CN	Manufacturing Plants	Firm-level Total Factor Productivity (TFP)	511,352
Stevens 2019[28]	US	Berry pickers in CA	Pounds of berries picked per hour	229
Adhvaryu et al 2020[29]	IN	Garment workers	Over target output ratio	74,939
Bao and Fan 2020[30]	CN	Dragon Nest online player games	Number game missions completed	1,929,719
Somanathan et al 2021[2]	IN	Factory workers	Meters weaved/rail milled/efficiency	202
LoPalo 2023[31]	Global	DHS enumerators	Interviews completed per hour	314,723
Zhang et al 2023[32]	CN	Construction sector	Industrial product per labor force	1,736

Table S2: **Summary of analysis samples**

Outcome	Level of analysis	Sample	Non-missing obs
Double Faults	Player-match	All tournaments 2002-2017	152,656
Win Probability	Player-match	All tournaments 2002-2017	183,770
Match Duration	Match	All tournaments 2002-2017	177,868
Retirement	Match	All tournaments 2002-2017	177,868
Serve Speed	Player-point	Grand Slams 2011-2017	1,154,392
Distance Run	Player-point	Grand Slams 2015-2017	229,866
Rally Length	Point	Grand Slams 2015-2017	173,473

Table S3: **Linear effect of match temperature on labor productivity measures of tennis players (% change per °C)**

	Dependent variable:						
	Probability match retirement	Match duration	Rally length	Double fault	Serve speed	Distance run	Win probability
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Match temperature (°C)	2.119***	0.008	-0.521***	0.525***	0.023	-0.717***	
	(0.512)	(0.014)	(0.071)	(0.060)	(0.019)	(0.221)	
Previous match temperature (°C)							-0.103**
							(0.052)
Tournament-year FE	YES	YES	YES	YES	YES	YES	YES
Player FE	YES	YES	YES	YES	YES	YES	YES
Observations	177,868	177,868	173,473	152,656	1,155,186	229,866	183,770
R^2	0.184	0.862	0.050	0.286	0.332	0.264	0.170
Adjusted R^2	0.079	0.845	0.045	0.255	0.332	0.262	0.123
Observation level	Match	Match	Point	Player-match	Player-point	Player-point	Player-match
Mean dependent variable	3.1% matches	92.2 min	4.3 shots	3.2 df	100.8 MPH	37.1 ft	50%

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table S4: **Previous heat on win probability**, Actual vs Market prediction

	Dependent Variable: Win probability			
	All	Men	Women	Men - Women
	(1)	(2)	(3)	(4)
	Panel A: Actual Win/Loss			
Δ previous match temperature	-0.0010864^{**}	-0.0012585^{**}	-0.0008538	-0.0003858
	(0.0004405)	(0.0005970)	(0.0006479)	(0.0008970)
	Panel B: Pooled bookmakers			
Δ previous match temperature	-0.0007682^{***}	-0.0007736^{***}	-0.0007616^{**}	-0.0000997
	(0.0002081)	(0.0002932)	(0.0002873)	(0.0004009)
	Panel C: Actual Win/Loss - Pooled Bookmakers			
Δ previous match temperature	-0.0003181	-0.0004849	-0.0000923	
	(0.0004869)	(0.0006640)	(0.0007093)	