Labour Economics 87 (2024) 102509

Contents lists available at ScienceDirect

Labour Economics

journal homepage: www.elsevier.com/locate/labeco

The impact of high temperatures on performance in work-related activities☆

Matteo Picchio [a,c,d,e], Jan C. van Ours [b,d,e,f,*]

[a] Department of Economics and Social Sciences, Marche Polytechnic University, Italy
[b] Erasmus School of Economics and Tinbergen Institute, The Netherlands
[c] Department of Economics, Ghent University, Belgium
[d] IZA – Institute of Labor Economics, Bonn, Germany
[e] GLO – Global Labor Organization
[f] CEPR, London, United Kingdom

ARTICLE INFO

JEL classification:
J24
J81
Q51
Q54

Keywords:
Climate change
Temperatures
Tennis
Performance
Productivity

ABSTRACT

High temperatures can have a negative effect on work-related activities because workers may experience difficulties concentrating or have to reduce effort in order to cope with heat. We investigate how temperature affects performance of professional tennis players in outdoor singles matches in big tournaments. We find that performance significantly decreases with ambient temperature. This result is robust to including wind speed and air pollution in the analysis. There are no differences between men and women. However, there is some heterogeneity in the magnitude of the temperature effect in other dimensions. In particular, we find that the temperature effect is smaller when there is more at stake. Our findings also suggest that the negative temperature effect is smaller if the heat lasts, i.e. there is some adaptation to high temperatures.

1. Introduction

According to the World Health Organization (WHO) human beings have an indoor thermal comfort range of 18–24 °C (64–75° F). 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). 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. People can protect themselves against low temperatures through their clothes. 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 laboratory settings, with subjects being randomly assigned to situations with varying temperatures performing cognitive and physical tasks. Particularly with higher temperature, productivity related to cognitive tasks significantly drops. The temperature effect on productivity is direct, but also indirect. Poor outdoor weather

☆ We acknowledge the ERA5-Land dataset and Global Reanalysis (EAC4) dataset from the EU-funded Copernicus Climate Change Service and Atmosphere Monitoring 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 wish to thank participants at the 2023 AIEL conference (Genoa), the LISER seminar (Luxembourg), the ESEA annual conference (Cork), the REUS workshop (Vienna), the ROSES online seminar, and the Masaryk University seminar for comments on previous versions of our paper.

* Correspondence to: Department of Applied Economics, Erasmus University Rotterdam, Burg. Oudlaan 50, 3062PA Rotterdam, The Netherlands.
E-mail addresses: m.picchio@staff.univpm.it (M. Picchio), vanours@ese.eur.nl (J.C. van Ours).

https://doi.org/10.1016/j.labeco.2024.102509
Received 5 September 2023; Received in revised form 1 December 2023; Accepted 8 January 2024
Available online 18 January 2024

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. In our summary overview of previous studies, we distinguish between studies on the effect of high temperatures on health and cognitive performance, work-related activities and sports. High temperatures appear to have a negative effect on physical and mental health, cognitive capacities and workplace productivity. The effects of high temperatures on sports activities are mostly studied because the outcomes may be applicable to work-related activities in regular industries. The current study has the same purpose. It analyzes the relationship between high temperatures and performance in tennis matches to better understand how heat affects work-related activities.

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 workers' mood 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.

As indicated before, our study is on the effects of temperature on performance in tennis matches. 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 game which allow us to study how temperature affects individual performance: first serve made rates and second serve made 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 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. Our study is not the first one to use sports data to investigate the relationship between temperature and performance. In the next section, we discuss this in more detail.

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 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 students do an exam. Further examples, to name a few, are army special forces, fire-fighters, emergency doctors, surgeons and professional performers (e.g. dancers and musicians).

The contribution of our paper to the existing literature on temperature and work-related activities 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 made rates and second serve made 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 particular serve or what is at stake in a particular match. At the second serve there is more at stake because, if this is failed, players loses a point. Furthermore, 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. gender, age, quality) and working environment (e.g. different surfaces: clay, hard court or grass).

The set-up of our 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

There are various studies relating temperature to economic outcomes. We ignore the studies on economic growth and focus on individual outcomes, i.e. health and cognitive performance, work-related activities and sports performance.

2.1. Health and cognitive performance

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. Mullins and White (2019) study the relationship between mental health outcomes and temperature measured at the US county 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. 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. (2021a) 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 more pronounced for disadvantaged students, i.e. students from racial or ethnic minorities and low income families. 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. The main conclusion is that high outdoor temperatures significantly reduce cognitive performance indoors.

2.2. Work-related activities

In terms of work-related activities, previous studies investigated the effect of high temperatures on workplace injuries, working time and labor productivity. Dillender (2021) and Park et al. (2021b) for the US, Filomena and Picchio (2022) for Italy and Ireland et al. (2023) for Australia unambiguously find that workplace injury rates significantly increase with temperature. Analyzing US data, Graff Zivin and Neidell (2014) 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 and 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 introduction 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. Bellet et al. (2024) is a related study on the effects of weather on labor productivity. Although this paper does not find a significant direct effect of temperature on productivity, it finds that sunshine positively affects productivity with happiness as the intermediate variable.

2.3. Sports 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. 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 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. 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.

There are also two recent studies using tennis data like we do. 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 authors hypothesize that, in combination with fatigue, high temperatures decrease the level of fine motor control in women's play. Burke et al. (2023) study match level data from ATP/WTA matches whereby the time period depended on the variable of interest: 2002–2017 for all tournaments and 2011–2017 or 2015–2017 for Grand Slams. They find that the probability of match retirement and the number of double faults increase with temperature, while the temperature effect on rally length, distance run and the probability to win the next match is negative. Temperature does not affect match duration and serve speed.

Our study differs from Smith et al. (2018) and Burke et al. (2023) in a number of ways. Smith et al. (2018) analyze women's matches while we study the impact of high temperature on a pooled sample of men and women. Furthermore, we use all the ATP tour and WTA tour tennis matches from 2003 (2007 for women) until 2021, which allow us to study if the effect of temperature on performance varies with the importance of the match, among other heterogeneity sources. Our paper also has some overlaps with Burke et al. (2023), who analyze ATP and WTA matches, though over a shorter period of time. The difference in terms of our main variables is that we study the first serve made rate and the second serve made rate, which they do not. Furthermore, we analyze the double fault rates, while Burke et al. (2023) study the total number of double faults in a given match. Differently from both Smith et al. (2018) and Burke et al. (2023), we explore if extreme temperature exposure may accumulate over time and we investigate whether wind speed and air pollution affect tennis performance and potentially bias the estimated temperature effects.

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-Sabater et al., 2021), a global land surface dataset spanning from 1950 until present.[1] 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 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.[2]

We matched the temperature dataset with tennis singles matches gathered from two sources. From *Tennis-Data.co.uk*, we retrieved match results of the ATP (WTA) tour seasons from 2003 (2007) until 2021.[3] 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/WTA 1000, etc.); surface; if the match was played indoor or outdoor; match round (e.g. final, semifinal, etc.); for men if the match was best of 3 or 5 sets; winner's and loser's name; set and game scores; players' ATP/WTA 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,[4] we had 84,895 matches, of which 72,385 played outdoors.

Although *Tennis-Data.co.uk* data contains the date of each match, it does not include 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[5] at https://github.com/JeffSackmann. 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 to match all the observations and we were left with 81,204 matches, of which 69,348 played outdoors. After keeping only outdoor matches and deleting observations from the first or last percentile of the temperature distribution (1,366 observations), matches lasting less than 30 min (235 cases), matches with missing values for some of the variables used in the regression analysis, we were left with 67,473 matches.[6] 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 successful second serves. For every point in a tennis match, players have two opportunities to serve a ball into the 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.[7] Both successful first serves and second serves are stand-alone indicators, i.e. they originate from decisions and behaviors of the server, without the opponent being directly involved. Nevertheless, both indicators may be influenced by the (expected) strength of the receiver. 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 server wins the point with a legal serve which is not touched by the receiver) or the fraction of first serves won, because they involve the counter-performance of the opponent, 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 serve 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 second serve made rate is another interesting performance metric, simply because if the second serve is not made the server has made a double fault and loses the point.

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 served in the opponent's service box, is equal to 61.4%. The double fault rate, which is the fraction of the served points ending with a point loss due to two faults on the same served point, is 4.4%. The second serve made rate, i.e. the fraction of second serves served in the opponent's service box, is equal to 88.7%. Clearly, there is a big difference in the nature of the first serve and the second serve.

Panel (b) of Table 1 shows that the temperature at 3 pm of the day and location of the match was about 21 °C, 42% of the players are women and the average age at the start of the tournament was 26 years old. Only about 15% of the observations are from matches in the last part of the tournament (quarterfinal or later rounds) 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

[1] For more details see https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview (last accessed November 24th, 2023).

[2] Usually only the first match in a particular day has a specific starting time. Later on that day there is some randomness. Later matches are "followed by but not before" a specific time. That is even the case for semifinals. Finals usually started around the time of the day when we have temperature information (3 pm).

[3] Data are downloadable from http://www.tennis-data.co.uk/alldata.php (last accessed on November 24th, 2023).

[4] 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).

[5] See https://www.jeffsackmann.com/ (last accessed on November 27th, 2023) for Jeff Sackmann's short bio or https://www.tennisabstract.com/ (last accessed on November 27th, 2023) for the website he created, which is a comprehensive database of professional tennis results and statistics.

[6] We also removed the 2009 Australian Open male match between Müller and López, because for both players a 100% first serve made rate in more than 4 h match was reported, and 3 matches for which the number of second serves was higher than the number of faulted first serves.

[7] Although the focus of our analysis is on first serves and second serves, we also report results for double faults as this is a common measure of performance in tennis.

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

Table 1
Summary statistics.

	Mean	Std. Dev.	Min.	Max.
(a) Outcome variables				
First serve made rate (%)	61.442	8.361	0.000	100.000
Double fault rate (%)	4.370	3.246	0.000	37.705
Second serve made rate (%)	88.718	8.079	0.000	100.000
(b) Covariates				
Temperature (°C)	20.543	4.630	8.871	31.444
Female	0.418	0.493	0.000	1.000
Best of 5 sets	0.140	0.347	0.000	1.000
Age (years at tournament start)	25.977	4.084	14.100	46.900
|Difference in players' ATP/WTA ranking|	69.595	105.152	1.000	2,090.000
Sum in player's ATP/WTA ranking	148.456	137.371	3.000	2,646.000
Playing home[a]	0.119	0.324	0.000	1.000
Round				
Less than quarterfinal	0.846	0.361	0.000	1.000
Quarterfinal	0.089	0.284	0.000	1.000
Semifinal	0.044	0.204	0.000	1.000
Final	0.022	0.146	0.000	1.000
Tournament series[b]				
Grand Slam[c]	0.239	0.427	0.000	1.000
ATP/WTA 1000	0.295	0.456	0.000	1.000
ATP/WTA 500	0.218	0.413	0.000	1.000
ATP/WTA 250	0.248	0.432	0.000	1.000
Surface				
Grass	0.130	0.337	0.000	1.000
Clay	0.352	0.478	0.000	1.000
Hard	0.517	0.500	0.000	1.000
Quarter				
January-February-March	0.290	0.454	0.000	1.000
April-May-June	0.347	0.476	0.000	1.000
July-August-September	0.320	0.467	0.000	1.000
October-November-December	0.043	0.203	0.000	1.000
# of observations[d]	134,946			

[a] 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.
[b] These indicators are not used as covariates in models with tournament fixed effects because they are time constant within tournaments.
[c] We included in the category Grand Slam also the 30 matches of the 2003 and 2004 editions of the male Masters Cup, which were exceptionally played outdoors in Houston.
[d] Since in 9 cases there were no faults in the first serve in the whole match, we could not compute the second serve made rate. The number of observations for the second serve made rate is therefore 134,937.

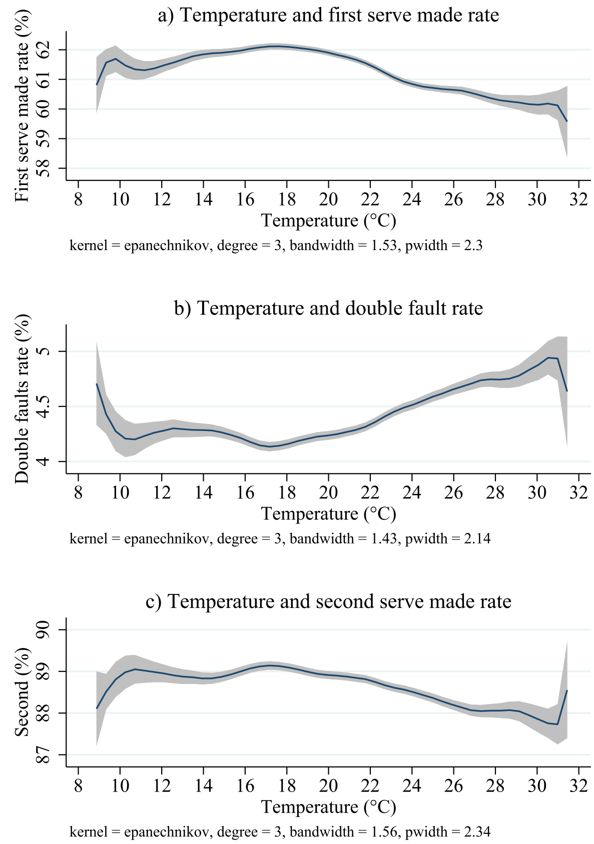

Fig. 1. Kernel-weighted local polynomial smoothing of the relation between temperature and tennis performance.
Notes: This figure is obtained using 134,946 player-level observations. The gray areas are 95% confidence intervals.

the matches were played on hard courts (typically synthetic/acrylic layers on top of a concrete/asphalt base), with the grass the least played surface (around 13%). The schedule of the ATP and WTA tour 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).

In order to investigate the unconditional relationship between temperatures and tennis outcomes, we present in Fig. 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 4.2% to about 5% at 30 °C. The first serve made rate decreases from 62% to about 60% at 30 °C. In combination, this implies that the second serve made rate decreases from about 89% to 88%: the first serve made rate goes down more than the second serve made 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 gender specific fixed effects (FE) at tournament and year level. In the richest specification, we included the interaction between the year indicators, the tournament indicators and gender. 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. Fig. 2 graphically displays this identification source, focusing on 2019 ATP 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 model by assuming that players choose p to optimize their play.[9]

The player optimizes the shot power p. 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: $\underline{p} \le p \le 1$. 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 $a(p)$, which is assumed to be strictly decreasing in power in both first and second serve,[10] is interpreted as the probability that a ball passes the net and lands in the service box, with $0 < a(p) < 1$. 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 that the trade-off between p and $a(p)$ is

[9] Gale (1971) and Gerchak and Kilgour (2017) assume that the main variable of interest is the probability of having a good serve.
[10] This is a simplifying but plausible assumption also used by Gerchak and Kilgour (2017).

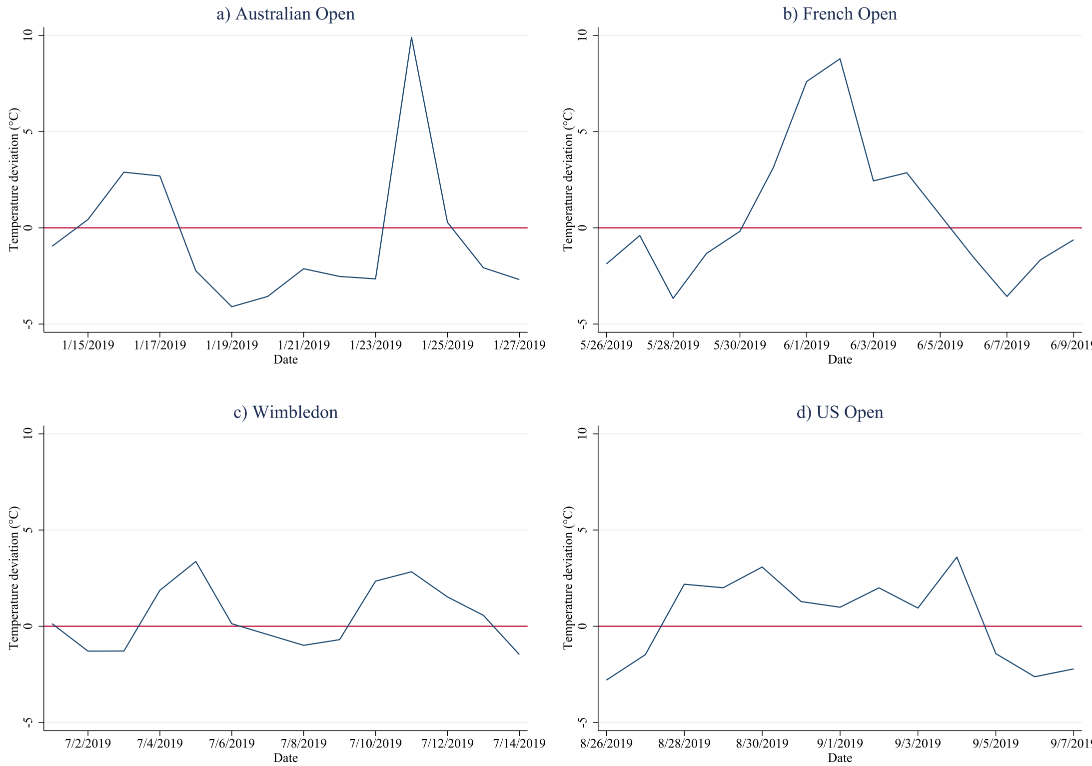

Fig. 2. Temperature deviations from tournament edition mean during 2019 ATP Grand Slams tournaments.

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 a valid first serve is equal to $a(p_1)$ but, if the first serve is unsuccessful, 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 than the second one.[11] First serves are found to be 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.[12]

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, i.e. if it is a valid serve. 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 player and of the match: age, height, importance of the match, economic rewards of winning the match, quality of the opponent, and so on. The marginal effect of temperature on accuracy is

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

The first part of Eq. (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 Eq. (4) may be positive. However, the direct effect of temperature on accuracy, the second part of Eq. (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, we hypothesize that the temperature effect may be stronger at the first serve.

3.3. Modeling tennis performance

Players accomplish maximum ball speed with a combination of effort and technique. Both are unobserved. We observe whether or not

[11] From an analysis of data collected at Australian Open matches from 2012 to 2014, Reid et al. (2016) conclude that for men (women) the mean first serve speed was equal to 184 (156) km/h, while the mean second serve speed was equal to 152 (131) km/h. Smith et al. (2018) find that the ball speed in women's tennis at the first serve is approximately 150 km/h while at the second serve it is approximately 125 km/h.

[12] 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.

the first serve is successful. If the first serve is not successful we look at the second serve. In case also the second serve is unsuccessful, a double fault is made. So, the dependent variables in our empirical analysis are related to the accuracy of shots, but they are not perfect measures of accuracy. In its most general form, we specify the following model for tennis performance y_{ijmte} of player i, playing against player j, in match date m of tournament t in edition e:

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

where γ_{te} are tournament-edition (gender specific) FE, obtained by the interaction among tournament indicators, edition (year) indicators and gender dummy; δ_i are player FE; η_j are opponent FE; $\mathbf{x}_{ijmte}$ is the set of explanatory variables shown in Table 1;[13] $f(temp_{mte}; \boldsymbol{\alpha})$ is a function of the outdoor 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 $f(temp_{mte}; \boldsymbol{\alpha})$: a linear specification (i.e. $\alpha \times temp_{mte}$); 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 first bin for daily temperatures below 14 °C, and the last one for those above 28 °C.[14]

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 ambient temperatures. For example, there may be players who anticipate that their performance will suffer from hot temperatures and therefore avoid to play in tournaments which are usually 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 its 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 FE 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 FE 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 Eq. (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.[15]

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 the surface or the attendance figures, which may affect players' performances. About the latter correlation, each player has her/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 152 different tournaments and 1,728 different players.

4. Results

4.1. Main results

Table 2 shows the main parameter estimates of Eq. (5) if temperature is assumed to have a linear effect.[16] Column (1) reports the results for the first serve made rate, column (2) for the double fault rate and column (3) for the second serve made rate. We focus our discussion on the first and second serve made rates. Temperature has a significant negative effect on performance. A temperature rise of 10 °C decreases the first serve made rate by 1.1 percentage points, it lowers the second serve made rate by 0.6 percentage points, and it causes therefore an increase in the double fault rate by 0.4 percentage points. As expected, temperature has a bigger effect on the first serve than on the second serve.[17] In Table 2 temperature is assumed to have a linear effect. Figs. 3 shows the temperature effect of serve performance by using temperature intervals. Clearly, the temperature effects on the performance indicators is close to being linear.[18]

The remaining parameter estimates in Table 2 give an indication on the effects of personal characteristics of the player, the strength of the opponent and the stage in the tournament on the three performance indicators.[19] When a match result is determined by the best of 5 sets, the second serve made rates are significantly lower probably because a match is more exhausting. The difference in ranking between two players also has a significant effect on first serve rate. The more a match is uneven, i.e. the absolute value of the difference in the ATP/WTA ranking is larger, the lower is the first serve made rate. 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, probably because both players take more risks on the first serve since they both face an opponent with a high quality response execution. We also investigated whether there is a home advantage in tennis (see Koning, 2011), and we find no

[13] When we estimate the tennis performance equation in its most general specification as described by Eq. (5), we do not include gender, because of collinearity with the player FE, and the tournament series and surface, because of collinearity with the tournament-edition FE.

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

[15] Furthermore, estimating Eq. (5) by OLS is equivalent to instrumental variable estimation on a modified model without tournament-edition FE and where each regressor is instrumented by its own tournament-edition-demeaning value.

[16] The tables in the main text show parameter estimates for a pooled sample of male and female tennis players. Appendix C.1 shows separate estimates by gender. Clearly, these parameter estimates are very much the same.

[17] The effect on the first serve made rate is significantly different from the one on the second serve made rate (p-value = 0.0127).

[18] 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 (see notes of Table 2). This suggests 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.

[19] We also estimate the effects of age on performance; see Appendix C.4.

Table 2
Estimation results of tennis performance Eq. (5).

Dependent variable:	(1) First serve made rate (%)	(2) Double fault rate (%)	(3) Second serve made rate (%)
Temperature at 3 pm (°C)	−0.1061***	0.0365***	−0.0643***
	(0.0130)	(0.0058)	(0.0139)
Best of 5 sets	−0.1654	0.1737	−0.5562**
	(0.6628)	(0.1109)	(0.2463)
Ranking difference[a]	−0.1757***	0.0234	0.0034
	(0.0608)	(0.0222)	(0.0500)
Ranking sum/100	0.1958***	−0.0008	−0.0731
	(0.0658)	(0.0201)	(0.0464)
Home advantage	0.0596	−0.0430	0.0657
	(0.0995)	(0.0330)	(0.0791)
Round - Reference: Before quarterfinal			
Quarterfinal	0.6937***	−0.2546***	0.4594***
	(0.1159)	(0.0451)	(0.1025)
Semifinal	1.0034***	−0.4328***	0.7665***
	(0.1874)	(0.0732)	(0.1535)
Final	1.4713***	−0.5917***	1.1604***
	(0.2848)	(0.1096)	(0.2312)
# of observations[b]	134,098	134,098	134,089
# of players[b]	1728	1728	1728
# of tournaments	152	152	152
Adjusted R^2	0.3010	0.2613	0.2431

* 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 0.804 for Model (1), 0.663 for Model (2), 0.487 for Model (3). All the models include player FE, opponent FE and tournament-edition FE. They also include dummies for the day of the week, for the quarter of the year and a flexible specification for age (yearly dummies apart from those younger then 19 and those older than 35 grouped into single dummies). The corresponding parameters are not reported for the sake of brevity and they are available from the authors upon request. Young's (2019) randomization-t p-value for Westfall–Young multiple testing of the null of complete insignificance of temperature across equations is 0.0003 (1000 randomization iterations).

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

[b] The number of observations are smaller than those reported in Table 1 because, when estimating the model with tournament-edition, player FE and opponent FE, 848 players were not used in the estimation because singleton observations.

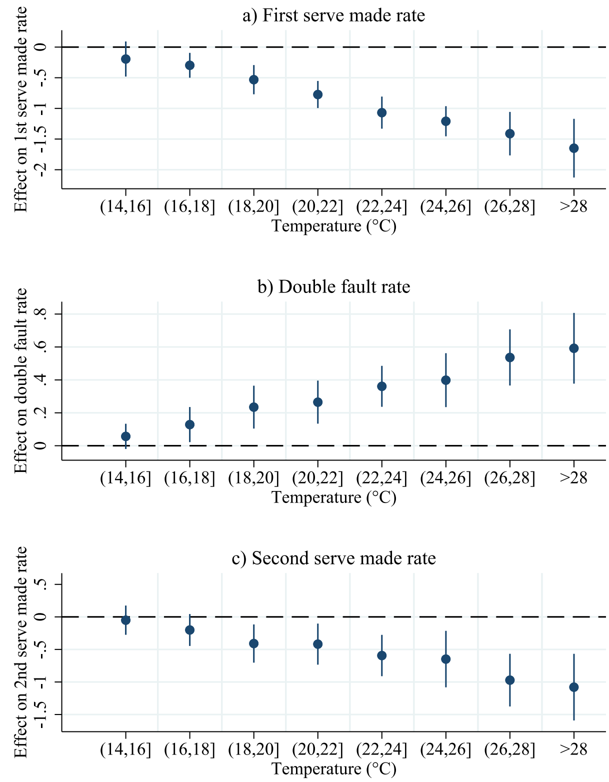

Fig. 3. Non linear effect of temperatures on tennis performance.
Notes: The reference category is temperature below 14°C. Estimation results of the parameters of the other regressors are available from the authors upon request. The number of observations is the same as those reported in Table Table 2. Segments are 95% confidence intervals computed with two-way clustered standard errors; clusters are at the level of tournaments and players.

evidence of this. Finally, the stage of the tournament is quite important in explaining serve performance: the first and second serve made rates strongly increase when approaching the final of the tournament.

The main conclusion from Table 2 is that there are significant temperature effects. With an increase of 1 °C, the first serve rate goes down by about 0.11 percentage points, while the second serve made rate goes down by about 0.06 percentage points. An important question is whether this is a substantial effect or a trivial one. Appendix A provides additional evidence on the temperature effects confirming that these are non-trivial. There, we show for example that the decrease in tennis performance generated by going from about 18–20 °C to 28 °C is of the same magnitude as the difference in performance when a player is in the top 10 and when the same player is above the 70th position in the ATP/WTA ranking.

We also investigated the relationship between outdoor temperatures and indoor performance. 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 B, we find no relationship or a weak relationship between outdoor temperatures and indoor performance.

4.2. Sensitivity analysis

The results from Table 2 are clear in terms of the temperature effects on performance of tennis players. The performance progressively drops with increasing temperatures. As a first check on the robustness of our main findings, we assessed if they are spurious because of the confounding effect of other weather-related variables whose short-term variations may correlate with that of temperature. From the global greenhouse gas reanalysis (EGG4) of the Copernicus Atmosphere Monitoring Service (Inness et al., 2019), we obtained daily data on wind speed, particular matter 2.5 ($PM_{2.5}$), ozone (O_3) and dew point temperature at surface at 3 pm from 2003 until 2021, with 0.75° × 0.75° horizontal resolution. Wind speed may change with temperature and it may simultaneously affect serve performance. PM2.5 and ozone are measures of air pollution. Recent empirical studies suggest that exposure to ambient air pollution reduces labor supply (Hanna and Oliva, 2015) and productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; He et al., 2019). Using football data, Lichter et al. (2017) find negative effects exposure of air pollutants, particular matter and ozone, on players' productivity, namely the total number of passes per match. Air pollution affecting our measures of tennis performances would not be a problem by itself. However, if air pollutants and temperature short-term variations are correlated, our estimates would suffer from the standard omitted variable problem. Using a panel data model with meteorological stations FE, Liu et al. (2020) showed that in China temperature negatively affects $PM_{2.5}$ and positively impacts on O_3, suggesting that it may be important in our framework to assess if our estimated effects are partly induced by short-term variations in air pollutants. Table C.2 in Appendix C reports the raw correlation between temperature and air quality variables, indicating that in our players' level observations temperature is moderately and positively correlated to O_3 and weakly correlated to $PM_{2.5}$. Panel (a) of Table 3 shows that the estimates of the temperature effect are very much in line with the benchmark results. Air pollution, namely ozone, has a

Table 3
Estimation results with air quality controls.

Dependent variable:	(1) First serve made rate (%)	(2) Double fault rate (%)	(3) Second serve made rate (%)
(a) Wind speed and air pollution as further controls			
Temperature at 3 pm (°C)	−0.0900***	0.0363***	−0.0681***
	(0.0116)	(0.0053)	(0.0128)
Wind speed at 3pm (m/sec)	0.0674***	0.0160**	−0.0661***
	(0.0194)	(0.0069)	(0.0162)
$PM_{2.5}$ at 3pm (mg/kg)	−1.3108	0.3734	−0.9739
	(0.9492)	(0.4060)	(0.9700)
O_3 at 3pm (mg/kg)	−6.3005***	2.3553***	−4.4469**
	(2.3148)	(0.7257)	(1.9769)
(b) Humidex index instead of temperature			
Humidex index at 3 pm (°C)	−0.0679***	0.0215***	−0.0359***
	(0.0092)	(0.0045)	(0.0105)
# of observations	134,058	134,058	134,049
# of players	1726	1726	1726
# of tournaments	152	152	152

* *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. All the models also include player FE, opponent FE, tournament-edition FE and all the other covariates included in the benchmark specification. The corresponding parameters are not reported for the sake of brevity and they are available from the authors upon request. We lose 40 observations of male matches played on January the 1st, 2003, as the data of the global greenhouse gas reanalysis (EGG4) of the Copernicus Atmosphere Monitoring Service are available since January the 2nd, 2003.

significantly negative effect on tennis performance, in line with the previous literature.

As a further sensitivity analysis, exploiting the dew point temperature downloaded from the Copernicus Atmosphere Monitoring Service, we replaced temperature with the Humidex index calculated as in Blazejczyk et al. (2012), which combines ambient temperature and dew point temperature. This is aimed at assessing the robustness of our findings if we use a measure which should be closer to the temperature perceived by human body. Panel b of Table 3 confirms previous findings from our benchmark specifications.

Finally, we redid all the estimates by: (i) using the natural logarithm of the performance measures as dependent variables; (ii) removing the player and the opponent FE. As the results in Table C.3 show, the conclusions are very much the same.

We also investigated 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 Appendix C.5 there are no significant relationships between average temperature and serve performance measures across the tournaments.

4.3. Effect heterogeneity

To detect potential heterogeneity of the temperature effect on performance, we interacted the temperature variable with a set of dummies capturing different gradients of heterogeneity and re-estimated the baseline model with tournament-edition FE, player FE and opponent FE. The main parameters are presented in Table 4.

We first investigated whether the temperature effects are gender-specific, finding that this is not the case. Panel a of Table 4 shows that both first serve and second serve made rates do not go down with temperature for females as much as they do for males, but the differences are small and not significantly different from zero.

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 players' performance. 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. As expected and as shown in panel b of Table 4, we find that the temperature gradient is stronger on clay, especially for the second serve made rate. Nevertheless, although sizeable, the clay differential effects are either not significantly different from zero or, for the second serve made rate, significant at 10%.

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. 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. This was clearly the case when comparing first serve and second serve made rates. Panel c of Table 4 shows that there is no difference in temperature effects on first serve made rates between Grand Slam tournaments and non-Grand Slam tournaments. For the second serve made rate the temperature effect is significantly stronger in Grand Slam tournaments. As shown in panel d, if the potential reward is measured with the tournament round of a match, we find instead that the first serve made rate declines more mildly with temperature when there is more at stake, i.e. in quarterfinals or later. However, there is no such effect for the second serve made rate. It could be that for the second serve made rate, players in quarterfinals or later were already at their peak to deal with high temperatures. Some support for this comes from a comparison of the temperature effect in quarterfinals or later: the temperature effect is about the same for the first serve made rate as it is for the second serve made rate.

Panel e shows that a variation in player's quality does not influence the temperature effect. The temperature effect is as strong for a player who was not in the top 50% of the ATP/WTA ranking than it was when that same player was in the top 50% of the ATP/WTA ranking.

Panel f shows that the way temperature affects performance is age-specific. Young players are less severely affected by higher temperatures than older players are in terms of first serve made rate. Perhaps, they are physically better able to deal with high temperatures such that their accuracy does not suffer too much when hitting the ball with a lot of power at the first serve. For the second serve made rate the age effect is opposite. Young players suffer more in their second serve made rate if temperature goes up. Apparently, when it matters most, i.e. at the second serve, older players can handle high temperature better than younger players. Probably, older players, thanks to their larger experience, can handle better those situations in which the mental focus is more important and are therefore impacted less intensively by high temperatures. It should also be noted that, in line with this, for young workers the temperature effect is about the same for the first serve made rate and the second serve made rate.

Panel g of Table 4 focuses on differential temperature effects between home players and away players. We do not detect significant differences across this heterogeneity dimension in the temperature gradient.

Table 4
Effect heterogeneity.

Dependent variable:	(1) First serve made rate (%)	(2) Double fault rate (%)	(3) Second serve made rate (%)
a. Effect by gender (male is the reference)			
Temperature 3 pm	−0.1076***	0.0404***	−0.0770***
	(0.0010)	(0.0010)	(0.0010)
Temperature 3 pm × female	0.0038	−0.0071	0.0263
	(0.7752)	(0.4635)	(0.1239)
b. Effect by surface (hard or grass is the reference)			
Temperature 3 pm	−0.0959***	0.0309***	−0.0500**
	(0.0010)	(0.0010)	(0.0150)
Temperature 3 pm × clay	−0.0256	0.0164	−0.0411*
	(0.3796)	(0.1439)	(0.0859)
c. Effect by tournament series (non Grand Slam tournament is the reference)			
Temperature 3 pm	−0.1002***	0.0297***	−0.0452***
	(0.0010)	(0.0010)	(0.0020)
Temperature 3 pm × Grand Slam tournaments	−0.0166	0.0218**	−0.0595***
	(0.6204)	(0.0170)	(0.0010)
d. Effect by tournament round (before quarterfinal is the reference)			
Temperature 3 pm	−0.1134***	0.0383***	−0.0658***
	(0.0010)	(0.0010)	(0.0010)
Temperature 3 pm × quarterfinals or later	0.0422***	−0.0045	−0.0035
	(0.0010)	(0.6184)	(0.8591)
e. Effect by ATP/WTA player's ranking (not in the top 50% is the reference)[a]			
Temperature 3 pm	−0.1159***	0.0371***	−0.0602***
	(0.0010)	(0.0010)	(0.0010)
Temperature 3 pm × in the top 50%	0.0191	0.0008	−0.0118
	(0.2488)	(0.9750)	(0.4855)
f. Effect by age (age ≥ P_{66} is the reference)[b]			
Temperature 3 pm, age	−0.1236***	0.0340***	−0.0493***
	(0.0010)	(0.0010)	(0.0010)
Temperature 3 pm × < P_{33}	0.0328***	0.0042	−0.0255**
	(0.0030)	(0.4635)	(0.0170)
Temperature 3 pm × P_{33} ≤ age < P_{66}	0.0185	0.0060	−0.0241**
	(0.2358)	(0.3686)	(0.0120)
g. Effect on home advantage (not playing home is the reference)			
Temperature 3 pm	−0.1039***	0.0375***	−0.0670***
	(0.0010)	(0.0010)	(0.0010)
Temperature 3 pm × playing home	−0.0183	−0.0002	0.0049
	(0.3796)	(0.9750)	(0.8591)
h. Young's (2019) randomization-t p-values for Westfall–Young multiple testing of the null of complete insignificance of heterogeneous effects[c]			
Randomization-t p-value	0.1143	0.3750	0.1353

* p-value <0.10, ** p-value <0.05, *** p-value <0.01. In parenthesis, we report Romano and Wolf's (2005a, 2005b) step-down adjusted p-values robust to multiple hypothesis testing, with two-way clusters at the level of tournaments and players (1000 bootstrap replications). The number of observations is 134,098 in model (1) and (2) and 134,089 in model (3).

[a] The median of the ATP/WTA ranking is 53.

[b] P_i stands for the ith percentile of the age distribution across matches The 33rd and 66th percentiles of age are 24 and 28 years, respectively.

[c] For each outcome variable, we used the Westfall–Young approach to test the joint significance of heterogeneous effects on the basis of Young's (2019) randomization-t procedure with 1000 replications. We report the p-values for the null of complete irrelevance of heterogeneous effects.

If anything, Table 4 shows that there is a heterogeneous temperature effects along a few dimensions of heterogeneity, but there are also quite a few dimensions in which this heterogeneity is not present. For each outcome variable, we used the Westfall–Young approach to test the joint significance of heterogeneous effects on the basis of Young's (2019) randomization-t procedure. We reported the p-values for the null of complete irrelevance of heterogeneous effects in panel h of Table 4. They show that, overall, the heterogeneous effects are insignificant. This is no surprise as we investigated heterogeneity on seven dimensions finding that only two dimensions seem to be relevant when individually considered: age and tournament round for the first serve and age and tournament importance for the second serve.

4.4. 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, 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. Empirically, we cannot make a distinction between exhaustion and concentration. But, we can investigate whether there is exhaustion between games due to high

Table 5
Cumulative dynamic estimates of temperature effect on tennis performance.

Dependent variable:	(1) First serve made rate (%)	(2) Double fault rate (%)	(3) Second serve made rate (%)
Current temperature $\hat{\alpha}_0$	−0.1211***	0.0374***	−0.0595***
	(0.0161)	(0.0068)	(0.0186)
Temperature previous match $\hat{\alpha}_1$	0.0285**	−0.0056	0.0078
	(0.0134)	(0.0045)	(0.0126)
$\hat{\alpha}_0 + \hat{\alpha}_1$	−0.0926***	0.0318***	−0.0517**
	(0.0172)	(0.0082)	(0.0234)
H_0: $\alpha_0 = \alpha_1 = 0$, p-value=	0.0000	0.0000	0.0047
# of observations	62,271	62,271	62,268
# of players	1176	1176	1176
# of tournaments	151	151	151
Adjusted R^2	0.3173	0.2625	0.2488

* 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, opponent FE, tournament-edition FE and all the covariates as in the baseline model.

temperatures, i.e. whether long spells of hot weather have a cumulative effect. 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

$$y_{ijmte} = \alpha_0 temp_{mte} + \alpha_1 temp_{m-1te} + \boldsymbol{\beta}\mathbf{x}_{ijmte} + \gamma_{te} + \delta_i + \eta_i + \varepsilon_{ijmte}, \tag{6}$$

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, which accounts for about 46% of the total sample. 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 dynamics.[20] By summing the α's, we obtain the cumulative effect of having one more Celsius degree both in the current and in the previous match.

Table 5 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 significantly mitigate the negative temperature impact on the first serve made rate in the current game, which is a sign of short-term adaptation and acclimation to heat.

We run a further heterogeneity analysis for testing the acclimation hypothesis by 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.

5. Conclusions

Human beings have a thermal comfort zone. Outside this comfort zone, there is a negative effect on work-related activities, in particular with high temperatures. Previous studies showed that high outdoor temperatures have a negative effect on the quality of test scores of students doing an exam, productivity of factory workers and performance of athletes and increase work-related injury rates. 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 cope 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 professional tennis players focusing on two measures of individual performance: first serve made rates and second serve made rates. First serves and second serves differ from each other 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 hypothesized that high temperatures affect the first serve more because at the second serve there is more at stake.

We used data about outdoor singles tennis matches of the ATP/WTA tour 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 second serve made rates. A temperature increase by 10 °C decreased the first serve made rate by 1.1 percentage points and the second serve made rate by about 0.6 percentage points. So, the effect of temperature was indeed larger at the first serve, when there is less at stake. We investigated the heterogeneity of the temperature effects, but we found that heterogeneity is limited. We did not find different effects by gender, type of surface, player ranking or whether or not players played in their home country. We detected heterogeneous effects according to the stage in the tournament a match was played. From the quarterfinal onward the temperature effects were smaller. We interpreted this as being due to higher stakes which is in line with the difference between the temperature effects on first serve made rates and second serve made rates. Furthermore, we found heterogeneous effects by age. When there was less at stake, i.e. in the first serve, young players were less severely affected by high temperatures than older players. However, when there was more at stake, i.e. in the second serve, older players caught up and the temperature effects were milder for them. We also found that the temperature in the previous match had a positive effect on performance, suggesting short-term adaptation to high temperatures.

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 is rarely met in regular work-related activities. However, professional tennis players most likely are much more physically fit than regular workers. 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 examples of industries where climate control is largely absent. In manufacturing industries, climate control is possible but not always easy or very costly to implement.

[20] We tried with the lag of order 2 of temperature, losing therefore first and second rounds of each tournament (about 74% of the total sample). The associated coefficient was not significantly different from zero.

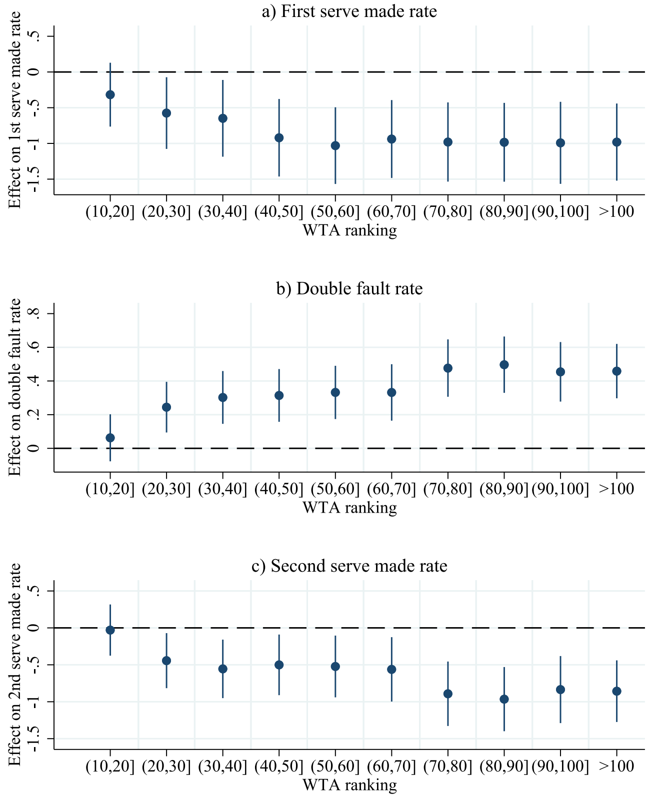

Fig. A.1. Relation between ATP/WTA ranking and tennis performance with player and opponent FE.
Notes: The reference category is ATP/WTA ranking in [1, 10]. The number of player-level observations is 134,098 (134,089 when the outcome if the second serve made rate). Segments are 95% confidence intervals computed with clustered standard errors at player's level.

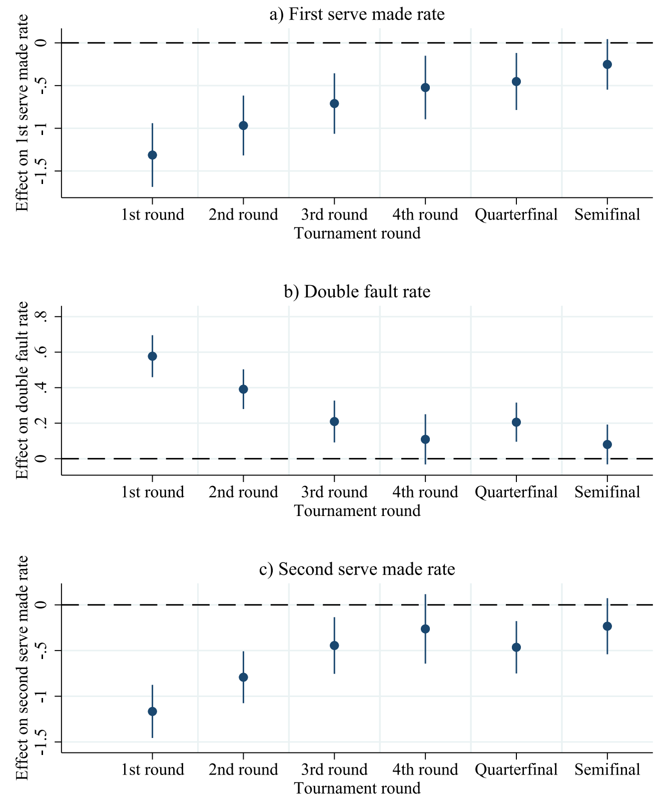

Fig. A.2. Relation between tournament round and tennis performance with player and opponent FE.
Notes: The reference category is the tournament *final*. The number of player-level observations is 134,098 (134,089 when the outcome if the second serve made rate). Segments are 95% confidence intervals computed with clustered standard errors at player's level.

If we extrapolate the results from our analysis of tennis data to regular work activities our main conclusions are the following. High temperatures have a negative effect on workplace productivity in terms of the precision of the work. The magnitude of this negative effect is substantial and larger when there is less at stake, i.e. the mistake has less serious consequences. The temperature effect does not vary a lot with characteristics of the workers and does not vary with the nature of the work activity. The productivity of older and younger workers is differently affected by high temperatures. When there is less at stake younger workers are affected less. When there is more at stake, i.e. the mistake has more serious consequences, older workers are better able to deal with high temperatures, although there is still a negative temperature effect. We find evidence of adaptation: when temperatures are high over a longer time period, the negative workplace performance effects are smaller.

CRediT authorship contribution statement

Matteo Picchio: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Jan C. van Ours:** Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix A. On the magnitude of the temperature effects

To illustrate the magnitude of the temperature effects we compare them with the individual differences in performance by ATP/WTA ranking and the individual differences in performance by tournament round.

First, we regressed our performance measures on the ATP/WTA ranking, player FE and opponent FE. In order to capture non-linearity, we specified the ATP/WTA ranking as a vector of indicator variables falling into 10-ranking bins, apart for the last indicator variable which is equal to one for players above the 100th position in the ATP/WTA ranking. Fig. A.1 shows the estimated parameters.[21] By contrasting Fig. 3 with Fig. A.1, it is clear that the decrease in tennis performance generated by going from about 18–20 °C to 28 °C is of the same magnitude as the performance gap between a tennis player with an excellent performance being in the top 10 and the same tennis player with a normal performance about the 70th position in the ATP/WTA ranking.

We conducted a second exercise in the same spirit by focusing on the variation of performance across tournament rounds. Fig. A.2 shows the estimated relation between tournament round and tennis performance, conditional on player FE and opponent FE. The increase in tennis performance generated by going from about 28 °C to 20 °C is similar to the performance growth that is observed on average when progressing from the 1st round to the final or semifinals.

[21] The coefficient of the dummy for the top 10 players of the ATP/WTA ranking is normalized to 0.

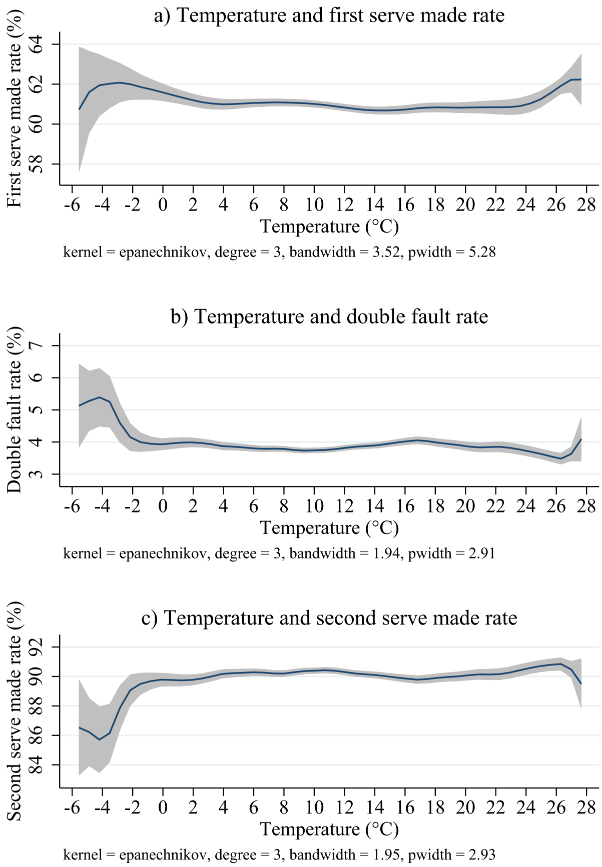

Fig. B.1. Kernel-weighted local polynomial smoothing of the relation between outdoor temperature and indoor tennis performance.
Notes: This figure is obtained using 23,126 player-level observations. The gray areas are 95% confidence intervals.

From these comparisons, we conclude that the estimated temperature effects on tennis performance have a substantial magnitude.

Appendix B. Outdoor temperatures and indoor performances

Considering that other studies found that outdoor temperatures may influence indoor behavior even when the job activity is performed indoors in good quality, climate-controlled environments, we dig deeper into our main findings and redid the analysis with only indoor matches, which we excluded from our main sample. We first present in Fig. B.1 the smoothed values of kernel-weighted local third-order polynomial regression of indoor tennis outcomes on outdoor temperatures. It shows that the profile of the temperature–performance relation is very flat. Second, we estimated the regression model in Eq. (5) using a step function of the temperature impact on tennis performance. Fig. B.2 displays the results. Whereas for the second serve made rate – and the double fault rate – the main finding is that temperature has no clear effect for the first serve made rate there seems to be a negative effect that increases with temperature.

Table B.1 shows the parameter estimates for indoor matches confirming the results in Fig. B.2a. For the effect of outdoor temperature on first serve made rate of indoor tennis, we do find a significant negative effect. For the second serve made rate (and the double fault rate) there is no significant temperature effect. The magnitude of the effect is about half the effect of temperature on outdoor matches but it

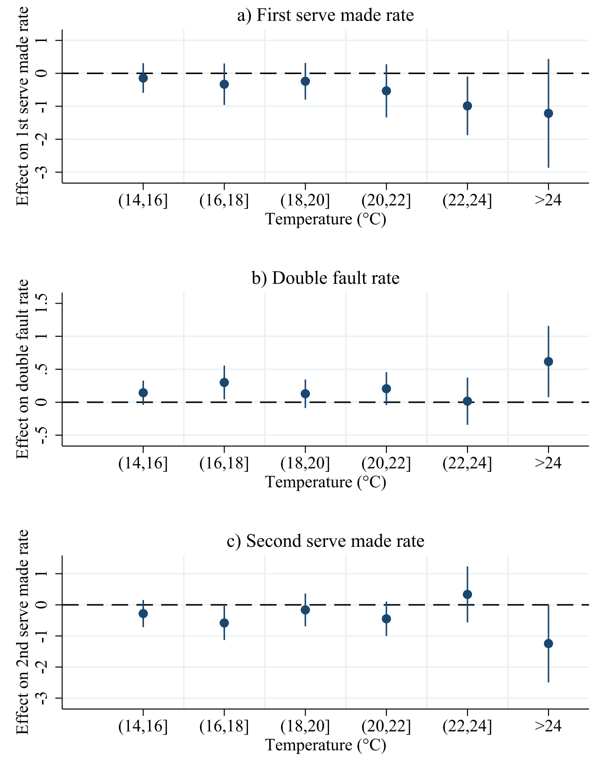

Fig. B.2. Non linear effect of outdoor temperatures on indoor tennis performance.
Notes: The reference category is temperature below 14°C. The number of observations is the same as those reported in Table B.1. Segments are 95% confidence intervals computed with two-way clustered standard errors; clusters are at the level of tournaments and players.

Table B.1
Estimation results of tennis performance Eq. (5) for indoor matches.

Dependent variable:	(1) First serve made rate (%)	(2) Double fault rate (%)	(3) Second serve made rate (%)
Temperature at 3 pm (°C)	−0.0542***	0.0160	−0.0271
	(0.0185)	(0.0101)	(0.0237)
Ranking difference[a]	−0.2779**	0.0635	−0.0680
	(0.1180)	(0.0422)	(0.1243)
Ranking sum/100	0.2220*	−0.0353	0.0159
	(0.1197)	(0.0418)	(0.1263)
Home advantage	−0.2938	0.0566	−0.0354
	(0.1990)	(0.0630)	(0.1651)
Round - Reference: Before quarterfinal			
Quarterfinal	0.2022	−0.2485**	0.6113**
	(0.2587)	(0.1086)	(0.2818)
Semifinal	0.5882*	−0.6957***	1.6778***
	(0.2960)	(0.1387)	(0.3811)
Final	1.9457***	−0.8182***	1.3299***
	(0.4695)	(0.1504)	(0.3826)
# of observations	22,434	22,434	22,434
# of players	975	975	975
# of tournaments	54	54	54
Adjusted R^2	0.2771	0.2375	0.2288

* 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 0.726 for Model (1), 0.440 for Model (2) and 0.417 for Model (3). All the models include player FE, opponent FE and tournament-edition FE. They also include dummies for the day of the week, for the quarter of the year and a flexible specification for age (yearly dummies apart from those younger then 19 and those older than 35 grouped into single dummies). The corresponding parameters are not reported for the sake of brevity and they are available from the authors upon request.
[a] The ranking difference is the absolute value of the difference in the ATP/WTA rankings divided by 100.

Table C.1
Estimation results of tennis performance Eq. (5) by gender.

Dependent variable:	*Men*			*Women*		
	(1) First serve made rate (%)	(2) Double fault rate (%)	(3) Second serve made rate (%)	(4) First serve made rate (%)	(5) Double fault rate (%)	(6) Second serve made rate (%)
Temperature at 3 pm (° C)	−0.1069***	0.0404***	−0.0773***	−0.1052***	0.0333***	−0.0507**
	(0.0139)	(0.0062)	(0.0144)	(0.0177)	(0.0076)	(0.0197)
Best of 5 sets	−0.1302	0.1460	−0.5138			
	(0.6867)	(0.2532)	(0.6279)			
Ranking difference[a]	−0.1544*	0.0305	−0.0408	−0.2234**	0.0174	0.0553
	(0.0796)	(0.0250)	(0.0559)	(0.0868)	(0.0388)	(0.0853)
Ranking sum/100	0.2173***	−0.0170	−0.0229	0.1686*	0.0214	−0.1340
	(0.0771)	(0.0224)	(0.0499)	(0.0971)	(0.0381)	(0.0888)
Home advantage	0.0510	−0.0725**	0.1590*	0.0936	−0.0021	−0.0724
	(0.1307)	(0.0356)	(0.0854)	(0.1519)	(0.0631)	(0.1414)
Round - Reference: Before quarterfinal						
Quarterfinal	0.6525***	−0.1634***	0.2497***	0.7200***	−0.3563***	0.6930***
	(0.1521)	(0.0454)	(0.0901)	(0.1296)	(0.0667)	(0.1738)
Semifinal	0.9115***	−0.3245***	0.5900***	1.0773***	−0.5485***	0.9551***
	(0.2336)	(0.0727)	(0.1369)	(0.1964)	(0.1061)	(0.2697)
Final	1.2692***	−0.3844***	0.7518***	1.6708***	−0.8081***	1.5766***
	(0.3867)	(0.1059)	(0.2025)	(0.3127)	(0.1560)	(0.3843)
# of observations	78,128	78,128	78,124	55,970	55,970	55,965
# of players	973	973	973	755	755	755
# of tournaments	91	91	91	108	108	108
Adjusted R^2	0.2900	0.2012	0.1725	0.3061	0.2453	0.2078

* 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 0.735 for Model (1), 0.259 for Model (2), 0.495 for Model (3), 0.195 for Model (4), 0.671 for Model (5) and 0.694 for Model (6). All the models include player FE, opponent FE and tournament-edition FE. They also include dummies for the day of the week, for the quarter of the year and a flexible specification for age (yearly dummies apart from those younger then 19 and those older than 35 grouped into single dummies). The corresponding parameters are not reported for the sake of brevity and they are available from the authors upon request.

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

Table C.2
Correlation between temperature and other air-related variables.

	Temperature (°C)	Dew point temp. (°C)	Wind speed (m/sec)	Ozone (mg/kg)	$PM_{2.5}$ (mg/kg)
Temperature (°C)	1.0000				
Dew point temp. (°C)	0.6282***	1.000			
Wind speed (m/sec)	−0.1229***	−0.0470***	1.000		
Ozone (mg/kg)	0.3540***	−0.0027	0.1249***	1.000	
$PM_{2.5}$ (mg/kg)	0.0081***	0.1600***	−0.1646***	−0.2774***	1.000

*** p-value <0.01.

is still present for indoor matches. We speculate that the negative effect of outdoor temperature on the indoor first serve made rate has to do with spillovers from outdoor events prior to the match.

Appendix C. Additional results

C.1. Main estimation results by gender

See Fig. C.1 and Table C.1.

C.2. Correlation between temperature and other air-related variables

See Table C.2.

C.3. Natural logarithm tennis performance and estimation without player and opponent FE

See Table C.3.

C.4. Age effects

In a model with individual FE and calendar time FE it is not possible to distinguish a linear age trend from a linear calendar time trend. Conditional on this trend, the age pattern can be determined as follows (De Ree and Alessie, 2011). The dummy variables for age taking values on $(1, \dots, a_{max})$ are defined as: $D^A_\alpha(a_{it}) = 1$ if $a_{it} = \alpha$, 0 otherwise, where i is the individual identifier and t is the calendar year identifier. The age profile can be restricted in such a way that the parameters of the age dummy variables add up to zero over the relevant range and are orthogonal to a linear trend:

$$\tilde{D}^A_\alpha(a_{it}) = D^A_\alpha(a_{it}) + (\alpha-2)D^A_1(a_{it}) - (\alpha-1)D^A_2(a_{it}), \alpha = 3, \dots, a_{max}.$$

The first two age dummies can be derived as follows

$$\tilde{\delta}_1 = \sum_{\alpha=3}^{a_{max}} \tilde{\delta}_\alpha(\alpha-2), \tilde{\delta}_2 = -\sum_{\alpha=3}^{a_{max}} \tilde{\delta}_\alpha(\alpha-1),$$

so that the parameters satisfy the restrictions

$$\sum_{\alpha=1}^{a_{max}} \tilde{\delta}_\alpha = 0, \sum_{\alpha=1}^{a_{max}} \tilde{\delta}_\alpha \times a = 0.$$

The $\tilde{\delta}$ parameters are presented in Fig. C.2.

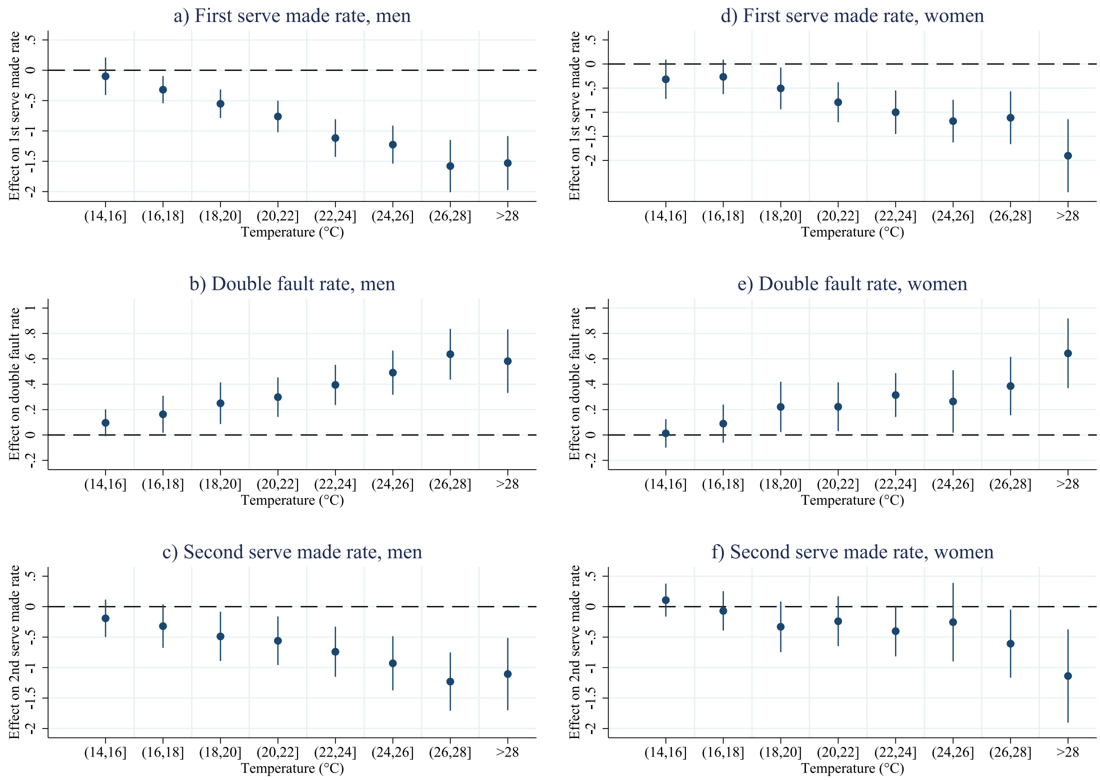

Fig. C.1. Non linear effect of temperatures on tennis performance by gender.

Notes: The reference category is temperature below 14°C. Estimation results of the parameters of the other regressors are available from the authors upon request. The number of observations is as in Table Table C.1. Segments are 95% confidence intervals computed with two-way clustered standard errors; clusters are at the level of tournaments and players.

Table C.3
Estimation results of natural logarithm tennis performance equation and of main model without player and opponent FE.

Dependent variable:	*Natural log performance*			*No player & opponent FE*		
	(1) Ln of first serve made rate (%)	(2) Ln of double fault rate (%)	(3) Ln of second serve made rate (%)	(4) First serve made rate (%)	(5) Double fault rate (%)	(6) Second serve made rate (%)
Temperature at 3 pm (°C)	−0.0017***	0.0154***	−0.0007***	−0.1087***	0.0308***	−0.0484***
	(0.0002)	(0.0026)	(0.0002)	(0.0134)	(0.0064)	(0.0157)
Best of 5 sets	−0.0016	0.3170***	−0.0063	−0.6481	−1.3209***	3.6793***
	(0.0107)	(0.0827)	(0.0074)	(0.4886)	(0.1499)	(0.3455)
Ranking difference[a]	−0.0031***	−0.0213**	−0.0005	−0.0881	−0.0059	0.0668
	(0.0010)	(0.0107)	(0.0007)	(0.1093)	(0.0370)	(0.0882)
Ranking sum/100	0.0033***	0.0221**	−0.0003	0.0623	0.0467	−0.1569*
	(0.0011)	(0.0096)	(0.0007)	(0.1165)	(0.0371)	(0.0856)
Home advantage	0.0013	−0.0334*	0.0011	−0.0884	−0.1383	0.3804**
	(0.0017)	(0.0177)	(0.0010)	(0.2929)	(0.0866)	(0.1816)
Round - Reference: Before quarterfinal						
Quarterfinal	0.0109***	−0.0905***	0.0054***	0.8176***	−0.2870***	0.5170***
	(0.0019)	(0.0245)	(0.0016)	(0.1575)	(0.0539)	(0.1321)
Semifinal	0.0166***	−0.1822***	0.0097***	1.1777***	−0.4349***	0.7481***
	(0.0030)	(0.0471)	(0.0019)	(0.2417)	(0.0941)	(0.2376)
Final	0.0236***	−0.2475***	0.0150***	1.8219***	−0.5963***	1.0881***
	(0.0046)	(0.0610)	(0.0029)	(0.3572)	(0.1329)	(0.3132)
# of observations	134,098	134,098	134,089	134,946	134,946	134,937
# of players	1728	1728	1728	2152	2152	2152
# of tournaments	152	152	152	152	152	152
Adjusted R^2	0.2778	0.1315	0.1727	0.0654	0.0875	0.0802
Player & opponent FE	Yes	Yes	Yes	No	No	No

* *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 0.826 for Model (1), 0.124 for Model (2), 0.838 for Model (3), 0.777 for Model (4), 0.428 for Model (5), and 0.599 for Model (6). Since the double fault rate is equal to 0 for 12,598 observations, in order not to lose them when applying the natural logarithm, we used as dependent variable the natural logarithm of the double fault rate plus 0.01 percentage points. This also applies to the first serve made rate, because in 2 (7) cases the first (second) serve made rate is equal to 0.

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

Fig. C.2. Age effects.

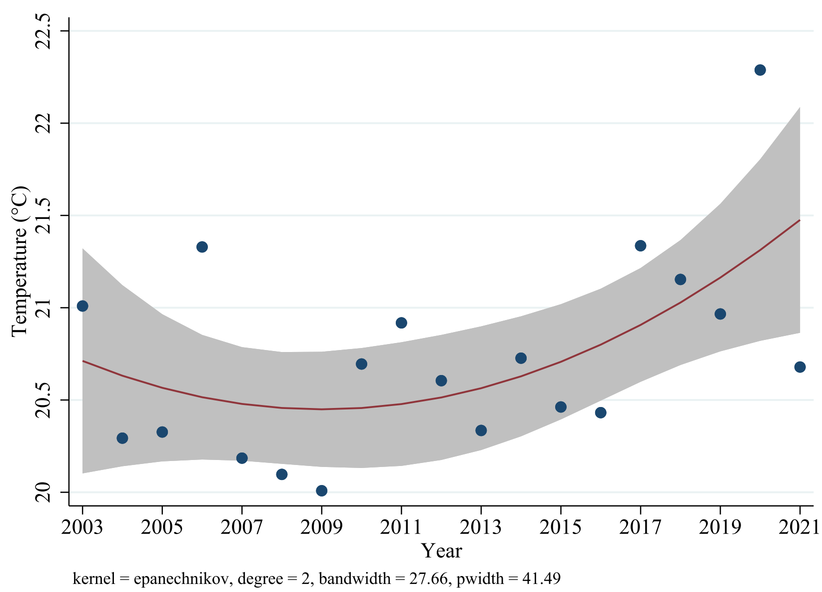

Fig. C.3. Average temperatures by calendar year.*Note:* The red line represents the local polynomial smooth.

The first serve made rate has a clear peak at age 26, the second serve made rate is somewhat higher in the age range 25 to 30 while the double fault rate has no clear age pattern.

C.5. 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 FE. The effects of between-tournament differences in average temperature are absorbed by these FE. Fig. C.3 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 FE and regressed them on the average temperature in the corresponding tournament-edition, tournament FE and year FE. The main parameter estimates are presented in Table C.4. The relations between differences in average temperature and serve performance measures are insignificant and small.

Table C.4
Estimates of the effect of average temperature in a tournament-edition on the estimated tournament-edition FE.

Dependent variable:	First serve made rate (%)	Double fault rate (%)	Second serve made rate (%)
Average temperature (°C)	0.0229	−0.0084	0.0158
	(0.0185)	(0.0078)	(0.0167)
# of observations	1541	1541	1541
# of tournaments	125	125	125
Adjusted R^2	0.6859	0.7628	0.7799

In this analysis 35 observations are excluded because they are tournaments which were in our sample only once (singleton observations); standard errors in parentheses are clustered at tournament level; * p-value <0.10, ** p-value <0.05, *** p-value <0.01. All the models also include year FE and gender specific tournament FE.

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