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TEMPERATURE AND PRODUCTIVITY IN SOCCER

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Temperature and Productivity in Soccer

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Abstract:
This paper examines the impact of temperature on soccer team productivity using match-level data from ten countries across three continents. The results show that temperature affects multiple performance metrics, often in non-linear ways. Specifically, attacking efficiency is enhanced in warmer conditions, leading to increased goal productivity and improved shot conversion rates. Conversely, defensive performance appears to weaken in warmer conditions, with a decrease in defensive pressure and passing accuracy. Player aggression follows an inverted U-shaped pattern in relation to temperature. The effects of temperature vary across different leagues and climate regions. The relationship between temperature and outcome measures tends to be stronger in lower leagues, while the Champions League is the least influenced overall. Teams from colder regions experience a larger decline in passing volume when playing in high temperatures, with the effect being particularly pronounced in Brazil.

JEL: K14, K42, K49
Keywords: Football, Soccer, Temperature, Weather, Productivity

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1 Introduction

The impact of environmental factors on economic outcomes remains an open question that has attracted considerable attention in economic research (Dell et al. (2014), LoPalo (2023)). Current research has focused mainly on aggregate outcome variables such as GDP and labor income (most notably Hsiang (2010), Burke et al. (2015) or Heal and Park (2013)), while less attention has been paid to the role of temperature in individual worker productivity and behavior. Investigating weather effects on worker-level is challenging especially because the data is usually in short supply. Therefor, some of the existing studies are made on employee data from individual firms, while other use firm-level datasets, LoPalo (2023). The literature on human physiology suggests that people‘s productivity drops quickly when they are forced to work in uncomfortable temperatures (i.e. Anderson (1989) or Cramer and Jay (2016)). Heal and Park (2013) examines the effect of outdoor temperature on judicial decision-making, finding that a 10°F increase reduces favorable rulings by 1.075 percent. Greenstone et al. (2010) analyzes productivity spillovers from new plants to incumbent firms, highlighting gains among those sharing labor pools. Deschênes and Greenstone (2007) estimates the impact of climate change on US agricultural profits, revealing modest overall effects with significant regional variation. According to existing studies, higher temperatures generally exhibit a negative correlation with productivity and economic output, particularly in warmer climates, while cooler regions experience marginal gains. Deviations from optimal temperature ranges, especially towards higher values, induce performance decline.

This paper investigates the impact of temperature on human productivity, utilizing a comprehensive dataset of professional soccer matches spanning ten countries across three continents, encompassing various performance metrics. The use of soccer data offers several advantages for this analysis. Firstly, the detailed nature of this data allows for the measurement of productivity through a multitude of indicators: overall efficiency as measured by goals scored and conversion rates, team effort quantified by the number of shots, and player cooperation assessed through pass completion and accuracy. Secondly, this setting provides an opportunity to examine the influence of temperature on human aggression, as reflected in the number of fouls committed and the issuance of yellow and red cards. Thirdly, soccer data enables an investigation into whether the effect of temperature differs between highly skilled players in top-tier leagues and those in lower divisions. Fourthly, the analysis of soccer data allows for the exploration of home and away team effects, specifically whether individuals accustomed to the prevailing temperatures of their locality exhibit better adaptation compared to those from climatically distinct regions. While the findings may offer insights into other sporting contexts, their direct applicability to diverse industrial sectors is questionable and requires further research.

Joly and Dik (2021) examined the impact of cold weather on the National Football League (NFL) and found a statistically significant home-field advantage for teams playing in cold weather climates during the winter months. This advantage suggests that extreme weather conditions can indeed influence game outcomes, particularly in sports played outdoors. Burke et al. (2023) investigated the effects of hot temperatures on professional tennis performance. This research revealed that high temperatures lead to increased errors and retirements, as well as reduced win probability in subsequent matches. The study found that top players were less affected by heat and that there was no adaptation to heat shown by the athletes.

Koch and Panorska (2013) analyzed Major League Baseball (MLB) games from 2000-11, finding that warm temperatures significantly increase offensive production, including runs scored, batting average, and home runs, while decreasing walks. The American League showed a stronger temperature impact than the National League. Fesselmeyer (2021) examined the effect of temperature on MLB umpire accuracy, revealing that high temperatures significantly decrease the accuracy of ball and strike calls.

Prior research on environmental effects in soccer has primarily focused on data from the Chinese Super League (CSL), the top professional league in Mainland China[1]. Yuan et al. (2024) found that elevated temperatures and precipitation during matches lead to a significant decrease in total running distances, the number of passes, and the number of fouls, with these effects being more pronounced for away teams. Wei et al. (2023) posits an inverted-U shaped relationship between temperature and players' physical performance. Conversely, scholars such as Zhou et al. (2019) and Zhang et al. (2024) found only a negligible impact of relative air humidity and air quality index on the performance of soccer players in the CSL league.

To the best of my knowledge, this paper represents the first study to examine the effects of temperature on productivity in soccer using a large-scale dataset from top-tier soccer leagues across three continents. My research question focuses on isolating the impact of temperature on soccer productivity. I use panel data models with fixed effects at the team-season and region-season levels to control for unobserved heterogeneity and to identify the effects of temperature on soccer productivity within teams and regions across seasons. The findings suggest that temperature has a significant, though generally modest, effect on various aspects of team performance. Specifically, the analysis indicates that attacking efficiency is enhanced in warmer conditions, with teams scoring more goals and demonstrating greater

[1]Note that these existing studies are based on relatively small data samples compared to this paper, with a maximum of four seasons analyzed.

effectiveness in converting set-piece opportunities. Conversely, defensive performance and overall game control deteriorate under higher temperatures. Furthermore, player aggression follows an inverted U-shaped pattern, initially increasing with rising temperatures before declining at extreme heat levels.

The sensitivity to temperature fluctuations is observed to vary across different leagues and in relation to climatic origins. For instance, teams originating from colder regions appear to experience greater difficulty with passing accuracy in high-temperature environments, particularly in the case of Brazilian leagues. Additionally, the magnitude of the temperature effect differs across league levels, with a more pronounced increase in fouls observed in second divisions and a less significant decline in passing accuracy compared to top-tier leagues. Notably, the Champions League appears to be the least susceptible to variations in temperature.

The rest of the paper is structured as follows. section 2 provides a summary of the data. section 3 details the identification strategy of the models used in the analysis, and section 4 discusses the key findings. Finally, section 5 concludes the paper.

2 Data

The analysis focuses on data from the Champions League and the following countries: UK, Germany, Spain, Italy, Portugal, France, Netherlands, Brazil, Argentina, and USA. The data are structured at the match level, where each individual match is represented by two distinct records, corresponding to the home and away teams involved. This structure allows for panel data analysis, tracking the same teams across different match weeks and seasons. This article uses data from two sources: soccer data from LIVESPORT[2] and weather data from the OpenWeather API, matched using home team geo-coordinates at the start of the match. [3]. Data covers the period from 2006 to 2024, and not all variables are available for all states and leagues (see Table 19, Table 20 and Table 21 for a detailed description of which data is available for which league). For the purposes of measuring a team's productivity in a game, I divided the variables into two main categories: Attacks and Defense & Aggression. An overview, including subcategories, is provided in Table 1.

Figure 1 shows histograms of temperatures across countries and leagues. The coldest weather is in the UK and the Champions League, while the warmest weather is in Brazil, Argentina and the USA. Table 2 shows the variation in temperatures within each country. While in the Netherlands, Germany or the UK the average differences between home teams are minimal, in Spain, Brazil and the USA the difference between the coldest and warmest home football team is more than 10'C. The variation in temperature therefore occurs across time, as the league season progresses towards warmer or colder weather, and across locations as teams travel to colder or warmer places. Figure 3 illustrates temperature deviations per week within each country and indicates the timing of winter and summer breaks across the leagues. Finally, Table 22, Table 24, and Table 23 present summary statistics for all productivity variables across countries.

[2]http://www.livesport.cz

[3]https://openweathermap.org/api

Attacks	
Number of goals scored	Score
Shot conversion rate	Score / Total shots
On-target shot conversion rate	Score / Shots on target
Shots	Total shots
Shots on target	Total shots on target
Shooting accuracy	Shots on target / Total shots
Corners	Total number of corners
Corner conversion rate	Score / Corners
Free kicks	Total number of free kicks
Free kick conversion rate	Score / Free kicks
Defense & Aggression	
Shot blocking rate	Blocked shots / Total shots
Passes	Total number of passes
Passing accuracy	Successful passes / Passes
Fouls	Total number of fouls
Yellow cards	Total number of yellow cards
Red cards	Total number of red cards

Table 1: Metrics for Measuring Football Team Productivity

Country	min	mean	max
Champions league	7.59	11.7	15.79
UK	7.61	9.07	10.54
Germany	7.45	9.33	10.85
Spain	6.83	14.2	19.68
Italy	10.19	13.12	18.56
Portugal	12.68	14.45	17.65
France	9.33	11.55	16.05
Netherlands	9.05	9.53	9.98
Brazil	16.08	21.5	28.02
Argentina	14.16	17.63	19.57
USA	13.32	17.59	24.27

Note:

Table 2: Temperature variability within countries and leagues

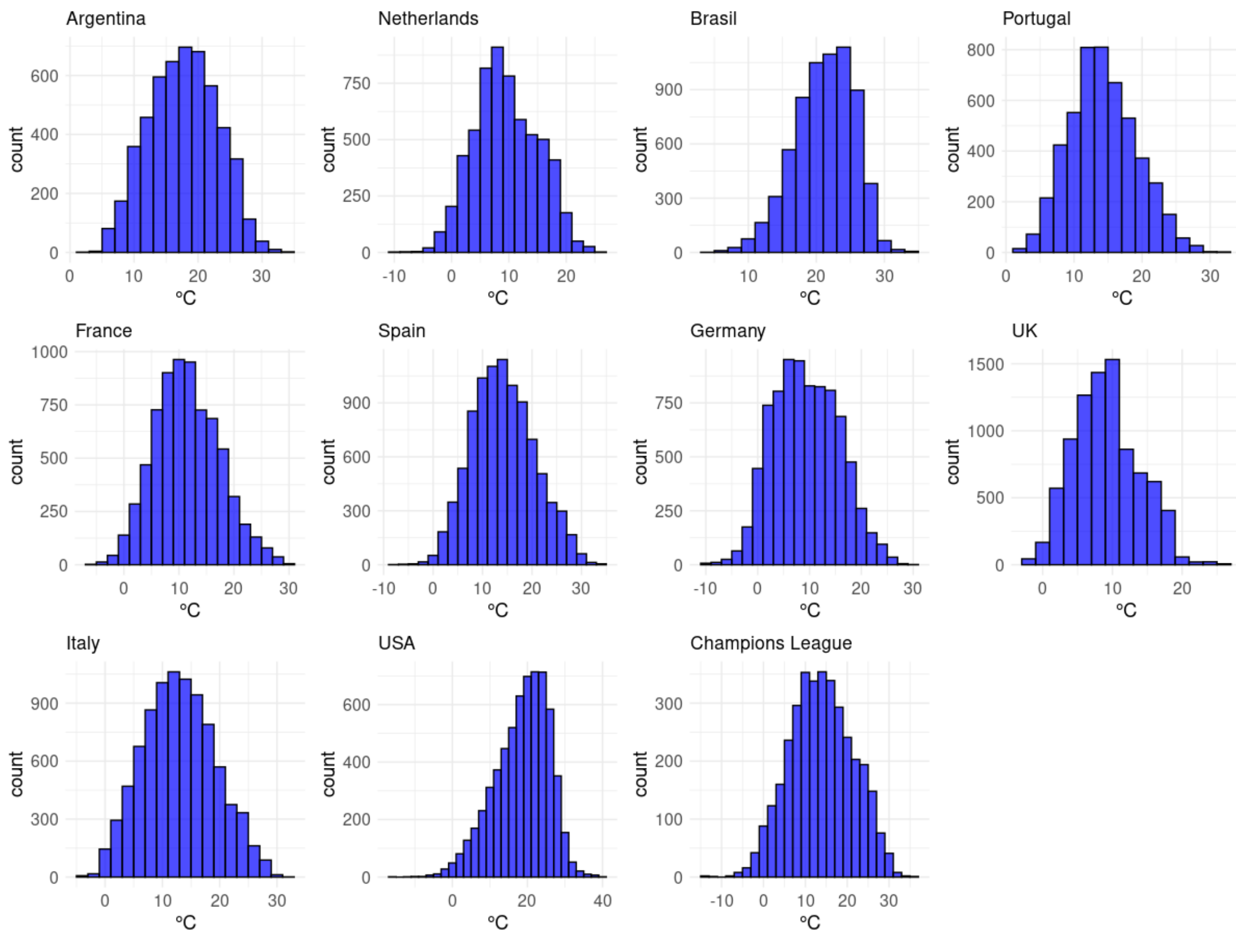

Figure 1: Histogram of temperatures in leagues.

3 Methodology

In this section, I develop an econometric model to examine the relationship between weather and soccer-related productivity. The identification strategy is presented in three specifications. Equations Equation 1, Equation 2, and Equation 4 include a comprehensive set of fixed effects to control for time-invariant unobserved heterogeneity that might be specific to a particular country, league, or team. Specifically, the identification strategies employ a within time-country approach, isolating variations in temperature across matches.[4] [5]

3.1 Identification strategy

The main specification examines the effect of temperature on productivity by dividing temperature into six temperature bins: $< 6\,°\mathrm{C}$, $6 - 10\,°\mathrm{C}$, $10 - 14\,°\mathrm{C}$, $14 - 18\,°\mathrm{C}$, $18 - 22\,°\mathrm{C}$, $\geq 22\,°\mathrm{C}$ (Equation 1). This breakdown was chosen to cover all the leagues and countries in the dataset (recall Figure 1). A middle bin of $10 - 14\,°\mathrm{C}$ is the omitted category to test for a possible inverted U-shape between productivity and temperature. Temperature variation within season-league is employed for estimation:

$$Productivity_{s,d} = \sum_{i=1}^{6} \alpha^i \cdot T^i_{s,d} + \beta^P \cdot P_{s,d} + FE_{s,d} + \epsilon_{s,d} \tag{1}$$

Where $T^i_{s,d}$ stand for the six temperature bins, P denotes precipitation dummy, $FE_{s,d}$ is the set of fixed effects and $\epsilon_{s,d}$ stands for the error term. All in day d and stadium s. I incorporate fixed effects for the home team stadium-by-year (which also represents the location where the match was played), away team-by-year fixed effects, and the referee in a given season.

Another possible hypothesis is that teams that come from climatically different places are more sensitive to temperature. Therefore, in Equation 2, I test whether teams from the coldest cities react differently to high temperatures when they play in a high-temperature

[4] As a robustness check, regressions were also run exclusively on teams participating in the Champions League.

[5] Since temperature and precipitation patterns on a particular day may be correlated across geographic areas, I cluster all standard errors at the home stadium level. The productivity variables, which are count variables (such as the number of fouls or goals per game), are modeled using Poisson regression, while the remaining variables are estimated using OLS regression.

environment. In other words, this part examines whether players can adapt equally well regardless of where they are used to playing home games and training. This analysis is done for leagues from three states – the USA, Brazil, and Spain – because only there is sufficient within-state variability in mean temperature (see Table 2):

$$
\begin{aligned}
Productivity\_away_{s,d} = {} & \beta^{T} \cdot T^{E}_{s,d} + \beta^{TC} \cdot T^{E}_{s,d} \cdot Climate_{s,d} \\
& + \beta^{C} \cdot Climate_{s,d} + \beta^{P} \cdot P_{s,d} + FE_{s,d} + \epsilon_{s,d}
\end{aligned}
\tag{2}
$$

An alternative approach refines this idea by dividing teams into three climate groups based on the mean temperature of their home locations. Specifically, teams are categorized into terciles within each country: the coldest third, the middle third, and the warmest third. This specification allows for a more granular test of climate adaptation effects by accounting for a broader range of climatic conditions teams are accustomed to.

$$
\begin{aligned}
Productivity_{s,d} = {} & \beta^{away} \cdot D\_away + \beta^{away\_Climate} \cdot D\_away \cdot Climate\_group \\
& + \beta^{away\_Climate\_temp} \cdot T \cdot D\_away \cdot Climate\_group + FE_{s,d} + \epsilon_{s,d}
\end{aligned}
\tag{3}
$$

Where $Productivity\_away_{s,d}$ denotes the productivity variable measured for the visiting team. In Equation 3, $Climate\_group$ is a categorical variable dividing teams into terciles based on the long-term average temperature of their home location, rather than a binary classification. The term D_away is an indicator for whether the team is playing an away game. T stands for the temperature during the match. The interaction term $D\_away \cdot Climate\_group$ captures differences in away-game performance across climate terciles, while $T \cdot D\_away \cdot Climate\_group$ measures whether these differences are further moderated by high temperatures on game day. To isolate the temperature effect, I use fixed effects for home team stadium-by-year, away team stadium-by-year, and referee-season. This approach improves on Equation 2 by allowing for more variation in climate adaptation effects, rather than restricting the comparison to only the coldest teams versus the rest.

Finally, the paper tests the hypothesis whether the effect of temperature is different for different divisions. In other words, whether players adapt to high temperatures differently when playing in the top league in their country than when playing in lower leagues. Therefore, Equation 4 examines the interaction between the dummy variable Div (equals 1 based on whether the match is played in the top division, or second, third top league, or European champions league.) and the dummy variable T^{22+} which is equal to 1 if the match was played in more than 22 degrees Celsius on that day, otherwise 0 - the same temperature threshold as in the Equation 1:

$$Productivity_{s,d} = \beta^{T22+} \cdot T^{22+}_{s,d} + \beta^{TDiv} \cdot T^{22+}_{s,d} \cdot Div + \beta^{Div} \cdot Div + \beta^{P} \cdot P_{s,d} + FE_{s,d} + \epsilon_{s,d} \tag{4}$$

4 Results

In general, the results portray a complex relationship between temperature and a soccer team productivity, assessed using a variety of performance measures. Certain gameplay elements tend to vary non-linearly (inverted U-shape relationship) with temperature changes, while others exhibit a clear threshold effect when temperatures are high.

Compared to the baseline temperature range of 10–14°C, matches contested in conditions exceeding 22°C demonstrate a statistically significant enhancement in overall goal productivity. Specifically, teams achieve a greater number of goals, exhibit improved shot conversion rates (both overall and on-target), and undertake a higher volume of both total and on-target shots (Table 3). Furthermore, the efficiency of set-piece situations is augmented, as evidenced by elevated conversion rates from both corner kicks and direct free kicks (Table 3). This suggests that attacking play becomes more efficacious in elevated temperature environments.

Conversely, defensive performance experiences a decline under higher temperature conditions. The number of blocked shots decreases, indicative of diminished defensive pressure (Table 4). Moreover, teams concede a greater number of goals from set pieces, which suggests a weakening in defensive organization during these scenarios. Game control is also negatively impacted, as evidenced by a reduction in the total number of passes and passing accuracy (Table 4). This decline in structured play and defensive stability implies that elevated temperatures disrupt coordinated team movements and defensive cohesion, thereby complicating the maintenance of match control.

An inverted U-shaped relationship is observed between temperature and metrics of aggressiveness, encompassing the number of fouls committed and the issuance of yellow cards (Table 4). This suggests that player aggression intensifies with rising temperatures up to a certain point, before subsequently diminishing at excessively high heat levels. A similar pattern emerges for the total number of corners taken, indicating that attacking teams generate more set-piece opportunities under moderate temperature conditions, yet this trend reverses in instances of extreme heat (Table 3).

The observed effects on foul-related behavior and passing patterns are particularly pronounced within the United Kingdom and the Netherlands, implying that teams competing in these leagues may exhibit greater sensitivity to temperature fluctuations. However, within the context of the UEFA Champions League, these temperature-related effects are either negligible or statistically insignificant.

In summation, these findings underscore that while elevated temperatures contribute to a reduction in defensive stability and passing efficiency, they simultaneously foster a more aggressive and direct attacking style of play. The inverted U-shaped pattern observed in both aggression and set-piece generation further accentuates the necessity of considering non-linear effects when evaluating the influence of environmental factors on team performance. Overall, while temperature impacts team performance, the observed effects are relatively small.

Table 3: Regression Results - Attacks

	Dependent variable:									
	Total Score	Score per Shot	Score per Shot on Target	Total Shots	Total Shots on Target	Shooting Accuracy	Corners	Corner Conversion Rate	Free Kicks	Free Kick Conversion Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
< 6 °C	−0.030***	−0.003***	−0.014***	−0.004	0.009*	0.005**	−0.010**	−0.008*	0.001	−0.002
	(0.009)	(0.001)	(0.003)	(0.003)	(0.005)	(0.002)	(0.005)	(0.004)	(0.003)	(0.002)
6–10 °C	−0.013	−0.001	−0.005**	−0.003	0.004	0.002	−0.005	−0.003	0.005*	−0.001
	(0.008)	(0.001)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.003)	(0.003)	(0.001)
14–18 °C	0.001	−0.001	0.001	0.005**	−0.003	−0.004***	−0.004	−0.0001	−0.003	−0.001
	(0.008)	(0.001)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.003)	(0.003)	(0.001)
18–22 °C	0.029***	0.001	0.005*	0.014***	0.002	−0.005***	−0.001	0.006	−0.018***	0.003**
	(0.009)	(0.001)	(0.003)	(0.003)	(0.005)	(0.002)	(0.005)	(0.004)	(0.003)	(0.002)
> 22 °C	0.066***	0.003**	0.010***	0.024***	0.026***	−0.001	−0.009*	0.018***	−0.039***	0.010***
	(0.011)	(0.001)	(0.003)	(0.003)	(0.006)	(0.002)	(0.005)	(0.005)	(0.004)	(0.002)
Rain	0.014***	0.001	0.003**	0.009***	0.006**	−0.001	0.013***	−0.001	−0.004**	0.002***
	(0.005)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Constant	0.728***	0.121***	0.244***	3.005***	2.180***	0.476***	2.199***	0.290***	1.010***	0.092
	(0.080)	(0.009)	(0.022)	(0.025)	(0.042)	(0.014)	(0.040)	(0.033)	(0.200)	(0.087)
Observations	75,044	74,915	74,874	74,915	74,912	74,911	74,912	74,909	52,352	52,315
(Pseudo) R^2	0.10	0.09	0.09	0.14	0.11	0.12	0.11	0.09	0.10	0.12
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Omitted Category (10–14 °C)	2.59	0.11	0.29	24.02	9.03	0.38	9.88	0.28	31.99	0.08

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: Regression Results - Defense & Aggression

	Dependent variable:					
	Shot blocking rate	Passes	Passing accuracy	Fouls	Yellow cards	Red cards
	(4)	(5)	(6)	(1)	(2)	(3)
$< 6\,^{\circ}$C	0.002	0.226***	0.743***	−0.006*	−0.039***	−0.018
	(0.002)	(0.001)	(0.086)	(0.003)	(0.008)	(0.034)
6−10 °C	0.002*	0.139***	0.384***	0.002	−0.010*	−0.009
	(0.001)	(0.001)	(0.069)	(0.003)	(0.006)	(0.028)
14−18 °C	0.001	−0.081***	−0.214***	−0.007***	0.005	0.017
	(0.001)	(0.001)	(0.067)	(0.003)	(0.006)	(0.026)
18−22 °C	−0.001	−0.120***	−0.340***	−0.015***	0.010	0.014
	(0.002)	(0.001)	(0.079)	(0.003)	(0.007)	(0.030)
$> 22\,^{\circ}$C	−0.006***	−0.256***	−0.720***	−0.032***	−0.020**	0.008
	(0.002)	(0.001)	(0.092)	(0.003)	(0.008)	(0.035)
Rain	0.001	0.017***	0.045	−0.007***	0.010**	−0.0001
	(0.001)	(0.0004)	(0.042)	(0.002)	(0.004)	(0.017)
Constant	0.164***	6.622***	1.106	3.325***	1.683***	0.341
	(0.017)	(0.006)	(0.724)	(0.024)	(0.056)	(0.225)
Observations	52,532	37,870	23,380	68,390	72,473	14,807
(Pseudo) R^2	0.09	0.09	0.11	0.12	0.10	0.10
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓
Omitted Category (10–14 °C)	0.24	882.93	0.75	27.66	4.60	1.07

Note: *p<0.1; **p<0.05; ***p<0.01

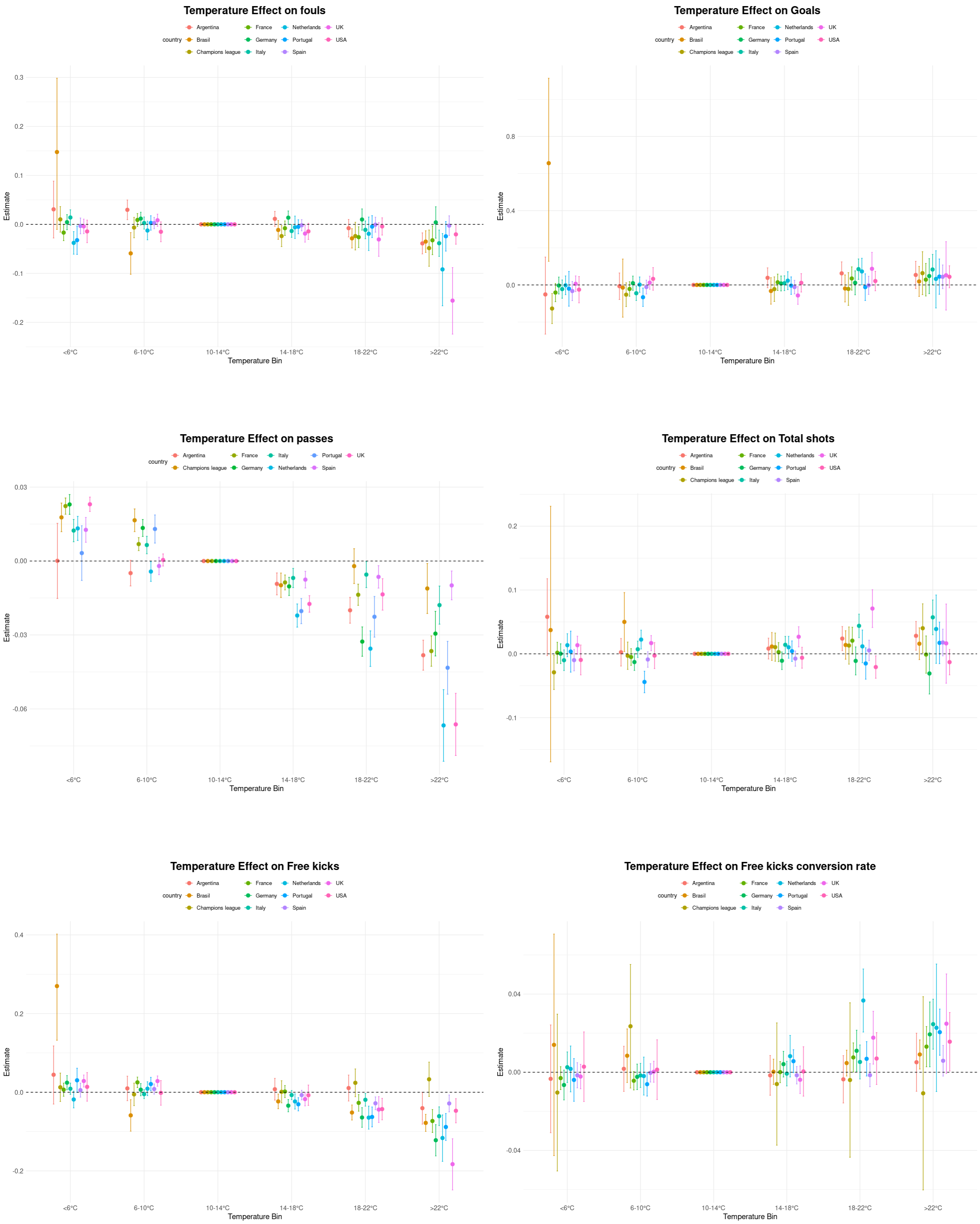

Figure 2: Temperature effects on different match statistics.

Climatic Origin and Hot Weather Effects

In this paragraph I comment on whether the results in the previous main section are stronger if the club comes from a climatically cooler location and plays a match on a hot day. My analysis finds that the only performance metric significantly affected by a team's climatic origin is the total number of passes (Table 5 and Table 6). Teams from colder cities experience a stronger decline in passing volume when playing in high temperatures compared to teams from warmer locations. This effect is observed across the USA, Brazil, and Spain, with the strongest impact in Brazil. The heightened sensitivity in Brazil may be attributed to it being the warmest country in the dataset (see Table 2), suggesting that teams from colder regions struggle more when exposed to extreme heat in already warm climates.

Table 5: Regression Results

	Dependent variable:					
	Passes			Passing accuracy		
	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)
Climate	-0.125^{***}	-0.313^{***}	-0.059^{***}	0.138	-1.125	0.042^{**}
	(0.004)	(0.015)	(0.006)	(0.504)	(2.947)	(0.017)
T^E	-0.023^{***}	-0.067^{***}	-0.005^{*}	-0.071	-0.974^{*}	-0.005
	(0.002)	(0.002)	(0.003)	(0.174)	(0.555)	(0.008)
Climate $\cdot T^E$	-0.070^{***}	-0.596^{***}	-0.040^{***}	-1.381	2.988	-0.011
	(0.010)	(0.016)	(0.007)	(1.729)	(4.108)	(0.021)
Constant	6.376^{***}	6.922^{***}	6.814^{***}	4.671^{*}	1.262	1.256^{***}
	(0.021)	(0.018)	(0.034)	(2.567)	(5.516)	(0.073)
Observations	4,993	3,937	3,243	2,651	2,767	1,744
(Pseudo) R^2	0.10	0.09	0.11	0.10	0.10	0.09
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓
Away team stadium-by-year FE	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 6: Regression Results

	Dependent variable:					
	Passes			Passing accuracy		
	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)
T	-0.004^{***}	-0.122^{***}	-0.001^{***}	-0.019	0.411^{***}	-0.001^{***}
	(0.0001)	(0.0002)	(0.0002)	(0.016)	(0.077)	(0.0005)
$Climate\_2 \cdot T$	-0.008^{***}	-0.001	-0.001^{***}	-0.002	-0.097	0.0004
	(0.0002)	(0.0003)	(0.0003)	(0.024)	(0.116)	(0.001)
$Climate\_3 \cdot T$	-0.023^{***}	-0.061^{***}	0.0001	-0.031	-0.190	-0.001
	(0.0002)	(0.0005)	(0.0003)	(0.025)	(0.185)	(0.001)
Constant	7.273^{***}	4.653^{***}	6.614^{***}	2.372^{***}	-5.067	1.400^{***}
	(0.005)	(0.017)	(0.006)	(0.720)	(5.154)	(0.013)
Observations	4,993	3,937	3,243	2,651	2,767	1,744
(Pseudo) R^2	0.08	0.09	0.10	0.10	0.08	0.08
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓
Away team stadium-by-year FE	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓
Note:				*p<0.1; **p<0.05; ***p<0.01		

Temperature Effects on Productivity Across League Levels

The impact of high temperatures varies across league divisions. The effect on the number of fouls is stronger in the second-highest division compared to the top league in a given country, suggesting that lower-tier teams exhibit more aggressive behavior under heat. Similarly, the number of corners is more affected in the Champions League than in the top domestic leagues, indicating that set-piece generation is more sensitive to temperature in elite international competition, Table 7.

Passing metrics also show differential effects. The impact of high temperatures on both the total number of passes and passing accuracy is lower in the second-highest division than in the top league, suggesting that top-tier teams experience a greater decline in structured play under heat. However, the effect on the number of passes is stronger in the Champions League than in domestic top leagues, implying that temperature influences game control more in international matches, Table 8.

Shooting-related metrics follow a similar pattern, with the effect on shots on target and shooting accuracy being weaker in the second-highest division compared to the top league.

Table 7: Regression Results: Attacks

	Dependent variable:						
	Total Shots	Total Shots on Target	Shooting accuracy	Corners	Corner conversion rate	Free kicks	Free kick conversion rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T^{22+}	0.017***	0.034***	0.005**	−0.002	0.016***	−0.030***	0.008***
	(0.003)	(0.006)	(0.002)	(0.005)	(0.005)	(0.004)	(0.002)
E1	−0.047***	0.008	0.023***	0.004	−0.002	0.042***	−0.006***
	(0.004)	(0.006)	(0.002)	(0.006)	(0.005)	(0.004)	(0.002)
E2	−0.216***	−0.043**	0.077***	0.048***	−0.023*	0.083***	−0.020***
	(0.011)	(0.017)	(0.006)	(0.016)	(0.014)	(0.012)	(0.005)
Champ	0.285	0.060	−0.065	0.680	−0.512	0.371	0.022
	(0.311)	(0.534)	(0.177)	(0.468)	(0.412)	(0.268)	(0.129)
Rain	0.010***	0.005**	−0.002*	0.013***	−0.001	0.003	0.002***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
$T^{22+}\cdot$ E1	0.002	−0.031***	−0.012***	−0.014*	−0.006	−0.005	0.003
	(0.006)	(0.009)	(0.003)	(0.009)	(0.007)	(0.006)	(0.003)
$T^{22+}\cdot$ E2	−0.041	−0.054	−0.002	−0.074*	0.019	−0.009	−0.002
	(0.031)	(0.048)	(0.016)	(0.045)	(0.037)	(0.027)	(0.012)
$T^{22+}\cdot$ Champ	0.001	0.025	0.010	−0.008	0.033	0.052***	−0.010
	(0.017)	(0.027)	(0.010)	(0.027)	(0.023)	(0.018)	(0.008)
Observations	74,915	74,912	74,911	74,912	74,909	52,352	52,315
(Pseudo) R^2	0.14	0.11	0.12	0.11	0.09	0.10	0.12
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓
Away team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: Regression Results: Defense & Aggression

	Dependent variable:					
	Passes	Passing accuracy	Shot blocking rate	Fouls	Yellow cards	Red cards
	(4)	(5)	(6)	(1)	(2)	(3)
T^{22+}	0.234***	0.690***	−0.004**	−0.028***	−0.024***	−0.001
	(0.001)	(0.091)	(0.002)	(0.003)	(0.008)	(0.035)
E1	−0.021***	−0.261**	−0.002	0.040***	0.038***	0.021
	(0.001)	(0.117)	(0.002)	(0.004)	(0.008)	(0.037)
E2	−0.038***	−0.191	−0.019***	0.011	0.095***	0.035
	(0.003)	(0.443)	(0.006)	(0.011)	(0.025)	(0.132)
Champ	−0.168***	−0.301	0.123	0.093	−1.069	−0.363
	(0.030)	(2.590)	(0.143)	(0.297)	(0.905)	(1.019)
Rain	0.030***	0.074*	0.001	−0.007***	0.012***	0.001
	(0.0004)	(0.042)	(0.001)	(0.002)	(0.004)	(0.017)
$T^{22+}\cdot$ E1	−0.145***	−0.512***	−0.003	0.012**	−0.001	−0.002
	(0.001)	(0.140)	(0.003)	(0.005)	(0.013)	(0.056)
$T^{22+}\cdot$ E2	−0.180***	−0.486	0.004	0.001	0.030	0.047
	(0.014)	(1.067)	(0.018)	(0.035)	(0.065)	(0.353)
$T^{22+}\cdot$ Champ	0.052***	0.017	−0.004	0.001	−0.045	−0.026
	(0.004)	(0.410)	(0.008)	(0.016)	(0.040)	(0.277)
Observations	37,870	23,380	52,532	68,390	72,473	14,807
(Pseudo) R^2	0.09	0.08	0.10	0.11	0.08	0.07
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓
Omitted Category (10–14 °C)	0.24	882.93	0.75	27.66	4.60	1.07

Note: *p<0.1; **p<0.05; ***p<0.01

5 Conclusion

In this paper, I have documented the relationship between temperature and various performance metrics in professional football across ten countries and the Champions League. The findings reveal notable trends.

Regarding attacking performance, my analysis indicates a clear enhancement in efficiency under elevated temperature conditions. Teams exhibit a greater propensity to score goals, coupled with improved shot conversion rates and a more effective utilization of set-piece opportunities.

Conversely, the study reveals a decline in defensive performance as temperatures rise. This is evidenced by a reduction in defensive actions, specifically fewer blocked shots, and a greater vulnerability to conceding goals, particularly from set-piece situations. Furthermore, the capacity for maintaining structured play, as reflected in passing accuracy, appears to be negatively impacted by higher temperatures.

Moreover, my findings suggest an inverted U-shaped relationship between temperature and player aggression. While aggression, as measured by fouls, tends to increase with rising temperatures up to a certain point, it appears to diminish at the highest heat levels.

Teams originating from colder climatic regions demonstrate a more pronounced decrease in passing volume when competing in warmer conditions. Additionally, the impact of temperature appears to vary across different league levels, with a more substantial increase in fouls observed in lower-tier leagues compared to top divisions. While the Champions League exhibits greater sensitivity in specific areas such as set-piece generation, it generally appears to be less affected by temperature fluctuations overall in the performance indicators analyzed.

In conclusion, these findings highlight the influence of temperature on football performance. The observed increase in attacking efficiency under warmer conditions, leading to higher goal productivity, suggests that matches played in elevated temperatures may be more engaging for spectators. Furthermore, the non-linear effects (inverted U-shape relationship) and the varying impact across different leagues emphasize the importance of considering environmental factors when analyzing team performance. It is important to note that climate effects, or global warming, do not appear to be major concerns in this specific context, as the observed effects are primarily related to the immediate impact of temperature during matches. Beyond the described performance effects, football could potentially benefit from increased attendance due to the more attractive nature of matches played in warmer weather. While these results provide valuable insights into the impact of temperature on football performance, the observed responses suggest potential applicability to other physical sports contexts. However, the direct transferability of these findings to diverse industrial settings requires further research.

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6 Appendix

6.1 Tables

Table 9: Regression Results

	Dependent variable:								
	Fouls			Yellow cards			Red cards		
	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate	0.012	−0.004	0.089***	−0.058	−0.244*	0.070*	−0.272	−0.845	0.206
	(0.023)	(0.057)	(0.021)	(0.058)	(0.148)	(0.041)	(0.257)	(0.629)	(0.190)
T^E	−0.019*	0.001	−0.009	−0.031	−0.013	−0.040*	0.069	0.165	0.085
	(0.011)	(0.010)	(0.010)	(0.026)	(0.025)	(0.022)	(0.115)	(0.100)	(0.095)
Climate $\cdot T^E$	−0.026	−0.061	−0.050*	0.031	−0.044	−0.004	−0.007	−0.132	−0.557
	(0.055)	(0.063)	(0.030)	(0.141)	(0.165)	(0.069)	(0.598)	(0.727)	(0.393)
Constant	3.245***	3.046***	3.335***	0.878***	1.707***	1.759***	−3.029***	−0.908	−1.461***
	(0.061)	(0.087)	(0.030)	(0.163)	(0.204)	(0.058)	(1.076)	(0.960)	(0.261)
Observations	6,291	6,622	8,255	6,300	6,657	9,275	6,300	6,657	9,275
(Pseudo) R^2	0.10	0.11	0.13	0.09	0.09	0.13	0.12	0.14	0.13
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Note:	*p<0.1; **p<0.05; ***p<0.01								

Table 10: Regression Results

	Dependent variable:								
	Score			Shot conversion			Shot conversion on target		
	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate	−0.087	0.248	0.001	−0.045	0.248	0.018	−0.073	0.120	0.049
	(0.065)	(0.223)	(0.065)	(0.323)	(1.109)	(0.297)	(0.194)	(0.636)	(0.178)
T^E	−0.015	0.037	0.037	−0.003	0.064	0.014	0.003	0.095	0.035
	(0.031)	(0.035)	(0.032)	(0.153)	(0.174)	(0.150)	(0.092)	(0.100)	(0.090)
Climate $\cdot T^E$	0.045	−0.237	−0.111	−0.035	−0.254	−0.132	−0.065	−0.085	−0.097
	(0.156)	(0.256)	(0.097)	(0.809)	(1.302)	(0.472)	(0.488)	(0.664)	(0.279)
Constant	0.596***	0.790**	0.790***	−2.520**	−2.180	−2.163***	−1.477**	−1.484	−1.289***
	(0.201)	(0.310)	(0.086)	(0.998)	(1.550)	(0.399)	(0.606)	(0.905)	(0.244)
Observations	6,300	6,657	9,275	6,293	6,645	9,269	6,290	6,644	9,263
(Pseudo) R^2	0.10	0.10	0.11	0.12	0.10	0.09	0.10	0.14	0.13
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11: Regression Results

	Dependent variable:											
	Total shots			Total shots on target			Shooting accuracy			Shot blocking rate		
	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Climate	−0.018	0.020	−0.101	−0.225	0.109	−0.048	−0.002	0.032	−0.052	−0.021	−0.005	0.008
	(0.022)	(0.068)	(0.517)	(0.348)	(0.117)	(0.034)	(0.011)	(0.035)	(0.159)	(0.230)	(0.030)	(0.010)
T^E	−0.021**	−0.032***	0.323	−0.198	−0.040**	0.015	−0.001	−0.001	−0.005	0.012	0.001	−0.010**
	(0.010)	(0.011)	(0.268)	(0.162)	(0.019)	(0.017)	(0.005)	(0.006)	(0.083)	(0.108)	(0.005)	(0.005)
Climate $\cdot T^E$	0.085*	0.025	−0.091	0.836	−0.117	−0.012	0.005	−0.038	−0.013	−0.002	0.014	−0.009
	(0.051)	(0.067)	(0.798)	(0.827)	(0.129)	(0.051)	(0.027)	(0.036)	(0.248)	(0.546)	(0.037)	(0.014)
Constant	3.148***	3.105***	20.306***	8.167***	2.352***	2.136***	0.363***	0.509***	−0.838***	−1.457**	0.289***	0.213***
	(0.060)	(0.093)	(0.718)	(0.943)	(0.158)	(0.047)	(0.031)	(0.049)	(0.217)	(0.627)	(0.046)	(0.014)
Observations	6,293	6,645	9,269	6,293	6,645	9,269	6,293	6,645	9,269	6,205	5,068	8,212
(Pseudo) R^2	0.10	0.09	0.09	0.14	0.11	0.12	0.11	0.09	0.10	0.12		
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: Regression Results

	Dependent variable:											
	Corners			Corner conversion rate			Free kicks			Free kick conversion rate		
	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Climate	0.022	−0.041	−0.523*	−0.021	0.282	0.119	−0.426	2.781	0.019	−0.141	0.023	0.001
	(0.036)	(0.099)	(0.310)	(0.032)	(0.722)	(0.181)	(1.280)	(2.849)	(0.022)	(0.495)	(0.021)	(0.008)
T^E	−0.017	−0.040**	0.022	0.003	0.084	0.024	−0.202	−0.650	−0.005	−0.034	0.004	0.005
	(0.017)	(0.017)	(0.161)	(0.015)	(0.105)	(0.092)	(0.600)	(0.469)	(0.011)	(0.236)	(0.003)	(0.004)
Climate $\cdot T^E$	0.052	0.086	−0.347	0.065	−0.381	−0.004	0.575	2.259	−0.038	0.308	−0.018	−0.016
	(0.082)	(0.105)	(0.478)	(0.077)	(0.815)	(0.265)	(2.916)	(3.351)	(0.033)	(1.148)	(0.024)	(0.011)
Constant	2.232***	2.275***	11.003***	0.203**	−1.336	−1.479***	4.608	31.621***	3.593***	−2.351	0.073**	0.063***
	(0.096)	(0.146)	(0.430)	(0.088)	(0.938)	(0.252)	(3.560)	(4.156)	(0.029)	(3.186)	(0.030)	(0.011)
Observations	6,292	6,645	9,268	6,291	6,645	9,268	2,499	5,909	6,280	2,488	5,902	6,279
(Pseudo) R^2	0.10	0.10	0.11	0.09	0.10	0.12	0.13	0.10	0.09	0.08	0.12	0.11
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: Regression Results

	Dependent variable:								
	Fouls			Yellow cards			Red cards		
	USA	Brasil	Spain	USA	Brasil	Spain	USA	Brasil	Spain
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate	0.012	−0.004	0.089***	−0.058	−0.244*	0.070*	−0.272	−0.845	0.206
	(0.023)	(0.057)	(0.021)	(0.058)	(0.148)	(0.041)	(0.257)	(0.629)	(0.190)
T^E	−0.019*	0.001	−0.009	−0.031	−0.013	−0.040*	0.069	0.165	0.085
	(0.011)	(0.010)	(0.010)	(0.026)	(0.025)	(0.022)	(0.115)	(0.100)	(0.095)
Climate $\cdot T^E$	−0.026	−0.061	−0.050*	0.031	−0.044	−0.004	−0.007	−0.132	−0.557
	(0.055)	(0.063)	(0.030)	(0.141)	(0.165)	(0.069)	(0.598)	(0.727)	(0.393)
Constant	3.245***	3.046***	3.335***	0.878***	1.707***	1.759***	−3.029***	−0.908	−1.461***
	(0.061)	(0.087)	(0.030)	(0.163)	(0.204)	(0.058)	(1.076)	(0.960)	(0.261)
Observations	6,291	6,622	8,255	6,300	6,657	9,275	6,300	6,657	9,275
(Pseudo) R^2	0.10	0.11	0.13	0.09	0.09	0.13	0.12	0.14	0.13
Home team stadium-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14: Regression Results

	Dependent variable:		
	Fouls	Yellow cards	Red cards
	(1)	(2)	(3)
$< 6\,^{\circ}$C	0.003	-0.035^{**}	-0.049
	(0.007)	(0.017)	(0.085)
6$-$10 °C	-0.003	-0.027^{**}	-0.017
	(0.006)	(0.014)	(0.068)
14$-$18 °C	-0.011^{*}	-0.006	0.024
	(0.006)	(0.014)	(0.069)
18$-$22 °C	-0.025^{***}	0.005	0.036
	(0.008)	(0.019)	(0.095)
$> 22\,^{\circ}$C	-0.037^{***}	-0.020	0.010
	(0.011)	(0.026)	(0.131)
Rain	-0.007^{**}	-0.00003	-0.009
	(0.003)	(0.009)	(0.043)
Constant	3.460^{***}	1.433^{***}	0.463
	(0.049)	(0.123)	(0.500)
Observations	15,266	14,952	2,724
(Pseudo) R^2	0.1	0.1	0.1
Note:	Only teams playing Champions league. *p<0.1; **p<0.05; ***p<0.01		

Table 15: Regression Results

	Dependent variable:		
	Total Score	Score per Shot	Score per Shot on Target
	(1)	(2)	(3)
$< 6\,^{\circ}$C	-0.046^{***}	-0.004^{*}	-0.010^{**}
	(0.016)	(0.002)	(0.005)
$6-10\,^{\circ}$C	-0.039^{***}	-0.003^{*}	-0.007^{*}
	(0.015)	(0.002)	(0.004)
$14-18\,^{\circ}$C	0.006	-0.001	0.003
	(0.015)	(0.002)	(0.004)
$18-22\,^{\circ}$C	-0.014	-0.005^{**}	-0.002
	(0.018)	(0.002)	(0.005)
$> 22\,^{\circ}$C	0.028	0.001	0.003
	(0.023)	(0.003)	(0.007)
Rain	0.008	0.0001	0.003
	(0.010)	(0.001)	(0.003)
Constant	2.174^{***}	0.182^{***}	0.443^{***}
	(0.439)	(0.060)	(0.145)
Observations	15,617	15,567	15,567
(Pseudo) R^2	0.11	0.09	0.12
Home team stadium-by-year FE	✓	✓	✓
Away team stadium-by-year FE	✓	✓	✓
Referee-by-year FE	✓	✓	✓
Note:	Only teams playing Champions league. *p<0.1; **p<0.05; ***p<0.01		

Table 16: Regression Results

	Dependent variable:	
	Passes	Passing accuracy
	(1)	(2)
$< 6\,°C$	0.017***	0.002
	(0.002)	(0.005)
$6-10\,°C$	0.007***	0.005
	(0.001)	(0.004)
$14-18\,°C$	−0.010***	0.001
	(0.001)	(0.004)
$18-22\,°C$	−0.018***	−0.013**
	(0.002)	(0.006)
$> 22\,°C$	−0.018***	−0.028***
	(0.003)	(0.008)
Rain	0.005***	0.001
	(0.001)	(0.003)
Constant	6.834***	1.516***
	(0.014)	(0.039)
Observations	7,428	5,211
(Pseudo) R^2	0.10	0.09
Home team stadium-by-year FE	✓	✓
Away team-by-year FE	✓	✓
Referee-by-year FE	✓	✓
Note:	Only teams playing Champions league. *p<0.1; **p<0.05; ***p<0.01	

Table 17: Regression Results

	Dependent variable:			
	Total Shots	Total Shots on Target	Shooting accuracy	Shot blo
	(1)	(2)	(3)	(
< 6 °C	−0.007	−0.008	−0.001	−0
	(0.007)	(0.011)	(0.004)	(0.
6−10 °C	−0.003	−0.011	−0.003	0.
	(0.006)	(0.009)	(0.003)	(0.
14−18 °C	0.011**	0.003	−0.005	−0
	(0.006)	(0.009)	(0.003)	(0.
18−22 °C	0.025***	−0.010	−0.016***	−0
	(0.008)	(0.013)	(0.005)	(0.
> 22 °C	0.035***	0.033*	−0.004	−0
	(0.011)	(0.018)	(0.006)	(0.
Rain	0.010***	0.0001	−0.004*	0.
	(0.003)	(0.006)	(0.002)	(0.
Constant	3.265***	2.532***	0.497***	0.1
	(0.065)	(0.104)	(0.037)	(0.
Observations	15,567	15,568	15,567	12
(Pseudo) R^2	0.10	0.10	0.11	0
Home team stadium-by-year FE	✓	✓	✓	
Away team-by-year FE	✓	✓	✓	
Referee-by-year FE	✓	✓	✓	

Note: Only teams playing Champions league. *p<0.1; **p<0.05;

Table 18: Regression Results

	Dependent variable:			
	Corners	Corner conversion rate	Free kicks	Free kick conversion
	(1)	(2)	(3)	(4)
$< 6\,°\mathrm{C}$	−0.003	−0.010	0.019***	−0.007*
	(0.011)	(0.010)	(0.007)	(0.004)
6−10 °C	−0.007	−0.007	0.012**	−0.006**
	(0.009)	(0.008)	(0.006)	(0.003)
14−18 °C	0.005	−0.004	−0.004	−0.0003
	(0.009)	(0.008)	(0.006)	(0.003)
18−22 °C	0.008	−0.014	−0.021***	0.002
	(0.013)	(0.012)	(0.008)	(0.004)
$> 22\,°\mathrm{C}$	0.030*	−0.0003	−0.027**	0.007
	(0.017)	(0.016)	(0.011)	(0.006)
Rain	0.007	−0.001	−0.005	0.003*
	(0.005)	(0.005)	(0.004)	(0.002)
Constant	2.487***	0.269***	3.602***	0.076**
	(0.102)	(0.093)	(0.070)	(0.037)
Observations	15,568	15,568	12,637	12,629
(Pseudo) R^2	0.10	0.11	0.12	0.10
Home team stadium-by-year FE	✓	✓	✓	✓
Away team-by-year FE	✓	✓	✓	✓
Referee-by-year FE	✓	✓	✓	✓

Note: Only teams playing Champions league. *p<0.1; **p<0.05; ***p

6.2 Graphs

Table 19: Data availability among leagues – Part 1

Country	League	Score	Fouls	Yellow cards	Red cards	Total shots	Shots on target
Europe	Champions League	Y	Y	Y	Y	Y	Y
UK	E0	Y	Y	Y	Y	Y	Y
UK	E1	Y	Y	Y	Y	Y	Y
UK	E2	Y	Y	Y	Y	Y	Y
Germany	E0	Y	Y	Y	Y	Y	Y
Germany	E1	Y	Y	Y	Y	Y	Y
Germany	E2	Y	Y	Y	Y	Y	Y
Spain	E0	Y	Y	Y	Y	Y	Y
Spain	E1	Y	Y	Y	Y	Y	Y
Italy	E0	Y	Y	Y	Y	Y	Y
Italy	E1	Y	Y	Y	Y	Y	Y
Portugal	E0	Y	Y	Y	Y	Y	Y
Portugal	E1	Y	Y	Y	Y	Y	Y
France	E0	Y	Y	Y	Y	Y	Y
France	E1	Y	Y	Y	Y	Y	Y
Netherlands	E0	Y	Y	Y	Y	Y	Y
Netherlands	E1	Y	Y	Y	Y	Y	Y
Brazil	E0	Y	Y	Y	Y	Y	Y
Brazil	E1	Y	Y	Y	Y	Y	Y
Argentina	E0	Y	Y	Y	Y	Y	Y
Argentina	E1	Y	Y	Y	Y	Y	Y
USA	E0	Y	Y	Y	Y	Y	Y
USA	E1	Y	Y	Y	Y	Y	Y

Note: Y = available, N = not available. E0, E1 and E2 stand for the top, second and third highest leagues in the country, respectively.

Table 20: Data availability among leagues – Part 2

Country	League	Blocked shots	Throw-in	Off sides	Corners	Free kicks	Passes
Europe	Champions League	Y	Y	Y	Y	Y	Y
UK	E0	Y	Y	Y	Y	Y	Y
UK	E1	Y	Y	Y	Y	Y	Y
UK	E2	Y	Y	Y	Y	Y	Y
Germany	E0	Y	N	Y	Y	Y	Y
Germany	E1	Y	N	Y	Y	Y	Y
Germany	E2	Y	N	Y	Y	Y	N
Spain	E0	Y	Y	Y	Y	Y	Y
Spain	E1	Y	Y	Y	Y	Y	Y
Italy	E0	Y	Y	Y	Y	Y	Y
Italy	E1	Y	Y	Y	Y	Y	Y
Portugal	E0	Y	Y	Y	Y	Y	Y
Portugal	E1	Y	Y	Y	Y	Y	N
France	E0	Y	Y	Y	Y	Y	Y
France	E1	Y	Y	Y	Y	Y	Y
Netherlands	E0	Y	Y	Y	Y	Y	Y
Netherlands	E1	Y	Y	Y	Y	Y	Y
Brazil	E0	Y	Y	Y	Y	Y	Y
Brazil	E1	Y	Y	Y	Y	Y	Y
Argentina	E0	Y	Y	Y	Y	Y	Y
Argentina	E1	Y	Y	Y	Y	Y	Y
USA	E0	Y	Y	Y	Y	Y	Y
USA	E1	Y	Y	Y	Y	Y	Y

Note: Y = available, N = not available. E0, E1 and E2 stand for the top, second and third highest leagues in the country, respectively.

Table 21: Data availability among leagues – Part 3

Country	League	Successful passes	Centers	Successful centers	Tackles	Successful tackles
Europe	Champions League	Y	N	N	N	N
UK	E0	Y	N	N	N	N
UK	E1	Y	N	N	N	N
UK	E2	Y	N	N	N	N
Germany	E0	Y	N	N	N	N
Germany	E1	Y	N	N	N	N
Germany	E2	N	N	N	N	N
Spain	E0	Y	N	N	N	N
Spain	E1	Y	N	N	N	N
Italy	E0	Y	N	N	N	N
Italy	E1	Y	N	N	N	N
Portugal	E0	Y	N	N	N	N
Portugal	E1	N	N	N	N	N
France	E0	Y	N	N	N	N
France	E1	Y	N	N	N	N
Netherlands	E0	Y	N	N	N	N
Netherlands	E1	Y	N	N	N	N
Brazil	E0	Y	Y	Y	Y	Y
Brazil	E1	Y	N	N	N	N
Argentina	E0	Y	N	N	N	N
Argentina	E1	Y	N	N	N	N
USA	E0	Y	Y	Y	Y	Y
USA	E1	Y	N	N	N	N

Note: Y = available, N = not available. E0, E1 and E2 stand for the top, second and third highest leagues in the country, respectively.

Country	Total number of passes	Yellow cards	Red cards	Total number of fouls	Total shots	Total shots on target
Champions League	1007.30	4.17	1.03	26.75	24.91	9.68
UK	824.24	3.60	1.00	22.07	24.26	8.20
Germany	847.88	4.14	1.00	26.52	24.77	9.54
Spain	816.99	5.17	1.06	27.71	22.54	7.95
Italy	836.85	4.90	1.09	28.44	23.46	8.88
Portugal	801.83	5.31	1.11	30.94	21.93	8.33
France	878.46	3.74	1.09	26.31	22.62	8.21
Netherlands	879.78	3.21	1.00	22.08	24.63	10.01
Brazil	836.44	4.84	1.11	29.96	24.42	8.24
Argentina	765.30	5.01	1.13	26.53	23.71	8.07
USA	873.29	4.03	1.05	24.74	25.20	8.91

Table 22: Summary statistics (Part 1)

Country	Blocked shots / Total shots	Total number of corners	Score / Corners	Total number of free kicks	Score / Free kicks	Score
Champions League	0.21	9.65	0.29	28.60	0.10	2.68
UK	0.27	10.10	0.27	24.26	0.11	2.58
Germany	0.23	9.77	0.30	28.16	0.11	2.80
Spain	0.23	9.47	0.26	31.37	0.08	2.32
Italy	0.25	9.90	0.27	33.02	0.08	2.49
Portugal	0.23	10.34	0.25	33.42	0.08	2.46
France	0.23	9.23	0.28	30.04	0.09	2.44
Netherlands	0.24	10.07	0.32	25.63	0.12	3.02
Brazil	0.23	10.33	0.23	32.99	0.07	2.21
Argentina	0.22	9.39	0.24	25.53	0.08	2.18
USA	0.24	9.74	0.30	27.78	0.11	2.79

Table 23: Summary statistics (Part 2)

Country	Score / Total shots	Score / Shots on target	Score / Crosses
Champions League	0.11	0.28	-
UK	0.11	0.32	-
Germany	0.12	0.30	-
Spain	0.10	0.30	-
Italy	0.11	0.29	-
Portugal	0.11	0.30	-
France	0.11	0.30	-
Netherlands	0.13	0.31	-
Brazil	0.09	0.27	0.07
Argentina	0.09	0.27	-
USA	0.11	0.32	0.09

Table 24: Summary statistics (Part 3)

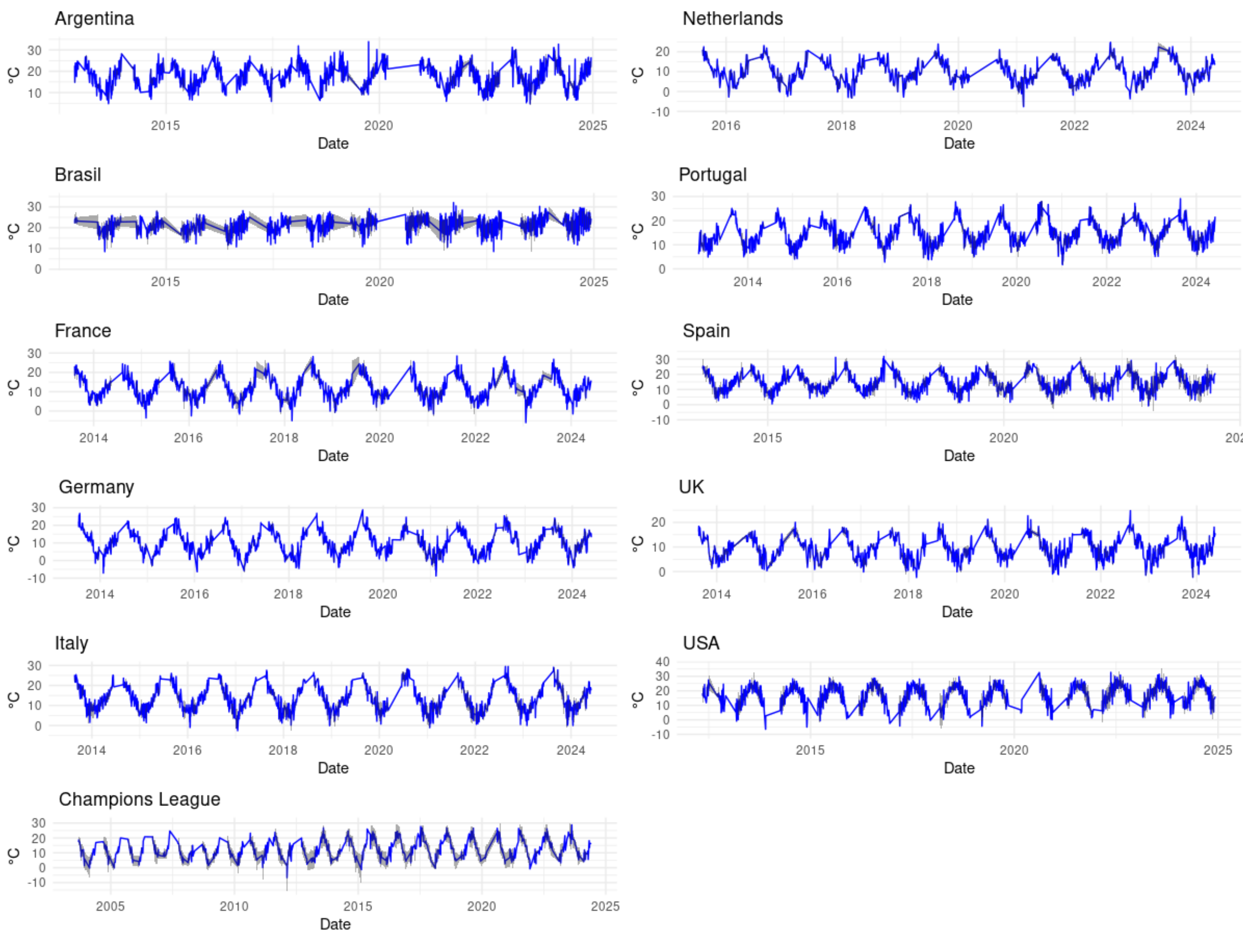

Figure 3: Temperature deviations from the mean.

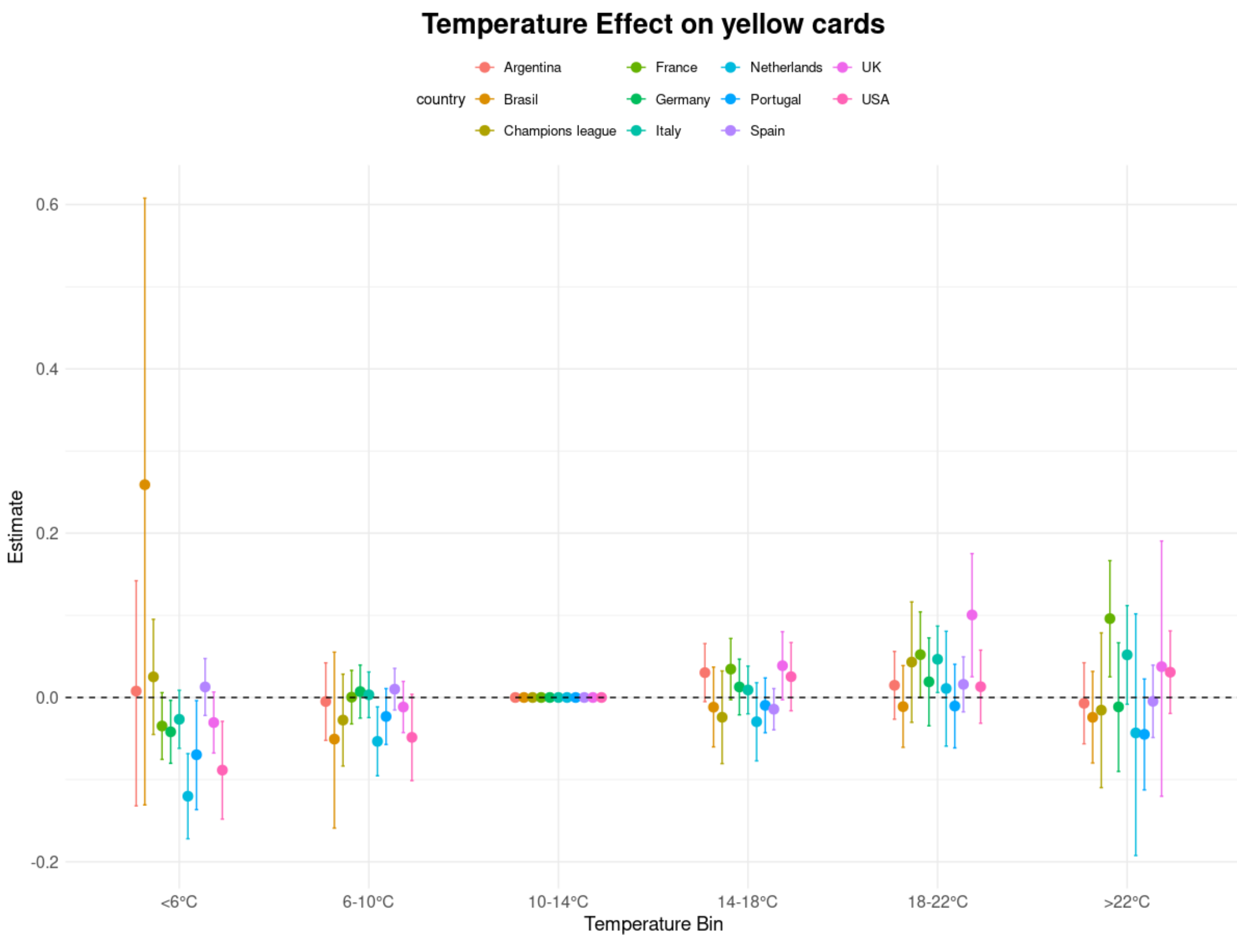

Figure 4: Temperature effect on yellow cards.

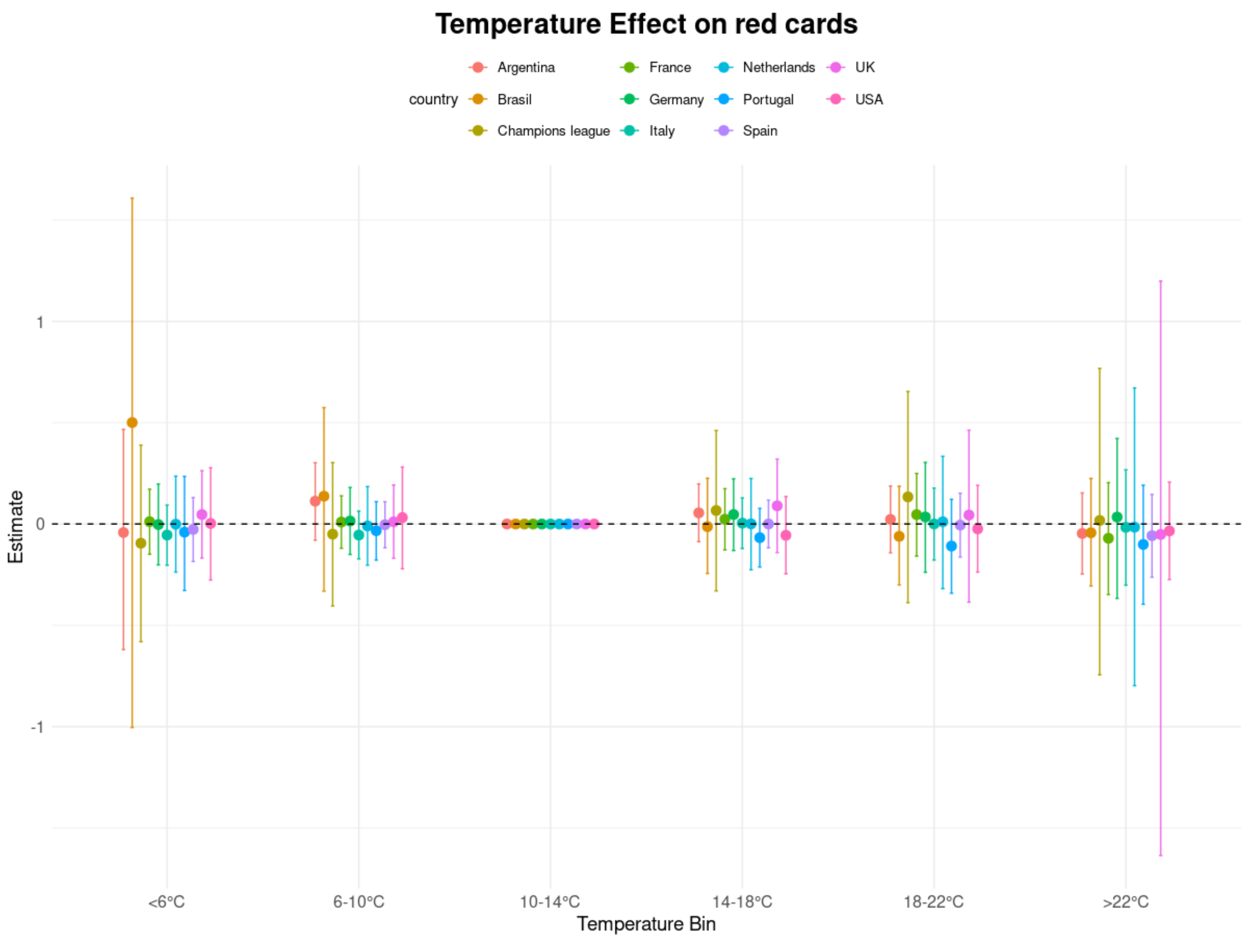

Figure 5: Temperature effect on red cards.

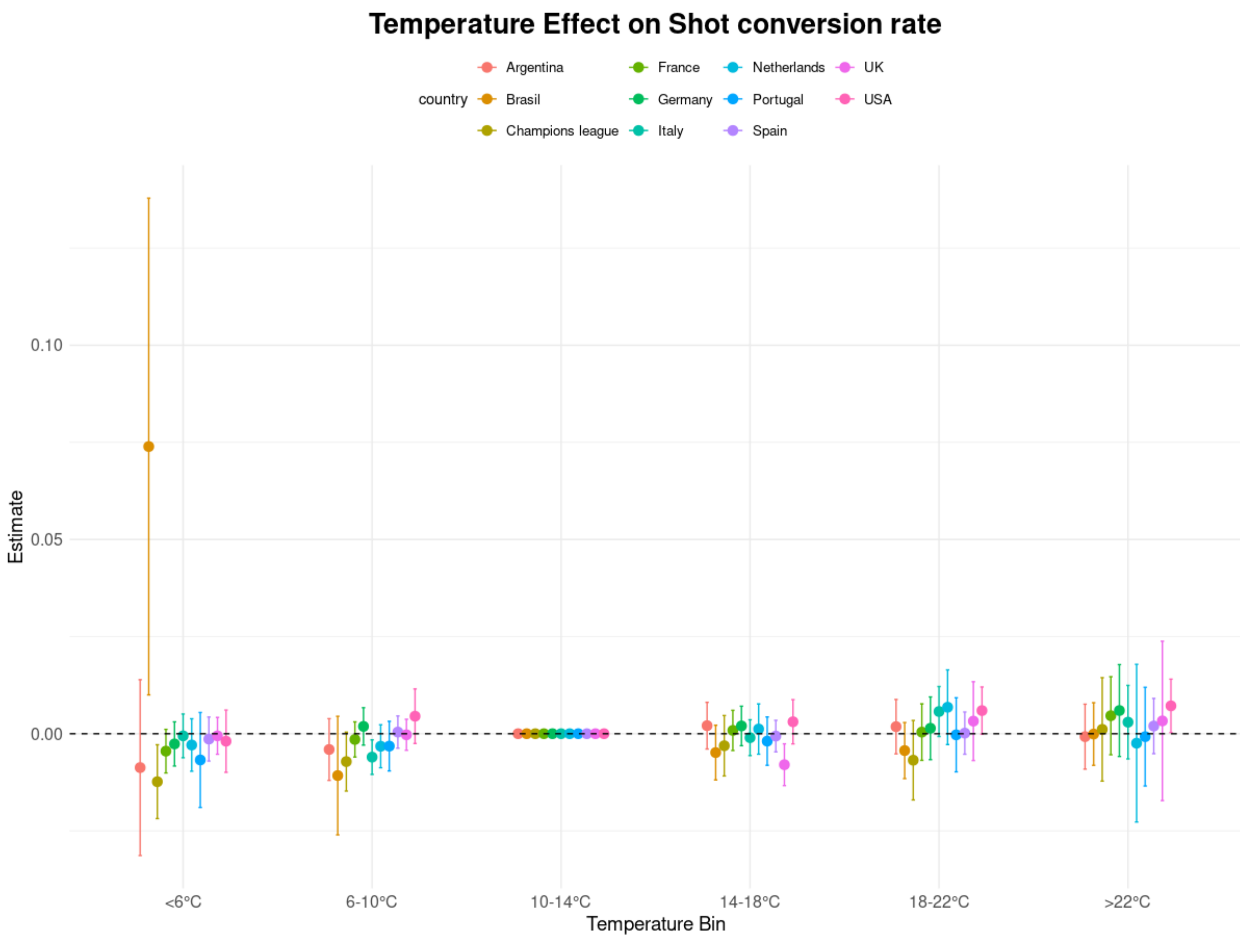

Figure 6: Temperature effect on shot conversion rate.

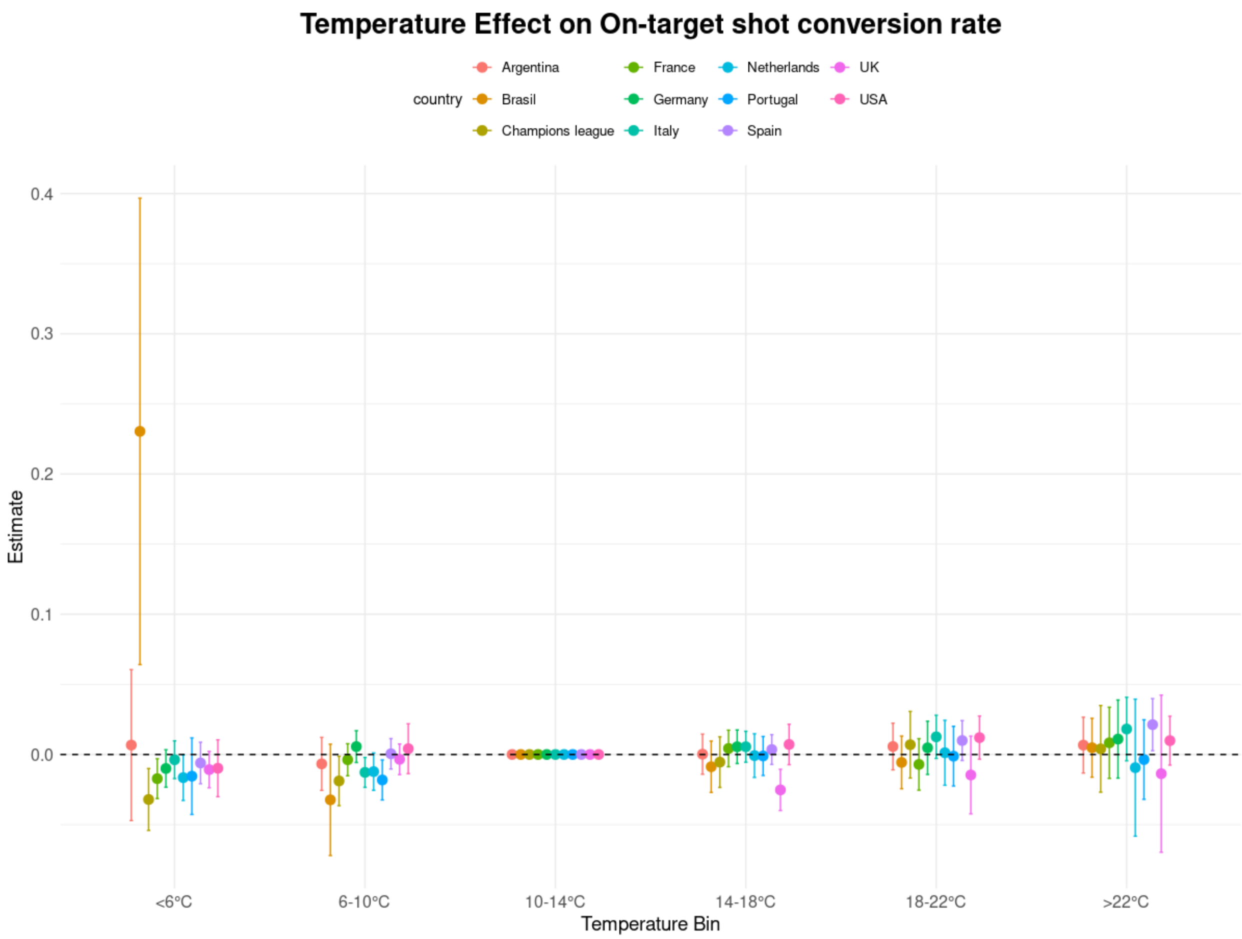

Figure 7: Temperature effect on on-target shot conversion rate.

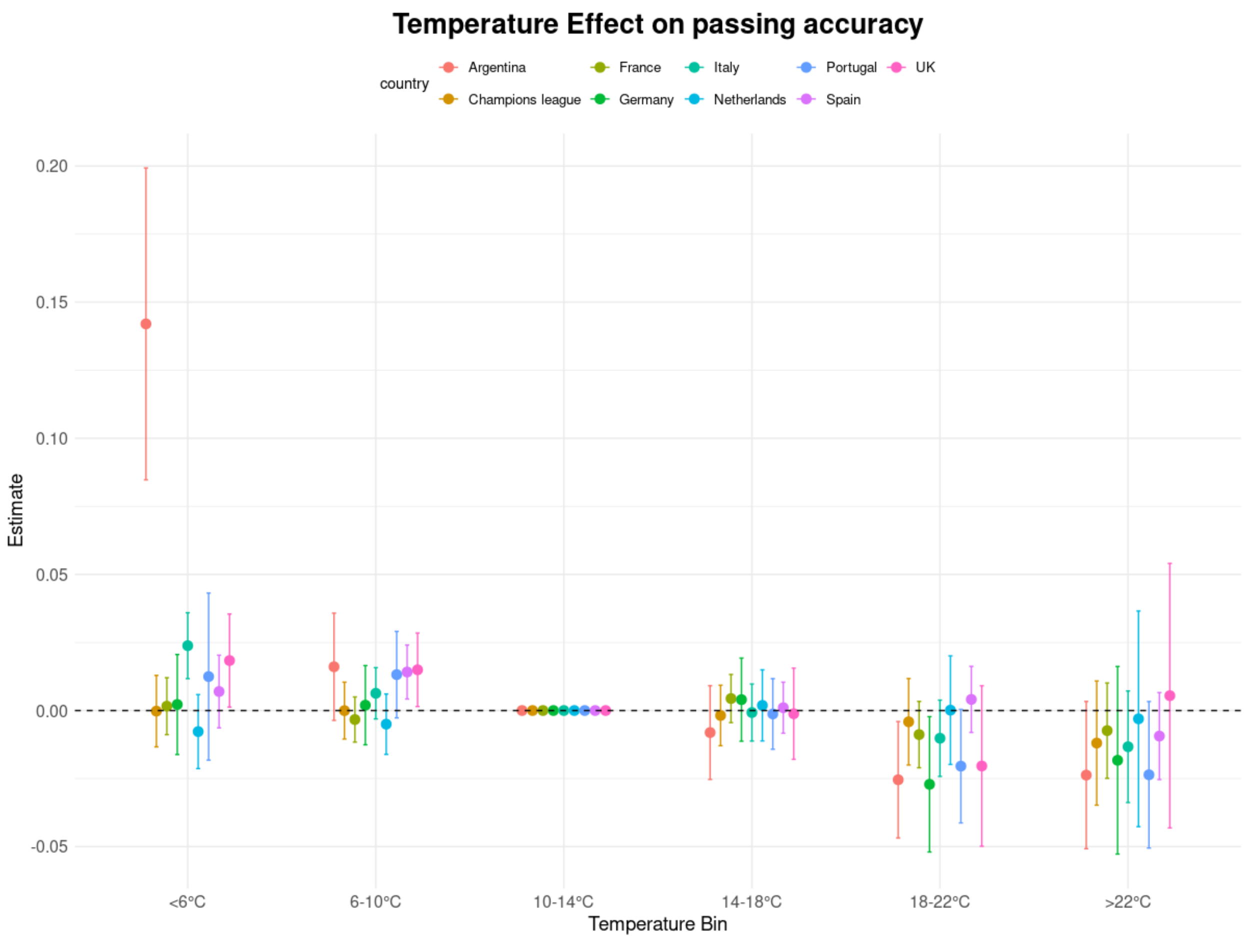

Figure 8: Temperature effect on passing accuracy.

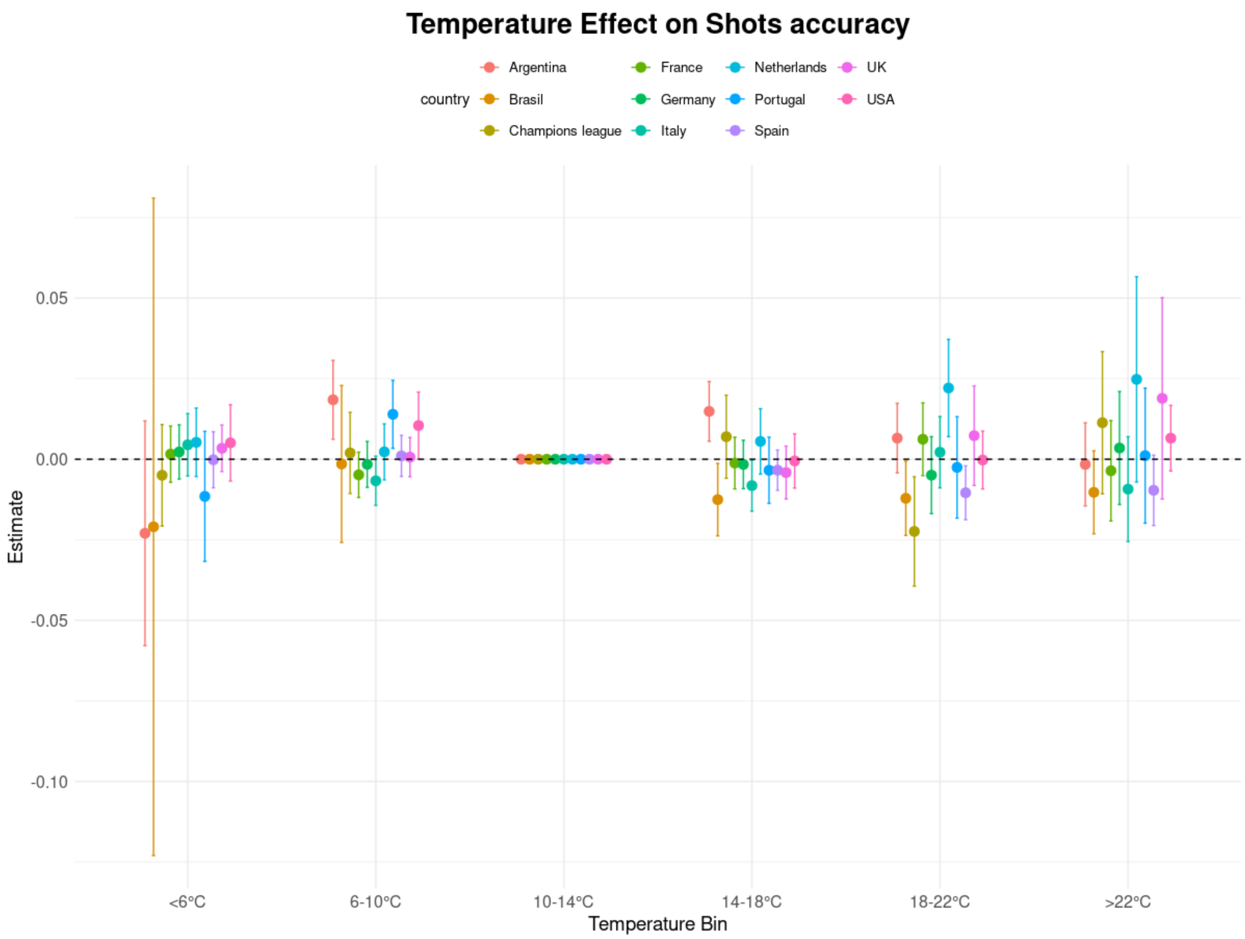

Figure 9: Temperature effect on shooting accuracy.

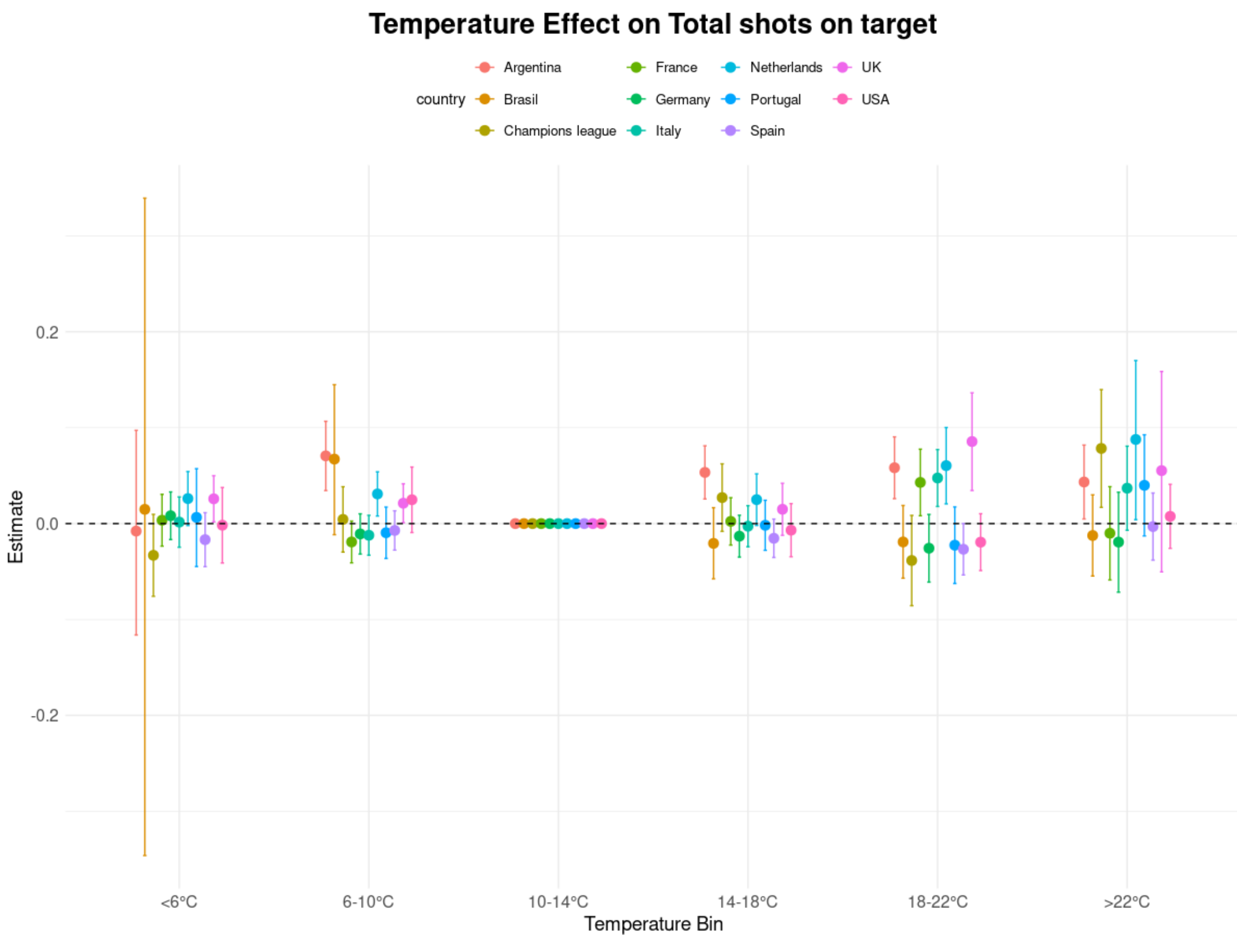

Figure 10: Temperature effect on total shots on target.

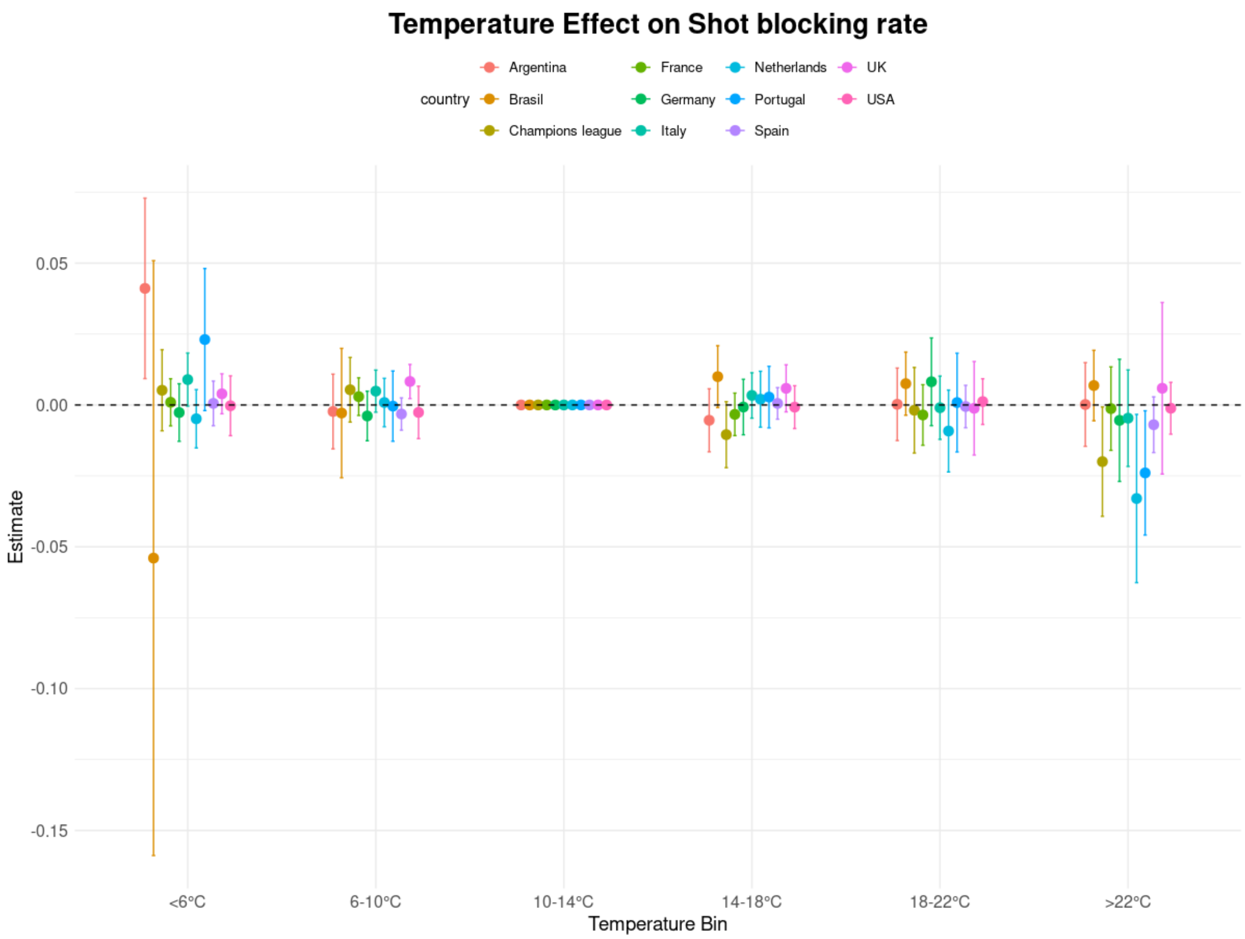

Figure 11: Temperature effect on shot blocking rate.

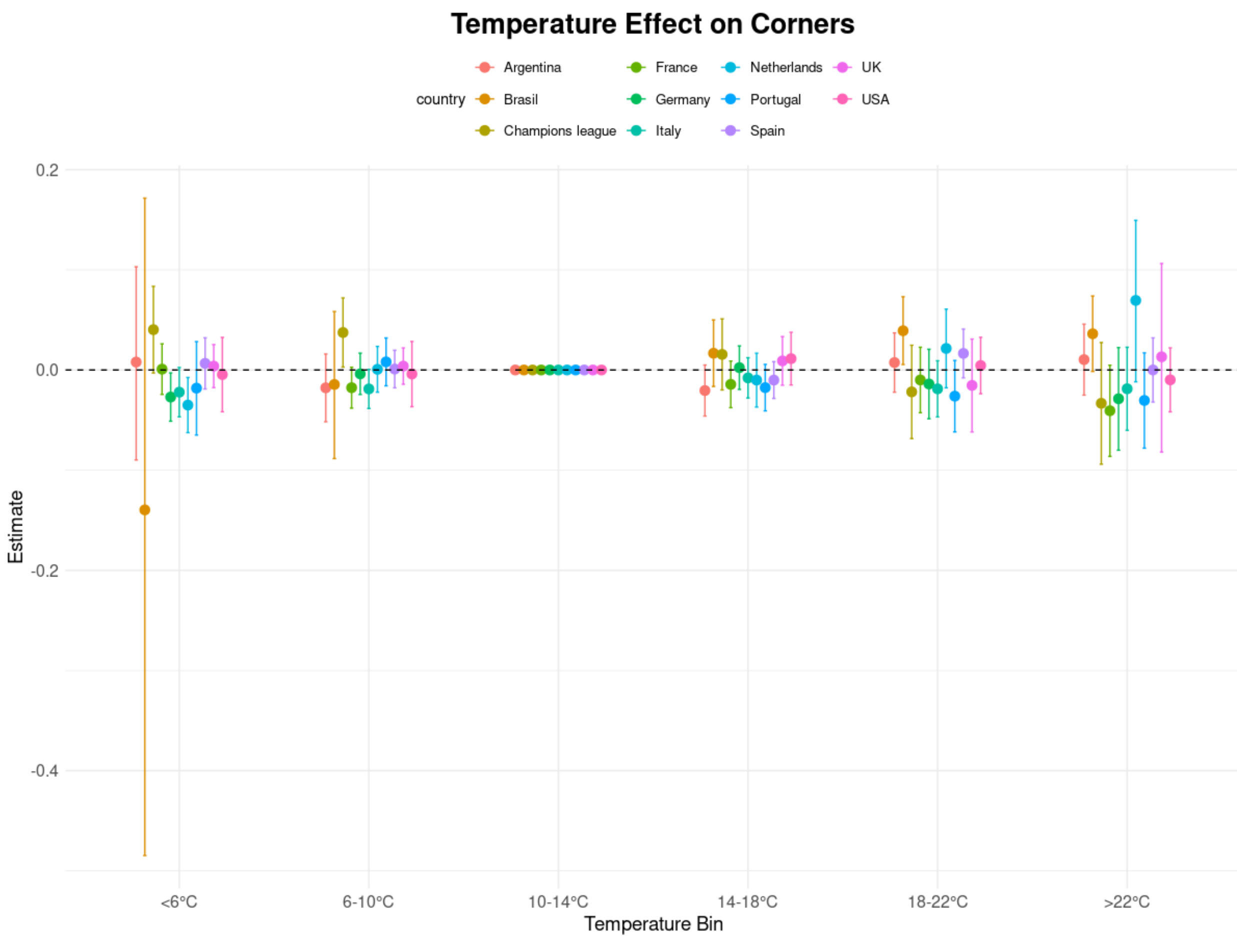

Figure 12: Temperature effect on corners.

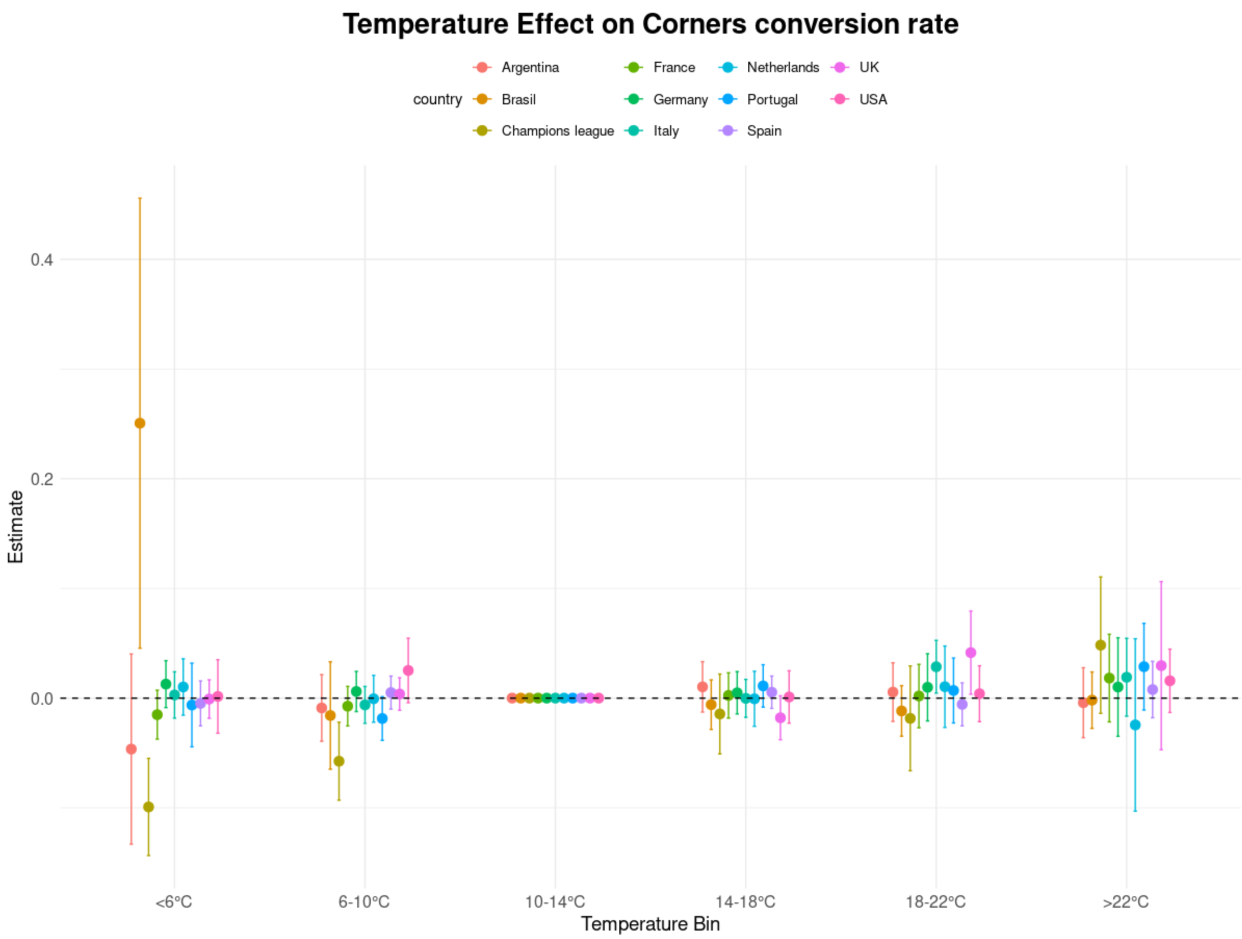

Figure 13: Temperature effect on corner conversion rate.

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