I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16431

The Impact of High Temperatures on Performance in Work-Related Activities

Matteo Picchio
Jan C. van Ours

SEPTEMBER 2023

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16431

The Impact of High Temperatures on Performance in Work-Related Activities

Matteo Picchio
Marche Polytechnic University, Ghent University and IZA

Jan C. van Ours
Erasmus School of Economics and Tinbergen Institute, IZA and CEPR

SEPTEMBER 2023

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Impact of High Temperatures on Performance in Work-Related Activities*

High temperatures can have a negative effect on work-related activities. Labor productivity may go down because mental health or physical health is worse when it is too warm. Workers may experience difficulties concentrating or they have to reduce effort in order to cope with heat. We investigate how temperature affects performance of male professional tennis players. We use data about outdoor singles matches from 2003 until 2021. Our identification strategy relies on the plausible exogeneity of short-term daily temperature variations in a given tournament from the average temperature over the same tournament. We find that performance significantly decreases with ambient temperature. The magnitude of the temperature effect is age-specific and skill-specific. Older and less-skilled players suffer more from high temperatures than younger and more skilled players do. The effect of temperature on performance is smaller when there is more at stake. Our findings also suggest that there is adaptation to high temperatures: the effects are smaller if the heat lasts for several days.

JEL Classification: J24, J81, Q51, Q54
Keywords: climate change, temperatures, tennis; performance, productivity

Corresponding author:
Jan C. van Ours
Department of Applied Economics
Erasmus University Rotterdam
Burg. Oudlaan 50
3062PA Rotterdam
The Netherlands
E-mail: vanours@ese.eur.nl

* We acknowledge the ERA5-Land dataset from the EU-funded Copernicus Climate Change Service. Neither the European Commission nor ECMWF is responsible for any use that may be made of the Copernicus Information or Data it contains. We thank participants of ESEA 2023 for their comments on a previous version of the paper.

1 Introduction

According to the World Health Organization (WHO) human beings have an indoors thermal comfort range of 18-24°C (64-75°F).[1] Indoors, climate control can be arranged through heating or air conditioning. Outdoors, it is much easier for people to shield against low temperatures than it is to accommodate to high temperatures (Wyndham, 1969). People can protect themselves against low temperatures through their cloths. People find it more difficult to protect themselves against high temperatures other than through reducing their level of activity.

Temperature may affect productivity at the workplace. Heating or cooling to adjust indoor environment to outside temperatures is important to maintain a level of productivity. However, not all jobs can benefit from climate control. Some workers are inevitably confronted with high temperatures and other unpleasant weather conditions. From a labor economics point of view, the question is what the consequences of high temperatures are in terms of labor supply and labor productivity.

For a long time weather conditions did not play an important role in economic research. It is hard to relate regional differences in economic outcomes to differences in climate since there are also different regional non-economic circumstances that matter. By using time series information within geographical areas, economic research has made an important step forward if only because with climatic variables reverse causality is unlikely to be a major concern. Dell et al. (2014) provide a systematic overview of the "new weather economy" literature. The impact of temperature on productivity has been investigated in a laboratory setting with subjects being randomly assigned to situations with varying temperatures performing cognitive and physical tasks. Particularly with higher temperature, there is a significant loss in productivity related to cognitive tasks. There is a direct effect of temperature on productivity, but also an indirect effect. Poor outdoor weather conditions may stimulate indoor productivity, as outdoor leisure activities are less attractive (Lee et al., 2014). In recent years, there have been quite a few studies on the influence of weather conditions, in particular temperature, on labor input and labor productivity. We provide a summary overview in the next section.

Our study is on the effects of temperature on performance in tennis matches. Us-

[1] The guidelines for this range are based on health protection of individuals. Thermal comfort does not only depend on temperature but also on air movement, humidity and ventilation. Furthermore, it depends on activity and clothing worn as well as personal characteristics such as age, health status and gender (Ormandy and Ezratty, 2012).

ing sports data to understand general economic relationships is increasingly popular. Palacios-Huerta (2023) argues that sports represent natural laboratory settings, with experienced participants and large stakes. For many sports, large-scale detailed micro data on individual performance and teams performance are available allowing for in-depth analysis of relevant economic phenomena. According to Palacios-Huerta (2023) "in sports settings, although exposure is not under the control of the scientist, the process governing exposure often resembles random assignment featuring many conditions that pave the way for causal inference."[2]

Our study is not the first to use sports data to investigate the relationship between temperature and performance. Hoffmann et al. (2002a) present an analysis of success at Olympic games where, in addition to economic determinants, also climate plays a role. The argument is that the development of sporting talent may be influenced by outdoor playing activities. The authors find an inverse U-shaped relationship between sporting success and average annual temperature measured in a country's capital, with maximum success at 14°C. Similarly, Hoffmann et al. (2002b) find an inverse U-shaped relationship between international performance in football games and temperature. Both studies rely on cross-country time-invariant differences in average climate as a determinant of access to sporting activities. Temperature may also have a direct effect on the performance of individual players where variation over time is important. Larrick et al. (2011) study data from US Major League Baseball (MLB) finding that higher temperatures lead to more aggressive behavior. Smith et al. (2018), analyzing 2014-2016 Australian Open matches for women, conclude that high temperatures do not affect first serves but they do increase double faults. The average serve speeds are not affected by high temperatures with the ball speed at first serve ($\approx$ 150 km/h) being much higher than the ball speed at second serve ($\approx$ 125 km/h). The authors hypothesize that, in combination with fatigue, high temperatures decrease the level of fine motor control in women's play. Fesselmeyer (2021) uses data from MLB, including weather conditions at the start of a match, to study the effect of short-run variations in temperature on the quality of umpire decisions finding that higher temperatures lead to lower accuracy. Fesselmeyer (2021) argues that this is due to higher temperatures causing umpires physical and mental discomfort. He also argues that his findings have implications outside baseball. In industries where air conditioning

[2] Palacios-Huerta (2023) discusses various studies using tennis data to investigate relationships that go beyond the sport itself. He mentions the possibility to compare solo work (singles) to team work (doubles), to establish whether some players are team players, to study strategic choice of effort and to analyze the effects of skill-altering technical change (e.g. when in tennis new composite rackets were introduced).

cannot be easily used to mitigate exposure to heat, higher temperatures may lead to lower productivity. Sexton et al. (2022) analyze data on the relationship between temperature and the performance of athletes focusing on strength, sprint and endurance events. They find negative temperature effects only for endurance. This is not surprising as their data are from Spring tournaments when the maximum temperature is about 24°C.[3] Callahan et al. (2023) find that an increase in temperature has a positive effect on performance in baseball games in terms of home runs. The main mechanism of this relationship is air density. With higher temperatures air density is reduced and the ball speed goes up.

An important issue when analyzing sports data is the external validity of the results, i.e. the extent to which observed relationships are specific to the sport analyzed. Tennis is an individual sport in which effort and mental skills are combined, requiring physical strength, technical proficiency, tactical awareness and fine motor control to be successful (Kovacs, 2007; Mathers, 2017). While at work, i.e. when playing a match in a high-stake tournament, tennis players have to make decisions that may have far reaching consequences. They may lose a match and have to leave a tournament prematurely or they can win a match which, in case of the tournament final, implies winning a substantial amount of money. The short time span in combination with a high stake environment, accuracy and focused decision making in tennis is comparable to situations in which judges have to decide on a legal issue and comparable to students doing an exam. Further examples, to name a few, are army special forces, fire-workers, emergency doctors, surgeons and professional musicians.

Our interest is not in the relationship between temperature and outcomes of tennis matches. If both players are affected by higher temperatures, it may even be the case that match outcomes are temperature invariant. We focus on two elements of the matches that allow us to study the way temperature affects individual performance: first serve success rates and double fault rates. These two performance indicators differ fundamentally from each other in terms of the combination of power and accuracy. At the first serve, power is more important and, as a consequence, accuracy is less relevant. If the first serve fails, there is the option of a second serve. At the second serve, the player cannot risk playing inaccurately, because a further serving error implies the loss of the point. Therefore, at the second serve, power is typically reduced to increase accuracy. We hypothesize that

[3] They also find evidence of heat adaptation. Athletes who are exposed to high temperatures regularly suffer less from high temperatures. This is also what Mullins (2018) finds for athletes exposed to high ozone levels. The negative effect of high ozone levels on performance is reduced after recent exposure to higher ozone levels.

temperature has a bigger effect on the first serve because in the second serve there is more at stake: losing a point rather than having the option of a second serve.

The contribution of our paper to the existing literature on temperature and labor productivity is threefold. First, we investigate how high temperatures affect the performance of tennis players during matches. This is equivalent to studying the effect of high temperatures on individual labor productivity. Although two players are involved in each match, we can still measure how the individual performance of each player is affected by high temperatures. We investigate first serve rates and double fault rates, both of which should not be influenced by how the opponent reacts to temperatures. Second, we investigate whether the effect of temperature on productivity depends on the importance of a match. Matches are played as part of tournaments with high prizes for players who win a tournament or end up high in the final ranking. Because we know the importance of a match in terms of expected monetary value of a win, we can investigate whether for matches with high stakes the relationship between temperature and productivity is different. Third, our data allow us to study the heterogeneity in the relationship between temperature and productivity in terms of player characteristics (e.g. age, quality) and working environment (e.g. different surfaces: clay, hard court or grass).

Our threefold contribution enriches the evidence provided by Smith et al. (2018) on the relation between temperature and alterations in matchplay and behavioural characteristics in women's tennis in several directions. First, we focus on the impact of temperatures on men's serving performances, which may be different from women's, given that men and women may have different service strategies, with men relying more on their serve to win a point (O'Donoghue and Ingram, 2001). Second, we use all the ATP tennis matches from 2003 until 2021, which allow us to study if the effect of temperature on performance varies with the importance of the tournament, among other heterogeneity sources. Third, we explore if extreme temperature exposure may accumulate over time or may have an effect in subsequent matches. The accumulation and the adaptation hypotheses are not tackled in Smith et al. (2018).

The set-up of this paper is as follows. In section 2 we present an overview of previous studies on the effects of high temperatures on economic outcomes. Section 3 illustrates our data sources and describes the methodology of the statistical analysis. Section 4 reports and discusses the main findings. Section 5 concludes.

2 Previous studies on temperature and economic outcomes

Studies on the effects of temperature on economic growth relate calendar time differences in economic growth to calendar time variations in temperatures. Dell et al. (2012) for example finds that in poor countries a one degree increase in temperature reduces economic growth by 1.3 percentage points. Higher temperatures have a negative effect on agricultural and industrial output in poor countries and a negative effect on political stability. Burke et al. (2015) show in a time-series cross-country analysis that there is an inverse U-shaped relationship between overall economic productivity and temperature with a maximum productivity at 13°C and a strong decline at higher temperatures. Colacito et al. (2019) analyze the effect of average seasonal temperatures on US state level economic growth rates. The main finding is that a higher temperature has a negative effect on economic growth, especially in summer. Kalkuhl and Wenz (2020) relate within-country regional economic production to temperature finding that increases in temperature rise production in cold regions and reduce production in hot regions. Technological change did not make economies less sensitive to temperature, while the net effect of increasing temperatures on economic production is negative. Moscona and Sastry (2023), studying the effects of climate change on US agriculture, conclude that technological change can only partly compensate for temperature related damages to production.

In terms of work-related activities, previous studies investigated the effect of high temperatures on health, workplace injuries, working time and labor productivity. Temperature may affect both physical health, including mortality, and mental health. Wyndham (1969) is an early study on the relationship between temperature and mortality. He concludes, from studying workers in South-African gold mines, that below 25°C the risk of heat-stroke is negligible. Above 33°C the risks of fatal (and non-fatal) heat-strokes increase sharply. Barreca et al. (2016) find a twentieth century decline in US mortality associated with high temperatures, which they attribute to the diffusion of residential air conditioning from the 1960s onward.

There are a couple of recent studies on the effect of temperature on mental health. Mullins and White (2019) study the relationship between mental health outcomes and temperature measured at the US country level. The authors use a variety of mental health indicators including suicide rates. The main findings are that cold temperatures have a positive effect on mental health, while hot temperatures have a negative effect. Their results are not influenced by air conditioning penetration rates. The authors suggest that sleep disruption may be the primary mechanism through which temperature has a negative effect on mental health. In a sensitivity analysis they also include other weather variables; precipitation and sunlight have a positive effect on mental health, while humidity has a negative effect. Baylis (2020) provides evidence about the effect of high temperatures on mood using Twitter data. He finds an inverse relationship between temperature and various mood indicators, with strong negative effects of temperatures above 30°C. Heyes and Saberian (2019) analyze how decisions by immigration judges are influenced by average outdoor temperatures. Although the trials are indoors in good quality, climate-controlled environments, higher outdoor temperatures reduce decisions favorable to people applying for asylum. In addition to temperature, the analysis also includes other weather indicators such as dew point temperature, precipitation, wind speed, air pressure and sky cover as well as pollution indicators (ozone, carbon monoxide, particulate matter) and a series of fixed effects for judge, day of the week and calendar year. In a sensitivity analysis the temperature indicator is replaced by a heat index that combines temperature and humidity into a measure that captures how hot it feels. As potential channels from outdoor temperature affecting indoor climate controlled decision making, the authors mention mood and cognitive acuity, i.e. high temperatures affecting temper, irritability and other emotions. Lee et al. (2014) consider how good outdoor weather leads to cognitive distractions of people working indoors. Using information on workers in a Japanese bank, they find that bad weather can lead to workers focusing more on their work and, therefore, they are more productive than in case of good weather when they get distracted. Graff Zivin et al. (2018) investigate the relationship between high temperatures and cognitive performance of children measured in match and reading tests. They find that short-run fluctuations in temperature have a significant negative effect on math scores while reading scores are not affected. The negative effects materialize beyond 26°C and are present also when air conditioning is available. For long run variations in temperature no significant effects are found. Park et al. (2020) also investigate how within-student variation in heat exposure in the US affects math and reading test scores. The heat measure used is the average maximum temperature experienced during school days in the year prior to the test. The main findings are that high temperatures have a negative effect on test scores and therefore on cognitive capacities, while air conditioning at school largely offsets these effects. Park et al. (2021) present an international cross-country analysis as well as a US cross-county analysis finding that high temperatures have a negative effect on educational test scores of 15-year old students. The negative effects are present more for disadvantaged students, i.e. students from racial or ethnic minorities and low income families.

The evidence that hot temperatures negatively impacts on health, cognition and task performing raises the question if extreme temperatures may increase the risk of work-related injuries. Dillender (2021) and Park et al. (2021) for the US and Filomena and Picchio (2022) for Italy unambiguously find that workplace injury rates significantly increase with temperature. Graff Zivin and Neidell (2014) analyzing US data find that temperature affects the allocation of time over labor and leisure, both indoors and outdoors. The patterns of the relationships are different. At high temperatures labor time declines depending on whether or not work is exposed to the outdoor climate. With a high exposure labor time drops substantially, in particular by the end of the working day. For leisure time there is an inverse U-shaped relationship for outdoor activities and a U-shaped relationship for indoor activities.

There are a few recent studies on the effects of high temperatures on workplace productivity. Heal and Park (2016) review previous studies on the economics of extreme heat stress, focusing among others on the temperature effects on labor supply and labor productivity. They report that performance outside 18 and 22°C drops, especially at the high end. With high temperatures extended periods of outdoor activity are impossible because human bodies can no longer dissipate heat. According to Heal and Park (2016) high temperatures may affect physical or mental discomfort and may alter the marginal return to time or effort. Adhvaryu et al. (2020) study the relationship between temperature and productivity in garment factories in India focusing on the effect of replacing fluorescent lamps with light-emitting-diode (LED) lighting, which reduced waste heat and caused in-factory temperature to drop. Production efficiency increased after the introducing of LED. Somanathan et al. (2021) study how heat affects production in Indian manufacturing, distinguishing between the effect on absenteeism and productivity. The main findings are that in the absence of climate control worker productivity declines on hot days while, even in the presence of climate control, absenteeism increases on hot days. LoPalo (2023) examines the impact of weather conditions on productivity of interviewers of household survey data. She found that on the hottest and most humid days interviewers complete fewer interviews per hour. However, the daily productivity is not affected, because interviewers react to heat by starting earlier in the day and spending more hours in the field with the same total pay.

Whereas in some situations the consequences of high temperatures can be dealt with through changes in time use, in other situations this is not possible. Park (2022) investigates the effect of temperature on cognitive performance in exams which are considered to be high-stakes environments since the performance is over a relatively short time period with potentially long-lasting consequences. Although cognitive performance is likely to be influenced by classroom temperature, in the analysis outdoor weather variables are used, i.e., temperature, precipitation and dew point readings. The main conclusion is that high outdoor temperatures significantly reduce cognitive performance indoors.

There are various issues in the research on temperature and work-related activities that are unresolved. For example, it is unclear to what extent outside climate has an effect on indoor work activities. Some studies suggest that there is an effect either through the shadow costs of leisure time when potentially being outdoors or because outside weather affects workers mentally so they take the outside weather with them to work. Other studies find that air conditioning facilities affect labor productivity suggesting that the difference between outdoor and indoor climate is relevant. It is also unclear whether the effect of high temperatures affects labor productivity through effects of physiology or psychology. Clearly, if temperatures are high and artificial cooling is not possible, the only way body temperature can remain in a safe range is by reducing physical activity. However, high temperatures can also affect labor productivity through their effect on mood of workers or by making it more difficult to perform regular tasks, especially when this requires precision work. Finally, it is unclear which type of activities are affected most by high temperatures. Workers may reduce effort less when there is a lot at stake and they may reduce effort more on more complex tasks because they experience problems in focusing.

3 Methods

3.1 Data and sample

We conducted the empirical analysis by merging different data sources. We gathered meteorological data from Copernicus Climate Change Service, the European Union funded Earth Observation Program. More specifically, we used ERA5-Land (Muñoz Saba ter, 2019), a global land surface dataset spanning from 1950 until present.[4] The dataset provides grid fields at a horizontal spacing resolution of $0.1^{\circ} \times 0.1^{\circ}$ in regular latitude/longitude coordinates (about 9 km^2). We retrieved the daily temperatures registered

[4]For more details see https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?-tab=overview (last accessed December 2nd, 2022).

at 3 pm two meters above the surface, as an approximation of the temperatures experienced both in early and late matches of the tournament day. In our tennis datasets, information on the time of day is not available and we are therefore forced to stick to this measurement error.

We matched the temperature dataset with male tennis singles matches gathered from two sources. From *Tennis-Data.co.uk*, we retrieved match results of the ATP seasons from 2003 until 2021.[5] In those years the information on the day in which each match was played is available, as well as other information at match level, like: location; tournament series (e.g. Grand Slam, ATP 1000, etc.); surface; if the match was played indoor or outdoor; match round (e.g. final, semifinal, etc.); if the match was best of 3 or 5 sets; winner's and loser's name; set and game scores; players' ATP rankings and points before the start of the tournament; if the match was not completed and, if not completed, if it was due to the retirement of one of the two players. After dropping matches that were cancelled,[6] or for which some of the variables which we used in the regression analysis were missing, or which lied in the first or last percentile of the temperature distribution, we have 39,546 singles matches played outdoor.

Although the *Tennis-Data.co.uk* data is able to provide us with the information on the date in which each match was played, it does not contain match statistics to compute performance measures. Our second source of tennis data fills this gap. We gathered performance-related statistics from GitHub, which are organized and made publicly available by Jeff Sackmann at https://github.com/JeffSackmann. We faced however two limits resulting in loss of some observations. First, match statistics useful for our purposes are available for women only starting from 2016, which is the reason for which we limit our analysis to men. Second, although Jeff Sackmann's data are richer in match and player statistics than *Tennis-Data.co.uk* data, they do not report the precise date of the match, but only the starting date of the tournament. Hence, we could not directly merge Jeff Sackmann's data with the daily meteorological information from the ERA5-Land database. We overcame this problem by matching the two tennis databases by match level variables which are common with both Jeff Sackmann's and *Tennis-Data.co.uk* datasets, like players' surnames, their ATP ranking and points, the game and set scores, the surface, and the tournament round. However, in merging the two tennis datasets, we were not able

[5]Historical data are downloadable from http://www.tennis-data.co.uk/alldata.php (last accessed on December 2nd, 2022).

[6]Some matches were cancelled for pre-match withdrawal (*walkover*, about 0.5% of the matches) or suspended because a player was disqualified (*default*, only 2 cases).

to match 174 observations. We also removed the 2009 Australian Open match between Müller and López because for both players a 100% first serve made rate in more than 4 hours match was reported, which is very likely a data bug. After deleting observations with missing values for some of the variables used in the regression analysis (359 observations) and matches lasting less than 30 minutes (194 matches) or more than 5 hours (24 matches) or with missing information about their duration (980 matches of which 937 played in 2015), we were left with 38,034 male matches. For each of these matches and for each player, Jeff Sackmann's dataset contains variables for the number of served points, number of aces, number of double faults, number of first serves made, number of first serves won, number of second serves won, number of served games, number of break points saved, and number of break points faced. Furthermore, it includes player's features like age, height and serving hand.

In our empirical analysis, we focus on two performance indicators: successful first serves and double faults. For every point in a tennis match, players have two opportunities to serve a ball into the correct service box to initiate play. A successful first serve occurs if the ball does not hit the net and lands in the service court on the other side of the net. A fault is counted for if the ball does not land in the service court of the opponent. If the server makes two consecutive faults, it is known as a double fault and the server loses the point. Both successful first serves and double faults are stand-alone indicators, i.e. they originate from decisions and behaviors of the player who serves, without the other player being directly involved. Nevertheless, both indicators may be influenced by the (expected) strength of the opponent. Hence, they measure the ability of serving without being directly affected by the counter-performance of the receiver. We decided not to use other performance indicators like the number of aces (an ace is when the player correctly serves the ball in the opponent's service box and the ball does not touch the receiver's racquet) or the fraction of first serves won, because they involve the counter-performance of the receiver, which may be as well affected by the ambient conditions. A first serve performance indicator is likely to be a good measure of the overall tennis performance because the first service in tennis is considered as the most important shot. If the first serve is well executed, it provides very large chances to win the point, especially for men (Johnson et al., 2006; Mecheri et al., 2016). Since in serving there is a second chance, the first serve is very often struck with maximum power and taking the maximum risk, in order to force the opponent in a disadvantageous situation and make it more likely to win the point. The double fault rate is another good performance metric, simply because the server loses the point in case of a double fault.

Table 1 reports summary statistics of the variables used in the multivariate statistical analysis. Panel a) focuses on the dependent variables, whilst panel b) on covariates. The first serve made rate, i.e. the fraction of first serves correctly served in the opponent's service box, is equal to 60.9%. The double fault rate, which is the fraction of the served points ending with a point loss due to two faults on the same serve, is about 3.8%. Taken together, since 39.1% of the first serves resulted in a fault, this implies that the fraction of correct second serves is equal to 90.3%. Clearly, there is a big difference in the nature of the first serve and the second serve.[7]

Panel b) of Table 1 shows that the temperature at 3 pm of the day and location of the match was about 20.7°C. On average players were 26.7 years old, 186 cm tall, and left handed in 13.2% of the cases. Only about 16% of the observations are from matches in the last part of the tournament (quarterfinal of more) and about one fourth are from the four Grand Slam tournaments,[8] the most important annual professional tennis tournaments, characterized by offering the most ranking points, rewarding with the highest prize money, and attracting the greatest public and media attention. About one half of the matches were played on hard courts (typically synthetic/acrylic layers on top of a concrete/asphalt base), around 39% on clay, and the remaining 13% on grass. The schedule of the ATP events is such that the outdoor singles matches are well spread over the year, apart from the last quarter (less than 5% of the observations), since in November only the Masters cup is scheduled, which is typically played indoor, and in December no outdoor tournament has been in agenda. Finally, on weekends the smallest number of matches are played (less than 13%), as workdays are typically left for classification rounds and weekends for semifinals and finals.

In order to investigate the unconditional relationship between temperatures and tennis outcomes, we present in Figure 1 the smoothed values of kernel-weighted local third-order polynomial regression of tennis outcomes on temperatures. The graphs are highly suggestive of a strong influence of temperatures on our tennis performance metrics. For temperatures larger than 17°C, the double fault rate steadily increases from 3.5% to about 4.5% at 30°C, while the first serve made rate decreases from 62% to about 59% at 30°C,

[7]From an analysis of data collected at Australian Open matches from 2012 to 2014, Reid et al. (2016) conclude that for men the mean first serve speed was equal to 184 km/h, while the mean second serve speed was equal to 152 km/h.

[8]We included in the category Grand Slam also the 30 matches of the 2003 and 2004 editions of the Masters Cup, because they were exceptionally played outdoor in Houston.

Table 1: Summary statistics

	Mean	Std. Dev.	Min.	Max.
a) Outcome variables				
First serve in rate (%)	60.905	8.160	24.074	100.000
Double fault rate (%)	3.766	2.788	0.000	34.146
b) Covariates				
Temperature (°C)	20.672	4.593	8.871	31.444
Best of 5	0.241	0.427	0.000	1.000
Age (years at tournament start)	26.669	3.945	15.400	43.800
Height (cm)[(a)]	185.975	6.856	168.000	211.000
Left handedness[(a)]	0.132	0.338	0.000	1.000
Difference in players' ranking (absolute value)	69.393	102.623	1.000	1,815.000
Sum in players' ranking	147.468	132.889	3.000	2,646.000
Playing home[(b)]	0.130	0.336	0.000	1.000
Round				
Less than quarterfinal	0.842	0.365	0.000	1.000
Quarterfinal	0.091	0.287	0.000	1.000
Semifinal	0.045	0.206	0.000	1.000
Final	0.022	0.148	0.000	1.000
Tournament series[(c)]				
Grand Slam[(d)]	0.241	0.428	0.000	1.000
ATP 1000	0.228	0.420	0.000	1.000
ATP 500	0.132	0.338	0.000	1.000
ATP 250	0.399	0.490	0.000	1.000
Surface[(c)]				
Grass	0.133	0.340	0.000	1.000
Clay	0.392	0.488	0.000	1.000
Hard	0.475	0.499	0.000	1.000
Quarter				
January-February-March	0.292	0.455	0.000	1.000
April-May-June	0.357	0.479	0.000	1.000
July-August-September	0.308	0.462	0.000	1.000
October-November-December	0.043	0.203	0.000	1.000
Day of the week				
Monday	0.182	0.386	0.000	1.000
Tuesday	0.247	0.431	0.000	1.000
Wednesday	0.187	0.390	0.000	1.000
Thursday	0.148	0.355	0.000	1.000
Friday	0.108	0.311	0.000	1.000
Saturday	0.071	0.257	0.000	1.000
Sunday	0.057	0.231	0.000	1.000
# of observations		76,068		

In the model specification, we also used year indicators, whose summary statistics are not reported for the sake of brevity.

(a) These players' physical characteristics will not be used in models with player fixed effects because they are time constant within players.

(b) The variable 'Playing home' is a dummy indicator equal to 1 if the nationality of the player matches the country where the match is played, 0 otherwise.

(c) These indicators will not be used as covariates in models with tournament fixed effects because they are almost time constant within tournaments.

(d) We included in the category Grand Slam also the 30 matches of the 2003 and 2004 editions of the Masters Cup, which were exceptionally played outdoor in Houston.

a drop of 3 percentage points. In combination this implies that the second serve made rate decreases from 90.8% to 89% at 30°C, a drop of 1.8 percentage points. With a rise of temperatures the first serve pass rate goes down more than the second serve pass rate.

To make the identification of the causal effect of temperatures on tennis outcomes more credible and get rid of eventual omitted variable bias, we estimated a series of models conditional on the set of covariates reported in Table 1 and different combinations of fixed effects (FE) at tournament and year level. In the richest specification, we included the interaction between the year indicators and the tournament indicators. By doing so, we exploit the deviation in the daily temperature from the average temperature in the corresponding tournament edition as plausibly exogenous identifying information. Figure 2 graphically displays this identification source, focusing on 2019 Grand Slam tournaments only for the sake of clarity.

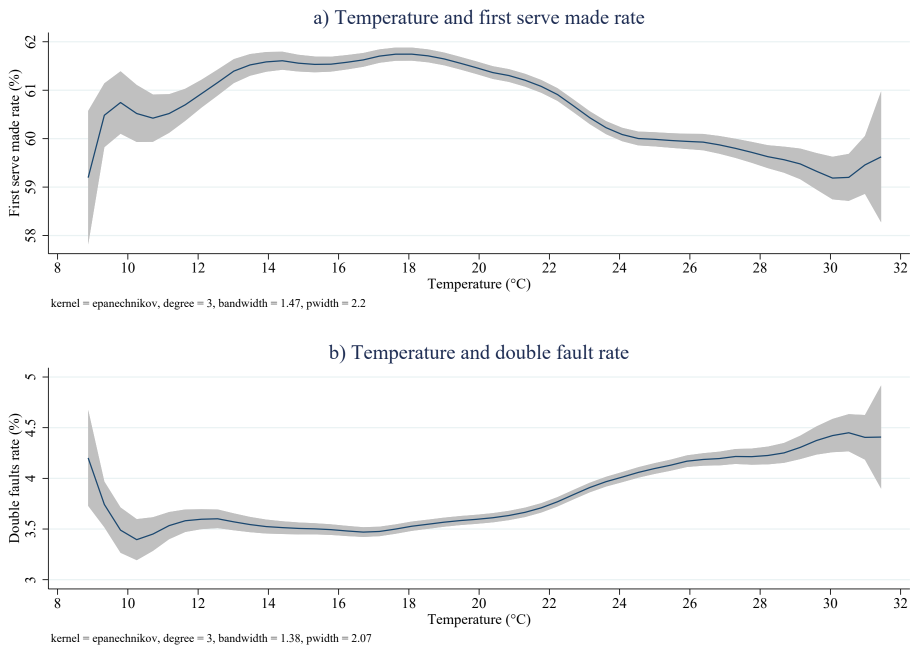
3.2 Empirical strategy

Tennis is a sport that combines various skills and attributes such as technique, tactics, psychological fitness, speed, agility, endurance, strength, balance, flexibility, anticipation and power (Kovacs, 2006). In first serves and second serves, power and accuracy are the main attributes. Gale (1971) and Gerchak and Kilgour (2017) model the difference in behavior between the first and second serve, arguing that, if tennis players want to maximize the probability of winning a point, they take into account that at the second serve the payoff is different from the one at the first serve. Their line of reasoning starts with the second serve. We follow their line of reasoning, but change the modeling assuming that players choose effort to optimize their play.[9]

The player optimizes the power p of his shot. There is a lower bound of $\underline{p}$, since a shot has to have a minimum speed to pass the net, and an upper bound normalized to 1: $\underline{p} \leq p \leq 1$. The more powerful a serve is, the more likely it is that it leads to success either immediately or in the following rally. However, shots with more power are less accurate and players take this into account. Accuracy $a(p)$ is interpreted as the probability that a ball passes the net and lands in the correct service box, with $0 < a(p) < 1$. Accuracy is strictly decreasing in power. Serve performance is assumed to be the product of power and accuracy $P(p) = p \cdot a(p)$. Players maximize serve performance taking into account

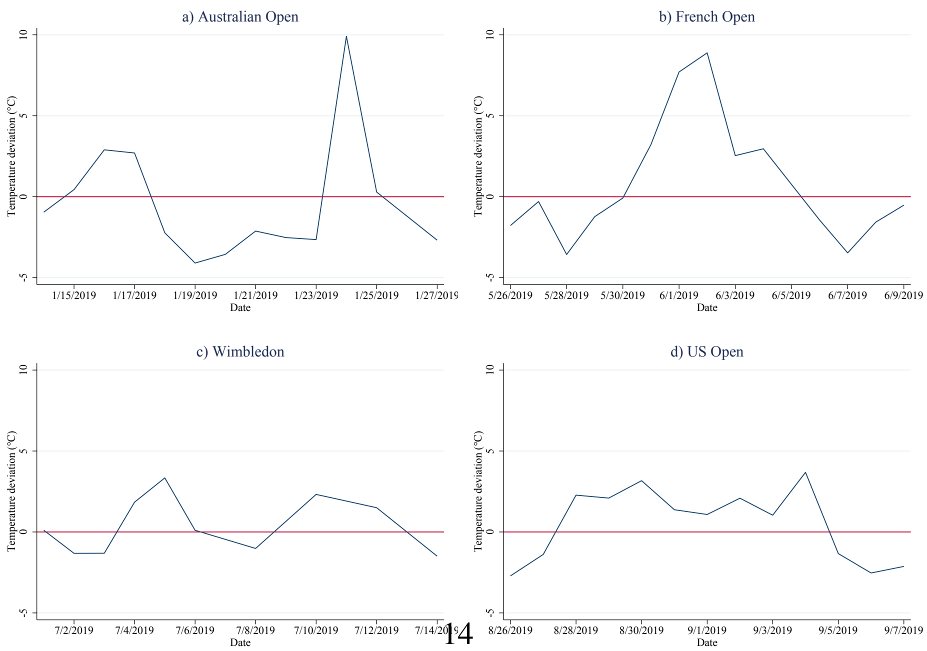
[9] Gale (1971) and Gerchak and Kilgour (2017) assume that the main variable of interest is the probability of having a good serve.

Figure 1: Kernel-weighted local polynomial smoothing of the relation between temperature and tennis performance



Notes: This figure is obtained using 76,068 player-level observations for men and 21,470 for women. The grey areas are 95% confidence intervals.

Figure 2: Temperature deviations from tournament edition mean during 2019 ATP Grand Slams tournaments



that the trade-off between p and $a(p)$ is different for the first and second serve. If players miss the second serve, they indeed lose a point. The optimal second serve that passes the net with power p_2^* is determined by the first order condition of performance P:

$$\frac{\partial[p_2 \cdot a(p_2)]}{\partial p_2} = a(p_2^*) + p_2^* \cdot a'(p_2^*) = 0. \tag{1}$$

At the first serve, players know that missing the serve does not mean losing a point directly, because there is still the second serve. The probability of winning a point at the first serve is equal to $a(p_1)$ but, if the first serve is wrong, there is a second opportunity with probability $[1 - a(p_1)]$. The optimal first serve is determined by the first order condition

$$\frac{\partial\{p_1 \cdot a(p_1) + [1 - a(p_1)] \cdot p_2^* \cdot a(p_2^*)\}}{\partial p_1} = a(p_1^*) + p_1^* \cdot a'(p_1^*) - a'(p_1^*) \cdot p_2^* \cdot a(p_2^*) = 0 \tag{2}$$

Under some regularity conditions, it can be shown that $p_1^* > p_2^*$ and $a(p_1^*) < a(p_2^*)$ (see Gerchak and Kilgour, 2017). This theoretical conclusion is in line with the empirical finding that the first serve is much faster but less accurate than the second one, suggesting that at the first serve power is more important while at the second serve power is reduced in favor of accuracy.[10]

Performance in terms of first serve and second serve is a function of power (effort) and accuracy, both of which may be influenced by temperature. In our analysis, we focus on whether a serve is accurate. Temperature may affect accuracy of a shot both directly and indirectly through the effect on power:

$$a = a[\mathbf{x}, p(\mathbf{x}, temp), temp] \tag{3}$$

where $temp$ is temperature and $\mathbf{x}$ represents characteristics of the match: the importance of the match, economic rewards of winning the match, the quality of the opponent, and so on. Therefore,

$$\frac{\mathrm{d}a}{\mathrm{d}temp} = \frac{\partial a}{\partial p}\frac{\mathrm{d}p}{\mathrm{d}temp} + \frac{\partial a}{\partial temp}. \tag{4}$$

[10] A simple functional form example is: $a(p) = \alpha - \beta p$ with $\alpha > \beta$ and $(\alpha - 1)/\beta \leq p \leq 1$. Then, for the second serve $a(p_2^*) = 0.5\alpha$ and $p_2^* = \alpha/2\beta$, while for the first serve $a(p_1^*) = \alpha^2/4\beta$ and $p_1^* = \alpha/\beta - \alpha^2/4\beta^2$. It is straightforward to show that, with $\alpha = 1.8$ and $\beta = 1.35$, $a(p_1^*)$ = 0.6 and $a(p_2^*)$ = 0.9. Despite the simple functional form, the optimal probabilities are not very different from the empirical probabilities in Table 1, from which we can infer that the probability of a first (second) serve being correct is 60.9% (90.3%).

The effect of temperature on effort is straightforward. The first part of Equation (4) is the indirect effect through the power of the shot. To avoid body overheating, players may reduce effort when temperature goes up. When reducing effort accuracy increases. Therefore, the first part of Equation (4) may be positive. However, the direct effect of temperature on accuracy, the second part of Equation (4), may be negative, because with higher temperatures players may find it more difficult to concentrate. The sum of the two parts are likely negative. There is a clear difference between a first serve and a second serve, since there is more at stake at the second serve. Players are more likely to concentrate despite higher temperature at the second serve. Therefore, the effect of temperature is likely to be stronger at the first serve.

3.3 Modelling tennis performance

The dependent variables in our empirical analysis are related to the accuracy of shots, but they are not perfect measures of accuracy. We use whether or not the first serve is correct and not whether the first serve is accurate. We also use whether the served point results in a double fault. A double fault is indeed an inaccurate shot. In its most general form, we specify the following model for tennis performance y_{imte} of player i, in match date m of tournament t in edition e:

$$y_{imte} = f(temp_{mte}; \boldsymbol{\alpha}) + \boldsymbol{\beta}\mathbf{x}_{imte} + \gamma_{te} + \delta_i + \varepsilon_{imte}, \tag{5}$$

where $\mathbf{x}_{imte}$ is the set of explanatory variables shown in Table 1;[11] γ_{te} are tournament-edition FE, obtained by the interaction among tournament indicators and edition (year) indicators; δ_i are player FE; $f(temp_{imte}; \boldsymbol{\alpha})$ is a function of the temperature registered at 3 pm of the day of the match in the tournament location; finally ε_{imte} is an idiosyncratic error term.

We tried with different specifications of the function $f(temp_{imte}; \boldsymbol{\alpha})$: a linear specification (i.e. $\alpha \times temp_{imte}$); a continuous spline function with the first knot at 14°C, one further knot each 2°C, and the last knot at 28°C; with a step function after dividing the support of the temperature in equally sized bins of two Celsius degrees, apart from the

[11] When we estimate the tennis performance equation in its most general specification as described by Equation (5), we do not include player's physical characteristics (height, and left-handedness), because of collinearity with the player FE, and the tournament series and surface, because of collinearity with the tournament-edition FE.

first bin for daily temperatures below 14°C, and the last one for those above 28°C.[12]

The player FE δ_i purges the estimates from spurious components induced by player's characteristics which may affect tennis performance and, at the same time, be correlated to the ambient temperatures. For example, there may be players who anticipate that their performance will suffer hot temperatures and therefore avoid to play in tournaments which usually are characterized by heat waves.

The tournament-edition FE γ_{te} controls for features which are unique to a particular tournament edition and, as such, not only capture the tournament FE, but also their evolution over time. For example, the Australian Open is the first of the four Grand Slams and it is annually played from the middle of January in Melbourne. Being one of the four most important tennis tournaments, with one of the highest prizes and public attention, players' performances may be systematically different from those in less relevant tournaments. This fixed effect may however vary over time. The Australian Open has indeed an extreme heat policy, which has changed over years, depending on the problems generated by the heat waves and the application of the heat policy. The Australian Open extreme heat policy is an example of a time-varying fixed effect at tournament level which may be correlated to the temperatures typical of Melbourne and players' performances. Hence, the inclusion of the tournament-edition FE allows us to purge the estimates from this kind of potential omitted variables.

Thanks to the inclusion of tournament-edition FE, we base the identification of the causal effect on the deviation of the temperature of a match of tournament t in edition e from the average temperature registered during the same tournament edition. This short-term variability is plausibly exogenous with respect to eventual omitted covariates determining tennis performances. The estimation of Equation (5) by Ordinary Least Squares (OLS) is indeed equivalent to estimating by OLS a modified model in which all the variables are subtracted their within tournament-edition mean.[13]

Finally, the idiosyncratic error term may be correlated across observations, especially within tournament t and player i. The former correlation may be due to the fact that, when there are anomalous heat waves, they may last for several days and affect several matches of the same tournament. Moreover, each tournament has its own features, like

[12]In the step function specification we chose the bin for temperatures below 14°C as the reference point and the corresponding indicator variable is excluded from the set of regressors entering Equation (5).

[13]Furthermore, estimating Equation (5) by OLS is equivalent to estimating by two stage least squares (2SLS) a modified model without tournament-edition FE and where each regressor is instrumented by its own within tournament-edition mean.

the surface or the attendance figures which may affect players' performances. About the latter correlation, each player has his own style of playing and strengths/weaknesses, generating within-player correlation in terms of performances. This makes us suspect that observations are not independent within tournaments and players. Hence, in estimating the variance-covariance matrix, we use the two-way cluster-robust variance estimator proposed by Cameron et al. (2011), with clusters at tournament and player levels. The number of clusters is sufficiently large in both dimensions, since in our sample we have 88 different tournaments and 1,061 different players.

4 Results

4.1 Main results

Table 2 shows the main parameter estimates of Equation (5). In columns (1) and (2) player fixed effects are included, in columns (3) and (4) they are not included. The parameter estimates for the first serve made rate presented in column (1) show that temperature has a significant negative effect. Column (2) shows that temperature has a significant positive effect on the double fault rate. A temperature rise of 1°C decreases the first serve made rate by 0.1 percentage points. Similarly, the double fault rate is increased by 0.04 percentage points for each rise in temperature of 1°C. This implies that a rise in temperature of 1°C reduces the second serve pass rate with 0.07 percentage points. As expected, temperature has a bigger effect on the first serve than on the second serve. Comparing the parameter estimates of the temperature effects in columns (1) and (2) with those in columns (3) and (4) it is clear that including or ignoring player fixed effects is not important. In Equation (5) temperature is assumed to have a linear effect. Figure 3a shows that the effect of temperature on the first serve made rate by using temperature intervals; Figure 3b does the same for the double fault rate. Clearly, the temperature effects on both performance indicators is close to being linear.[14] Figure 3c and Figure 3d show that this is also the case if no player fixed effects are included in the analysis.

[14]After the estimation of the models with continuous spline specification of the temperature function, we tested whether the slope changes at the different knots were significantly different from zero, by both joint and single Wald statistics. In all the models and for all the dependent variables used, we were never able to reject the null hypothesis, suggesting that the linear specification cannot be rejected in favor of a more general nonlinear functional form. Hence, in the following tables we report estimation results for the linear specification of the temperature function.

The remaining parameter estimates in Table 2 give an indication on the effects of personal characteristics of the player, the strength of the opponent, the stage in the tournament, the quarter of the year and the day of the week on the two performance indicators. Age has a predominantly negative but non-linear effect on the first serve made rate and a positive non-linear effect on the double fault rate.[15] As players grow older the effect of age becomes stronger. The difference in ranking between two players also has a significant effect on performance. The more the match is uneven, i.e. the absolute value of the difference in the ATP ranking is larger, the lower is the serving performance (the first serve made rate is smaller and the double fault rate is bigger). This may be explained by players putting less effort in the match if the match is uneven. Because of the empirical finding that the overall quality of the match may be important too (Klaassen and Magnus, 2001), we also included the sum of the players' rankings as explanatory variable. In higher quality matches, i.e. with a smaller sum of the rankings, the first serve made rate is significantly lower and the double fault rate is significantly higher. We also investigated whether there is a home advantage in tennis (see Koning, 2011) and find some weak evidence. The first serve made rate is no different for players who play in their native country or for foreign players. There is, however, an effect on the double fault rate (significant at 10%). Players who play in their home country have a smaller double fault rate. Apparently, effort is the same but accuracy is somewhat affected by playing at home. Of course, it could be that the main effect of home advantage is present in the rallies and not so much at the first or second serve. The first serve made rate is not significantly affected by the stage of the tournament, the quarter of the year or the day of the week. This is different for the double fault rate which is less likely to occur in the finals of tournaments and in the period April to September and more likely to occur on Mondays and Tuesdays.

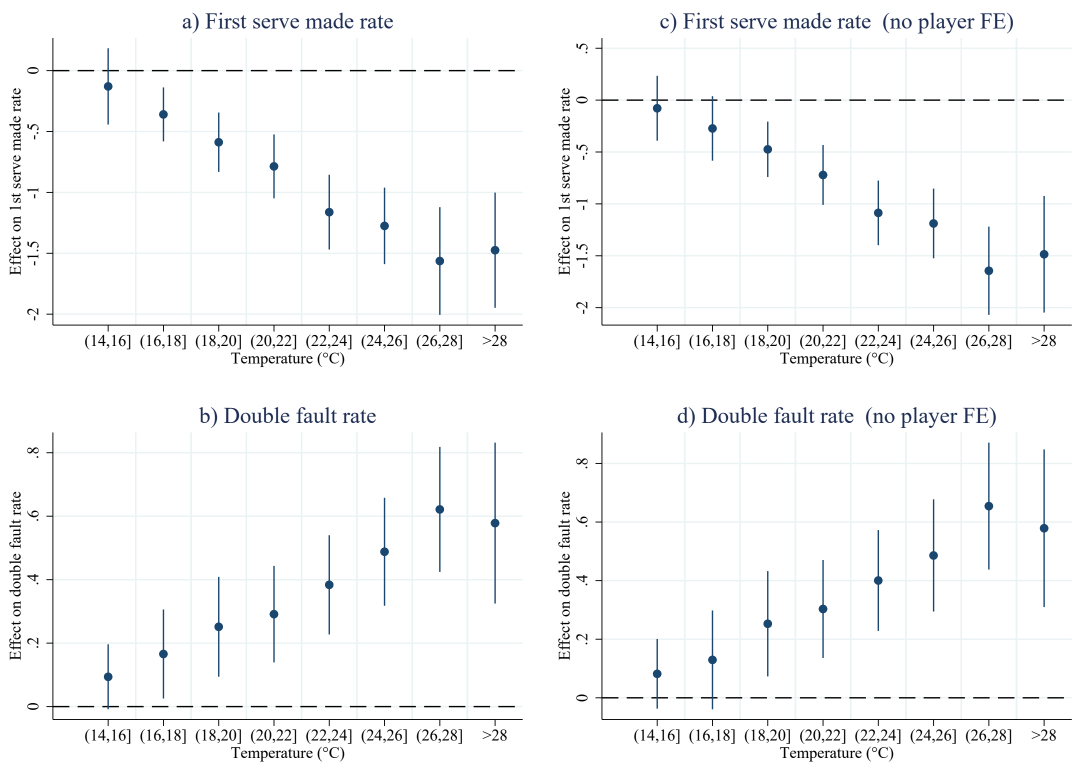
The results from Table 2 are clear in terms of the temperature effects on performance of tennis players. The performance drops with increasing temperatures. As a check on the robustness of our main findings, we investigated the relationship between indoor performance and outdoor temperatures. Whereas in some circumstances outdoor temperatures may affect indoor productivity even with climate control, this is unlikely to be the case in professional tennis matches. Indeed, as shown in Appendix A, we find no relationship between outdoor temperatures and indoor performance.

[15] We can identify the age impact after including tournament-edition and player FE because age is measured at the beginning of the tournament and tournaments start in different days (sometimes in different weeks and, more rarely, in different months) over the years.

To further investigate the robustness of our main findings to the specification of Equation (5), we redid all the estimates using the natural logarithm of the first serve made rate and the double fault rate as dependent variables. As the results in Table B.1 and Figure B.1 show, the conclusions are very much the same.

We also investigate whether the relationship between temperature and performance is restricted to within-tournament variation in temperature. For this, we related average performance over a specific tournament, conditional on the quality of the participating players, to average temperature in that tournament. As shown in Table B.2 of Appendix B, we find that first serve pass rates are unaffected by temperature differences but double fault rates increase with temperature. This suggests that there is some evidence of a negative temperature effect on work-related activities which goes beyond short-run fluctuations.

Figure 3: Non linear effect of temperatures on tennis performances, with tournament-edition and player FE (graphs a)-b)) and only tournament-edition FE (graphs c)-d))



The estimation results of the parameters of the other regressors are available from the authors upon request. They are very close to those reported in Table 2.

Table 2: Estimation results of tennis performance Equation (5)

Dependent variable:	(1) First serve made rate (%) Coeff. (Std. Err.)	(2) Double fault rate (%) Coeff. (Std. Err.)	(3) First serve made rate (%) Coeff. (Std. Err.)	(4) Double fault rate (%) Coeff. (Std. Err.)
	With tournament-edition and player FE		*With only tournament-edition FE*	
Temperature at 3 pm (°C)	-0.1058***	0.0395***	-0.1091***	0.0412***
	(0.0139)	(0.0061)	(0.0145)	(0.0063)
Best of 5 sets	-0.3705	0.1287	-0.3048	0.2442
	(0.4295)	(0.2532)	(0.4659)	(0.1894)
Age (years)	0.6407**	-0.1215	0.4317	-0.1586
	(0.2637)	(0.0743)	(0.3547)	(0.0962)
Age squared	-0.0192***	0.0055***	-0.0080	0.0027
	(0.0047)	(0.0013)	(0.0065)	(0.0018)
Ranking difference[(a)]	-0.3257***	0.0656***	0.0161	-0.0404
	(0.0742)	(0.0229)	(0.1472)	(0.0436)
Ranking sum/100	0.4232***	-0.0636***	0.0116	0.0783*
	(0.0724)	(0.0220)	(0.1507)	(0.0437)
Home advantage	0.0475	-0.0629*	-0.0681	-0.0722
	(0.1316)	(0.0351)	(0.3810)	(0.0957)
Height (cm)			0.0348	0.0159*
			(0.0405)	(0.0085)
Left-handedness			1.8479**	0.1319
			(0.7818)	(0.1924)
Round - Reference: Before quarterfinal				
Quarterfinal	0.5818***	-0.1424***	0.9856***	-0.2679***
	(0.1600)	(0.0427)	(0.2136)	(0.0613)
Semifinal	0.7628***	-0.2845***	1.3994***	-0.4633***
	(0.2326)	(0.0684)	(0.2848)	(0.0870)
Final	1.0733***	-0.3383***	2.0237***	-0.6058***
	(0.3697)	(0.1015)	(0.4247)	(0.1234)
Quarter - Reference: January-February-March				
April-May-June	0.7261	-0.2559***	1.5755***	-0.3937**
	(0.4533)	(0.0925)	(0.2860)	(0.1579)
July-August-September	-0.1378	-0.2489**	0.9545**	-0.5514***
	(0.5357)	(0.1068)	(0.4740)	(0.1564)
October-November-December	-0.2855	-0.0912	0.7107	-0.4262**
	(0.6442)	(0.1593)	(0.7606)	(0.1979)
Day of the week - Reference: Sunday				
Monday	-0.2498	0.1893**	-0.3204	0.2292**
	(0.2152)	(0.0890)	(0.2660)	(0.0989)
Tuesday	-0.1164	0.1678*	-0.0322	0.1898*
	(0.2317)	(0.0896)	(0.2910)	(0.0974)
Wednesday	0.2895	0.0134	0.3309	0.0218
	(0.2354)	(0.0862)	(0.2917)	(0.0947)
Thursday	0.2521	-0.0233	0.3652	-0.0301
	(0.2324)	(0.0945)	(0.3005)	(0.1030)
Friday	0.3056	-0.0614	0.2703	-0.0397
	(0.2051)	(0.0831)	(0.2892)	(0.0968)
Saturday	0.2305	-0.0161	0.2402	0.0016
	(0.2447)	(0.0952)	(0.2890)	(0.1037)
# of observations[(b)]	75,922	75,922	76,068	76,068
# of players[(b)]	915	915	1,061	1,061
# of tournaments	88	88	88	88
Adjusted R^2	0.2794	0.1984	0.0791	0.0748
Player FE	Yes	Yes	No	No
Tournament-edition FE	Yes	Yes	Yes	Yes

* p-value$<$0.10, ** p-value$<$0.05, *** p-value$<$0.01. Two-way clustered standard errors are in parenthesis; clusters are at the level of tournaments and players. In the continuous spline specifications of the temperature function, the Wald test for the joint significance of the slope changes at the different knots returned p-values equal to 0.8474 for Model (1), 0.0615 for Model (2), 0.7776 for Model (3), and 0.1390 for Model (4).

[(a)] The ranking difference is the absolute value of the difference in the ATP rankings divided by 100.

[(b)] The number of observations are smaller when estimating the model with player FE because 146 players in Models (1) and (2) were removed from the sample because they had only one observation (singleton observations).

4.2 Effect heterogeneity

To investigate potential heterogeneity of the temperature effect on performance, we did a range of sensitivity analyses of which the main parameters are presented in Table 3.

Tennis can be played on various surfaces. The way the ball moves on a surface influences the game and a good player takes this into account when competing or planning a strategy. Hard courts, clay and grass are the three main types of surface on which professional tennis is played. The type of surface determines how fast a game is played (Martin and Prioux, 2016). Grass is the fastest court on which the ball bounces less high and there is less loss of horizontal velocity when the ball hits the surface. A clay court has a slow surface inducing a higher bounce. Hard courts are in between grass and clay in terms of speed of play. Tennis activity consists of alternating periods of high-intensity and low-intensity exercise. Fitzpatrick et al. (2019) relate grass and clay tennis court surfaces to performance of the players. Service is most dominant on grass and least dominant on clay. Rallies, i.e. the number of times a ball is hit before a point is scored, last longest on clay. Therefore, tennis play on clay courts is most tiring and it may be that any effect of temperature on performance is more likely to occur on these courts. This could be more so since clay courts absorb and retain heat more than other surfaces. Panel a of Table 3 shows that the effects of temperature on performance is stronger on clay courts. The first serve rate made drops more with temperature on clay courts than it does on hard courts or grass. However, the difference in temperature effects is not significant. For the double fault rate there is a significant difference (at a 10%-level). The double fault rate goes up stronger with temperature on clay courts than it does on hard courts or grass.

The potential rewards of winning may affect the relationship between effort and temperature. As indicated before, Park (2022) argues that the effect of temperature on performance is less likely to be negative if the stakes are high enough to override the direct disutility cost of putting in extra effort. Although the first service made rates do not seem to be affected by the stage of the tournament, it could still be that the effect of temperature on performance depends on the stage of a tournament. For the relationship between temperature and performance in tennis, this could imply that the effect of heat depends on the type of match being played. With a lot at stake, tennis players may be able to play more precisely despite high temperatures than they would if there were less at stake. Panel b of Table 3 shows that there is no difference in temperature effects on performance between Grand Slam tournaments and non-Grand Slam tournaments. Panel c of Table 3 shows that the successful first serve rates decline stronger with temperature when there is less at stake. The temperature gradient is twice as strong before the quarterfinals than it is in quarterfinals or later. Taken together the results in panels b and c suggest that it is not the nature of the tournament that matters but what is at stake in a tournament. When there is more at stake, temperature still has a negative effect on the first serve pass rate, but the players are more able to be precise.

Panel d shows that the quality of a player affects the temperature effect on the first serve made rate but not the double fault rate. The temperature effect is stronger for players who are not in the 50 ATP ranking than for players who are in the 50 ATP ranking (significant at a 10% level). Top players are skillful and therefore more able to compensate for high temperatures.

Panel e shows that the way temperature affects performance in terms of the first serve made is age-specific. Young players are less severely affected by higher temperatures than older players are. Perhaps, they are physically better able to deal with high temperatures such that their accuracy does not suffer too much. For the double fault rate there is no age-specific temperature gradient. Apparently, when it matters more, older players can handle high temperature as well as younger players.

Panel f of Table 3 shows the effect of temperature on performance distinguishing between the difference in ATP ranking between the two players. There is no difference in the temperature-gradient if players have a small or a large difference in ATP ranking. In the intermediate range apparently there is no significant negative effect of temperature on performance.

Panel g of Table 3 gives separate estimates for home players and away players. As shown for the first serve made rate, there is no difference in the temperature effect. The effect of temperature on the double fault rate is larger for away players than it is for home players, although the difference is not statistically significant.

4.3 Accumulation and adaptation

The empirical analysis conducted so far has only addressed the contemporaneous effect of temperature exposure. It has not accounted yet for the potentially dynamic relation between temperature and performance. Nevertheless, extreme temperature exposure may accumulate over time or may have an effect in subsequent matches. High temperatures generate larger risks of exhaustion, higher physical and mental stress (Heal and Park,

Table 3: Effect heterogeneity

Dependent variable:	(1) First serve made rate (%) Coeff. (Std. Err.)	(2) Double fault rate (%) Coeff. (Std. Err.)
a. Effect by surface		
Temperature at 3 pm (°C) on clay	-0.1259***	0.0517***
	(0.0167)	(0.0058)
Temperature at 3 pm (°C) on hard of grass	-0.0904***	0.0301***
	(0.0172)	(0.0098)
Wald test of equality of coefficients, p-value=	0.1424	0.0551
b. Effect by tournament series		
Temperature at 3 pm (°C) in Grand Slam tournaments	-0.1071***	0.0482***
	(0.0250)	(0.0087)
Temperature at 3 pm (°C) in non Grand Slam tournaments	-0.1051***	0.0348***
	(0.0168)	(0.0075)
Wald test of equality of coefficients, p-value=	0.9494	0.2404
c. Effect by tournament round		
Temperature at 3 pm (°C) before quarterfinals	-0.1160***	0.0406***
	(0.0150)	(0.0065)
Temperature at 3 pm (°C) in quarterfinals or later	-0.0600***	0.0348***
	(0.0221)	(0.0078)
Wald test of equality of coefficients, p-value=	0.0116	0.4542
d. Effect by player's ranking		
Temperature at 3 pm (°C), players in the 50 ATP ranking	-0.0886***	0.0392***
	(0.0113)	(0.0053)
Temperature at 3 pm (°C), players not in the 50 ATP ranking	-0.1220***	0.0399***
	(0.0195)	(0.0084)
Wald test of equality of coefficients, p-value=	0.0538	0.9186
e. Effect by age		
Temperature at 3 pm (°C), age < 25	-0.0883***	0.0414***
	(0.0163)	(0.0069)
Temperature at 3 pm (°C), $25 \leq$ age < 29	-0.1044***	0.0401***
	(0.0172)	(0.0071)
Temperature at 3 pm (°C), age ≥ 29	-0.1294***	0.0363***
	(0.0172)	(0.0064)
Wald test of equality of coefficients, p-value=	0.0254	0.6383
f. Effect by difference in the ATP ranking[(a)]		
Temperature at 3 pm (°C), difference in the ATP ranking ≤ 25	-0.1081***	0.0429***
	(0.0162)	(0.0056)
Temperature at 3 pm (°C), $25 <$ difference in the ATP ranking < 63	-0.0131	-0.0036
	(0.0117)	(0.0051)
Temperature at 3 pm (°C), difference in the ATP ranking ≥ 63	-0.0980***	0.0397***
	(0.0156)	(0.0063)
Wald test of equality of coefficients, p-value=	0.0001	0.0000
g. Effect on home advantage		
Temperature at 3 pm (°C), home players	-0.1077***	0.0347***
	(0.0212)	(0.0066)
Temperature at 3 pm (°C), away players	-0.1055***	0.0403***
	(0.0152)	(0.0064)
Wald test of equality of coefficients, p-value=	0.9284	0.3572

* p-value<0.10, ** p-value<0.05, *** p-value<0.01. Two-way clustered standard errors are in parenthesis; clusters are at the level of tournaments and players. The number of observations is 75,922 from 915 players and 88 tournaments.

[(a)] The 33rd and 66th percentiles of the difference in the ATP ranking are 25 and 62.

2016) and greater energy usage (Deschênes and Greenstone, 2011), which may slow down both physical and mental recovery between matches and therefore have a lagged effect on the performance at the next match. To dig into this issue, we modified the baseline model and, in the same spirit as in Deschênes and Moretti (2009), we estimated by OLS the following equation

$$y_{imte} = \alpha_0 temp_{mte} + \alpha_1 temp_{m-1te} + \boldsymbol{\beta}\mathbf{x}_{imte} + \gamma_{te} + \delta_i + \varepsilon_{imte}, \quad (6)$$

where α_0 is the temperature effect in current match m and α_1 is the effect of temperature experienced by the same player in the previous round of the same tournament. This dynamic structure is highly demanding in terms of observations, because we disregard all the matches played in the first round of each tournament. It also generates sample selectivity, because it reduces the sample only to those players who were able to win the first match of each tournament. For these reasons, we do not present results with richer specifications of the dynamic.[16] By summing the α's, we obtain the cumulative effect of having one more Celsius degree in the current and previous match.

Table 4 shows the results of this accumulation exercise. We find that the temperature coefficient in the previous match does not reinforce the temperature effect in the current match. We do not find therefore evidence of accumulation. In fact, we find that higher temperatures in the previous game tend to mitigate the negative impact on performance of the temperatures in the current game, which is a sign of short-term adaptation and acclimation to heat.

In addition, we investigated acclimation with two exercises, finding no statistically significant results. First, we interacted the temperature effect with the average temperature in the previous 7 days of the tournament. The number of observations shrank to 2,613, with relevant loss of statistical power which may justify the lack of significance. Second, we run a further heterogeneity analysis after splitting players into two groups according to the long-term weather condition of the country of their nationality. The hypothesis was that specific populations may have physical and mental adaptation capabilities. In one group we included players from the coldest countries, i.e. in climatic zone I of the ICH Stability Climatic Zone classification (WHO, 2009). We considered all the remaining players in the other group. We find that the temperature effect is statistically the same in the two groups and does not depend on players coming from colder countries.

[16] We tried with the lag of order 2. The associated coefficient was not significantly different from zero.

Table 4: Cumulative dynamic estimates of temperature effect on tennis performance

	(1)	(2)
Dependent variable:	First serve made rate (%)	Double fault rate (%)
	Coeff.	Coeff.
	(Std. Err.)	(Std. Err.)
Current temperature (°C), $\widehat{\alpha}_0$	-0.1112***	0.0398***
	(0.0212)	(0.0059)
Temperature in the previous match (°C) , $\widehat{\alpha}_1$	0.0380**	-0.0104**
	(0.0156)	(0.0052)
$\widehat{\alpha}_0 + \widehat{\alpha}_1$	-0.0732***	0.0294***
	(0.0253)	(0.0074)
Joint significance test $\alpha_0 = \alpha_1 = 0$, p-value=	0.0000	0.0000
# of observations	36,464	36,464
# of players	647	647
# of tournaments	87	87
Adjusted R^2	0.3000	0.1983

* p-value<0.10, ** p-value<0.05, *** p-value<0.01. Two-way clustered standard errors are in parenthesis; clusters are at the level of tournaments and players. The estimated equation includes also player FE, tournament-edition FE and all the covariates as in the baseline model.

5 Conclusions

Human beings have a thermal comfort zone with temperatures between 18 and 24°C (64-75°F). Outside this comfort zone, in particular high temperatures, have a negative effect on work-related activities. Previous studies have shown that high outdoor temperatures have a negative effect on the quality of decision-making of immigration judges, test scores of students doing an exam, productivity of factory workers and performance of athletes. Whereas with high temperatures for indoor work-related activities climate control can be an option, this is not the case for outdoor activities. Labor productivity of workers may go down because of negative effects on mental or physical health. Workers may experience difficulties to concentrate when it is hot or have to reduce effort in order to copy with heat.

We added to the literature on the relationship between temperature and work-related activities a study based on sports data. We investigated how fluctuations in temperature affect performance of male professional tennis players. We did not study the effect of high temperatures on match outcomes. After all, both players may be affected by high temperatures and therefore these may not determine who wins a match. We focused on two measures of individual performance: first serve made rates and double fault rates. First serves and second serves differ from each other in input in terms of effort and accuracy.

If the first serve fails, there is the option of a second serve. Therefore, at the first serve power is more important and accuracy is less relevant. At the second serve, the server wants to avoid losing a point and, to increase accuracy, power is reduced. We hypothesize that high temperatures affect the first serve more because at the second serve there is more at stake.

We used data about outdoor male singles tennis matches from 2003 until 2021. Our identification strategy relied on the plausible exogeneity of short-term daily temperature variations in a given tournament from the average temperature over the same tournament. We found that performance significantly decreases with ambient temperature. A higher temperature had a negative effect on first serve made rates and a positive effect on double fault rates. A temperature increase by 1°C decreased the first serve made rate by 0.10 percentage points and increased the double fault rate by 0.04 percentage points. This is equivalent to a reduction in the successful second serve rate by 0.07 percentage points. So, the effect of temperature was larger at the first serve, when there is less at stake. We investigated the heterogeneity of the temperature effects, but we found that these effects were generally present across the board with the age and skills of the player as the main exception. Older and less skillful players suffered more from high temperatures than younger and more skilled players do. Furthermore, we found that the effect of high temperatures on performance was smaller when in the match there was more at stake, because it was later on in the tournament.

As a counterfactual we related outdoor temperatures to performance at indoor tennis matches finding no effect. We also investigated whether temperature effects accumulated and we analyzed whether there were adaptation effects. By using information about temperatures in previous matches in the same tournament, we found lagged temperatures to have a positive effect on performance, thereby reducing the effect of current temperatures. This suggests that there is short-term adaptation to high temperatures. Finally, we investigated whether temperature effects were short-term restricted to within tournament effects. We found that temperature differences between tournaments affected double fault rates but not first serve made rates. This suggests that there is some evidence of longer term negative temperature effects on work-related activities.

When it comes to using sports data, a natural question concerns external validity. In our case, the question is to what extent our main findings about professional tennis have external validity to regular work-related activities. Playing professional tennis requires a combination of intense physical activity and mental focus. The intense physical activity will rarely be met in regular work-related activities, but the tennis player will most likely be much more physically fit than a regular worker. Therefore, the relative input in physical activities may well be comparable to workers in regular jobs. The mental focus is required also in regular work-related activities to ensure a high labor productivity. We think that professional tennis play is comparable to regular work-related activities that require physical input and mental focus in an environment in which climate control activities are absent or too costly to implement. Agriculture and construction are example of industries where climate control is largely absent. In manufacturing industries climate control is possible but not always easy or very costly to implement.

Our main conclusion from our study is that high temperatures have a negative effect on workplace productivity in terms of the precision of the work. The magnitude of this negative effect depends on characteristics of the workers and the nature of the work activity. We found that the labor productivity of older and less-skilled workers is more affected by high temperatures. We also found that when there is more at stake, i.e. when a mistake has more serious consequences, workers are better able to deal with high temperatures. In these circumstances, there is still a negative temperature effect, but the magnitude of the effect is smaller. Finally, we found evidence of adaptation: when temperatures are high over a longer time period, the negative workplace performance effects are smaller than they are in the short run.

References

Adhvaryu, A., N. Kala, and A. Nyshadham (2020). The light and the heat: Productivity co-benefits of energy-saving technology. *The Review of Economics and Statistics 102*(4), 779–792.

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. S. Shapiro (2016). Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy 124*(1), 105–159.

Baylis, P. (2020). Temperature and temperament: Evidence from Twitter. *Journal of Public Economics 184*, 104161.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Global non-linear effect of temperature on economic production. *Nature 527*(7577), 235–239.

Callahan, C. W., N. J. Dominy, J. M. DeSilva, and J. S. Mankin (2023). Global warming, home runs, and the future of America's pastime. *Bulletin of the American Meteorological Society 104*, E1006–E1016.

Cameron, A., J. Gelbach, and D. Miller (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics 29*(2), 238–249.

Colacito, R., B. Hoffmann, and T. Phan (2019). Temperature and growth: A panel analysis of the United States. *Journal of Money, Credit and Banking 51*(2-3), 313–368.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature 52*(3), 740–98.

Deschênes, O. and M. Greenstone (2011). Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics 3*(4), 152–185.

Deschênes, O. and E. Moretti (2009). Extreme weather events, mortality, and migration. *The Review of Economics and Statistics 91*(4), 659–681.

Dillender, M. (2021). Climate change and occupational health. *Journal of Human Resources 56*(1), 184–224.

Fesselmeyer, E. (2021). The impact of temperature on labor quality: Umpire accuracy in Major League Baseball. *Southern Economic Journal 88*(2), 545–567.

Filomena, M. and M. Picchio (2022). Unsafe temperatures, unsafe jobs: The impact of ambient temperatures on work related injuries. Working Paper No. 472, Department of Economics and Social Sciences, Marche Polytechnic University, Ancona, Italy.

Fitzpatrick, A., J. A. Stone, S. Choppin, and J. Kelley (2019). Important performance characteristics in elite clay and grass court tennis match-play. *International Journal of Performance Analysis in Sport 19*(6), 942–952.

Gale, D. (1971). Optimal strategy for serving in tennis. *Mathematics Magazine 44*(4), 197–199.

Gerchak, Y. and D. M. Kilgour (2017). Serving strategy in tennis: Accuracy versus power. *Mathematics Magazine 90*(3), 188–196.

Graff Zivin, J., S. M. Hsiang, and M. Neidell (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists 5*(1), 77–105.

Graff Zivin, J. and M. Neidell (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics 32*(1), 1–26.

Heal, G. and J. Park (2016). Reflections—temperature stress and the direct impact of climate change: A review of an emerging literature. *Review of Environmental Economics and Policy 10*(2), 347–362.

Heyes, A. and S. Saberian (2019). Temperature and decisions: Evidence from 207,000 court cases. *American Economic Journal: Applied Economics 11*(2), 238–265.

Hoffmann, R., L. C. Ging, and B. Ramasamy (2002a). Public policy and Olympic success. *Applied Economics Letters 9*(8), 545–548.

Hoffmann, R., L. C. Ging, and B. Ramasamy (2002b). The socio-economic determinants of international soccer performance. *Journal of Applied Economics 5*(2), 253–272.

Johnson, C., M. McHugh, T. Wood, and B. Kibler (2006). Performance demands of professional male tennis players. *British Journal of Sports Medicine 40*(8), 696–699.

Kalkuhl, M. and L. Wenz (2020). The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management 103*, 102360.

Klaassen, F. J. G. M. and J. R. Magnus (2001). Are points in tennis independent and identically distributed? Evidence from a dynamic binary panel data model. *Journal of the American Statistical Association 96*(454), 500–509.

Koning, R. H. (2011). Home advantage in professional tennis. *Journal of Sports Sciences 29*(1), 19–27.

Kovacs, M. S. (2006). Applied physiology of tennis performance. *British Journal of Sports Medicine 40*(5), 381–386.

Kovacs, M. S. (2007). Tennis physiology: Training the competitive athlete. *Sports Medicine 37*(3), 189–198.

Larrick, R. P., T. A. Timmerman, A. M. Carton, and J. Abrevaya (2011). Temper, temperature, and temptation: Heat-related retaliation in baseball. *Psychological Science 22*(4), 423–428.

Lee, J. J., F. Gino, and B. R. Staats (2014). Rainmakers: Why bad weather means good productivity. *The Journal of Applied Psychology 99*(3), 504—513.

LoPalo, M. (2023). Temperature, worker productivity, and adaptation: Evidence from survey data production. *American Economic Journal: Applied Economics 15*(1), 192–229.

Martin, C. and J. Prioux (2016). Tennis playing surfaces: The effects on performance and injuries. *Journal of Medicine and Science in Tennis 21*(1), 11–18.

Mathers, J. F. (2017). Professional tennis on the ATP tour: A case study of mental skills support. *The Sport Psychologist 31*(2), 187–198.

Mecheri, S., F. Rioult, B. Mantel, F. Kauffmann, and N. Benguigui (2016). The serve impact in tennis: First large-scale study of big Hawk-Eye data. *Statistical Analysis and Data Mining: The ASA Data Science Journal 9*(5), 310–325.

Moscona, J. and K. A. Sastry (2023). Does directed innovation mitigate climate damage? Evidence from U.S. agriculture. *Quarterly Journal of Economics 138*(3), 637–701.

Mullins, J. T. (2018). Ambient air pollution and human performance: Contemporaneous and acclimatization effects of ozone exposure on athletic performance. *Health Economics 27*, 1189–1200.

Mullins, J. T. and C. White (2019). Temperature and mental health: Evidence from the spectrum of mental health outcomes. *Journal of Health Economics 68*, 102240.

Muñoz Saba ter, J. (2019). Era5-land hourly data from 1981 to present. Climate Data Store (CDS). Accessed on November 2022, 10.24381/cds.e2161bac.

O'Donoghue, P. and B. Ingram (2001). A notational analysis of elite tennis strategy. *Journal of Sports Sciences 19*(2), 107–115.

Ormandy, D. and V. Ezratty (2012). Health and thermal comfort: From WHO guidance to housing strategies. *Energy Policy 49*, 116–121.

Palacios-Huerta, I. (2023). The beautiful dataset. *Journal of Economic Literature*, fortcoming.

Park, R., N. Pankratz, and A. Beher (2021). Temperature, workplace safety, and labor market inequality. IZA Discussion Paper No. 14560, IZA Institute of Labor Economics, Bonn, Germany.

Park, R. J. (2022). Hot temperature and high stake exams: Evidence from New York City public schools. *Journal of Human Resources 57*(2), 400–434.

Park, R. J., A. P. Behrer, and J. Goodman (2021). Learning is inhibited by heat exposure, both internationally and within the United States. *Nature Human Behaviour 5*, 19–27.

Park, R. J., J. Goodman, M. Hurwitz, and J. Smith (2020). Heat and learning. *American Economic Journal: Economic Policy 12*(2), 306–339.

Reid, M., S. Morgan, and D. Whiteside (2016). Matchplay characteristics of Grand Slam tennis: Implications for training and conditioning. *Journal of Sports Sciences 34*(19), 1791–1798.

Sexton, S., Z. Wang, and J. T. Mullins (2022). Heat adaptation and human performance in a warming climate. *Journal of the Association of Environmental and Resource Economists 9*(1), 141–163.

Smith, M. T., M. Reid, S. Kovalchik, T. Wood, and R. Duffield (2018). Heat stress incidence and matchplay characteristics in Women's Grand Slam Tennis. *Journal of Science and Medicine in Sport 21*, 666–670.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy 129*(6), 1797–1827.

WHO (2009). 43rd report of the who expert committee on specifications for pharmaceutical preparations. WHO Technical Report Series No. 953, WHO Press, Geneva.

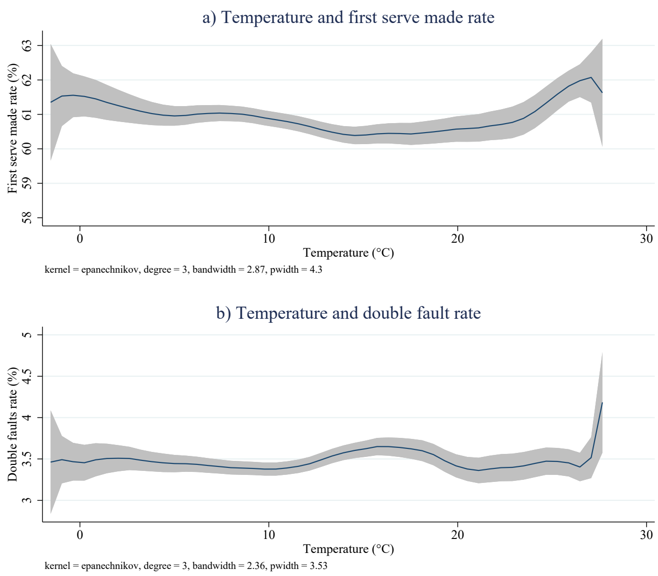
Wyndham, C. H. (1969). Adaptation to heat and cold. *Environmental Research 2*(5), 442–469.

Appendix

A Outdoor temperatures and indoor performances

To investigate the robustness of our main findings, we redid the analysis for indoor performances with outdoor temperature as one of the explanatory variables. We first present in Figure A.1 the smoothed values of kernel-weighted local third-order polynomial regression of indoor tennis outcomes on temperatures. Table A.1 presents the parameter estimates. The main finding is that temperature has no significant effects neither on the first serve made rate nor on the double fault rate. This result is similar to Callahan et al. (2023), who found that in open-air stadiums temperature affects baseball games, while this is not the case in games played under closed domes. Many, but not all, other parameter estimates are similar to those presented in Table 2: age has a negative effect on performance, ranking difference has a negative effect, ranking sum has a positive effect. Many parameter estimates are insensitive to whether or not individual fixed effects are included.

Figure A.1: Kernel-weighted local polynomial smoothing of the relation between outdoor temperature and indoor tennis performance



Notes: This figure is obtained using 16,784 player-level observations. The grey areas are 95% confidence intervals.

Table A.1: Estimation results of tennis performance Equation (5) for indoor matches

Dependent variable:	(1) First serve made rate (%) Coeff. (Std. Err.)	(2) Double fault rate (%) Coeff. (Std. Err.)	(3) First serve made rate (%) Coeff. (Std. Err.)	(4) Double fault rate (%) Coeff. (Std. Err.)
	With tournament-edition and player FE		*With only tournament-edition FE*	
Temperature at 3 pm (°C)	-0.0269	0.0089	-0.0336	0.0157
	(0.0253)	(0.0107)	(0.0225)	(0.0106)
Best of 5 sets	1.5551**	0.0326	1.6504**	-0.2510
	(0.7353)	(0.3012)	(0.7397)	(0.1964)
Age (years)	0.6330	-0.0348	0.8174**	-0.1416
	(0.4064)	(0.1113)	(0.3617)	(0.0914)
Age squared	-0.0239***	0.0048***	-0.0153**	0.0026
	(0.0068)	(0.0017)	(0.0066)	(0.0017)
Ranking difference[(a)]	-0.3298***	0.0906	-0.0720	0.0451
	(0.1092)	(0.0687)	(0.1739)	(0.0472)
Ranking sum/100	0.4155***	-0.0787	0.0884	0.0213
	(0.1219)	(0.0578)	(0.1671)	(0.0418)
Home advantage	-0.2368	0.0564	-0.5878	0.0891
	(0.2325)	(0.0637)	(0.3650)	(0.0803)
Height (cm)			0.1149***	0.0168*
			(0.0363)	(0.0083)
Left-handedness			2.0214***	0.0765
			(0.5800)	(0.1682)
Round - Reference: Before quarterfinal				
Quarterfinal	0.6100*	-0.1762	0.4180	-0.0947
	(0.3211)	(0.1428)	(0.2835)	(0.1791)
Semifinal	0.6917*	-0.7153***	-0.0525	-0.6123**
	(0.3856)	(0.1902)	(0.5967)	(0.2342)
Final	0.7786	-0.4206**	0.3878	-0.4081**
	(0.6564)	(0.1640)	(0.7560)	(0.1753)
Day of the week - Reference: Sunday				
Monday	-0.1988	0.2409	-0.9129*	0.3170**
	(0.5555)	(0.1457)	(0.4591)	(0.1358)
Tuesday	-0.4008	0.2006	-1.0369**	0.2425
	(0.5229)	(0.1389)	(0.4917)	(0.1592)
Wednesday	-0.2045	0.1270	-0.7399	0.1884
	(0.5655)	(0.1419)	(0.5054)	(0.1654)
Thursday	0.1507	0.0240	-0.3573	0.0397
	(0.5413)	(0.1389)	(0.4812)	(0.1530)
Friday	-0.2483	-0.0026	-0.4900	-0.1011
	(0.5446)	(0.1378)	(0.5588)	(0.1644)
Saturday	-0.1000	0.5070***	0.3188	0.3758**
	(0.5349)	(0.1281)	(0.4305)	(0.1417)
# of observations[(b)]	16,598	16,598	16,784	16,784
# of players[(b)]	628	628	814	814
# of tournaments	34	34	34	34
Adjusted R^2	0.2592	0.1769	0.0884	0.0599
Player FE	Yes	Yes	No	No
Tournament-edition FE	Yes	Yes	Yes	Yes

* p-value<0.10, ** p-value<0.05, *** p-value<0.01. Two-way clustered standard errors are in parenthesis; clusters are at the level of tournaments and players. In the continuous spline specifications of the temperature function, the Wald test for the joint significance of the slope changes at the different knots returned p-values equal to 0.4552 for Model (1), 0.1026 for Model (2), 0.4509 for Model (3), and 0.0158 for Model (4). Compared to the specification for outdoor matched, we did not include dummies for the quarter of the year because no indoor match was played in the second quarter and the indicator for the fourth quarter is collinear with the tournament-edition FE.

[(a)] The ranking difference is the absolute value of the difference in the ATP rankings divided by 100.

[(b)] The number of observations are smaller when estimating the model with player FE because 186 players in Models (1) and (2) were removed from the sample because they had only one observation (singleton observations).

B Additional estimates

B.1 Natural logarithm of performance

Table B.1: Estimation results of natural logarithm tennis performance equation

Dependent variable:	(1) Ln of first serve made rate	(2) Ln of double fault rate[c]	(3) Ln of first serve made rate	(4) Ln of double fault rate[c]
	With tournament-edition and player FE		*With only tournament-edition FE*	
Temperature at 3 pm (°C)	-0.0018***	0.0173***	-0.0018***	0.0182***
	(0.0002)	(0.0032)	(0.0003)	(0.0040)
Best of 5 sets	-0.0049	0.3305***	-0.0036	0.3438***
	(0.0072)	(0.1228)	(0.0081)	(0.0844)
Age (years)	0.0107**	-0.1451***	0.0072	-0.0675
	(0.0044)	(0.0368)	(0.0059)	(0.0514)
Age squared	-0.0003***	0.0035***	-0.0001	0.0011
	(0.0001)	(0.0007)	(0.0001)	(0.0010)
Ranking difference[a]	-0.0054***	0.0299**	0.0003	-0.0405
	(0.0012)	(0.0127)	(0.0024)	(0.0272)
Ranking sum/100	0.0070***	-0.0388***	0.0002	0.0487*
	(0.0012)	(0.0129)	(0.0025)	(0.0266)
Home advantage	0.0007	-0.0378	-0.0010	-0.0260
	(0.0022)	(0.0257)	(0.0064)	(0.0482)
Height (cm)			0.0006	0.0076*
			(0.0007)	(0.0042)
Left-handedness			0.0307**	0.0462
			(0.0124)	(0.1198)
Round - Reference: Before quarterfinal				
Quarterfinal	0.0099***	-0.0728***	0.0166***	-0.1565***
	(0.0027)	(0.0258)	(0.0036)	(0.0401)
Semifinal	0.0131***	-0.1347**	0.0237***	-0.2619***
	(0.0038)	(0.0551)	(0.0047)	(0.0657)
Final	0.0181***	-0.1780***	0.0338***	-0.3705***
	(0.0061)	(0.0612)	(0.0069)	(0.0814)
Quarter - Reference: January-February-March				
April-May-June	0.0140*	-0.1166	0.0281***	-0.1982**
	(0.0074)	(0.0717)	(0.0047)	(0.0952)
July-August-September	-0.0005	-0.0616***	0.0176**	-0.2760***
	(0.0088)	(0.0153)	(0.0077)	(0.0388)
October-November-December	-0.0032	-0.1906**	0.0136	-0.3787***
	(0.0105)	(0.0865)	(0.0125)	(0.1016)
Day of the week - Reference: Sunday				
Monday	-0.0041	0.0486	-0.0053	0.0677
	(0.0037)	(0.0437)	(0.0045)	(0.0470)
Tuesday	-0.0019	0.0253	-0.0006	0.0320
	(0.0039)	(0.0426)	(0.0049)	(0.0448)
Wednesday	0.0050	-0.0462	0.0057	-0.0470
	(0.0040)	(0.0433)	(0.0049)	(0.0490)
Thursday	0.0044	-0.0669	0.0063	-0.0734
	(0.0040)	(0.0464)	(0.0051)	(0.0525)
Friday	0.0052	-0.0576	0.0046	-0.0457
	(0.0035)	(0.0510)	(0.0049)	(0.0600)
Saturday	0.0038	-0.0452	0.0040	-0.0355
	(0.0041)	(0.0655)	(0.0049)	(0.0666)
# of observations[b]	75,922	75,922	76,068	76,068
# of players[b]	915	915	1,061	1,061
# of tournaments	88	88	88	88
Adjusted R^2	0.2756	0.1106	0.0794	0.0478
Player FE	Yes	Yes	No	No
Tournament-edition FE	Yes	Yes	Yes	Yes

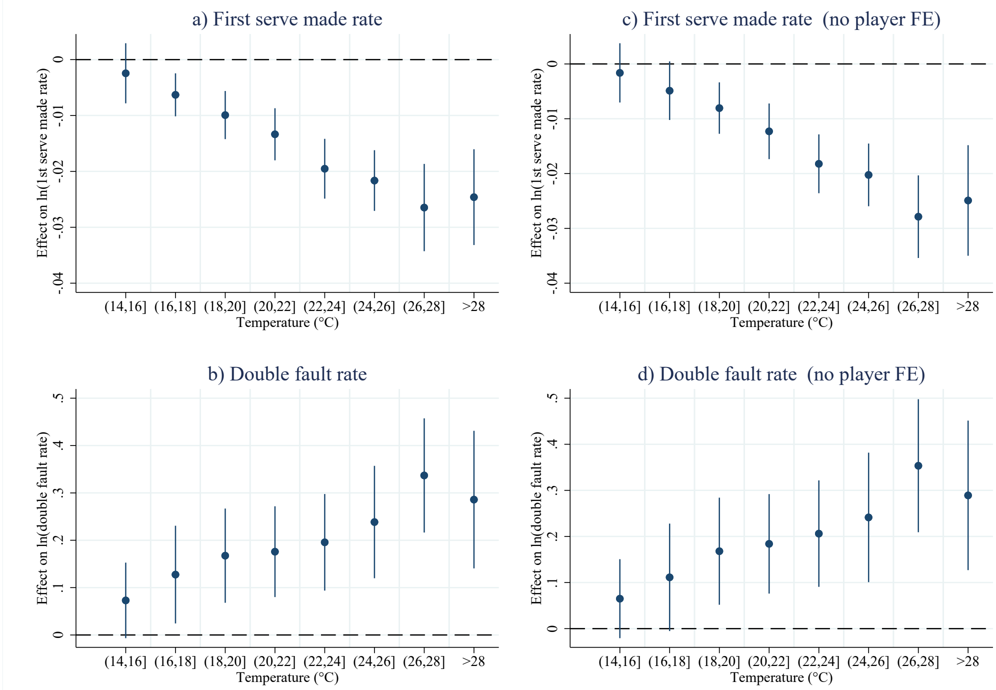
* p-value<0.10, ** p-value<0.05, *** p-value<0.01. Two-way clustered standard errors are in parenthesis; clusters are at the level of tournaments and players. In the continuous spline specifications of the temperature function, the Wald test for the joint significance of the slope changes at the different knots returned p-values equal to 0.8492 for Model (1), 0.1266 for Model (2), 0.8433 for Model (3), and 0.2233 for Model (4).

[a] The ranking difference is the absolute value of the difference in the ATP rankings divided by 100.

[b] The number of observations are smaller when estimating the model with player FE because 146 players in Models (1) and (2) were removed from the sample because they had only one observation (singleton observations).

[c] Since the double fault rate is equal to 0 for 8,154 observations and in order not to lose these observations when applying the natural logarithm, we used as dependent variable the natural logarithm of the double fault rate plus 0.01%.

Figure B.1: Non linear effect of temperatures on the natural logarithm of tennis performances, with tournament-edition and player FE (graphs a)-b)) and only tournament-edition FE (graphs c)-d))



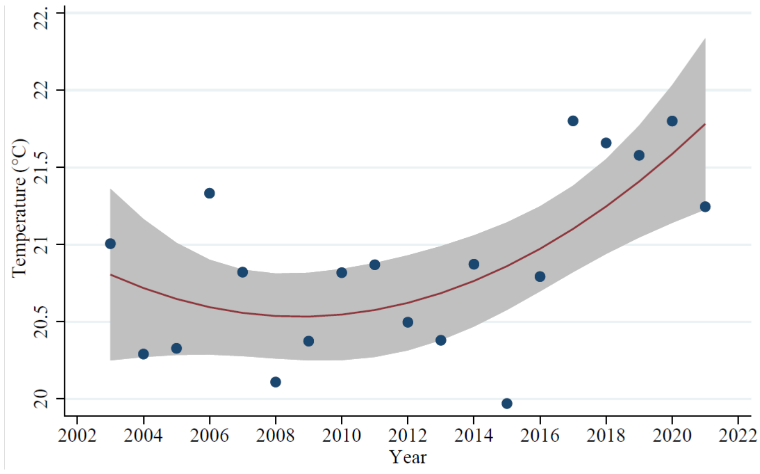
The estimation results of the parameters of the other regressors are available from the authors upon request. They are very close to those reported in Table B.1.

B.2 Temperature effects between tournaments

Our analysis is focused on the short-run relationship between tennis performance and fluctuations in temperature within each tournament since all our estimates contain tournament-edition fixed effects. The effects of between-tournament differences in average temperature are absorbed by these fixed effects. Figure B.2 shows the development of the yearly average temperature in the tournaments in our sample. There appears to be an increasing trend in temperature over time, especially since 2017.

To investigate whether temperature has an effect in addition to the short-run within-tournament effects, we collected the estimated tournament-edition fixed effects and regressed them on the average temperature in the corresponding tournament-edition, tournament fixed effects and year fixed effects. Thus, the effect of temperature on perfor-

Figure B.2: Average temperatures by calendar year



Note: The red line represents the local polynomial smooth.

mance is established using the interaction between tournament and year (edition). The main parameter estimates are presented in Table B.2. The effect of differences in average temperature on the first serve made rate is insignificant and very small, while the effect on the double fault rate is positive and significantly different from zero.

Table B.2: Estimates of the effect of average temperature in a tournament-edition on the estimated tournament-edition fixed-effects

Dependent variable:	First serve made rate (%)	Double fault rate (%)
Average temperature (°C)	0.0023	0.0196***
	(0.0187)	(0.0074)
# of observations	881	881
# of tournaments	80	80
Adjusted R^2	0.5578	0.5379
Edition (year) FE	Yes	Yes
Tournament FE	Yes	Yes

In the analysis 8 observations are excluded because these relate to tournaments that were in our sample only once; standard errors in parentheses are clustered at tournament level; * p-value<0.10, ** p-value<0.05, *** p-value<0.01.