# Religious Fasting and Workplace Productivity*

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**Abstract**

We investigate the effect of Ramadan fasting on individual worker productivity in a high-stakes, highly competitive setting in which workers face strong economic incentives, can be tracked individually over time, and produce output that is objectively measurable through algorithmic performance ratings. Crucially, because workers have no discretion over their hours or working conditions, we can isolate the direct productivity channel from the labor supply and behavioral responses that fasting typically induces. Drawing on sixteen years of granular worker-level data from two countries, we employ a difference-in-differences design comparing the relative performance of Muslim and non-Muslim workers within and outside Ramadan. At the worker level we find no significant Ramadan effect, while accounting for various measures of fasting intensity. We do, however, find suggestive evidence of moderate negative spillovers from Muslim colleagues, partly offset by a positive effect of facing Muslim workers in the competing firm. This pattern carries over to the firm level, where output declines in the number of Muslim workers a firm relies on during Ramadan. Finally, we find no evidence of labor demand responses at either the intensive or the extensive margin, and discuss several explanations for the predominantly null findings.

**Keywords**: Religion, Ramadan, Labor Productivity, Professional Sports
**JEL** classifications: J22, J24, Z12, Z22

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# 1 Introduction

Standard economic models of production largely abstract from workers' private lives. Yet, in practice, a clean separation is elusive, as religious and other personal practices routinely intersect with the workplace. In particular, Ramadan fasting has gained notable salience in recent years as societies have become more multicultural and the share of Muslim citizens has increased in Europe and North America (Pew Research Center, 2025a). Public debate over religious accommodation at work grounds, however, on scarce evidence. Understanding whether and how fasting affects job performance is therefore a question of clear economic and policy relevance. This paper exploits a unique setting to study the influence of Ramadan fasting on individual worker productivity.

While the prior literature establishes a negative association among fasting intensity and productivity at a macro-scale, e.g., GDP-growth rates (Campante and Yanagizawa-Drott, 2015) and agricultural outputs (Schofield, 2026), granular evidence at the worker-level is scarce. This is because it is empirically challenging to disentangle the direct effect of the reduced calorie intake acting through cognitive and physical fatigue, from indirect effects acting through labor supply contractions (Bertoli and Grembi, 2024; Campante and Yanagizawa-Drott, 2015; Hu and Wang, 2022), changes in working conditions, or behavioral adjustments (Bertoli and Grembi, 2024; Hu and Wang, 2022).

We address this estimation challenge and extend the literature on individual worker productivity by exploiting professional soccer as a natural laboratory (Bar-Eli et al., 2020; Kahn, 2000; Palacios-Huerta, 2025) and by leveraging algorithmic performance ratings at the worker-task (player-match) level. The setting is particularly well suited to examine the individual productivity effects of Ramadan fasting, as it constitutes a physically demanding, high-stakes elite environment in which workers face strong economic incentives. Beyond that, it offers several advantages that conventional workplace settings rarely provide. First, work schedules are effectively determined by a governing body well in advance and independent of Ramadan, so workers have no direct discretion over their labor supply. Second, the task itself is highly standardized, with a fixed duration and uniform rules across workers and over time, which keeps output comparable within and outside Ramadan. Third, output is closely and continuously monitored and tied to career prospects such as contract renewals and market valuations, which leaves little scope for 'shirking', i.e., strategic reductions in effort. Together, these features permit us to isolate the direct effect of Ramadan fasting on productivity. Lastly, while we focus on two countries (England and France) in which Muslims constitute an increasingly important minority, there exist no country-level institutional adjustments to Ramadan, mitigating concerns of exposure to treatment of non-Muslim workers.[1]

We therefore identify the productivity effect of Ramadan fasting through a difference-in-differences (DiD) approach comparing Muslim to non-Muslim workers within and outside of Ramadan, leveraging natural exogenous variation in fasting intensity from the shift of the Islamic lunar calendar. Moreover, the transparency of the setting enables us to cleanly identify and follow worker across time (16 seasons, 2009-2025), while accounting for a battery of worker characteristics and environmental factors. Since personal religious affiliation and fasting behavior cannot be directly observed, we rely on an intent-to-treat (ITT) design and which is why we classify treatment status in three complementary ways. First, our preferred approach follows prior literature (e.g., Bertoli and Grembi, 2024; Hornung et al., 2023) and assigns treatment based on a player's first and second citizenship, such that a player is treated if he holds citizenship of a country with a Muslim population share of at least 90%.[2] Second, we refine this classification for individually verified religious affiliation obtained through a Large Language Model (LLM)-assisted web search, thereby addressing the misclassification in both directions: Muslim players holding citizenship of religiously mixed or Muslim-minority countries, and a small number of non-Muslim players from Muslim-majority countries. A validation exercise confirms that this adjustment operates as intended: the citizenship rule correctly assigns treatment with a precision of approximately 95%, and the LLM-based refinement recovers the Muslim players it misses. Third, we probe the robustness of our results using continuous name-origin propensity scores.

[1] Bertoli and Grembi (2024) and Schofield (2026) also explore Muslim-minority countries looking into Spain and India, respectively.

[2] We find qualitatively identical results using a more lenient 50% majority rule, when relying on the first citizenship only, as well as when interacting Ramadan with the continuous Muslim population share instead of a binary indicator.

Reassuringly, our conclusions remain unchanged under this alternative approach.

Against this backdrop, the empirical analysis is structured in three parts. We first explore the effect of Ramadan fasting at the workers' level while allowing for heterogeneity in the degree of fasting intensity including weather conditions, effective fasting hours, sunset timing, as well as dynamic effects within but also before and after Ramadan. We do not find significant evidence of a substantial impact of Ramadan on the relative performance of Muslim workers. This null result is overwhelmingly robust to alternative performance measures including both basic as well as novel sophisticated metrics, alternative model specifications and sample selection procedures, and also holds when estimating a withing-group effect abstracting from the fairly strong underlying identifying assumptions required to hold for the DiD estimation. Yet, we find weak suggestive evidence in favor of the existence of negative spillover effects among colleagues (teammates) that are partly offset, on average, by a positive effect from facing Muslim competitors (opponents).

Such cumulative effects are also supported in the second part in which we conduct a firm-level (team-match level) analysis and observe that, during Ramadan, an increase in the number of Muslim workers significantly reduces a firm's success (i.e., the relative likelihood of winning a match) and decreases the overall output (team rating), while the number of Muslim workers in the competing firm increases both. Nevertheless, while significant, the effects are rather moderate and do not consistently replicate across all specifications and are more visible in one country than the other. Finally, we corroborate our methodological approach by demonstrating the absence of labor demand responses, both at the intensive and extensive margin. The analysis suggests that either managers (coaches) seem to correctly anticipate the predominantly null effects on Muslim workers' performance or fasting workers might still be marginally better than the next best alternatives.

We discuss several explanations for the predominantly insignificant findings. First, the setting is a prime example of organizational accommodation to the demands of Ramadan, with firms providing tailored nutrition plans and flexibility in how workers prepare for work, even as the timing of production itself remains fixed. Relatedly, many workers in our sample have accumulated fasting experience over many years, often under considerably harsher conditions than in the countries we study. In addition, while productivity in our setting is predominantly physical, peak effort is required only briefly and intermittently rather than continuously, which may limit the scope for fasting to affect measured output. Lastly, since Ramadan observance is inherently latent, the ITT design effectively captures a likelihood of exposure. Hence, our estimates may be attenuated by misclassification or non-compliance. We therefore regard our results as conservative lower-bound estimates. If anything, our analysis provides at most weak suggestive evidence of a moderate negative effect of Ramadan fasting.

This paper contributes most directly to the literature on the labor market and productivity effects of Ramadan fasting. At the country-level, Campante and Yanagizawa-Drott (2015) exploit latitudinal variation in fasting intensities arising from the shift of the Islamic Lunar calendar, and observe a negative impact of longer fasting hours on GDP growth in Muslim-majority countries. Notably, they argue that this decline cannot be primarily explained by a direct reduction in productivity, attributing it instead to shifts in relative preferences over work and religiosity that affect labor supply and occupational choices beyond Ramadan. By contrast, Schofield (2026) comes closest to isolating a productivity channel, exploiting heterogeneity in cropping cycles within and between Indian districts. Ruling out reductions in labor supply and finding little sign of offsetting input adjustments, she points to reduced caloric intake as the most likely mechanism, while describing the supporting evidence as suggestive. Although these estimates speak to aggregate output, the mechanism itself operates at the level of the individual worker.

Studies at the worker level face the same difficulty from the opposite direction. Cabanillas-Jiménez (2024) documents a gendered reallocation of hours between market and household work in Malawi, so that observed changes in market output reflect a decision about where to work as much as a change in productive capacity. Bertoli and Grembi (2024) find that workplace accidents among Muslim immigrants in Spain decline during Ramadan, a pattern consistent with reduced labor supply, with more flexible working conditions, and with behavioral adjustments in accordance with religious prescriptions. In both cases the outcome is informative about how workers respond to fasting, yet it does not

separate the physiological burden of the fast from the choices workers make in response to it. Across these settings, the direct effect of reduced caloric intake on output therefore remains entangled with the endogenous responses that fasting triggers in hours worked, in the timing and intensity of effort, and in the conditions under which work is performed.

Our paper is closest to Hu and Wang (2022), who study salespersons in an Indonesian cosmetics retail chain. They find that Muslim workers leave work earlier during Ramadan and reallocate effort within the day, raising productivity in the morning to offset the decline around sunset, but detect no significant difference in daily sales relative to non-Muslim colleagues. Our setting differs in three respects. First, and most important for identification, labor supply is rigid. Working time is fixed, workers can neither reduce their hours nor leave early, and the scheduling of work, and hence its position relative to sunset, is set externally rather than chosen by the worker. The two margins along which workers adjust in their setting, namely reductions in hours and the reallocation of effort across the working day, are therefore largely unavailable in ours. Second, the institutional environment is different in that Indonesia is a Muslim-majority country in which 87% of the population is Muslim and Ramadan reshapes the rhythm of economic activity, whereas England and France are Muslim-minority countries with no economy-wide institutional accommodation - though, as we discuss below, accommodation at the firm level in our setting is nonetheless substantial. Third, all workers in our sample are male professional athletes whose output depends largely on physical exertion, while 86% of the sales force they study is female and the work is predominantly interpersonal. Our estimates therefore speak to a margin of the fasting-productivity relationship in which physical rather than relational inputs bind.

Besides productivity, a body of literature on other economic outcomes generally observes negative or mixed effects of Ramadan fasting. For instance, several papers emphasize that in-utero exposure has adverse effects on children's long-term economic outcomes and distorts the formation of human capital (Almond and Mazumder, 2011; Almond et al., 2015; Aydilek and Karaoğlan, 2024; Majid, 2015; Van Ewijk, 2011). Works on student outcomes build on this literature and point to a similarly adverse influence, but evidence is overall more mixed (Hornung et al., 2023; Nuryakin et al., 2022; Oosterbeek and Klaauw, 2013). Other papers report evidence of increases in traffic accidents (Gulek, 2024) as well as more lenient judicial decisions during Ramadan (Mehmood et al., 2023).

We also speak to a literature in sports science and sports medicine examining the effect of fasting on performance in soccer and other professional sports. This work predominantly studies physical indicators (e.g., heart rate, hydration, sprint speed) typically in small controlled settings and over short time horizons, and the general consensus is that fasting induces deficits along these dimensions (DeLang et al., 2022). Our paper is distinct in that we measure output comprehensively, capturing a worker's overall contribution rather than isolated physical inputs, and observe it over sixteen seasons in a competitive setting where the stakes are high and performance has direct implications for workers' careers.

Our paper further contributes to the literature on the economics of religion (e.g., Becker et al., 2024; Iannaccone, 1998; Iyer, 2016), including work at the intersection of religious observance and secular leisure in the context of professional soccer (Krumer and Musau, 2026). Finally, due to the high physical demands that fasting imposes and because Ramadan alters sleep and eating patterns, our results also speak to prior work on sleep and productivity (Dou et al., 2026; Giuntella and Mazzonna, 2019; Giuntella et al., 2026), to the literature on heat, humidity, and worker output (Garg et al., 2025; LoPalo, 2023; Somanathan et al., 2021), including studies of professional tennis (Burke et al., 2023; Picchio and Van Ours, 2024) and soccer (Li et al., 2026), and to medical and physiological work on intermittent fasting, which documents pronounced daytime dehydration and impaired muscular performance under long fasts, particularly where work is physically demanding or carried out in the heat (Leiper et al., 2003), though more recent systematic reviews find little consistent effect on physical or cognitive performance outcomes specifically (Bamberg and Moreau, 2025; Mortezapour et al., 2025).

# 2 Background

## 2.1 Ramadan

Ramadan is observed by a large share of the world's roughly two billion Muslims (25.6% of the world population). It is a time of spiritual devotion during which Muslims commemorate the revelation of the Quran. A central component is the fast from food and drink during daylight hours, which serves as a means to draw closer to God, to express gratitude, and to show compassion for less fortunate members of society. All Muslims who have reached the age of puberty are supposed to fast during this period of 29 or 30 days, though exemptions exist for hardships including illness and travel. Ramadan occurs during the ninth month of the Islamic lunar calendar. Because the Islamic lunar calendar is 11 days shorter than the Gregorian calendar, Ramadan shifts 'forward' each solar year. Table 1 illustrates this shift for our sample period from 2009 to 2025 during which Ramadan moved from August/September in 2009 to February/March in 2025.

Table 1: Ramadan Dates - 2009 to 2025

| Year | Start | End |
|---|---|---|
| 2009 | Aug 22 | Sep 20 |
| 2010 | Aug 11 | Sep 10 |
| 2011 | Jul 31 | Aug 29 |
| 2012 | Jul 19 | Aug 18 |
| 2013 | Jul 08 | Aug 07 |
| 2014 | Jun 28 | Jul 28 |
| 2015 | Jun 17 | Jul 16 |
| 2016 | Jun 06 | Jul 05 |
| 2017 | May 26 | Jun 24 |
| 2018 | May 16 | Jun 14 |
| 2019 | May 05 | Jun 03 |
| 2020 | Apr 23 | May 23 |
| 2021 | Apr 12 | May 12 |
| 2022 | Apr 01 | May 01 |
| 2023 | Mar 22 | Apr 20 |
| 2024 | Mar 10 | Apr 09 |
| 2025 | Feb 28 | Mar 30 |

*Notes*: Start and end dates of Ramadan in the Gregorian calendar.

## 2.2 Ramadan Observance in Professional Soccer

While official data on Ramadan observance among Muslim soccer players does not exist to the best of our knowledge, survey data on the general population reports fasting rates typically exceeding 95% in Muslim-majority countries (e.g., Egypt, Morocco, Senegal) (Pew Research Center, 2012), and strict fasting rates of 83% among young Muslims aged 18 to 24 in France in 2025 (IFOP, 2025).[3] The same survey reports that 80% of Muslims in France consider themselves religious, compared with 48% among members of other religions, which supports the assumption that the large majority of the players we classify as Muslim observe the fast.

Moreover, Kuran and Zulfiqar (2026) note that despite accumulating evidence on the physiological and economic costs of long daily fasting windows, institutional and religious accommodation has remained limited, with observance widely understood as a religious obligation rather than a discretionary practice. While this literature concerns Muslim populations broadly rather than elite athletes specifically, interviews with prominent Muslim players suggest that observance is the norm in professional soccer as well (BBC Sport, 2026b). Further, unlike most workplaces, professional soccer has

[3]We could not find similar data for England, though it appears reasonable to expect Ramadan observance to be similar to that in France.

recently introduced substantial organizational accommodations (NYT, 2024) that should further lower the cost of fasting.

These accommodations reflect a broader development in professional soccer over the past two decades. Beginning in the late 2000s, performance management has become far more systematic, driven above all by a data revolution that allows clubs to measure and track players' productivity not only on but also off the pitch (Reade and Royle, 2025). Clubs have consequently become more involved in players' diet and daily routines. In this context, a growing number of clubs, most notably in the English Premier League, have become more attentive to the needs of Muslim players and have introduced formal accommodations. Qualitative interviews with medical staff suggest that these include tailored nutritional plans and, more recently, flexible individual training schedules (FIFPRO, 2026). Some clubs, among them Liverpool FC, have also adjusted team training times during Ramadan, and Premier League clubs increasingly draw on advice from the Muslim Player Association and local imams. Furthermore, in April 2021, the Premier League issued guidance allowing referees to pause matches so that Muslim players can break their fast when sunset occurs during a match. While many other European leagues have followed, the French Football Association has not permitted such breaks, citing the principle of secularism ('laïcité').[4]

Notwithstanding this broader trend toward accommodation, concerns about the performance consequences of fasting still occasionally surface among coaches. Anecdotal evidence suggests that in the late 1990s, before such accommodation took hold, some Muslim players fasted in secret, fearing repercussions from their coaches (NYT, 2024). Even as accommodation began to take shape, the then Inter Milan manager José Mourinho complained in 2009 that Ramadan fasting had reduced the performance of one of his players, a claim that drew strong public backlash (France24, 2009). More recently and more cautiously, Niko Kovač, head coach of the German Bundesliga club Borussia Dortmund, explained that he had left two key players out of the starting lineup because of their reduced energy intake during Ramadan, citing his responsibility to protect them (Kicker, 2026).

# 3 Data

We follow a growing literature in economics that exploits professional sports as a natural laboratory (Bar-Eli et al., 2020; Kahn, 2000; Palacios-Huerta, 2025). Specifically, we collect data from professional soccer at the player-match level for 16 seasons (2009-2025) of the Premier League and Ligue 1, the highest domestic tiers of England and France, respectively.[5] The main data sources are WhoScored.com and FBref.com, from which we retrieve performance measures as well as a wealth of player and match characteristics.[6] We enrich this data with player profiles from Transfermarkt.com, including citizenship and date of birth, as well as market values, which we merge as of the respective match date. Betting odds are obtained from Football-Data.co.uk.

In line with prior literature, we exclude goalkeepers from the analysis as they have distinct roles and their performance is difficult to compare to that of outfield players (Berri et al., 2024). Moreover, to mitigate statistical noise, we consider only player-matches with at least 30 minutes of effective playing time because soccer is a low-scoring game with few individual actions. Similarly, we exclude observations from player-seasons with fewer than five matches. Taken together, Table 2 shows that the final analysis sample consists of $n_{PL} = 131{,}166$ and $n_{L1} = 125{,}801$ player-match observations, involving more than 2,000 unique players in approximately 6,000 unique matches per league. Roughly 5% to 6% of player-matches occur during Ramadan. The table also reports the share of player-match observations involving players classified as Muslim under the alternative approaches described in more detail below.

## 3.1 Treatment Classification

Despite the transparent nature of our data, religious affiliation constitutes a private matter and is therefore not publicly disclosed, which is why we classify treatment status in three complementary

[4] In practice, players have at times feigned injuries so that Muslim teammates could break their fast.

[5] Two Welsh clubs (Cardiff City and Swansea City) also competed in the Premier League during our sample period.

[6] We omit a small number of player-match observations ($< 0.01\%$), for which no WhoScored or FBref data is available.

Table 2: Analysis Sample

| | | | | | | Muslim (% of player-match observations) | | | |
|---|---|---|---|---|---|---|---|---|---|
| League | N | Players | Matches | Seasons | Ramadan (%) | Citizenship 90% | Citizenship 50% | LLM | Name 50% |
| Premier League | 131,166 | 2,094 | 6,080 | 16 | 5.09 | 6.77 | 7.72 | 9.85 | 6.07 |
| Ligue 1 | 125,801 | 2,363 | 5,829 | 16 | 6.39 | 20.57 | 22.95 | 23.62 | 5.39 |

*Notes:* $N$ denotes the number of player-match observations. Players and Matches report the number of unique players and matches, respectively. Ramadan is the percentage of player-match observations occurring during Ramadan. The remaining columns report the percentage of player-match observations involving a player classified as Muslim under alternative classifications. Citizenship 90% and Citizenship 50% are based on the citizenship classification with 90% and 50% population-share threshold, respectively. LLM refers to the LLM-based classification, and Name 50% refers to the broad name-origin classification at a 50% threshold.

ways. First, we follow the prior literature (e.g., Bertoli and Grembi, 2024; Hornung et al., 2023) and assign treatment status, i.e., being Muslim or not, based on a players' first and second citizenship, where available. Specifically, we obtain data on the religious composition of countries from the Pew Research Center, with 2010 as our reference year (Pew Research Center, 2025b). We classify a player as Muslim if either country of citizenship has a Muslim population share of at least 90%, reflecting a deliberately conservative threshold to minimize false positives in anticipation of our adjustment procedure described below. Under this rule, 168 of 2,094 players in the Premier League and 530 of 2,363 in Ligue 1 are classified as Muslim, corresponding to 6.8% and 20.6% of player-match observations, respectively. We use both citizenships because France and England are traditional immigration destinations that have experienced repeated migration waves in recent decades, in part from Muslim-majority countries. This implicitly assumes that religious affiliation is likely to be transmitted across generations and thus often reflected in the second citizenship.[7]

A caveat of this conservative decision rule is that it fails to recognize Muslim players from religiously mixed countries. In a second step, we therefore address this concern by pursuing an LLM-based adjustment of misclassified players, with technical details reported in the Appendix. In brief, we instruct the model to conduct an extensive search of online sources, such as newspaper articles, press conferences, and social media posts, to classify each player as Muslim or non-Muslim. The model is required to cite the sources supporting each classification and to abstain where no public information is available, rather than to infer affiliation from a player's name or nationality. We manually verify these sources for all players the model classifies.[8] In total, 228 players in the Premier League and 592 players in Ligue 1 are classified as Muslim under the LLM-based classification, corresponding to 9.9% and 23.6% of player-match observations, respectively.

Table 3 reports the accuracy of the citizenship rule among players with verifiable information and shows that the two classifications overlap substantially (Cohen's $\kappa > 0.6$, agreement exceeding 80%).[9] Specifically, approximately 99% and 96% of players verified as non-Muslim are also classified as non-Muslim by the citizenship rule. Further, Table 4 reports the adjustments per group and league and shows that only 6 and 8 players, respectively, are reclassified as non-Muslim. The false-negative margin is more consequential, as the citizenship rule recovers only about 61 and 67 percent of players verified as Muslim. By design, the players it misses come predominantly from countries with religiously mixed populations (e.g., Bosnia and Herzegovina, Ghana, Ivory Coast) or from countries in which Muslims are a minority (e.g., France, Germany), and are therefore not captured under the high threshold.[10] In

[7]Nonetheless, the results are robust to a more lenient 50% threshold, to classifying players by their first citizenship only, and to interacting Ramadan with the continuous Muslim population share rather than a binary indicator.

[8]We use the LLM approach for refinement only and report it alongside, rather than in place of, our main treatment classification, as the likelihood of finding information is positively correlated with a player's popularity, talent, and career length, implying a potential selection bias. In addition, the LLM-based classification again indicates only a propensity to be Muslim, derived from publicly available information.

[9]Table 3 reports statistics only for the subset of players for whom the LLM returned verifiable information ($N_{PL}$ = 570 (27.22%); $N_{L1}$ = 404 (17.09%)). However, we contend that the likelihood of finding such information depends predominantly on a player's popularity, which should in most cases be orthogonal to religious affiliation. Moreover, by design of the prompt, we are more likely to find information for players who are in fact Muslim, so that players without verifiable information are more likely to be non-Muslim and are adequately captured by our conservative threshold.

[10]The mean Muslim population share across these players' countries of citizenship, taking the higher of the two shares for dual citizens, is 28.79% and 29.76%, respectively. Even a more lenient 50% threshold would not have accurately classified these players. By contrast, lowering the threshold further would disproportionately increase false positives,

Table 3: Validation of the Citizenship Classification Against the LLM Classification

| | LLM Classification | | |
|---|---|---|---|
| Citizenship Classification | Non-Muslim | Muslim | Total |
| *Panel A: Premier League* ($N = 570$) | | | |
| Non-Muslim | 395 | 66 | 461 |
| Muslim | 6 | 103 | 109 |
| Total | 401 | 169 | 570 |
| Accuracy | | | 0.874 |
| Sensitivity | | | 0.609 |
| Specificity | | | 0.985 |
| Cohen's $\kappa$ | | | 0.663 |
| *Panel B: Ligue 1* ($N = 404$) | | | |
| Non-Muslim | 186 | 70 | 256 |
| Muslim | 8 | 140 | 148 |
| Total | 194 | 210 | 404 |
| Accuracy | | | 0.807 |
| Sensitivity | | | 0.667 |
| Specificity | | | 0.959 |
| Cohen's $\kappa$ | | | 0.618 |

*Notes:* Cells report the number of players. Rows report the citizenship-based classification and columns report the LLM-based classification. The sample comprises players whose religious affiliation was verified through the LLM-assisted web search. Players without verifiable information are excluded. Accuracy denotes the overall share of players for whom the two classifications agree. Sensitivity denotes the share of verified Muslim players that the citizenship rule classifies correctly, and specificity the corresponding share among verified non-Muslim players. Cohen's $\kappa$ measures agreement between the two classifications, corrected for agreement expected by chance.

sum, the LLM-based refinement reclassifies 66 and 70 players as Muslim.

Because treatment classification is pivotal given our ITT design, we further assess the robustness of our findings using an alternative approach, common in prior literature, that exploits the information contained in names (e.g., Abramitzky et al., 2020; Fryer and Levitt, 2004; Olivetti and Paserman, 2015). Specifically, we use NamePrism (Ye et al., 2017), which assigns each player a predicted probability distribution over 39 leaf nationalities capturing ethnic origin. We consider three approaches to assigning treatment, based on a narrow and a broad classification of Muslim leaf origins, both binary coded,[11] as well as a propensity-weighted approach in which the weights are the Pew Muslim population shares used above.[12]

The use of name origin scores promises to better capture Muslim players from Muslim-minority countries as well as second- and third-generation immigrants who only hold one citizenship but whose family is of Muslim origin. At the same time, defining Muslim origins bears a higher degree of arbitrariness and adds an additional layer of uncertainty as compared to our preferred classification via a player's citizenship. It may also be less informative given the increasingly 'generic' first names of younger players in our sample.

In this vein, Tables 5 and 6 show that the name-based classification has important limitations. First, Table 5 reports only moderate correlations between the citizenship-based classification and the broad and narrow name-origin scores in both leagues, and a similar pattern emerges for the LLM-verified classification. Second, Table 6 compares the binary name-origin categories with the two other

underlining the value of the LLM-based adjustment.

[11]For the narrow approach we consider the following leaves as Muslim origins: *Muslim: Turk; Muslim: Maghreb; Muslim: Nubian; Muslim: Arabian Peninsula; Muslim: Pakistanis; Muslim: Persian; East Asian: Malay, Indonesia.* The broad classification additionally recognizes *African: West African; European: South Slavs* and *East Asian: Malay, Malaysia* as Muslim leaf origins.

[12]For both the narrow and the broad classification, we replicate the results using 50% and 90% threshold values. For the propensity approach, we rely on a natural majority rule of 50%.

Table 4: Player-Level Transition Matrix - Citizenship to LLM Classification

| | LLM Classification | | |
|---|---|---|---|
| Citizenship Classification | Non-Muslim | Muslim | Total |
| *Panel A: Premier League* | | | |
| Non-Muslim | 1,860 | 66 | 1,926 |
| Muslim | 6 | 162 | 168 |
| Total | 1,866 | 228 | 2,094 |
| *Panel B: Ligue 1* | | | |
| Non-Muslim | 1,763 | 70 | 1,833 |
| Muslim | 8 | 522 | 530 |
| Total | 1,771 | 592 | 2,363 |

*Notes:* Cells report the number of unique players in the analysis sample. Rows report the citizenship-based classification and columns report the LLM-based classification. Off-diagonal cells represent players whose status changes: 66 players in the Premier League and 70 in Ligue 1 are reclassified as Muslim, while 6 and 8 players, respectively, are reclassified as non-Muslim. Players for whom no verifiable information was found retain their citizenship-based classification. The share of Muslim players rises from 8.0% to 10.9% in the Premier League and from 22.4% to 25.1% in Ligue 1.

Table 5: Correlation of Continuous Name-Origin Scores with the Citizenship and LLM Classifications

| | Reference | Narrow | Broad |
|---|---|---|---|
| Premier League | Citizenship | 0.433 | 0.219 |
| | LLM | 0.402 | 0.242 |
| Ligue 1 | Citizenship | 0.324 | 0.132 |
| | LLM | 0.309 | 0.160 |

*Notes:* Cells report point-biserial correlations between the continuous name-origin scores and the binary classification listed in the Reference column, computed at the player level in the analysis sample ($N$ = 2,094 players in the Premier League, $N$ = 2,363 in Ligue 1).

classifications. While there is a high degree of overall agreement, this is predominantly driven by the large number of non-Muslim players and Cohen's $\kappa$ and the phi coefficient remain low to moderate. Most importantly, the name-origin approach classifies considerably fewer players as Muslim than our preferred citizenship approach. As Table 3 shows, among players for whom verification was possible, those classified as Muslim by the citizenship rule are almost invariably confirmed (103 of 109 in the Premier League and 140 of 148 in Ligue 1, a precision of approximately 95% in both leagues). That the name-based approach fails to identify even this near-certainly treated group suggests that names alone are not sufficiently informative of Muslim origin.[13] This is particularly pronounced in Ligue 1, irrespective of the category and threshold chosen.

Despite these caveats, we report results based on the name-origin classification as a robustness check, and find it reassuring that our findings remain broadly consistent across all three classifications.

### 3.2 Performance Measures

Our main performance measure is WhoScored.com's algorithmic performance rating, which is measured on a ten-point scale and available for all 16 seasons of our sample at both the player and team level.[14] The ratings have been widely used in prior academic literature (e.g., Berri et al., 2024; Holmes

[13]We also find that players additionally classified as Muslim by the LLM adjustment exhibit name-origin scores close to those of non-Muslim players (for instance, a median narrow score of 0.007 versus 0.001 in the Premier League), indicating that the low agreement is not an artifact of the chosen thresholds. For players from religiously mixed origin countries, religious affiliation varies within rather than between name origins, a margin that the name-based classification cannot recover by construction.

[14]For 27 player-matches in Ligue 1, WhoScored does not report a rating. These observations are dropped in specifications that use player ratings as the outcome but retained in all other models.

Table 6: Agreement of the Binary Name-Origin Classifications with the Citizenship and LLM Classifications

| | | vs. Citizenship | | | vs. LLM | | |
|---|---|---|---|---|---|---|---|
| Classifier | # Muslims | Agreement | $\kappa$ | $\phi$ | Agreement | $\kappa$ | $\phi$ |
| *Panel A: Premier League* | | | | | | | |
| Narrow, 90% cutoff | 18 | 0.927 | 0.170 | 0.296 | 0.899 | 0.124 | 0.250 |
| Narrow, 50% cutoff | 58 | 0.930 | 0.326 | 0.379 | 0.905 | 0.276 | 0.352 |
| Broad, 90% cutoff | 42 | 0.916 | 0.134 | 0.171 | 0.889 | 0.111 | 0.158 |
| Broad, 50% cutoff | 154 | 0.885 | 0.193 | 0.193 | 0.869 | 0.214 | 0.219 |
| Pew Propensity, 50% cutoff | 56 | 0.930 | 0.321 | 0.376 | 0.905 | 0.272 | 0.351 |
| *Panel B: Ligue 1* | | | | | | | |
| Narrow, 90% cutoff | 17 | 0.781 | 0.041 | 0.134 | 0.755 | 0.036 | 0.124 |
| Narrow, 50% cutoff | 74 | 0.793 | 0.145 | 0.241 | 0.769 | 0.132 | 0.232 |
| Broad, 90% cutoff | 52 | 0.766 | 0.012 | 0.023 | 0.744 | 0.019 | 0.040 |
| Broad, 50% cutoff | 170 | 0.756 | 0.077 | 0.094 | 0.742 | 0.099 | 0.126 |
| Pew Propensity, 50% cutoff | 76 | 0.793 | 0.143 | 0.236 | 0.770 | 0.136 | 0.238 |

*Notes:* # Muslims reports the number of players classified as Muslim by a given name-origin classifier. Agreement is the share of players classified identically by the two classifiers. Given the low share of Muslim players, the raw agreement is mechanically high even for uninformative classifiers. Cohen's $\kappa$ measures agreement between the classifications, corrected for agreement expected by chance. $\phi$ denotes the phi coefficient, that is the Pearson correlation between two binary indicators.

and McHale, 2024; Principe and Van Ours, 2022; Scarfe et al., 2024), but are also well established in the private sector where they are employed by club analysts, journalists, and bookmakers alike.[15]

The rating is computed as a weighted combination of over 200 individual performance measures based on raw event data from Opta, widely considered the largest data provider in professional soccer. By default, each player begins with a rating of 6.0 at the start of his effective playing time (kickoff or upon substitution). The ratings are subsequently adjusted every 30 seconds during a given match such that positive events (goals, assists, successful dribbles, etc.) increase the rating while negative events (failed passes, fouls, etc.) decrease it.[16] A final correction is applied after the match, accounting for match-level outcomes (e.g., goals scored and conceded, clean sheets, minutes played). Importantly, the algorithm weights each action by its relative importance, accounting for the type of action, its location on the pitch, and its outcome.[17] Finally, the ratings are position-adjusted and thus generally comparable across positions.

Figure 1 shows the rating categories as defined by WhoScored. Ratings between 6 and 7 count as average, while lower values indicate poor and higher values good or excellent performance. Figure 4 in the Appendix plots the distributions of ratings by league. In both leagues the ratings are approximately normally distributed, with a mean of about 6.8 and a standard deviation of about 0.7, though slightly right-skewed, with somewhat more mass in the upper tail. Thus, while very good and excellent performances are non-negligible in number, very poor ratings are considerably rarer and extremely poor performances are virtually never observed.[18]

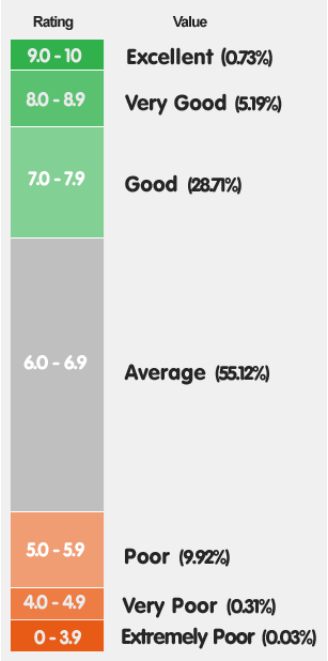
[15] WhoScored states that "Ratings are considered to be the most accurate, respected and well-known performance indicators in the world of football" (retrieved from https://www.whoscored.com/explanations on August 6, 2026).

[16] Because the ratings are built on Opta event data, they almost certainly capture only ball-based actions, whereas physical measures such as distance covered or sprints do not enter.

[17] For example, a decisive pass in the final third leading to a goal is weighted higher than a simple backward pass from a midfielder to a defender in a team's own half. While this illustrates the general logic, the exact underlying weighting scheme is not disclosed, and different providers appear to apply different weights, leading to divergent player ratings (Ball et al., 2025). The assigned weights might therefore be regarded as somewhat subjective. However, we conjecture that the exact selection of weights should be orthogonal to our treatment indicator and hence unproblematic for the purpose of this study.

[18] Only one player-match in Ligue 1 and seven player-matches in the Premier League received an 'extremely poor' rating. Arguably, this is because players who perform very poorly are likely to be substituted early or sent off, while

Figure 1: WhoScored Rating Categories




*Source*: WhoScored.com/explanations

As alternative indicators of individual performance, we retrieve selected metrics from FBref.com, including both basic and more advanced measures commonly used in prior research (e.g., Butler et al., 2024). The basic measures include goals and assists, as well as shots on target. These are available from 2014 to 2025. The advanced measures include expected goals (xG) and expected assists (xA), which FBref reports from 2017 onward.[19]

### 3.3 Fasting Intensity Indicators

Since each match is played at a known venue, we geocode stadium names to obtain latitude and longitude using the `geopy` interface to the Google Maps Geocoding API in Python. We then retrieve historical weather data and solar variables, including sunrise and sunset times, from Open-Meteo (Zippenfenig, 2023). The API provides access to reanalysis datasets that assimilate observations from weather stations, aircraft, buoys, and satellites into a numerical weather model. The model interpolates across gaps in the observational record and yields a physically consistent series on a regular grid, which allows for consistent comparisons of weather conditions across venues and over time. We obtain hourly data from the ERA5-Land and ERA5 reanalyses, which have a spatial resolution of approximately 11 and 25 kilometers, respectively.

As our main proxy for weather-based fasting intensity, we follow prior literature and rely on the wet bulb globe temperature (WBGT), which is an index that combines natural wet bulb temperature, globe temperature, and dry-bulb air temperature in fixed proportions of 0.7, 0.2, and 0.1.[20] It is preferable to a conventional dry-bulb air temperature control, since it also reflects other factors affecting heat perception, including humidity, wind, and solar radiation. Because direct measurement requires dedicated instruments, observed WBGT is rarely available. Hence, we follow Liljegren et al. (2008) and approximate WBGT from dry-bulb air temperature, dew point, wind speed, and solar radiation, together with the date and location coordinates, which determine the solar zenith angle. We compute the index using the `HeatStress` package in R (Casanueva et al., 2019).

coaches have little reason to substitute their best-performing players.

[19] Expected goals and expected assists are performance metrics that aggregate the value of a player's shooting and passing, with each chance valued according to historical conversion rates under comparable conditions, such as shot/passing position and angle. They can thus be viewed as informative measures of offensive productivity (Brechot and Flepp, 2020).

[20] The index was originally developed for the US military in the 1950s to limit heat casualties during recruit training.

Each fixture is assigned the hourly weather observation closest in time to kickoff at the corresponding stadium location. Based on sunrise and sunset times, we further compute daily fasting hours, as well as effective fasting hours, i.e., the time between sunrise and kickoff, where sunrise serves as a proxy for the start of the fast. Likewise, we assign a binary indicator to matches starting before sunset (1 = before sunset), as players are allowed to break their fast when matches take place during or after sunset.

Table 7 reports the number of distinct matches per year-month combination in each league. Because Ramadan fell into the European summer break between 2013 and 2018, it did not overlap with any Premier League matches in those years, nor with any Ligue 1 matches between 2013 and 2017. The remaining cells are well populated and illustrate how the shift of the Islamic calendar generates natural exogenous variation in fasting intensity, both in air temperature at kickoff and in effective and total fasting hours.[21]

Table 7: Ramadan Matches by Year and Month

| Year | Month | Matches | Temperature | Sunrise to Kickoff | Fasting Hours |
|---|---|---|---|---|---|
| *Panel A: Premier League* | | | | | |
| 2009 | Aug | 20 | 17.98 (2.79) | 9.09 (1.46) | 14.04 (0.26) |
| 2009 | Sep | 20 | 17.62 (2.07) | 8.28 (1.36) | 12.64 (0.26) |
| 2010 | Aug | 30 | 17.14 (2.55) | 9.45 (1.68) | 14.37 (0.39) |
| 2011 | Aug | 29 | 17.50 (2.27) | 9.12 (2.04) | 14.42 (0.39) |
| 2012 | Aug | 7 | 25.03 (2.80) | 9.49 (0.98) | 14.48 (0.12) |
| 2019 | May | 14 | 13.01 (2.08) | 10.04 (1.44) | 15.44 (0.21) |
| 2021 | Apr | 21 | 10.11 (2.03) | 11.92 (3.03) | 14.34 (0.30) |
| 2021 | May | 21 | 11.78 (3.00) | 11.85 (2.93) | 15.29 (0.25) |
| 2022 | Apr | 50 | 11.58 (3.33) | 9.85 (2.46) | 13.99 (0.64) |
| 2022 | May | 3 | 12.30 (0.52) | 9.28 (1.47) | 14.93 (0.12) |
| 2023 | Apr | 36 | 10.89 (2.03) | 9.74 (2.33) | 13.42 (0.38) |
| 2024 | Mar | 20 | 10.91 (1.96) | 9.54 (2.23) | 12.32 (0.63) |
| 2024 | Apr | 20 | 13.02 (2.99) | 11.20 (2.38) | 13.26 (0.14) |
| 2025 | Mar | 18 | 10.31 (3.82) | 9.31 (2.21) | 11.62 (0.24) |
| *Panel B: Ligue 1* | | | | | |
| 2009 | Aug | 20 | 23.84 (4.68) | 11.02 (1.35) | 13.66 (0.24) |
| 2009 | Sep | 20 | 20.24 (1.91) | 10.58 (1.36) | 12.53 (0.21) |
| 2010 | Aug | 30 | 22.33 (5.20) | 11.05 (1.34) | 13.91 (0.35) |
| 2011 | Aug | 40 | 23.34 (5.52) | 11.52 (1.64) | 14.13 (0.42) |
| 2012 | Aug | 17 | 26.34 (4.44) | 12.74 (1.11) | 14.28 (0.25) |
| 2018 | May | 10 | 18.33 (1.94) | 13.85 (0.21) | 15.20 (0.24) |
| 2019 | May | 35 | 15.93 (2.84) | 12.62 (2.25) | 15.03 (0.41) |
| 2021 | Apr | 21 | 14.40 (3.62) | 8.61 (2.96) | 13.97 (0.24) |
| 2021 | May | 19 | 17.28 (5.23) | 8.95 (2.82) | 14.66 (0.29) |
| 2022 | Apr | 53 | 12.78 (4.23) | 9.63 (2.81) | 13.64 (0.48) |
| 2022 | May | 7 | 17.39 (2.95) | 8.17 (2.47) | 14.33 (0.19) |
| 2023 | Mar | 1 | 16.00 (–) | 12.63 (–) | 12.68 (–) |
| 2023 | Apr | 29 | 12.62 (3.07) | 8.61 (2.77) | 13.25 (0.32) |
| 2024 | Mar | 24 | 12.80 (2.40) | 8.84 (3.06) | 12.19 (0.50) |
| 2024 | Apr | 9 | 18.10 (3.64) | 8.91 (3.08) | 13.18 (0.09) |
| 2025 | Feb | 1 | 10.10 (–) | 12.62 (–) | 11.16 (–) |
| 2025 | Mar | 35 | 10.74 (3.27) | 10.12 (2.21) | 11.84 (0.59) |

*Notes:* Matches denotes the number of distinct matches played during Ramadan by year-month combination and league. The remaining columns report the mean (standard deviation) for air temperature (°C), hours from sunrise to kickoff, and daily fasting hours. (–) indicates a single match, for which no standard deviation is defined.

[21]For ease of interpretation, we report dry-bulb air temperature and refer to it simply as air temperature in what follows. All temperatures are expressed in degrees Celsius.

# 4 Estimation

Our identification strategy follows the prior literature (e.g., Campante and Yanagizawa-Drott, 2015) and exploits the natural exogenous variation from the shift of the Islamic lunar calendar, as illustrated in Tables 1 and 7. We estimate the effect of Ramadan fasting via a DiD approach in which we compare the performance of Muslim players during and outside Ramadan relative to non-Muslim players. While we can identify and follow players over time, players do not appear in every match and leave the sample through transfers or retirement, which implies that the panel is unbalanced. Against this backdrop, our base model is specified as follows:

$$\begin{aligned} Y^p_{ims} = \beta_1 Muslim_i + \beta_2 Ramadan_m + \beta_3 Muslim_i \times Ramadan_m \\ + \gamma x_{i,m,s} + \text{Player}_{i,s} + \text{Position}_{i,m} + \epsilon_{i,m,s} \end{aligned} \tag{1}$$

$Y^p_{ims}$ denotes the performance of player $i$ in match $m$ of season $s$ along performance dimension $p$, $x_{i,m,s}$ is a vector of covariates, $\text{Player}_{i,s}$ and $\text{Position}_{i,m}$ denote player-season and position-group fixed effects, and $\epsilon_{i,m,s}$ is the error term. The estimation procedure adjusts to the scale of $p$. For continuous performance measures (e.g., player ratings, effective minutes played) we estimate linear models with high-dimensional fixed effects (HDFE), while for count outcomes (e.g., goals scored) we estimate Poisson pseudo-maximum likelihood (PPML) models with the same fixed effects, which account for the large share of zero outcomes common in match-level data and remain consistent under overdispersion (Santos Silva and Tenreyro, 2006). For binary outcomes (e.g., whether a player is included in the squad) we rely on linear probability models and report probit estimates as a robustness check only, since the incidental parameters problem biases estimates from nonlinear models with high-dimensional fixed effects. All models are estimated using `fixest` in R (Bergé et al., 2026).

We estimate the canonical DiD specification, where $Muslim_i$ is an indicator for players classified as Muslim under one of the three approaches described in Section 3.1,[22] and $Ramadan_m$ is an indicator for matches played during Ramadan. Accordingly, the coefficient on their interaction $\beta_3$ is the DiD parameter of interest. It measures the differential change in the performance of Muslim players during Ramadan, net of time-invariant differences between the two groups and of any shocks in the Ramadan period that affect both groups alike.[23] Since we do not have exact data on adherence to Ramadan fasting, our design is effectively an ITT and might suffer from attenuation bias. Hence, our estimates should be understood as a lower bound on the magnitude of the true effect of fasting.

We further exploit within-player variation by including player-season fixed effects, which difference out a player's baseline performance in a given season and isolate deviations from his 'typical' form during Ramadan. Because these fixed effects absorb anything constant within a player-season, they also remove cross-season confounders such as 'form', rule changes, or secular trends in ratings or playing styles that could otherwise be conflated with the timing of Ramadan.[24]

Moreover, while WhoScored ratings are in principle comparable across player positions, we nonetheless include four position-group fixed effects due to differential physical and tactical demands of playing positions (e.g., Sarmento et al., 2024).[25] We also estimate an alternative specification where we add match fixed effects to the model, accounting for any remaining heterogeneity at the match level that affects all players simultaneously, such as match relevance, the timing within the season, and environmental factors. However, since this specification absorbs a large degree of variance and identifying

[22] $Muslim_i$ is absorbed by the player-season fixed effects in all specifications that include them, so that $\beta_1$ is not separately identified.

[23] For the Premier League, identifying variation comes from 391 player-match observations of 85 distinct Muslim players in 224 distinct matches. For Ligue 1, it comes from 1,688 player-match observations of 347 players in 370 distinct matches. Table 19 in the Appendix reports the corresponding counts, mean ratings, and mean playing time for all four Ramadan × Muslim cells.

[24] As most players stay with the same team for the duration of at least one season, and only a few players switch teams within the same league during the winter or late summer transfer window, we do not include additional team fixed effects in our preferred specification. The baseline results are unaffected by this decision and remain robust to the inclusion of own- and opponent-team fixed effects.

[25] We form four position groups, namely defenders, midfielders, forwards, and substitutes. The data is not specific about a substitute's effective playing position.

variation is limited to players within the same match, we estimate our preferred specification without match fixed effects.

To further isolate the effect of Ramadan fasting, we condition on a vector of covariates $x_{i,m,s}$ that have been shown to affect performance in soccer and other professional sports, including a player's age, entered linearly and squared (e.g., Scarfe et al., 2024), air temperature (e.g., Picchio and Van Ours, 2024), as well as a home dummy to account for the home advantage (e.g., Peeters and Van Ours, 2021). We likewise use players' most recent market values as a proxy for ability and control for effective playing minutes.[26]

Building on this specification, Equation (2) extends the base model by further interacting the treatment with fasting intensity indicators at the match level, denoted $Intensity_m$, including WBGT, effective fasting hours, and a before-sunset dummy. $\beta_4$ gives the Ramadan effect for Muslim players at an intensity of zero. This corresponds to matches kicking off after sunset for the before-sunset dummy, to average heat exposure for the centered WBGT measure, and to zero elapsed fasting hours for effective fasting hours. $\beta_7$ measures how this effect changes as fasting conditions become harsher. All other model components remain as defined above.

$$\begin{aligned} Y^p_{ims} = {} & \beta_1 Muslim_i + \beta_2 Ramadan_m + \beta_3 Intensity_m \\ & + \beta_4 Muslim_i \times Ramadan_m + \beta_5 Muslim_i \times Intensity_m \\ & + \beta_6 Ramadan_m \times Intensity_m + \beta_7 Muslim_i \times Ramadan_m \times Intensity_m \\ & + \gamma x_{i,m,s} + \text{Player}_{i,s} + \text{Position}_{i,m} + \epsilon_{i,m,s} \end{aligned} \tag{2}$$

Finally, all of our specifications report two-way clustered standard errors (Cameron et al., 2011) at the player and match level, allowing for serial correlation across all matches of a given player, as well as for correlation across all players in a given match.

# 5 Part I: Individual Worker Productivity

## 5.1 Baseline Results - Player Ratings

This section examines the effect of Ramadan fasting on individual worker productivity. We begin by estimating Equation (1) with player ratings as the outcome variable.[27] Unless otherwise stated, treatment classification relies on the citizenship-based approach. The baseline results are presented in Table 8 where Panel A shows the results for the Premier League, and Panel B the results for Ligue 1. For brevity, we report only the DiD coefficient and provide the full output in Table 20 in the Appendix. The columns successively add fixed effects and control variables. Column (1) includes only the DiD components, while Columns (2) and (3) add player-season and position-group fixed effects, respectively. Column (4) presents an alternative specification in which we additionally include match fixed effects. Column (5) reports our preferred specification with player-season and position-group fixed effects while also including the full vector of covariates, as described in Section 4. Column (6) reports the same specification but relies on the LLM-based classification instead.

In brief, we find no evidence of a productivity effect. Across all specifications and both leagues, the interaction coefficient is statistically indistinguishable from zero. Setting inference aside, the point estimates themselves are small. The largest estimate across all specifications is $-0.042$ rating points on a ten-point scale, or less than six percent of a standard deviation. These conclusions are robust to replicating the estimation with the alternative performance measures as outcome variables. Table 21 in the Appendix reports these estimates, which are consistent with our baseline findings for player ratings.

[26] WhoScored.com reports effective playing minutes, which also account for extra time in both halves, as well as for short match interruptions. It may constitute a bad control if playing minutes respond to Ramadan among Muslim players. In Part III, we show that this is not the case, mitigating this concern. Likewise, the baseline results remain robust to the inclusion of playing minutes.

[27] We report results with the outcome expressed in levels. The estimates are qualitatively unchanged when the ratings are log-transformed, as shown in Table 30 in the Appendix.

Table 8: Baseline Results - Player Ratings

| | (1) Raw | (2) +Player | (3) +Position | (4) +Match | (5) Preferred | (6) LLM |
|---|---|---|---|---|---|---|
| *Panel A: Premier League* | | | | | | |
| Muslim × Ramadan | -0.042 | -0.022 | -0.018 | -0.009 | -0.011 | -0.014 |
| | (0.039) | (0.038) | (0.037) | (0.040) | (0.037) | (0.033) |
| N | 131,166 | 131,093 | 131,093 | 131,093 | 130,753 | 130,753 |
| Adj. $R^2$ | 0.000 | 0.134 | 0.154 | 0.183 | 0.208 | 0.208 |
| *Panel B: Ligue 1* | | | | | | |
| Muslim × Ramadan | -0.003 | -0.008 | -0.007 | -0.007 | -0.001 | -0.013 |
| | (0.023) | (0.021) | (0.020) | (0.020) | (0.019) | (0.018) |
| N | 125,774 | 125,687 | 125,687 | 125,687 | 124,917 | 124,917 |
| Adj. $R^2$ | 0.000 | 0.125 | 0.145 | 0.168 | 0.194 | 0.194 |
| Player×Season FE | No | Yes | Yes | Yes | Yes | Yes |
| Position FE | No | No | Yes | Yes | Yes | Yes |
| Match FE | No | No | No | Yes | No | No |
| Controls | No | No | No | No | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy. In columns (1)-(5), Muslim is a binary indicator based on the citizenship classification. Column (6) uses the LLM-based classification.

## 5.2 Treatment Intensity Indicators

The null findings of our baseline estimation essentially reflect an average treatment effect. Due to the shift of Ramadan, the intensity of fasting however varies across years, allowing us to explore potential heterogeneous effects according to weather conditions, fasting length, as well as dynamic effects in response to the progression of Ramadan. This section explores potential differential effects due to variation in fasting intensity.

### 5.2.1 Weather Conditions

The prior literature generally establishes a significant link between heat and humidity, and productivity in the workplace (e.g., Garg et al., 2025; LoPalo, 2023; Somanathan et al., 2021). With specific respect to sports, there is a general consensus in the literature on sports science and sports medicine emphasizing the differing physiological demands that varying weather conditions impose on athletic performance (e.g., Périard et al., 2015). More specifically, Burke et al. (2023) and Picchio and Van Ours (2024) examine the impact of heat and show the adverse effect it has on the performance of professional tennis players.

Soccer is likewise a physically demanding setting in which players are often exposed to harsh weather conditions.[28] In regards to Ramadan, one may therefore presume that high temperatures, solar radiation, and humidity exacerbate the difficulty of fasting, specifically the abstinence from liquids. For example, Leiper et al. (2003) review that Ramadan increases the risk of dehydration. It therefore seems plausible to conjecture that Muslim players' performance may be more affected when Ramadan occurs in the late spring to early fall. Importantly, since we match hourly weather data to precise kickoff times, we are also able to account for differences in weather conditions during one and the same day. For instance, a match that begins at 1:30 pm in August, when the sun is close to its peak, arguably imposes harsher playing conditions than a match played at 6:30 pm on the same day, when the sun is about to set, ceteris paribus.

[28]For example, Li et al. (2026) show that higher WBGT significantly erodes the home advantage, particularly when the away team is better adapted to the prevailing heat than the home side.

Similarly, Figure 3 in the Appendix plots the distributions of air temperatures and WBGT per league, both of which are approximately normally distributed. The figure illustrates clear differences across leagues. The Premier League mostly features moderately high temperatures, with only a few matches where the air temperature at kickoff reached 20 degrees Celsius or higher. In France, by contrast, a considerable share of matches occur at high temperatures, with some played in conditions of 30 degrees Celsius or above.[29] The WBGT figures likewise show this pattern. Table 7 also highlights the variation of mean air temperatures during Ramadan matches per year-month combination, a range of approximately 10 to 25 degrees Celsius for the Premier League and 10 to 26 degrees Celsius for Ligue 1. Especially in the early years of the sample when Ramadan occurred during August and September, mean air temperatures in France were typically considerably higher at kickoff than in the Premier League, emphasizing the variation across leagues and time once again.

Against this backdrop, we estimate Equation (2) with three measures of weather conditions to approximate the intensity of treatment mediated by environmental conditions. The results are depicted in Table 9. Columns (1) and (4) report the results when interacting Ramadan with WBGT, which combines several weather indicators into one and is often used as the preferred measure of weather intensity, while columns (2) and (5) portray the results when using air temperature instead. Both measures are centered around the mean. Finally, in specifications (3) and (6) we interact the treatment indicators with a dummy variable that takes the value one when the air temperature exceeds the 95th percentile, capturing a potentially differential impact of particularly hot match days. We observe that all indices exhibit a significant negative base coefficient, suggesting that, on average, performance decreases for all players, regardless of Ramadan, when temperatures increase and weather conditions become harsher. However, we do not find a differential effect of high temperatures during Ramadan, nor do we find that Muslim players are affected differently from non-Muslim players. These results remain robust to allowing for non-linear temperature measures, as well as when re-estimating the models based on the LLM-enriched classification presented in the Appendix in Tables 23 and 24, respectively.

### 5.2.2 Kickoff Timing and Fasting Length

During Ramadan, Muslims are expected to fast from dawn to dusk. Evidently, when Ramadan falls in the summer months and daylight hours are longer, Muslims need to fast longer hours, which can be seen as one dimension of fasting intensity. Similarly, earlier sunrises imply that Muslims need to get up earlier, potentially disrupting established sleep patterns, to consume food and drink before sunrise.

We consider two ways to test for a differential impact of the timing of fasting and fasting lengths, both depicted in Table 10. First, we estimate Equation (2) with a dummy indicating whether a match occurred before sunset. Since Muslims are permitted to break their fast after sunset, the null result in the baseline specification might partly reflect late matches in which Muslims were able to consume food and drink before the match.[30] In this case, we would expect to observe a significant coefficient on the additional interaction term $\beta_3$. Notwithstanding, for both leagues, we do not observe a differential effect of playing before sunset when defining treatment based on the citizenship approach. Intriguingly, for Ligue 1, we observe a marginally significant negative coefficient when relying on the LLM-enriched classification, shown in Table 22 in the Appendix. The estimate suggests that, on average, during Ramadan, the player ratings of Muslim players are 0.136 units lower compared to non-Muslim players, in matches where kickoff occurred before sunset. This result does not hold for the Premier League, however.

As a second measure, we compute effective fasting hours as the time between sunrise and kickoff.[31] If one believes in a negative impact of Ramadan fasting on performance, one would expect longer

[29] One should also note that we measure the air temperature at kickoff. Evidently, the maximum temperature during the day might have been even higher, specifically for matches with a late kickoff time.

[30] We argue that even in these instances, Ramadan fasting might still have an effect on performance, given the disruptive nature of the diet. Further, most games that begin after sunset start only shortly after it, reducing the time available for digestion and effectively permitting only light meals such as energy gels.

[31] This computation introduces marginal measurement error, as Muslims are expected to fast from dawn (*Fajr*), which occurs approximately 20 to 30 minutes earlier than the official reported sunrise time. However, we note that this error is consistent across matches and therefore unsystematic.

Table 9: Treatment Intensity - Weather Conditions

| | *Premier League* | | | *Ligue 1* | | |
|---|---|---|---|---|---|---|
| | (1) WBGT | (2) Temp | (3) Hot95 | (4) WBGT | (5) Temp | (6) Hot95 |
| Index | -0.001*** | -0.001*** | -0.005 | -0.002*** | -0.002*** | -0.033*** |
| | (0.000) | (0.000) | (0.010) | (0.000) | (0.000) | (0.012) |
| Muslim × Ramadan | -0.019 | -0.005 | -0.007 | -0.019 | -0.018 | -0.004 |
| | (0.045) | (0.044) | (0.038) | (0.022) | (0.022) | (0.021) |
| Muslim × Index | -0.000 | -0.000 | 0.024 | 0.001 | 0.001 | 0.009 |
| | (0.002) | (0.001) | (0.041) | (0.001) | (0.001) | (0.021) |
| Ramadan × Index | 0.002 | 0.002 | 0.003 | -0.001 | -0.001 | -0.024 |
| | (0.002) | (0.002) | (0.038) | (0.002) | (0.001) | (0.028) |
| Muslim × Ramadan × Index | 0.003 | -0.002 | -0.064 | 0.005 | 0.004 | 0.027 |
| | (0.009) | (0.009) | (0.196) | (0.003) | (0.003) | (0.053) |
| N | 130,753 | 130,753 | 130,753 | 124,917 | 124,917 | 124,917 |
| Adj. $R^2$ | 0.208 | 0.208 | 0.208 | 0.194 | 0.194 | 0.194 |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. WBGT computed following Liljegren et al. (2008). Hot denotes matches with air temperature above the 95th percentile (20 °C (PL)/25.4 °C (L1)). WBGT and air temperature are centered around the mean. Fixed effects include player×season and position. Muslim is a binary indicator based on the citizenship classification. Controls include age, age-squared, minutes played, market value, and a home dummy.

(effective) fasting hours to reduce Muslim players' performance more. We observe the opposite pattern, namely that Muslim players' performance improves slightly with the length of effective fasting hours during Ramadan. However, the coefficients for both leagues are only marginally significant. We conjecture that the coefficient is likely to capture the fact that better matches are often scheduled in the evenings. It should also be noted that the model reports a negative baseline effect of Muslim players during Ramadan when effective fasting hours are held at zero, which is also marginally significant. Nevertheless, as Table 7 suggests, the average effective fasting time during Ramadan for our sample corresponds to approximately 9 to 10 hours. The total effect ($\beta_2 + \beta_3$) at the mean is then again balanced to zero explaining the baseline null results reported above. What is more, in the LLM-enriched sample, the coefficients for the Premier League become insignificant while they become somewhat smaller for Ligue 1. Overall, we therefore caution against over-interpreting the marginally significant result.

### 5.2.3 Dynamic Effects - Ramadan Progression, Pre and Post-Treatment Effects

While periods of fasting are not unique to Islam and occur in many religions, what makes Ramadan distinct is that it lasts approximately 30 days, allowing effects to vary as Ramadan progresses. On the one hand, one may suspect that an effect should be more likely to be discerned towards the end of Ramadan, reflecting an accumulated impact of prolonged fasting and possibly depleted glycogen and adipose reserves. On the other hand, anecdotal evidence suggests that above all the first days of Ramadan pose challenges for believers due to the often abrupt transition into fasting, while one may become used to the demands of fasting over time.

We investigate dynamic treatment effects in two ways. First, Muslims often split Ramadan into 10-day periods. We follow this practice and allow for differential effects in each 10-day period during Ramadan. As before, matches outside Ramadan serve as the reference period. Table 11 depicts the results and suggests no indication of dynamic effects. If anything, we observe a positive coefficient for Muslims playing in the last ten days of Ramadan in Ligue 1, when relying on our preferred

Table 10: Treatment Intensity - Kickoff Timing and Effective Fasting Hours

| | *Premier League* | | *Ligue 1* | |
|---|---|---|---|---|
| | (1) Before Sunset | (2) Sunrise to Match | (3) Before Sunset | (4) Sunrise to Match |
| Muslim × Ramadan | 0.052 | -0.298* | 0.115 | -0.133* |
| | (0.156) | (0.167) | (0.113) | (0.072) |
| Muslim × Intensity | 0.007 | -0.004 | 0.012 | 0.002 |
| | (0.019) | (0.003) | (0.010) | (0.002) |
| Ramadan × Intensity | -0.014 | -0.002 | 0.043 | -0.008** |
| | (0.037) | (0.004) | (0.033) | (0.004) |
| Muslim × Ramadan × Intensity | -0.071 | 0.029* | -0.125 | 0.013* |
| | (0.158) | (0.017) | (0.113) | (0.007) |
| N | 130,753 | 130,753 | 124,917 | 124,917 |
| Adj. $R^2$ | 0.208 | 0.208 | 0.195 | 0.195 |
| Fixed Effects | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

*Notes*: Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim is a binary indicator based on the citizenship classification. Intensity is measured by a before-sunset dummy in columns (1) and (3), and by hours from sunrise to match kickoff in columns (2) and (4). Fixed effects include player×season and position. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

citizenship treatment classification. This would speak in favor of a familiarity logic, but could also reflect performance increases from psychological factors, for example, gaining additional motivation from being close to the finish line or in view of the upcoming festivities. However, the effect is not consistent and does not hold for the LLM-enriched classification, nor do we observe any similar pattern for the Premier League. In addition, while significant, the point estimate is 0.061, which is rather small in view of the ten-point scale of the outcome variable.

Second, we follow Hu and Wang (2022) and run an event study in weeks relative to Ramadan.[32] Each match is assigned to one of fifteen bins, namely the five weeks before the first day of Ramadan ($-5$ through $-1$), four bins within Ramadan ($R1$ through $R4$, where $R4$ runs from day 22 to the final day and thereby absorbs the difference between 29- and 30-day Ramadans), and the five weeks after the final day ($+1$ through $+5$). Weeks $-12$ through $-6$ before onset serve as the reference period. We include player-season fixed effects and the same covariates as in Equation 1.

Because Ramadan shifts through the playing calendar over our sample period, it falls entirely outside competitive play in several seasons, either during the European summer break (2013 through 2018) or, in 2020, during the COVID-19 suspension.[33] We therefore define event time only with respect to the Ramadan falling within a match's own season, identifying that Ramadan by match support rather than calendar overlap. Seasons without a single Ramadan matchday drop out of the event study and supply no treatment variation to the pooled estimates either.[34]

The design lets us investigate potential long-term effects that the baseline estimation may absorb, as well as pre-treatment effects. One reason to expect a pre-treatment deviation is that some Muslim players may prepare for Ramadan and adjust their rhythm incrementally rather than at a clean break at its onset.[35] A more concrete argument concerns compliance. While we presume that most players in our setting fast for the duration of Ramadan, there is anecdotal evidence that some occasionally break their fast for crucial matches and make up the missed days later in the year.[36] Such make-up

[32]The weekly separation may better mirror the soccer schedule, with typically one match per week in Ligue 1 (on the weekend) and two in the Premier League (one midweek and one on the weekend).

[33]The 2019-20 season nominally spans Ramadan 2020, but the Premier League was suspended between 13 March and 17 June, so no match fell in that window.

[34]These are seasons 2013-14 through 2017-18 and 2019-20 in the Premier League, and 2013-14 through 2016-17 and 2019-20 in Ligue 1.

[35]However, we are not aware of any reports that professional soccer players pursue such an incremental adaptation.

[36]For example, several key players were reported to have broken their fast before the 2018 UEFA Champions League

fasting may occur throughout *Shaban*, the month preceding Ramadan, though Hu and Wang (2022) detect an anticipation effect specifically in its first week. Under substantial non-compliance, we would therefore expect a differential impact in the fourth week before Ramadan (bin $-4$).[37]

Figure 2 plots the estimates for both leagues with 95% confidence intervals and reports the number of matches per bin in parentheses. Reassuringly, neither league exhibits a pre-Ramadan trend, and bin $-4$ is centered on zero in both, providing no evidence of anticipation or systematic non-compliance.[38] Within Ramadan, neither league shows a systematic progression across the four weeks. The Premier League estimates remain close to zero throughout, while in Ligue 1 only the final week ($R4$) shows a significant positive estimate. All five post-Ramadan weeks are indistinguishable from zero in both leagues, providing no evidence of a rebound once fasting ends.

The few within-Ramadan signals we do observe are confined to Ligue 1 and are sensitive to how treatment is defined. Under the LLM-based classification (Figure 5 in the Appendix), the positive final-week effect disappears, while the second week ($R2$) turns significantly negative, with a point estimate slightly below $-0.1$.[39] The Premier League estimates remain null throughout. Taken together, the within-Ramadan estimates provide at most weak and inconsistent evidence of a negative effect, concentrated in Ligue 1 and not robust across specifications. Finally, we re-estimate Equation (1), defining the month before and after Ramadan as treated, respectively, while omitting matches played during Ramadan. The results (Table 25 in the Appendix) align with the prior findings and underline the absence of pre-treatment or long-term effects of Ramadan fasting.

Table 11: Ramadan Progression (10-Day Windows)

| | *Premier League* | | *Ligue 1* | |
|---|---|---|---|---|
| | (1) Baseline | (2) LLM | (3) Baseline | (4) LLM |
| Muslim × Ramadan 1–10 | 0.068 | -0.001 | -0.040 | -0.034 |
| | (0.066) | (0.054) | (0.028) | (0.025) |
| Muslim × Ramadan 11–20 | -0.046 | 0.033 | -0.026 | -0.030 |
| | (0.065) | (0.057) | (0.027) | (0.026) |
| Muslim × Ramadan 21–30 | -0.012 | -0.023 | 0.061** | 0.033 |
| | (0.041) | (0.039) | (0.028) | (0.025) |
| N | 130,753 | 130,753 | 124,917 | 124,917 |
| Adj. $R^2$ | 0.208 | 0.208 | 0.194 | 0.194 |
| Fixed Effects | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Reference category: Outside Ramadan. Muslim is a binary indicator based on the citizenship classification. Columns (2) and (4) use the LLM-based classification. Fixed effects include player×season and position. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

### 5.3 Alternative Estimand - Within-Group Ramadan Effect

While we believe that a potential effect of Ramadan fasting on worker productivity is best studied in a DiD-format comparing the relative performance of non-Muslim to Muslim workers, this approach requires believing in parallel trends, that is, in the absence of fasting, Muslim players would follow the same performance trajectory as non-Muslim players during Ramadan. Similarly, one needs to impose

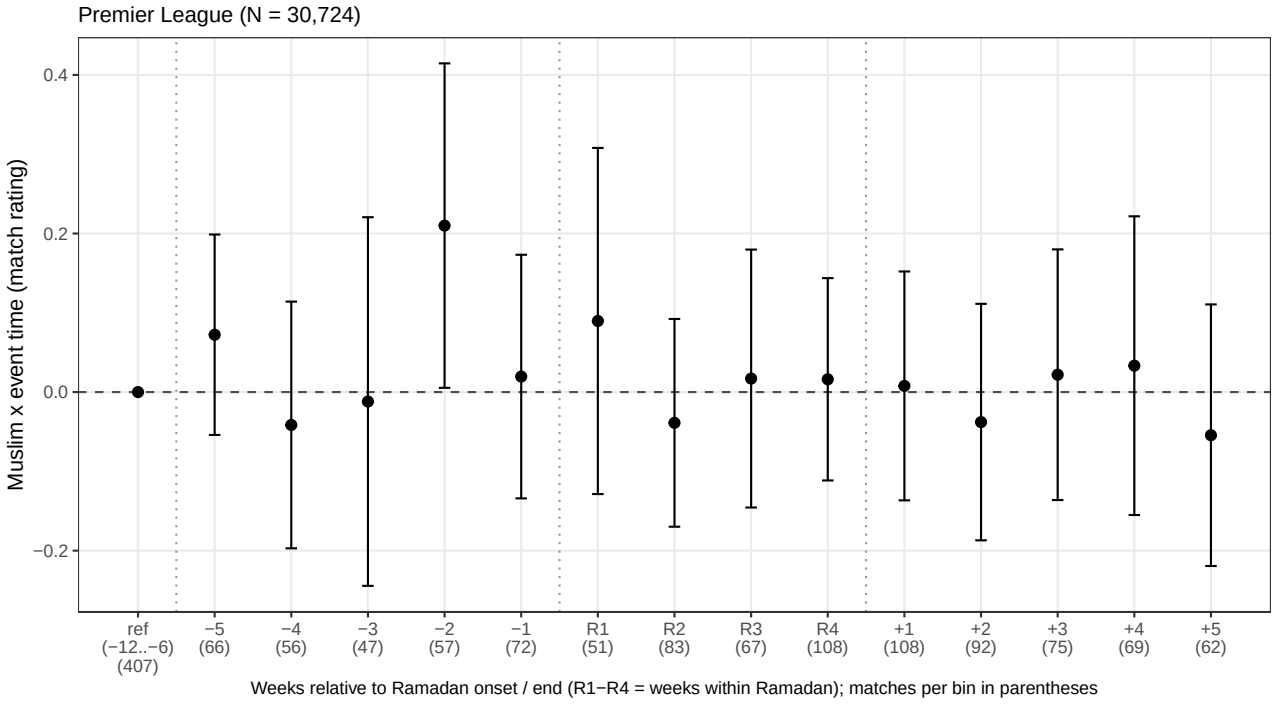
Final between Real Madrid and Liverpool FC on 26 May, during Ramadan (ESPN, 2018).

[37] Of course, this would only be implicit and suggestive evidence and would not allow us to fully rule out that some Muslim players do not fast.

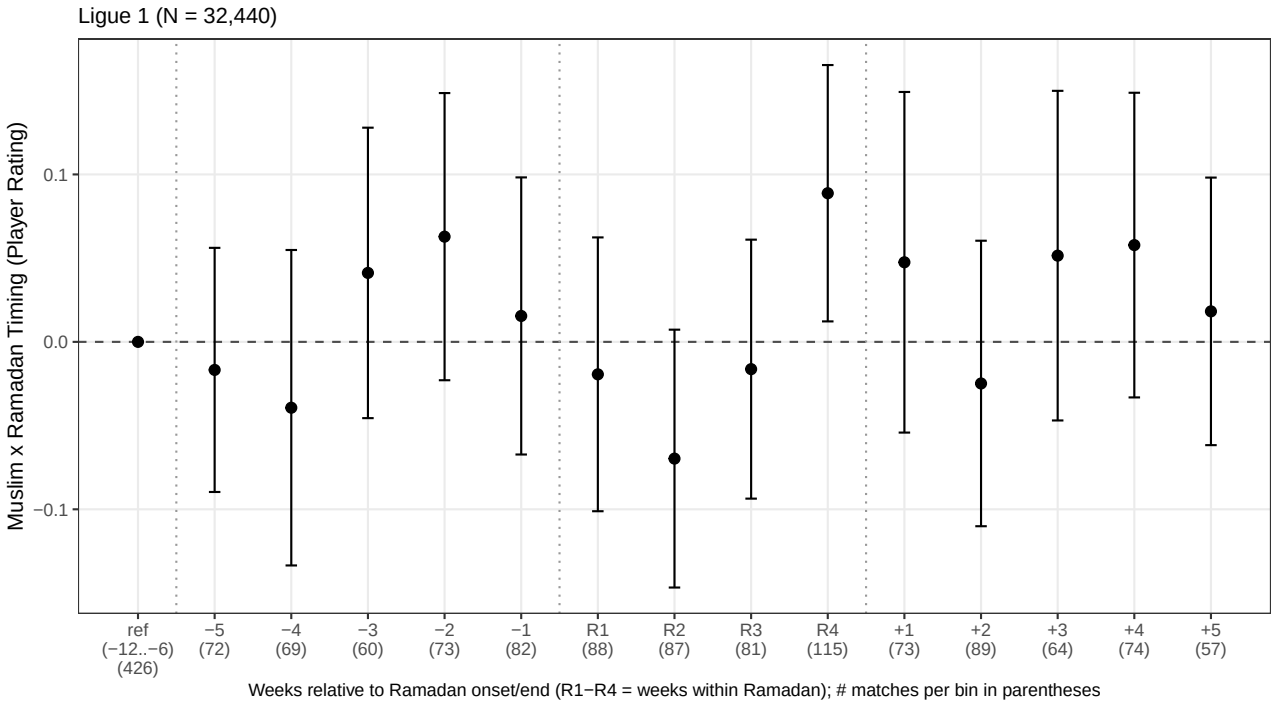
[38] The one exception is a borderline positive estimate two weeks before Ramadan (bin $-2$) in the Premier League baseline specification, which is not robust and vanishes under the LLM-based classification (Figure 5 in the Appendix).

[39] The coefficient in week $-3$ also becomes borderline significant but exhibits a positive sign.

Figure 2: Event Study - Player Ratings by Week Relative to Ramadan




(a) Premier League




(b) Ligue 1

*Notes:* Coefficients on Muslim × week-relative-to-Ramadan interactions with 95% confidence intervals. Reference period: -12 to -6 weeks pre-Ramadan. Specification includes Player×Season FE and the full set of controls (age, age-squared, air temperature, market value, and a home dummy). Standard errors clustered by player and match.

the Stable Unit Treatment Variation Assumption (SUTVA), implying that there are no spillovers of treated to untreated units. Since soccer is a team sport, one may wonder whether this assumption is violated if the fasting of Muslim teammates also affects non-fasting teammates. On the one hand, non-fasting teammates may 'overcompensate' for their fasting peers, e.g., by covering more distance. On the other hand, the performance of non-Muslim players may move in parallel with that of Muslim teammates in the presence of effort spillovers in team production (Cohen-Zada et al., 2024). However, it would arguably be difficult to reconcile either argument with our baseline results of no relative effect, as one would expect overcompensation or effort spillovers to be reflected in some performance response, either between groups or relative to performance outside Ramadan.[40]

Nevertheless, we investigate the robustness of our null finding and explore an alternative estimand that does not rely on a relative design, but identifies the effect of Ramadan within the treated and untreated groups separately, exploiting the natural exogenous variation that the shift of the lunar calendar brings about. Specifically, we estimate the following model:

$$Y^{p}_{i,m,s} = \delta Ramadan_{i,m,s} + \gamma x_{i,m,s} + \text{Matchday}_{m,s} + \text{Player}_{i,s} + \text{Position}_{i,m} + \epsilon_{i,m,s} \tag{3}$$

where we regress the performance of player $i$ on a simple Ramadan indicator and control for any confounding trends that go along with the shift in the intensity of the treatment via the inclusion of matchday fixed effects. We hence identify the effect of Ramadan across seasons within each subgroup, holding the effect of timing within the season constant.[41]

Table 12 presents the results, where the upper panel refers to the subsample of Muslims and the bottom panel to the non-Muslim players. Reassuringly, we do not observe any effect for either group, corroborating the robustness of the baseline results. Likewise, re-estimating the specifications using the LLM-enriched classification does not alter this conclusion either.

### 5.3.1 Spillover Effects

Although the split in the subsamples does not suggest a differential effect across groups, there may still be heterogeneous effects that depend on a team's exposure to Ramadan fasting. We test for this directly in Table 13, where we interact the Ramadan dummy with a count of Muslim players in the own and the opponent's team, respectively.

While the coefficient on Ramadan remains insignificant, as before, we find suggestive evidence of a negative influence of the number of Muslim players in the own team but a significant positive influence of the number of Muslim players in the opponent's team during Ramadan. For the Premier League, the negative effect of the number of Muslim teammates is observed among both Muslim and non-Muslim players and holds under the LLM-based classification for the non-Muslim subsample, suggesting spillover effects on all teammates. Holding all things constant, playing with one more fasting teammate reduces a player's own playing performance by about 0.045 to 0.081 units, a moderate effect given the ten-point scale of the dependent variable. For Ligue 1, we only observe a significant effect on other Muslim teammates but find no direct evidence of spillover effects on non-Muslim teammates. Moreover, we find evidence that the number of Muslim opponents during Ramadan may improve the performance of both Muslim and non-Muslim players in the Premier League by about 0.012 to 0.023 units, on average. However, we do not observe such an influence in Ligue 1.

Overall, we find weak suggestive evidence that Ramadan fasting may have an impact on teammates when a considerable number of Muslim players fasts. The results suggest that these spillovers affect Muslim and non-Muslim players similarly, so the two groups offset each other in the DiD comparison, partly explaining the null baseline results. Separately, for a given player, the negative influence of fasting teammates may be partly offset by fasting opponents, though this pattern is only observed in the Premier League and is weaker in magnitude than the influence of own fasting teammates. It

[40] Unfortunately, we cannot directly examine differences in effort provision, e.g., through running behavior, as this data is not publicly disclosed, to the best of our knowledge. As noted above, such measures are also likely not captured by the WhoScored algorithm, though they arguably enter indirectly through other ball-based events.

[41] We also find the same results using month fixed effects, and when including team-season and opponent-season fixed effects in combination with player fixed effects.

Table 12: Ramadan Effect by Muslim Status

| | *Muslim Sample* | | *non-Muslim Sample* | |
|---|---|---|---|---|
| | Full | LLM | Full | LLM |
| | (1) | (2) | (3) | (4) |
| *Panel A: Premier League* | | | | |
| Ramadan | 0.007 | 0.011 | 0.013 | 0.013 |
| | (0.034) | (0.031) | (0.011) | (0.011) |
| N | 8,832 | 12,862 | 121,921 | 117,891 |
| Adj. $R^2$ | 0.229 | 0.219 | 0.206 | 0.207 |
| *Panel B: Ligue 1* | | | | |
| Ramadan | -0.010 | -0.017 | 0.001 | 0.004 |
| | (0.018) | (0.017) | (0.010) | (0.010) |
| N | 25,585 | 29,399 | 99,332 | 95,518 |
| Adj. $R^2$ | 0.178 | 0.178 | 0.199 | 0.199 |
| Player×Season FE | Yes | Yes | Yes | Yes |
| Matchday FE | Yes | Yes | Yes | Yes |
| Position FE | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

*Notes:* The models are estimated separately within the Muslim and non-Muslim subsamples. Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim is a binary indicator based on the citizenship classification. Columns (2) and (4) use the LLM-based classification. The results are qualitatively unchanged when month FE used instead of matchday FE, and when team×season and opponent×season FE combined with player FE. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

should also be noted that the estimated effects are relatively moderate in magnitude, which helps explain why we do not observe a significant overall effect in Table 12.

Table 13: Teammate Spillovers during Ramadan

| | *Muslim Sample* | | *non-Muslim Sample* | |
|---|---|---|---|---|
| | Full | LLM | Full | LLM |
| | (1) | (2) | (3) | (4) |
| *Panel A: Premier League* | | | | |
| Ramadan | 0.034 | -0.037 | 0.026 | 0.040** |
| | (0.061) | (0.055) | (0.017) | (0.020) |
| # Muslim teammates | -0.017 | -0.005 | -0.013** | -0.009 |
| | (0.012) | (0.010) | (0.006) | (0.006) |
| # Muslim teammates × Ramadan | -0.081* | -0.012 | -0.066*** | -0.045*** |
| | (0.044) | (0.033) | (0.017) | (0.016) |
| # Muslim teammates (Opp.) | -0.011 | -0.024*** | -0.006 | -0.017*** |
| | (0.008) | (0.006) | (0.004) | (0.003) |
| # Muslim teammates (Opp.) × Ramadan | 0.046 | 0.049* | 0.043** | 0.019 |
| | (0.039) | (0.027) | (0.018) | (0.016) |
| N | 8,832 | 12,862 | 121,921 | 117,891 |
| Adj. $R^2$ | 0.230 | 0.220 | 0.207 | 0.208 |
| *Panel B: Ligue 1* | | | | |
| Ramadan | 0.054 | 0.084* | 0.012 | 0.031 |
| | (0.046) | (0.045) | (0.028) | (0.029) |
| # Muslim teammates | -0.001 | -0.002 | -0.006 | -0.005 |
| | (0.006) | (0.005) | (0.004) | (0.004) |
| # Muslim teammates × Ramadan | -0.025** | -0.024** | -0.006 | -0.009 |
| | (0.012) | (0.010) | (0.009) | (0.008) |
| # Muslim teammates (Opp.) | 0.020*** | 0.012*** | 0.023*** | 0.015*** |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| # Muslim teammates (Opp.) × Ramadan | 0.002 | -0.006 | 0.002 | 0.001 |
| | (0.011) | (0.009) | (0.009) | (0.008) |
| N | 25,585 | 29,399 | 99,332 | 95,518 |
| Adj. $R^2$ | 0.179 | 0.179 | 0.201 | 0.200 |
| Player×Season FE | Yes | Yes | Yes | Yes |
| Matchday FE | Yes | Yes | Yes | Yes |
| Position FE | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

*Notes:* The models are estimated separately within the Muslim and non-Muslim subsamples. # Muslim teammates excludes the player himself in the Muslim subsample and counts Muslim players in the own lineup in the non-Muslim sample. Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Columns (2) and (4) use the LLM-based classification. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

# 6 Part II: Team-Level Productivity

While the individual-level analysis in Part I did not detect a substantial impact of Ramadan on player ratings overall, we found suggestive evidence of moderate spillover effects, negative from Muslim teammates and positive from Muslim opponents. This suggests that team composition may affect a team's overall performance in ways not necessarily discernible in individual performance measures, as these effects may be partly offsetting at the individual level.[42] This section therefore examines the

[42]For example, Ramadan fasting may impair players' cognitive abilities (e.g., concentration) and physicality in ways that reduce the quality of team coordination without necessarily showing up in individual statistics, e.g., a pass is completed but lacks precision or timing, a run is made but not perfectly synchronized with a teammate's pass. Such execution-quality effects would likely not be captured by the selected performance metrics above.

marginal impact of playing with or against Muslim players during Ramadan at the team-match level.

First, to align with the player-level analysis, Table 14 presents the results of regressing team rating on the total number of Muslim players fielded per match in the own team and the opponent team, interacted with the Ramadan dummy. We include team-season fixed effects to account for a team's overall form during a season, as well as to capture differences in squad rosters and team quality that typically vary only across seasons. Moreover, we follow Peeters (2018) and control for the home advantage through a binary indicator, and also condition on pre-match betting odds that best predict a team's winning likelihood, thereby implicitly accounting for the relative importance of a match, a team's recent form, player injuries and illnesses, and other otherwise unobserved factors influencing winning chances.[43]

For both leagues, we observe a consistent negative impact of fielding one more Muslim player during Ramadan. As before, the effect is stronger for the Premier League, ranging between -0.028 and -0.055 units, while it is considerably smaller for Ligue 1, ranging between -0.013 and -0.016 units. Moreover, we observe a positive and significant effect only for the Premier League when the number of Muslim players in the opponent team increases. The effect is slightly smaller than the effect of Muslim teammates, ranging between 0.022 and 0.035 units.

Second, Table 15 presents the results of a linear probability model in which we use a binary win indicator as the outcome variable.[44] For the Premier League, we observe a negative impact of fielding one additional Muslim player during Ramadan on a team's winning chances, ranging between 4.2 and 5.6 percentage points. However, no such significant effect holds for Ligue 1. Moreover, for the Premier League, column (2) suggests that playing against one more Muslim player in the opponent team may benefit a team's winning likelihood by roughly the same margin by which fielding more Muslim players on the own team reduces it. Nevertheless, this result becomes insignificant under the LLM-based classification and does not replicate for Ligue 1.

Overall, the analysis indicates that fielding more Muslim players during Ramadan may harm a team's overall performance, whereas teams benefit from playing against teams with more Muslim players during Ramadan. Nevertheless, while non-negligible, the reported effect magnitudes are rather small. Moreover, we find consistent results for the Premier League but cannot replicate them for Ligue 1. This is intriguing insofar as there are considerably more Muslim players in Ligue 1 than in the Premier League as suggested by Table 2. One explanation might be that marginal changes are more detectable in the Premier League, where the median is one Muslim player per team per match (at most five), meaning an additional player represents a comparatively large relative shift. In France, where the median is three Muslim players per team per match (at most nine), the same marginal change represents a smaller share of an already larger group, making its effect easier to absorb.

# 7 Part III: Labor Demand Effects

While the prior literature observes labor supply responses to Ramadan, our setting is distinct in that agents do not have direct discretion over their labor supply. Notwithstanding, a critical reader may wonder whether labor demand also responds to Ramadan. Specifically, the null results could be partly attributable to negative labor demand responses if these sufficiently offset potentially predictable performance decreases of Muslim players during Ramadan. This may hold at the intensive margin, i.e., reducing average working hours (effective playing minutes), as well as at the extensive margin, i.e., reducing the number of workdays (sitting on the bench more or not being included in the matchday squad for recovery reasons). Anecdotally, the fact that a few coaches have publicly complained about the influence of Ramadan on players' performance gives further reason to assume that demand-sided responses could be at play. If this were true, comparing Muslim to non-Muslim players would be an inaccurate design decision and the net effect of Ramadan may in reality be negative. While it is reassuring that the within-group analysis shown in Part I supports the baseline null results, this

[43] Controlling for betting odds, we effectively measure the average marginal influence of fielding more Muslim players during Ramadan that goes beyond the market's expectation. Crucially, we find the same results upon the inclusion or exclusion of betting odds as a control, suggesting potential arbitrage opportunities.

[44] Table 31 in the Appendix replicates the same results when estimating a Probit model instead. Similarly, we observe the same pattern when using points won, or losses as the dependent variable as depicted in Table 32 in the Appendix.

Table 14: Team Ratings

| | *Premier League* | | | *Ligue 1* | | |
|---|---|---|---|---|---|---|
| | TSFE | Full | LLM | TSFE | Full | LLM |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| # Muslim players | -0.015** | -0.015** | -0.011** | -0.010*** | -0.009** | -0.008** |
| | (0.006) | (0.006) | (0.005) | (0.003) | (0.003) | (0.003) |
| # Muslim players × Ramadan | -0.055*** | -0.047*** | -0.028** | -0.013** | -0.014*** | -0.016*** |
| | (0.016) | (0.015) | (0.012) | (0.006) | (0.005) | (0.006) |
| # Muslim players (Opp.) | | 0.002 | 0.001 | | 0.005** | 0.002 |
| | | (0.003) | (0.003) | | (0.002) | (0.002) |
| # Muslim players (Opp.) × Ramadan | | 0.035** | 0.022* | | 0.004 | 0.003 |
| | | (0.014) | (0.013) | | (0.007) | (0.006) |
| N | 12,160 | 12,160 | 12,160 | 11,658 | 11,652 | 11,652 |
| Adj. $R^2$ | 0.167 | 0.268 | 0.268 | 0.146 | 0.232 | 0.232 |
| Team×Season FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | No | Yes | Yes |

*Notes:* # Muslim players counts all Muslim players that received playing time during a given match. Standard errors clustered by team and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Columns (3) and (6) use the LLM-based classification. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 15: Team Winning Probability

| | *Premier League* | | | *Ligue 1* | | |
|---|---|---|---|---|---|---|
| | TSFE | Full | LLM | TSFE | Full | LLM |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| # Muslim players | -0.001 | -0.002 | 0.001 | -0.005 | -0.004 | -0.000 |
| | (0.008) | (0.008) | (0.007) | (0.005) | (0.005) | (0.005) |
| # Muslim players × Ramadan | -0.056*** | -0.047** | -0.042*** | -0.004 | -0.005 | -0.011 |
| | (0.020) | (0.020) | (0.015) | (0.010) | (0.009) | (0.009) |
| # Muslim players (Opp.) | | 0.004 | 0.004 | | 0.013*** | 0.011*** |
| | | (0.005) | (0.004) | | (0.003) | (0.003) |
| # Muslim players (Opp.) × Ramadan | | 0.047** | 0.029 | | 0.011 | 0.008 |
| | | (0.019) | (0.019) | | (0.013) | (0.011) |
| N | 12,160 | 12,160 | 12,160 | 11,658 | 11,652 | 11,652 |
| Adj. $R^2$ | 0.088 | 0.160 | 0.160 | 0.062 | 0.125 | 0.125 |
| Team×Season FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | No | Yes | Yes |

*Notes:* # Muslim players counts all Muslim players that received playing time during a given match. Standard errors clustered by team and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Columns (3) and (6) use the LLM-based classification. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

section aims to examine potential labor demand effects more directly and to solidify our empirical approach.

Concretely, we first examine labor demand responses at the intensive margin and re-estimate Equation (1) using effective playing minutes as the outcome variable. Table 16 shows the results in the same format as before. Overall, we do not find that Muslim players receive fewer or more effective playing minutes during Ramadan than non-Muslim players. We do, however, observe a significant reduction in playing time for Ligue 1, in the raw and LLM-based specifications. The latter suggests that, on average, the effective playing time of Muslim players during Ramadan was approximately 0.95 minutes ($\approx$ 57 seconds) lower than that of non-Muslim players. While significant, this reflects only about 1/18th of a standard deviation and therefore carries little economic significance.

Next, we examine labor demand responses at the extensive margin in two ways. First, we estimate a linear probability model that examines differences in the conditional playing time of Muslim relative to non-Muslim players, as before. In particular, we investigate whether a player included in the squad received any playing time at all or sat on the bench for the entirety of the match. The results are presented in Table 17 and suggest no significant difference in the conditional playing probability between Muslim and non-Muslim players during and outside of Ramadan.[45]

Second, we create a pseudo-panel for each player-team-season combination to examine the margin of inclusion or exclusion from the matchday squad. We therefore omit all players from the sample that switched teams within the Premier League in a given season and also introduce the eligibility condition that a player appeared at least once in a team's squad in each half of the season, thereby implicitly excluding players who joined or dropped out of the league at any point during the season, be it due to a transfer or a long-term injury. Table 18 reports the results of a linear probability model and shows no significant differences between Muslim and non-Muslim players.[46]

Taken together, the results show that no labor demand responses to Ramadan occurred in either the Premier League or Ligue 1 over our sample period from 2009 to 2025. One way to interpret this finding is that coaches correctly anticipate the null effect of Ramadan fasting and hence do not make any substantial adjustments. However, the team-level results still suggest that there may be a weak negative performance effect of fielding more Muslim players. Importantly, even if coaches believed in or observed a true negative effect, rational win-maximizing coaches (e.g., Garcia-del-Barrio and Szymanski, 2009; Sloane, 1971) have strong incentives to always field their best players, and may therefore still play Muslim players as long as they are marginally better than the next best alternative, in expectation. Because most squad decisions are made during the pre-season, when the summer transfer window opens and players typically sign multi-year contracts, a potential impact of Ramadan may not be fully anticipated by club executive, leaving coaches little to no choice but to play Muslim players. This could in part explain the absence of labor demand responses. Crucially, our results suggest that no such negative impact exists at the individual level in the first place. While the team-level impact is significant and non-negligible, it remains rather small and may not be substantial enough for coaches to make significant changes to their starting eleven and tactical organization.[47]

[45]The result remains consistent when estimating a Probit model instead, presented in Table 33 in the Appendix.

[46]Table 34 in the Appendix replicates the same results when estimating a Probit model instead.

[47]It is also worth noting that soccer teams typically follow a consistent playing philosophy, and drastic tactical changes from one matchday to the next are rather uncommon. Given that Ramadan only lasts four weeks, this may also explain why we do not observe significant changes in playing time and squad appearances.

## 7.1 Intensive Margin - Playing Time

Table 16: Intensive Margin - Effective Playing Minutes

| | (1) Raw | (2) +PSFE | (3) +Pos | (4) +Match FE | (5) +Cov | (6) LLM |
|---|---|---|---|---|---|---|
| *A: Premier League* | | | | | | |
| Muslim × Ramadan | -0.514 | -1.641 | -1.157 | -1.119 | -1.181 | -1.031 |
| | (1.363) | (1.168) | (0.864) | (0.849) | (0.861) | (0.691) |
| N | 131,166 | 131,093 | 131,093 | 131,093 | 130,753 | 130,753 |
| Adj. $R^2$ | 0.001 | 0.250 | 0.605 | 0.606 | 0.604 | 0.604 |
| *B: Ligue 1* | | | | | | |
| Muslim × Ramadan | -1.405** | -0.706 | -0.534 | -0.575 | -0.545 | -0.947*** |
| | (0.645) | (0.576) | (0.362) | (0.369) | (0.360) | (0.339) |
| N | 125,801 | 125,715 | 125,715 | 125,715 | 124,945 | 124,945 |
| Adj. $R^2$ | 0.002 | 0.262 | 0.613 | 0.621 | 0.611 | 0.611 |
| Player×Season FE | No | Yes | Yes | Yes | Yes | Yes |
| Position FE | No | No | Yes | Yes | Yes | Yes |
| Match FE | No | No | No | Yes | No | No |
| Controls | No | No | No | No | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Controls in Column (5) and (6) include age, age-squared, air temperature, minutes played, market value, and a home dummy. In columns (1)-(5), Muslim is a binary indicator based on the citizenship classification. Column (6) uses the LLM-based classification.

## 7.2 Extensive Margin - Conditional Playing Time

Table 17: Extensive Margin - Conditional Playing Time

| | (1) DiD | (2) +PSFE | (3) +Match FE | (4) +Cov | (5) LLM |
|---|---|---|---|---|---|
| *A: Premier League* | | | | | |
| Muslim × Ramadan | -0.054** | -0.029 | -0.027 | -0.026 | -0.012 |
| | (0.022) | (0.018) | (0.018) | (0.018) | (0.013) |
| N | 199,727 | 199,727 | 199,727 | 196,735 | 196,735 |
| Adj. $R^2$ | 0.000 | 0.321 | 0.311 | 0.306 | 0.306 |
| *B: Ligue 1* | | | | | |
| Muslim × Ramadan | -0.014 | -0.011 | -0.011 | -0.013 | -0.014 |
| | (0.012) | (0.009) | (0.009) | (0.009) | (0.009) |
| N | 190,553 | 190,553 | 190,553 | 186,784 | 186,784 |
| Adj. $R^2$ | 0.000 | 0.304 | 0.294 | 0.294 | 0.294 |
| Player×Season FE | No | Yes | Yes | Yes | Yes |
| Match FE | No | No | Yes | No | No |
| Controls | No | No | No | Yes | Yes |

*Notes:* Outcome: *Played* = 1 if the player received any playing time (LPM). The sample includes all non-GK squad members (starters, substitutes, and bench players) for players with $\geq 5$ matchday-squad appearances in a given season. Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Controls include age, age-squared, air temperature, market value, and a home dummy. In columns (1)-(4), Muslim is a binary indicator based on the citizenship classification. Column (5) uses the LLM-based classification.

### 7.3 Extensive Margin - Squad Inclusion

Table 18: Extensive Margin - Squad Inclusions

| | (1) DiD | (2) +PSFE | (3) +Match FE | (4) +Cov | (5) LLM |
|---|---|---|---|---|---|
| *A: Premier League* | | | | | |
| Muslim × Ramadan | -0.004 | -0.027 | -0.028 | -0.027 | -0.006 |
| | (0.025) | (0.021) | (0.021) | (0.021) | (0.018) |
| N | 259,312 | 259,312 | 259,312 | 249,609 | 249,609 |
| Adj. $R^2$ | 0.000 | 0.288 | 0.279 | 0.264 | 0.264 |
| *B: Ligue 1* | | | | | |
| Muslim × Ramadan | 0.011 | 0.014 | 0.015 | 0.008 | 0.007 |
| | (0.013) | (0.011) | (0.011) | (0.011) | (0.011) |
| N | 246,183 | 246,183 | 246,183 | 235,486 | 235,486 |
| Adj. $R^2$ | 0.001 | 0.278 | 0.267 | 0.252 | 0.252 |
| Player×Season FE | No | Yes | Yes | Yes | Yes |
| Match FE | No | No | Yes | No | No |
| Controls | No | No | No | Yes | Yes |

*Notes:* Outcome: 1 if named in the matchday squad (starter or bench). Eligible = named to this team's matchday squad at least once in each half of the season, no within-season club switch; goalkeepers excluded. Standard errors clustered by player and match. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Controls include age, age-squared, air temperature, market value, and a home dummy. In columns (1)-(4), Muslim is a binary indicator based on the citizenship classification. Column (5) uses the LLM-based classification.

## 8 Robustness

This section examines the robustness of our baseline findings. We first report results across a series of alternative treatment classifications, namely name-origin scores, the first citizenship only, a more lenient 50% threshold, and the continuous Muslim population share. We also show that the findings are unaffected by the exclusion of defenders and substitutes. Finally, we find no significant difference between home and away matches, nor a substantial performance response to the introduction of in-game fasting breaks in the Premier League in April 2021.

### 8.1 Alternative Treatment Classifications

As a first alternative approach to identifying treatment status, we rely on name-origin propensities as described in Section 3.1. Table 38 in the Appendix summarizes the results, reporting the DiD coefficients based on the continuous name-origin scores for both the narrow and the broad treatment category. Taken together, we draw the same conclusions as before, observing predominantly null findings across both leagues and both categories. When classifying treatment narrowly, however, we estimate a statistically significant negative effect for the Premier League: during Ramadan, an increase in the narrow name-origin score from 0 to 1 is associated with a decline in match ratings of 0.130 to 0.145 units relative to matches outside Ramadan.[48] We note that this is a non-negligible but modest effect relative to the ten-point scale of the outcome. Further, the effect vanishes once match fixed effects are included and does not replicate under the broad classification, which adds three additional leaf nationalities. Moreover, the narrow specification draws identification from a thin margin of the sample: only $\approx 2.8\%$ of players ($\approx 2.0\%$ of player-match observations) in the Premier League analysis

[48] It is worth noting that this jump reflects a linear extrapolation, as few players carry name-origin scores close to 1.

sample carry a narrow score above 0.5, and the average narrow score per observation is 0.032.[49]

Second, our preferred specification classifies treatment status using both first and second citizenship, which we consider appropriate given that France and England are both major immigration destinations. However, fasting compliance rates are typically close to 100% in Muslim-majority countries, while they are substantial but somewhat lower in Muslim-minority countries, typically ranging between 70% and 90%. Against this background, it is reassuring that our results are qualitatively similar when treatment status is based on first citizenship alone, as shown in Table 35 in the Appendix. The results are further replicated using a more lenient 50% threshold for treatment assignment, following Hornung et al. (2023), as presented in Table 36 in the Appendix. Notwithstanding, a reasonable concern may still be that both binary classification rules are somewhat arbitrary. Akin to the name-origin scores, we therefore also re-estimate Equation (1) using the Muslim population shares as continuous proxies for the propensity to be treated. Table 37 in the Appendix supports the null findings.

### 8.2 Alternative Sample Selection - Excluding Defenders and Substitutes

Measuring the performance of defenders poses an empirical challenge since most performance measures are suited to assess offensive rather than defensive productions and because 'good' defending is often best described by the absence of any remarkable performance indicators.[50] In this vein, Butler et al. (2024) show that a battery of traditional defensive performance metrics can not sufficiently explain defenders' wages, implying that other factors may be better suited to assess defensive production in professional. Our algorithmic performance rating should partly mitigate these concerns as it combines more than 200 individual metrics and additionally adjusts the ratings by positional demands, making ratings comparable across positions. Nevertheless, Ball et al. (2025) suggest that algorithmic player ratings, including WhoScored ratings, may put more emphasis on measure of offensive rather than defensive production. We therefore test for the robustness of our results and re-estimate equation (1) omitting defenders from the sample.[51] Table 28 shows that the removal of defenders does not alter the results and we still conclude null findings.

Moreover, while we omit player-matches from the analysis in which a given player effectively played less than 30 minutes, we allow for the inclusion of substitutes. This decision might be criticized as so far as there could be endogenous reasons for why a player did not start a match but was substituted on early enough to be included in the estimation. It could for example be that fasting key players are protected by coaches and are only subbed in for the second half or the end of the match when the game succession requires it. In this case, their talent and the restricted playing time may partly offset a potentially negative impact of Ramadan fasting on performance. Nevertheless, Table 33 suggests that Muslim players are not more likely than non-Muslim players to sit on the bench during Ramadan.

Yet, soccer remains a low-scoring game with few individual actions making it to some extent difficult to leave a meaningful impact when not playing the full length of the match. Even tough we control for effective playing minutes, we likewise aim to show that the results do not hinge on the inclusion of substitutes and thus also re-estimate equation (1) excluding substitutes hence only comparing players who started the match, while again conditioning for effective playing time. Table 29 in the Appendix demonstrates the robustness of the baseline results.

### 8.3 Fasting Exemptions - Home vs. Away Matches

While believers are generally expected to fast for the length of Ramadan, some exceptions occur surrounding situations in which fasting would impose an additional burden. As such, believers who

[49] We observe the same patterns when classifying treatment in a binary fashion using a 50% and 90% decision rule for both categories and also relying on propensity-weighted classification in combination with a 50% threshold, where weights are again the observed Muslim shares reported by the Pew Research Center. Table 39 in the Appendix reports the results. While we overwhelmingly observe null findings, the handful of significant coefficients we do observe are attributable either to a small number of identifying units or simply to chance.

[50] For instance, the legendary Italian defender Paolo Maldini was known for his excellent ability of anticipation helping to prevent opponent attacks before they needed to be defended more rigorously.

[51] Another reason for excluding defenders could be that one may conjecture that Ramadan affects above all offensive players who typically cover longer distances, on average. If this were true, we would expect to see a negative significant coefficient upon the exclusion of defenders.

are traveling during Ramadan may abstain from fasting and make up for it at any point later in the year. Hence, it seems natural to test whether one can see a differential response to Ramadan among Muslim players when playing away relative to playing at home.

We therefore re-estimate Equation (2) including a binary home dummy that is interacted with all regressors allowing for differential impacts of playing at home versus playing away. Table 27 in the Appendix supports the robustness of the results showing that, on average, Muslim players do not play better or worse during Ramadan when playing at home or away.

### 8.4 Institutional Change - Introduction of In-Match Breaks in April 2021

In April 2021, the Premier League officially introduced guidance protocols on match pauses enabling Muslim players to break their fast when the sunset happens to occur during a match. Based on pre-match agreements among the referee and teams, the match would halt at an appropriate moment, e.g., a goal kick or throw-in. Importantly, the French football association (FFF) officially disallowed such match interruptions, citing secularism laws ('laicité').

While over the past two decades, clubs in both countries have generally increased their awareness of the demands that Ramadan imposes on players and undertook organizational adjustments, with teams in the Premier League especially having been ascribed role-model status. In this vein, one may conjecture that the guidance protocol mirrors this development and serves as an implicit proxy indicating a substantial increase in awareness of Ramadan as well as institutional support that concerns above all Muslim players in the Premier League but less so in the French Ligue 1. If sufficiently large, one might expect to observe a significant, presumably positive, performance response of Muslim players in England beginning from April 2021, while one would not expect to discern any change in France.

We examine this hypothesis by re-estimating Equation (2) including a binary Post indicator for all matches happening after the first official match break on April 26, 2021. Table 26 shows that one cannot observe any performance response of Muslim players following the introduction of the guidance protocols. The relative performance changes between Muslim and non-Muslim players during Ramadan were not significantly affected by the policy.

Furthermore, we run an event study in which we estimate annual treatment effects, which allows us to further inspect trends over time and across leagues. Figure 6 plots the annual DiD-coefficients for all years in which matches were played during Ramadan.[52] Overall, the figures corroborate the null findings with most confidence intervals centered around zero. The plots reveal a significant coefficient in only two seasons, namely 2021-2022 for the Premier League, and 2011-2012 for Ligue 1. While the coefficient for the Premier League is negative suggesting that Muslim players performed relatively worse during Ramadan in the 2021-2022 season compared to non-Muslim players, we observe the opposite sign in the French Ligue 1 for the 2011-2012 season. Both results are somewhat surprising. The Premier League finding follows shortly after the introduction of match breaks at the end of the prior season, while Ligue 1 finding coincides with a period of generally lower awareness of Ramadan in French soccer. Importantly, both patterns do not continue in the following years, suggesting that the results might simply reflect statistical outliers or could be driven by extraordinary circumstances surrounding Ramadan in the given leagues and seasons that we did not account for.

## 9 Concluding Discussion

This paper studies the individual productivity effects of Ramadan fasting using professional soccer as a natural laboratory. We overwhelmingly find no direct effect on individual worker productivity, and no evidence that Ramadan induces significant labor demand responses. Yet, we find suggestive evidence of moderate negative spillover effects among teammates that are partly offset by positive spillovers from Muslim opponents. These cumulative effects carry over to the team level, affecting a team's output in opposing directions. However, these effects are rather small and do not consistently replicate across leagues and specifications.

[52] In missing years, Ramadan either happened during the summer break (2013-2018) or matches were canceled or played at a later point due to the coronavirus pandemic (2018-2019).

The predominantly null findings are particularly intriguing given that soccer is a highly physically demanding sport. We therefore discuss several explanations to contextualize the results. First, a large share of Muslim players in our sample, especially in the Premier League, comes from Muslim-majority countries, which tend to be located closer to the equator and where fasting conditions are on average considerably harsher due to environmental factors such as high temperatures and direct solar radiation. In addition, Muslims usually begin fasting from the age of puberty. Consequently, most players have accumulated many years of fasting experience and know how to individually adjust their training routines, as well as their eating and sleeping patterns, to continue performing at the highest level.[53]

In this vein, two related points need to be emphasized. First, performance in soccer is highly concentrated and only truly matters during a match, which implies that players effectively need to achieve peak performance only for about two hours once or twice a week. This leaves room for adjustments during the training week, such as longer recovery sessions and lighter workouts, that help players cope with the increased demands during Ramadan.[54]

Second, organizational adjustments to the demands of Ramadan began on a larger scale in the mid-2000s, especially in the Premier League, owing to the increasing influence of Muslim players. At first, these adjustments involved bespoke diet and workout plans, and later also changes to team training hours during Ramadan. These organizational adjustments may have helped to mitigate, or in our case nullify, a potentially negative effect of fasting on productivity observed in other contexts and at larger scales in the prior literature. Nevertheless, the results are virtually the same across the two leagues, which somewhat weakens this argument. In France, such organizational accommodations also took place, though, from what is publicly known, the Premier League remained the role-model example, in part owing to the aforementioned secularism laws. Further, while the Premier League has institutionalized official guidance for match breaks during Ramadan, the FFF in France forbade such breaks, although unofficially, teammates have been observed to fake injuries to allow their Muslim teammates to break their fast. Notwithstanding, we do not see any differential performance impact past April 2021, when the policy was introduced in England but not in France. Likewise, we do not observe any differential trends over the course of the sample period in either league. However, as our sample period begins in 2009, it may of course be that both individual and organizational accommodation to Ramadan had already taken effect in both leagues. In this light, studying the years before 2009 would have been desirable, but ratings are not available for that period.

We likewise lack access to physical performance measures, such as running behavior, which might have offered additional insights, especially given that a body of sports science literature reports significant physiological performance decreases due to fasting. Yet, we contend that our holistic way of measuring performance is better suited to study the effect of Ramadan fasting on individual worker productivity. Nevertheless, fasting effects may be discernible only in some, predominantly physical, performance dimensions that this paper cannot address.

Moreover, Ramadan may affect the performance of fasting players not only physiologically but also through indirect channels, such as stricter adherence to the prescriptions of Islam, e.g., abstaining from alcohol and praying five times a day, or social effects from exposure to other believers, among other ways that might affect productivity. To the best of our knowledge, we are not aware of any prior literature examining the effects of religiosity on performance in professional soccer. Nonetheless, it seems reasonable to argue that the off-pitch behavior of most soccer players should not shift much during Ramadan, since most players would abstain from alcohol consumption anyway, for example. Nevertheless, we cannot fully rule out that the social dimension of Ramadan, e.g., increased time spent within the religious community, provides countervailing benefits that offset part of a negative fasting effect (Campante and Yanagizawa-Drott, 2015).

Finally, the null findings may also partly be mechanical and follow from our ITT design. We acknowledge that the estimates may be attenuated due to misclassification or non-compliance. However, we reassuringly find null effects across a wide range of robustness and sensitivity checks surrounding

[53] While coaching Manchester City, then head coach Pep Guardiola publicly remarked that Ramadan was nothing new for the Muslim players in his team and that they "know perfectly how to handle it" (BBC Sport, 2026a).

[54] We acknowledge that this is evidently a luxury that workers in many conventional workplace settings may not have, where the prior literature has hence observed labor supply reductions that may speak to a similar notion.

treatment classification, model specification, estimation procedures, and sample selection. This leads us to believe that if anything, a true, presumably negative, Ramadan effect must not be large. In particular, we find it reassuring that the results hold when identifying only the within-group of Muslim players who, owing to the conservative 90% threshold, are highly likely to be Muslim, as also supported by our LLM-based treatment validation exercise. Nevertheless, credible data on the actual fasting behavior of professional soccer players is unfortunately not available.

As argued above, survey data reveal high compliance rates among Muslims, in particular in the Muslim-majority countries from which many players originate, where fasting rates are reported to exceed 90%. Even in view of clear evidence on the physiological and economic harms of prolonged fasting, Kuran and Zulfiqar (2026) document that Muslim-majority countries have seen few institutional or religious adjustments and that fasting is regarded as a sacrosanct duty. We find it plausible that players from Muslim-majority countries likewise follow these principles. Although we cannot support this claim with statistical evidence, anecdotal evidence suggests that a vast majority of soccer players fast during Ramadan. The increase in awareness and organizational accommodation over our sample period should further enable players to observe Ramadan without fear of repercussions.[55]

Taken together, our paper adds to the prior literature by showing that Ramadan fasting does not necessarily have a direct productivity effect, while aligning with the interpretations and suggested mechanisms of prior works, namely that fasting triggers labor market responses as well as behavioral adjustments. We particularly find it plausible that individual and organizational adjustments allow players to compensate for the higher requirements and workload during Ramadan. We would encourage further work in settings where output depends less on physical exertion, such as non-manual or analytical work. Likewise, it would be interesting to explore individual sports, which may allow for even cleaner identification of the individual impact of Ramadan.

[55] Even before the increase in awareness in the 2000s, some players have retrospectively revealed that they fasted in secret, underlining the importance of fasting despite the high physical demands that professional soccer imposes.

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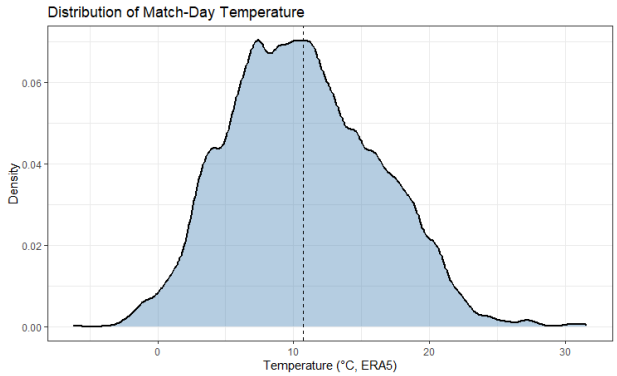
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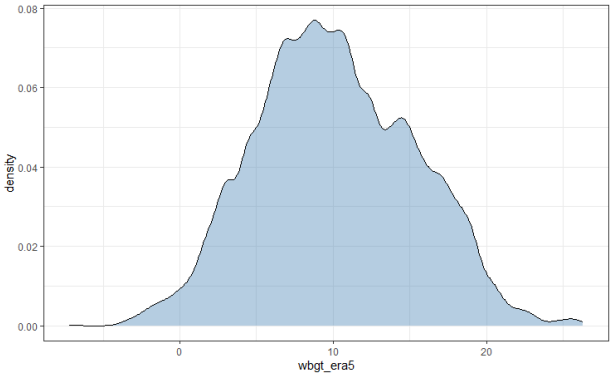
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# Appendix A - Supplementary Figures

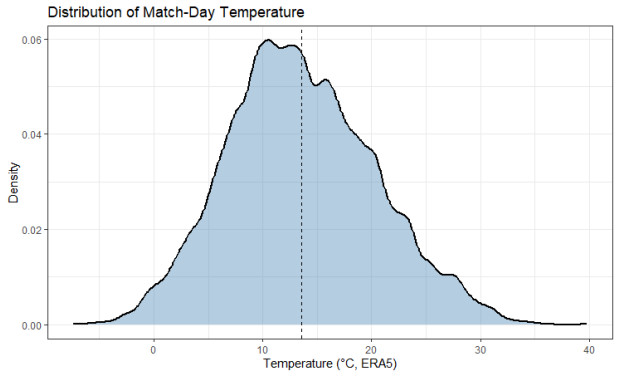
Figure 3: Distribution of Match-Day Air Temperature and WBGT.



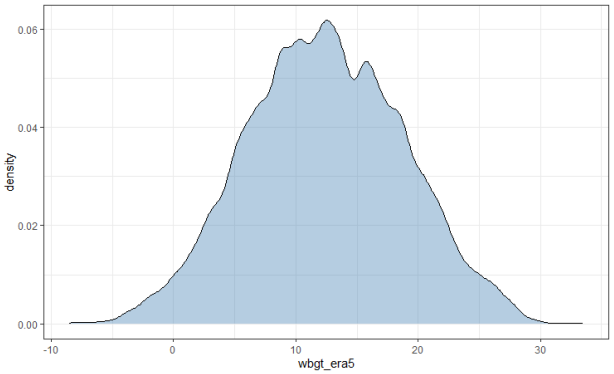

(a) Air Temperature (PL)




(b) WBGT (PL)

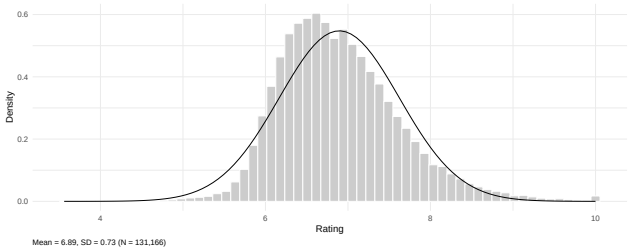



(c) Air Temperature (Ligue 1)

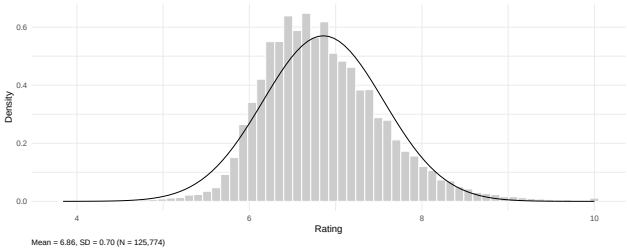



(d) WBGT (Ligue 1)

Figure 4: Distribution of Player Ratings

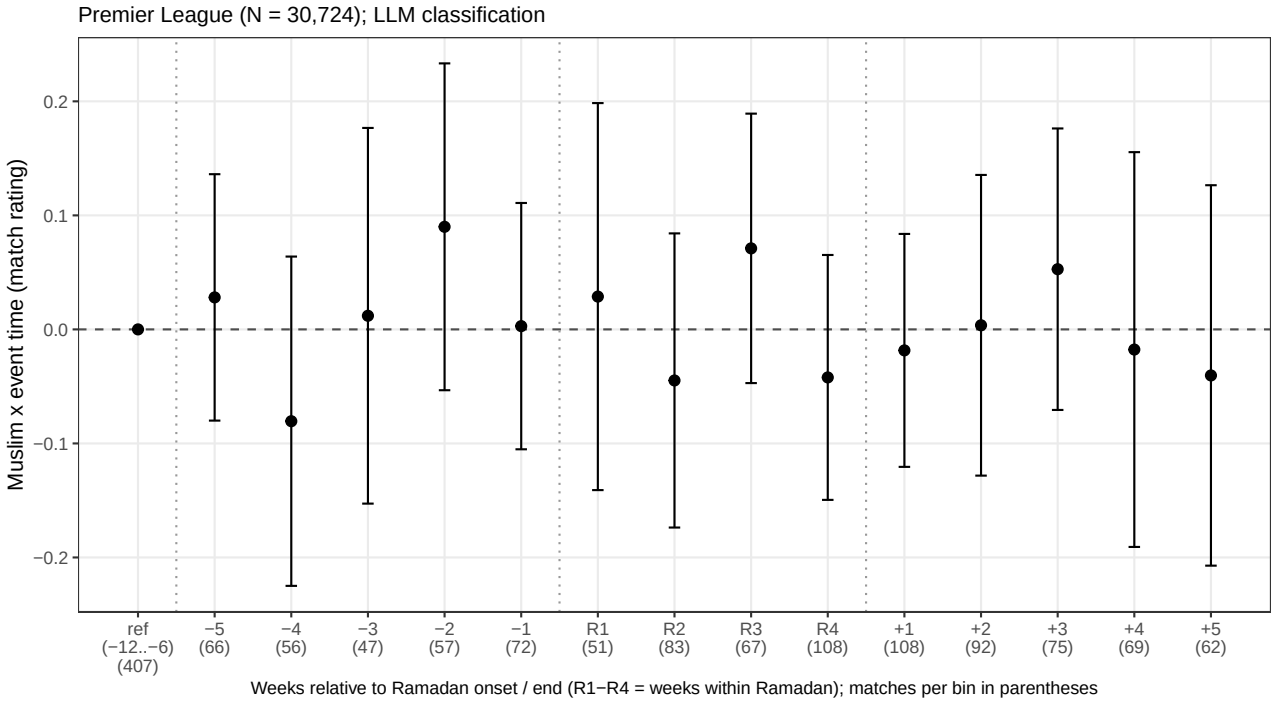



(a) Premier League

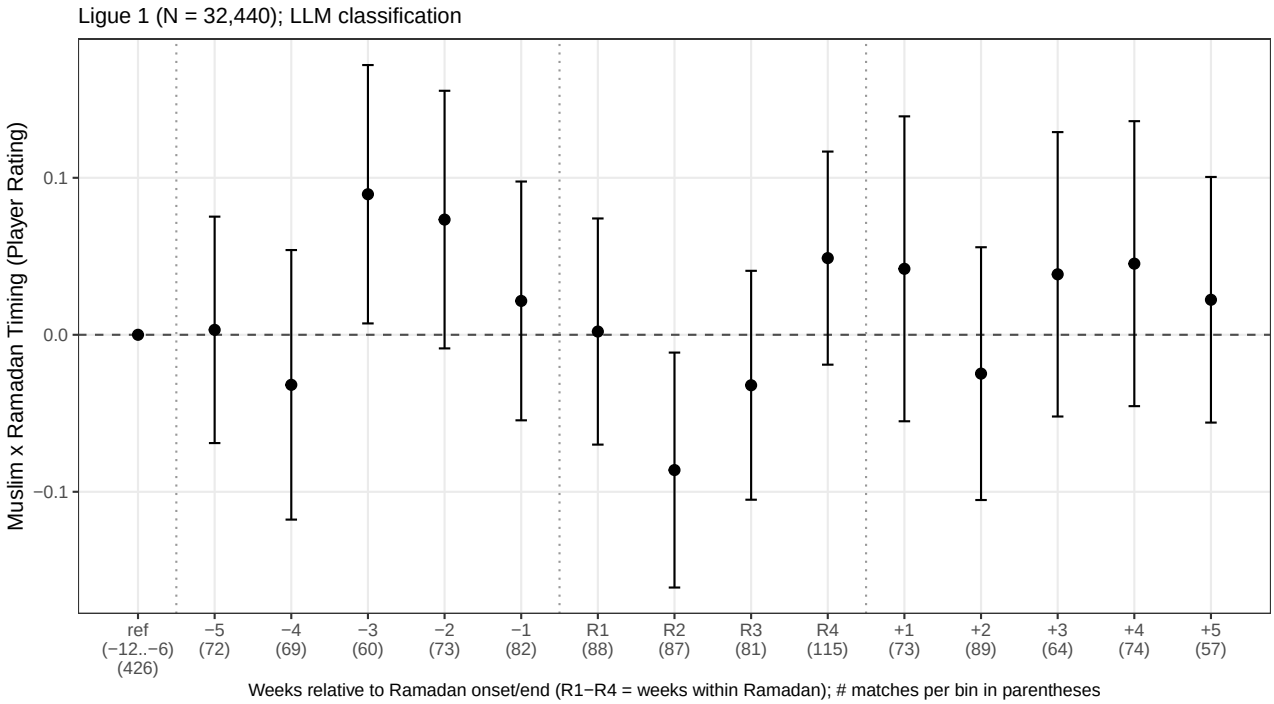



(b) Ligue 1

Figure 5: Event Study - Player Ratings by Week Relative to Ramadan - LLM-Classification



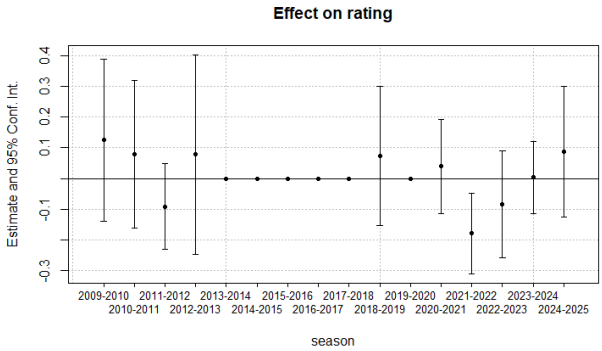

(a) Premier League



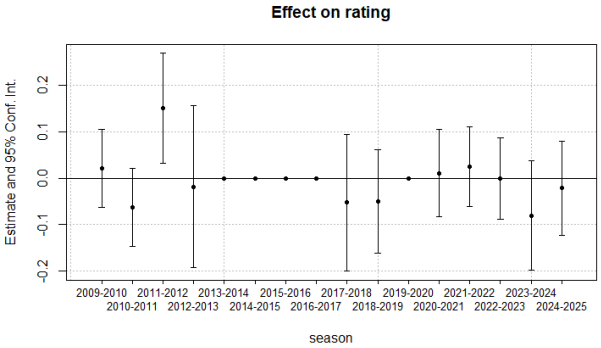

(b) Ligue 1

*Notes:* Coefficients on Muslim × week-relative-to-Ramadan interactions with 95% confidence intervals. Reference period: -12 to -6 weeks pre-Ramadan. Specification includes Player×Season FE and the full set of controls (age, age-squared, air temperature, minutes played, market value, and a home dummy.). Standard errors clustered by player and match.

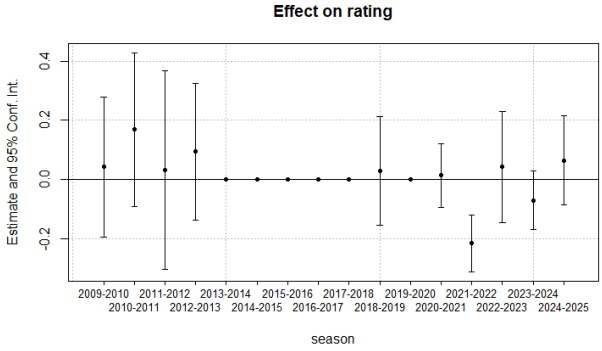
Figure 6: Event Study - Annual Treatment Effects



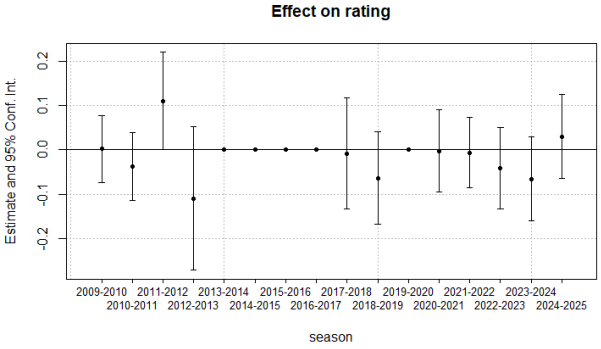

(a) Premier League




(b) Ligue 1




(c) Premier League (LLM)




(d) Ligue 1 (LLM)

*Notes:* Coefficients on Muslim × Ramadan interactions by season with 95% confidence intervals. Panels (a) and (b) use the baseline Muslim classification, panels (c) and (d) the LLM-based classification. Specification includes Player×Season FE and Position FE and the full set of controls (age, age-squared, air temperature, market value, and a home dummy). Standard errors clustered by player and match.

# Appendix B - Supplementary Tables

Table 19: Descriptive Statistics by Ramadan and Muslim Status

| | | | | | Rating | | Minutes | |
|---|---|---|---|---|---|---|---|---|
| Ramadan | Muslim | N | Players | Matches | Mean | SD | Mean | SD |
| *Panel A: Premier League* | | | | | | | | |
| 0 | 0 | 116,013 | 1,925 | 5,771 | 6.895 | 0.728 | 86.93 | 18.52 |
| 0 | 1 | 8,483 | 168 | 4,457 | 6.918 | 0.740 | 84.77 | 19.88 |
| 1 | 0 | 6,279 | 1,210 | 309 | 6.866 | 0.725 | 86.60 | 18.84 |
| 1 | 1 | 391 | 85 | 224 | 6.849 | 0.717 | 83.93 | 20.35 |
| *Panel B: Ligue 1* | | | | | | | | |
| 0 | 0 | 93,567 | 1,832 | 5,458 | 6.864 | 0.700 | 85.13 | 18.31 |
| 0 | 1 | 24,194 | 530 | 5,421 | 6.849 | 0.702 | 83.41 | 19.39 |
| 1 | 0 | 6,352 | 1,180 | 371 | 6.816 | 0.684 | 84.78 | 18.88 |
| 1 | 1 | 1,688 | 347 | 370 | 6.798 | 0.682 | 81.66 | 20.48 |

*Notes:* Muslim is a binary indicator based on the citizenship classification. $N$ denotes the total number of player-match observations. Players and Matches report the number of unique players and matches, respectively. Rating refers to the WhoScored player rating and Min to effective playing minutes. Mean and SD report the means and standard deviations within each Ramadan × Muslim cell.

Table 20: Baseline Model - Full Regression Output

| | *Premier League* | | *Ligue 1* | |
|---|---|---|---|---|
| | Baseline | LLM | Baseline | LLM |
| | (1) | (2) | (3) | (4) |
| Muslim × Ramadan | -0.011 | -0.014 | -0.001 | -0.013 |
| | (0.037) | (0.033) | (0.019) | (0.018) |
| Age | 0.034 | 0.034 | 0.031 | 0.031 |
| | (0.038) | (0.038) | (0.033) | (0.033) |
| Age$^2$ | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Temperature | -0.001*** | -0.001*** | -0.002*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Minutes played | 0.013*** | 0.013*** | 0.012*** | 0.012*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Market value | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Home | 0.146*** | 0.146*** | 0.146*** | 0.146*** |
| | (0.009) | (0.009) | (0.008) | (0.008) |
| N | 130,753 | 130,753 | 124,917 | 124,917 |
| Adj. $R^2$ | 0.208 | 0.208 | 0.194 | 0.194 |
| Player×Season FE | Yes | Yes | Yes | Yes |
| Position FE | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim is a binary indicator based on the citizenship classification. Columns (2) and (4) use the LLM-based classification. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 21: Selected Performance Metrics

| | (1) Goals | (2) Assists | (3) xG | (4) xA | (5) Shots |
|---|---|---|---|---|---|
| *Panel A: Premier League* | | | | | |
| OLS | 0.010 | 0.010 | -0.000 | 0.012* | 0.038 |
| | (0.018) | (0.017) | (0.011) | (0.007) | (0.076) |
| OLS (LLM) | -0.000 | 0.004 | -0.013 | 0.004 | 0.015 |
| | (0.014) | (0.014) | (0.008) | (0.006) | (0.061) |
| PPML | 0.049 | 0.100 | | | 0.021 |
| | (0.131) | (0.189) | | | (0.062) |
| N (OLS) | 90,421 | 90,421 | 66,076 | 66,076 | 90,421 |
| N (PPML) | 65,247 | 63,852 | | | 89,703 |
| Adj. $R^2$ | 0.122 | 0.050 | 0.277 | 0.146 | 0.355 |
| *Panel B: Ligue 1* | | | | | |
| OLS | -0.001 | -0.000 | 0.010 | -0.006 | 0.017 |
| | (0.014) | (0.010) | (0.008) | (0.006) | (0.041) |
| OLS (LLM) | 0.005 | -0.000 | 0.007 | -0.006 | 0.005 |
| | (0.012) | (0.010) | (0.008) | (0.005) | (0.037) |
| PPML | -0.016 | 0.012 | | | 0.015 |
| | (0.108) | (0.124) | | | (0.036) |
| N (OLS) | 84,739 | 84,739 | 60,565 | 60,565 | 76,739 |
| N (PPML) | 57,599 | 56,253 | | | 75,937 |
| Adj. $R^2$ | 0.133 | 0.044 | 0.281 | 0.160 | 0.354 |
| Player×Season FE | Yes | Yes | Yes | Yes | Yes |
| Position FE | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes |

*Notes:* Coefficients on Muslim × Ramadan reported by estimator. Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. PPML rows: goals, assists, and shots estimated via PPML with log minutes played as offset. OLS (LLM) uses the LLM-based classification. Adjusted $R^2$ refers to the OLS specification. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 22: Fasting Intensity - Effective Fasting Hours and Kickoff Timing - LLM-Classification

| | *Premier League* | | *Ligue 1* | |
|---|---|---|---|---|
| | Before Sunset | Sunrise to Match | Before Sunset | Sunrise to Match |
| | (1) | (2) | (3) | (4) |
| Muslim × Ramadan | -0.039 | -0.083 | 0.112 | -0.125* |
| | (0.139) | (0.142) | (0.079) | (0.065) |
| Muslim × Intensity | 0.007 | -0.003 | 0.011 | 0.001 |
| | (0.016) | (0.002) | (0.010) | (0.002) |
| Ramadan × Intensity | -0.022 | -0.001 | 0.050 | -0.008** |
| | (0.040) | (0.004) | (0.031) | (0.004) |
| Muslim × Ramadan × Intensity | 0.025 | 0.007 | -0.136* | 0.011* |
| | (0.140) | (0.014) | (0.079) | (0.006) |
| N | 130,753 | 130,753 | 124,917 | 124,917 |
| Adj. $R^2$ | 0.208 | 0.208 | 0.195 | 0.195 |
| Player×Season FE | Yes | Yes | Yes | Yes |
| Position FE | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim is a binary indicator based on the LLM-based classification. Intensity is measured by a before-sunset dummy in columns (1) and (3), and by hours from sunrise to match kickoff in columns (2) and (4). Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 23: Weather Conditions - LLM-Classification

| | *Premier League* | | | *Ligue 1* | | |
|---|---|---|---|---|---|---|
| | WBGT | Temp | Hot95 | WBGT | Temp | Hot95 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Index | -0.002*** | -0.001*** | -0.005 | -0.002*** | -0.002*** | -0.034*** |
| | (0.000) | (0.000) | (0.010) | (0.000) | (0.000) | (0.012) |
| Muslim × Ramadan | -0.047 | -0.032 | -0.017 | -0.025 | -0.024 | -0.014 |
| | (0.036) | (0.036) | (0.033) | (0.021) | (0.020) | (0.019) |
| Muslim × Index | 0.001 | 0.001 | 0.015 | 0.001 | 0.001 | 0.012 |
| | (0.001) | (0.001) | (0.029) | (0.001) | (0.001) | (0.021) |
| Ramadan × Index | 0.001 | 0.001 | -0.005 | -0.001 | -0.001 | -0.020 |
| | (0.003) | (0.002) | (0.039) | (0.002) | (0.001) | (0.027) |
| Muslim × Ramadan × Index | 0.012 | 0.007 | 0.070 | 0.003 | 0.002 | 0.006 |
| | (0.009) | (0.009) | (0.184) | (0.003) | (0.002) | (0.049) |
| N | 130,753 | 130,753 | 130,753 | 124,917 | 124,917 | 124,917 |
| Adj. $R^2$ | 0.208 | 0.208 | 0.208 | 0.194 | 0.194 | 0.194 |
| Player×Season FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Position FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim is a binary indicator based on the LLM classification. WBGT computed following Liljegren et al. (2008). Hot denotes matches with air temperature above the 95th percentile (20 °C (PL)/25.4 °C (L1)). WBGT and air temperature are centered around the mean. Controls include age, age-squared, minutes played, market value, and a home dummy.

Table 24: Weather Conditions - Non-Linear Temperature Measures

| | *Premier League* | | | | *Ligue 1* | | | |
|---|---|---|---|---|---|---|---|---|
| | WBGT | WBGT LLM | Temp | Temp LLM | WBGT | WBGT LLM | Temp | Temp LLM |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Index | -0.001*** | -0.002*** | -0.001*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Index$^2$ | -0.000 | -0.000 | 0.000 | 0.000 | -0.000 | -0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Muslim × Ramadan | -0.014 | -0.041 | -0.005 | -0.034 | -0.022 | -0.025 | -0.019 | -0.022 |
| | (0.044) | (0.036) | (0.044) | (0.035) | (0.023) | (0.022) | (0.023) | (0.021) |
| Muslim × Index | -0.000 | 0.001 | -0.000 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.002) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Ramadan × Index | -0.001 | -0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.002) | (0.002) | (0.002) | (0.002) |
| Muslim × Index$^2$ | 0.000 | 0.000 | -0.000 | -0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Ramadan × Index$^2$ | 0.000 | 0.000 | -0.000 | -0.000 | -0.000* | -0.000* | -0.000* | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Muslim × Ramadan × Index | 0.013 | 0.019* | -0.000 | 0.005 | 0.001 | 0.001 | 0.001 | 0.002 |
| | (0.013) | (0.011) | (0.013) | (0.011) | (0.005) | (0.004) | (0.004) | (0.004) |
| Muslim × Ramadan × Index$^2$ | -0.001 | -0.001 | -0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| N | 130,753 | 130,753 | 130,753 | 130,753 | 124,917 | 124,917 | 124,917 | 124,917 |
| Adj. $R^2$ | 0.208 | 0.208 | 0.208 | 0.208 | 0.194 | 0.194 | 0.194 | 0.194 |
| Player×Season FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Position FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. WBGT computed following Liljegren et al. (2008). WBGT and air temperature are centered around the mean. Muslim is a binary indicator based on the citizenship classification, except in the LLM columns, which use the LLM-based classification. Controls include age, age-squared, minutes played, market value, and a home dummy.

Table 25: Placebo Analysis - Pre-and Post Treatment Effects

| | *Premier League* | | | | *Ligue 1* | | | |
|---|---|---|---|---|---|---|---|---|
| | Placebo | Placebo LLM | Long-Run | Long-Run LLM | Placebo | Placebo LLM | Long-Run | Long-Run LLM |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Muslim × Pre | -0.011 | 0.005 | | | 0.038* | 0.036* | | |
| | (0.031) | (0.024) | | | (0.020) | (0.019) | | |
| Muslim × Post | | | -0.032 | -0.008 | | | 0.006 | -0.002 |
| | | | (0.027) | (0.024) | | | (0.019) | (0.018) |
| N | 124,084 | 124,084 | 124,084 | 124,084 | 116,908 | 116,908 | 116,908 | 116,908 |
| Adj. $R^2$ | 0.208 | 0.208 | 0.208 | 0.208 | 0.194 | 0.194 | 0.194 | 0.194 |
| Player×Season FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Position FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The sample is restricted to non-Ramadan games. Pre = 1 denotes games in the 30 days before Ramadan starts. Post-Ramadan = 1 denotes games within 30 days after Ramadan ends. Muslim is a binary indicator based on the citizenship classification, except in the LLM columns, which use the LLM-based classification.. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 26: Ramadan Effect Pre- and Post In-Match Breaks

| | *Premier League* | | *Ligue 1* | |
|---|---|---|---|---|
| | Baseline | LLM | Baseline | LLM |
| | (1) | (2) | (3) | (4) |
| Muslim × Ramadan | 0.030 | 0.042 | 0.004 | -0.009 |
| | (0.057) | (0.058) | (0.026) | (0.024) |
| Muslim × Ramadan × Post | -0.075 | -0.105 | -0.011 | -0.009 |
| | (0.066) | (0.067) | (0.037) | (0.034) |
| N | 130,753 | 130,753 | 124,917 | 124,917 |
| Adj. $R^2$ | 0.209 | 0.209 | 0.195 | 0.195 |
| Player×Season FE | Yes | Yes | Yes | Yes |
| Position FE | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Post equals one for matches after April 26, 2021. Muslim is a binary indicator based on the citizenship classification. Columns (2) and (4) use the LLM-based classification. Controls include age, age-squared, air temperature, market value, and a home dummy. Controls and Position FE are interacted with the Post dummy.

Table 27: Robustness - Home and Away

| | *Premier League* | | *Ligue 1* | |
|---|---|---|---|---|
| | Full | LLM | Full | LLM |
| | (1) | (2) | (3) | (4) |
| Muslim × Ramadan (Away) | 0.035 | 0.015 | -0.006 | -0.020 |
| | (0.050) | (0.040) | (0.029) | (0.027) |
| Muslim × Ramadan × Home | -0.072 | -0.051 | 0.017 | 0.017 |
| | (0.064) | (0.051) | (0.038) | (0.035) |
| N | 130,362 | 130,362 | 124,512 | 124,512 |
| Adj. $R^2$ | 0.206 | 0.206 | 0.194 | 0.194 |
| Player×Season FE | Yes | Yes | Yes | Yes |
| Position FE | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim is a binary indicator based on the citizenship classification. Columns (2) and (4) use the LLM-based classification. Controls include age, age-squared, air temperature, minutes played, and market value. All components are interacted with the home dummy.

Table 28: Excluding Defenders

| | Raw (1) | +PSFE (2) | +Pos (3) | +Match FE (4) | +Cov (5) | LLM (6) |
|---|---|---|---|---|---|---|
| *A: Premier League* | | | | | | |
| Muslim × Ramadan | -0.082* | -0.059 | -0.051 | -0.050 | -0.028 | -0.018 |
| | (0.043) | (0.042) | (0.039) | (0.044) | (0.040) | (0.039) |
| N | 84,485 | 83,851 | 83,851 | 83,851 | 83,654 | 83,654 |
| Adj. $R^2$ | 0.000 | 0.139 | 0.165 | 0.196 | 0.229 | 0.229 |
| *B: Ligue 1* | | | | | | |
| Muslim × Ramadan | 0.006 | 0.005 | 0.008 | 0.007 | 0.012 | 0.006 |
| | (0.029) | (0.027) | (0.026) | (0.025) | (0.025) | (0.023) |
| N | 80,876 | 80,240 | 80,240 | 80,240 | 79,816 | 79,816 |
| Adj. $R^2$ | 0.000 | 0.130 | 0.157 | 0.177 | 0.215 | 0.215 |
| Player×Season FE | No | Yes | Yes | Yes | Yes | Yes |
| Position FE | No | No | Yes | Yes | Yes | Yes |
| Match FE | No | No | No | Yes | No | No |
| Controls | No | No | No | No | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim is a binary indicator based on the citizenship classification. Last column uses the LLM-based classification. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 29: Excluding Substitutes

| | Raw (1) | +PSFE (2) | +Pos (3) | +Match FE (4) | +Cov (5) | LLM (6) |
|---|---|---|---|---|---|---|
| *A: Premier League* | | | | | | |
| Muslim × Ramadan | -0.032 | -0.003 | -0.003 | 0.003 | 0.003 | -0.005 |
| | (0.041) | (0.041) | (0.041) | (0.044) | (0.040) | (0.036) |
| N | 120,879 | 120,721 | 120,721 | 120,721 | 120,444 | 120,444 |
| Adj. $R^2$ | 0.000 | 0.130 | 0.130 | 0.161 | 0.188 | 0.188 |
| *B: Ligue 1* | | | | | | |
| Muslim × Ramadan | -0.007 | -0.010 | -0.010 | -0.007 | -0.007 | -0.023 |
| | (0.023) | (0.021) | (0.021) | (0.021) | (0.020) | (0.018) |
| N | 115,618 | 115,453 | 115,453 | 115,453 | 114,863 | 114,863 |
| Adj. $R^2$ | 0.000 | 0.118 | 0.119 | 0.143 | 0.173 | 0.173 |
| Player×Season FE | No | Yes | Yes | Yes | Yes | Yes |
| Position FE | No | No | Yes | Yes | Yes | Yes |
| Match FE | No | No | No | Yes | No | No |
| Controls | No | No | No | No | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim is a binary indicator based on the citizenship classification. Last column uses the LLM-based classification. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 30: Robustness - Log-Transformed Player Ratings

| | Raw (1) | +PSFE (2) | +Pos (3) | +Match FE (4) | +Cov (5) | LLM (6) |
|---|---|---|---|---|---|---|
| *A: Premier League* | | | | | | |
| Muslim × Ramadan | -0.006 | -0.003 | -0.003 | -0.001 | -0.002 | -0.002 |
| | (0.006) | (0.005) | (0.005) | (0.006) | (0.005) | (0.005) |
| N | 131,166 | 131,093 | 131,093 | 131,093 | 130,753 | 130,753 |
| Adj. $R^2$ | 0.000 | 0.133 | 0.153 | 0.184 | 0.210 | 0.210 |
| *B: Ligue 1* | | | | | | |
| Muslim × Ramadan | -0.000 | -0.001 | -0.001 | -0.001 | -0.000 | -0.002 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| N | 125,774 | 125,687 | 125,687 | 125,687 | 124,917 | 124,917 |
| Adj. $R^2$ | 0.000 | 0.124 | 0.144 | 0.168 | 0.195 | 0.195 |
| Player×Season FE | No | Yes | Yes | Yes | Yes | Yes |
| Position FE | No | No | Yes | Yes | Yes | Yes |
| Match FE | No | No | No | Yes | No | No |
| Controls | No | No | No | No | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Outcome: log player rating. Muslim is a binary indicator based on the citizenship classification. Last column uses the LLM-based classification. Controls include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 31: Team Winning Probability during Ramadan - Probit

| | *Premier League* | | | *Ligue 1* | | |
|---|---|---|---|---|---|---|
| | TSFE (1) | Full (2) | LLM (3) | TSFE (4) | Full (5) | LLM (6) |
| # Muslim players | -0.004 | -0.009 | 0.000 | -0.013 | -0.014 | -0.000 |
| | (0.024) | (0.027) | (0.021) | (0.015) | (0.016) | (0.014) |
| # Muslim × Ramadan | -0.173*** | -0.153** | -0.132*** | -0.012 | -0.011 | -0.030 |
| | (0.063) | (0.065) | (0.048) | (0.029) | (0.028) | (0.030) |
| # Muslim (Opp.) | | 0.015 | 0.015 | | 0.040*** | 0.035*** |
| | | (0.014) | (0.013) | | (0.009) | (0.009) |
| # Muslim (Opp.) × Ramadan | | 0.138** | 0.081 | | 0.025 | 0.019 |
| | | (0.059) | (0.057) | | (0.039) | (0.035) |
| N | 12,160 | 12,160 | 12,160 | 11,658 | 11,652 | 11,652 |
| Pseudo $R^2$ | 0.088 | 0.155 | 0.155 | 0.068 | 0.126 | 0.126 |
| Team×Season FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | No | Yes | Yes |

*Notes:* Probit coefficients reported (not marginal effects), pooled sample. Pseudo $R^2$ (McFadden). Standard errors clustered by team and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Columns (3) and (6) use the LLM-based classification. Controls include a home dummy and log betting odds.

Table 32: Team-Level Outcomes during Ramadan - Points and Losses

| Outcome | | *Premier League* | | *Ligue 1* | |
|---|---|---|---|---|---|
| | | Full (1) | LLM (2) | Full (3) | LLM (4) |
| Points | # Muslim × Ramadan | -0.139** | -0.111*** | -0.018 | -0.029 |
| | | (0.056) | (0.041) | (0.024) | (0.027) |
| | # Muslim (Opp.) × Ramadan | 0.152*** | 0.110** | 0.027 | 0.026 |
| | | (0.050) | (0.045) | (0.033) | (0.030) |
| Loss | # Muslim × Ramadan | 0.045* | 0.027 | 0.008 | 0.008 |
| | | (0.023) | (0.017) | (0.010) | (0.010) |
| | # Muslim (Opp.) × Ramadan | -0.058*** | -0.051*** | -0.005 | -0.010 |
| | | (0.017) | (0.013) | (0.011) | (0.011) |
| N | | 12,160 | 12,160 | 11,652 | 11,652 |
| Team×Season FE | | Yes | Yes | Yes | Yes |
| Controls | | Yes | Yes | Yes | Yes |

*Notes:* Each outcome estimated in a separate regression (full specification, pooled sample); only Ramadan interactions shown. Points via OLS, loss via LPM. Standard errors clustered by team and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Columns (2) and (4) use the LLM-based classification. Controls include a home dummy and log betting odds.

Table 33: Extensive Margin - Conditional Playing Time - Probit

| | DiD (1) | +PSFE (2) | +Match FE (3) | +Cov (4) | LLM (5) |
|---|---|---|---|---|---|
| *A: Premier League* | | | | | |
| Muslim × Ramadan | -0.172*** | -0.134 | -0.119 | -0.125 | -0.065 |
| | (0.066) | (0.084) | (0.089) | (0.084) | (0.067) |
| N | 199,727 | 152,188 | 152,188 | 149,853 | 149,853 |
| Pseudo $R^2$ | 0.000 | 0.225 | 0.245 | 0.220 | 0.220 |
| *B: Ligue 1* | | | | | |
| Muslim × Ramadan | -0.050 | -0.063 | -0.066 | -0.076 | -0.081* |
| | (0.041) | (0.049) | (0.051) | (0.050) | (0.049) |
| N | 190,553 | 143,163 | 143,090 | 139,653 | 139,653 |
| Pseudo $R^2$ | 0.001 | 0.217 | 0.239 | 0.213 | 0.213 |
| Player×Season FE | No | Yes | Yes | Yes | Yes |
| Match FE | No | No | Yes | No | No |
| Controls | No | No | No | Yes | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Outcome: *Played* = 1 if the player received any playing time. Probit coefficients reported (not marginal effects). The sample includes all non-GK squad members (starters, substitutes, and bench players) for players with $\geq 5$ matchday-squad appearances in a given season. Controls include age, age-squared, air temperature, market value, and a home dummy. Muslim is a binary indicator based on the citizenship classification. Last column uses the LLM-based classification.

Table 34: Extensive Margin - Squad Inclusion - Probit

| | DiD (1) | +PSFE (2) | +Match FE (3) | +Cov (4) | LLM (5) |
|---|---|---|---|---|---|
| *A: Premier League* | | | | | |
| Muslim × Ramadan | -0.011 | -0.097 | -0.094 | -0.099 | -0.020 |
| | (0.071) | (0.077) | (0.079) | (0.078) | (0.068) |
| N | 259,312 | 242,060 | 242,060 | 231,890 | 231,890 |
| Pseudo $R^2$ | 0.000 | 0.243 | 0.253 | 0.225 | 0.225 |
| *B: Ligue 1* | | | | | |
| Muslim × Ramadan | 0.032 | 0.058 | 0.063 | 0.039 | 0.033 |
| | (0.037) | (0.043) | (0.044) | (0.044) | (0.043) |
| N | 246,183 | 235,811 | 235,811 | 224,703 | 224,703 |
| Pseudo $R^2$ | 0.001 | 0.239 | 0.247 | 0.220 | 0.220 |
| Player×Season FE | No | Yes | Yes | Yes | Yes |
| Match FE | No | No | Yes | No | No |
| Controls | No | No | No | Yes | Yes |

*Notes:* Outcome: 1 if named in the matchday squad (starter or bench). Eligible = named to this team's matchday squad at least once in each half of the season, no within-season club switch; goalkeepers excluded. Probit coefficients reported (not marginal effects). Standard errors clustered by player and match. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Controls include age, age-squared, air temperature, market value, and a home dummy. Last column uses the LLM-based Muslim classification.

# Appendix C - Alternative Treatment Classifications

Table 35: Identification via the First Citizenship

| | Raw (1) | +PSFE (2) | +Pos (3) | +Match FE (4) | +Cov (5) |
|---|---|---|---|---|---|
| *A: Premier League* | | | | | |
| Muslim × Ramadan | -0.024 | -0.004 | -0.007 | 0.016 | -0.001 |
| | (0.046) | (0.046) | (0.043) | (0.046) | (0.045) |
| N | 131,166 | 131,093 | 131,093 | 131,093 | 130,753 |
| Adj. $R^2$ | 0.000 | 0.134 | 0.154 | 0.183 | 0.208 |
| *B: Ligue 1* | | | | | |
| Muslim × Ramadan | -0.041* | -0.040* | -0.039* | -0.041* | -0.031 |
| | (0.024) | (0.022) | (0.022) | (0.022) | (0.021) |
| N | 125,774 | 125,687 | 125,687 | 125,687 | 124,917 |
| Adj. $R^2$ | 0.000 | 0.125 | 0.145 | 0.168 | 0.194 |
| Player×Season FE | No | Yes | Yes | Yes | Yes |
| Position FE | No | No | Yes | Yes | Yes |
| Match FE | No | No | No | Yes | No |
| Controls | No | No | No | No | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim status identified via the player's first citizenship. Controls in Column (5) include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 36: Identification Using a 50% Threshold

| | Raw (1) | +PSFE (2) | +Pos (3) | +Match FE (4) | +Cov (5) |
|---|---|---|---|---|---|
| *A: Premier League* | | | | | |
| Muslim × Ramadan | -0.060* | -0.040 | -0.037 | -0.034 | -0.038 |
| | (0.035) | (0.035) | (0.034) | (0.036) | (0.034) |
| N | 131,166 | 131,093 | 131,093 | 131,093 | 130,753 |
| Adj. $R^2$ | 0.000 | 0.134 | 0.154 | 0.183 | 0.208 |
| *B: Ligue 1* | | | | | |
| Muslim × Ramadan | 0.004 | -0.001 | 0.001 | 0.002 | 0.003 |
| | (0.022) | (0.020) | (0.020) | (0.020) | (0.019) |
| N | 125,774 | 125,687 | 125,687 | 125,687 | 124,917 |
| Adj. $R^2$ | 0.000 | 0.125 | 0.145 | 0.168 | 0.194 |
| Player×Season FE | No | Yes | Yes | Yes | Yes |
| Position FE | No | No | Yes | Yes | Yes |
| Match FE | No | No | No | Yes | No |
| Controls | No | No | No | No | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim status identified using a 50% population-share threshold. Controls in Column (5) include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 37: Identification via a Continuous Treatment Propensity

| | Raw (1) | +PSFE (2) | +Pos (3) | +Match FE (4) | +Cov (5) |
|---|---|---|---|---|---|
| *A: Premier League* | | | | | |
| Muslim share × Ramadan | -0.011 | -0.004 | -0.003 | -0.004 | -0.001 |
| | (0.042) | (0.039) | (0.038) | (0.040) | (0.038) |
| N | 131,166 | 131,093 | 131,093 | 131,093 | 130,753 |
| Adj. $R^2$ | 0.000 | 0.134 | 0.154 | 0.183 | 0.208 |
| *B: Ligue 1* | | | | | |
| Muslim share × Ramadan | -0.001 | -0.002 | 0.001 | 0.003 | 0.006 |
| | (0.025) | (0.023) | (0.022) | (0.022) | (0.021) |
| N | 125,774 | 125,687 | 125,687 | 125,687 | 124,917 |
| Adj. $R^2$ | 0.001 | 0.125 | 0.145 | 0.168 | 0.194 |
| Player×Season FE | No | Yes | Yes | Yes | Yes |
| Position FE | No | No | Yes | Yes | Yes |
| Match FE | No | No | No | Yes | No |
| Controls | No | No | No | No | Yes |

*Notes:* Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Muslim share is the Muslim population share of the player's citizenship; for players with two citizenships, the larger of the two shares is used. The share is scaled to range from 0 to 1, so the coefficient reflects the effect of moving from a 0% to a 100% Muslim population share. Controls in Column (5) include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 38: Identification via Name Origins - Continuous Scores

| | Raw (1) | +PSFE (2) | +Pos (3) | +Match FE (4) | +Cov (5) |
|---|---|---|---|---|---|
| *A: Premier League* | | | | | |
| Narrow Score × Ramadan | -0.063 | -0.129* | -0.132* | -0.083 | -0.144** |
| | (0.089) | (0.078) | (0.073) | (0.074) | (0.065) |
| Broad Score × Ramadan | 0.004 | -0.020 | -0.014 | -0.010 | -0.009 |
| | (0.066) | (0.058) | (0.056) | (0.056) | (0.054) |
| N | 131,166 | 131,093 | 131,093 | 131,093 | 130,753 |
| Adj. $R^2$ | 0.001 | 0.134 | 0.154 | 0.183 | 0.208 |
| *B: Ligue 1* | | | | | |
| Narrow Score × Ramadan | 0.009 | -0.011 | -0.007 | -0.011 | 0.001 |
| | (0.062) | (0.056) | (0.054) | (0.056) | (0.050) |
| Broad Score × Ramadan | -0.042 | -0.050 | -0.038 | -0.039 | -0.026 |
| | (0.050) | (0.044) | (0.042) | (0.044) | (0.040) |
| N | 125,774 | 125,687 | 125,687 | 125,687 | 124,917 |
| Adj. $R^2$ | 0.001 | 0.125 | 0.145 | 0.168 | 0.194 |
| Player×Season FE | No | Yes | Yes | Yes | Yes |
| Position FE | No | No | Yes | Yes | Yes |
| Match FE | No | No | No | Yes | No |
| Controls | No | No | No | No | Yes |

*Notes:* Each pair of rows corresponds to a separate regression using either the continuous narrow or broad name-origin score. Because the number of observations (N) and the adjusted $R^2$ are virtually identical across the two specifications, we report both jointly for each pair. Standard errors clustered by player and match in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Controls in Column (5) include age, age-squared, air temperature, minutes played, market value, and a home dummy.

Table 39: Identification via Name Origins - Overview of Binary Classifications

| | Raw (1) | +PSFE (2) | +Pos (3) | +Match FE (4) | +Cov (5) |
|---|---|---|---|---|---|
| *A: Premier League* | | | | | |
| Narrow (0.90) | -0.095 | -0.117 | -0.135** | -0.092 | -0.129** |
| Narrow (0.50) | -0.035 | -0.034 | -0.034 | 0.008 | -0.054 |
| Broad (0.90) | -0.021 | 0.011 | 0.007 | 0.023 | 0.046 |
| Broad (0.50) | -0.018 | -0.021 | -0.015 | -0.010 | -0.017 |
| Propensity (0.50) | -0.029 | -0.038 | -0.039 | 0.007 | -0.056 |
| *B: Ligue 1* | | | | | |
| Narrow (0.90) | 0.105 | 0.057 | 0.034 | 0.032 | 0.032 |
| Narrow (0.50) | -0.033 | -0.054 | -0.046 | -0.054 | -0.029 |
| Broad (0.90) | 0.064 | -0.011 | -0.011 | -0.001 | -0.011 |
| Broad (0.50) | -0.052 | -0.063* | -0.050 | -0.049 | -0.035 |
| Propensity (0.50) | -0.014 | -0.027 | -0.018 | -0.023 | -0.005 |

*Notes:* Each cell is the Muslim × Ramadan coefficient from a separate regression; rows vary the name-origin classification, columns the specification. Standard errors clustered by player and match (omitted here for space). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

# Appendix D - Technical Details on the LLM-Based Refinement of Treatment Classification

We used Anthropic's Claude Sonnet 4.6 (`claude-sonnet-4-6`) via the Message Batches API in June 2026 to produce the verification classifications. Each player was processed in a separate API request containing no information from the classification of any other player. The model was given access to Anthropic's web-search tool, with a maximum of five searches per player, and was instructed to classify players on the basis of explicit evidence only.

Each prompt supplied the player's name, date of birth, country of birth, and citizenship. The prompt defined admissible evidence as direct statements by the player indicating religious affiliation or observance; observable religious practice, such as performing the Hajj, Quran recitation, or celebrating Eid; or credible third-party reporting that explicitly identified the player's religion. The model was instructed never to infer religious affiliation from a player's name, nationality, country of birth, ethnicity, or family background alone, and was told that names of Arabic or African origin do not by themselves imply Muslim affiliation. This restriction prevents the verification from reproducing the demographic inference that underlies the citizenship-based classification, since an override requires explicit religious evidence.

The prompt ranked player interviews and social media above club statements, major media outlets, and general web sources such as Wikipedia. A stopping rule instructed the model to end the search as soon as a credible source established the player's status in either direction.

The model was instructed to return a JSON object with three fields. The first is a classification equal to 2 if at least one credible source explicitly confirmed that the player is Muslim, 1 if at least one credible source explicitly confirmed that the player is not Muslim, and 0 if no qualifying religious evidence was identified. The second is a short justification, and the third is the single best supporting URL, which is empty for classifications of 0. This three-way coding distinguishes affirmative evidence that a player is not Muslim from cases in which no qualifying evidence was identified. Only classifications of 1 and 2 generate an adjustment, while players classified as 0 retain their citizenship-based status.

Responses were parsed programmatically. The classification field was converted to numeric form and validated against the admissible set $\{0, 1, 2\}$. Requests that failed or expired, responses that could not be parsed, and classifications outside the admissible set were recorded as missing and resubmitted through the same procedure, while classifications from the initial pass were retained. We verified every classification of 1 or 2 manually against the cited source. The exact prompt and implementation code are available upon request.

## Disclosure of LLM Use

We used a large language model (Claude, Anthropic) for language editing and as a coding aid during data preparation and analysis. All outputs were reviewed by the authors, who accept full responsibility for the content of this paper.