# Using gender disparities to measure the EURO 2020 match-induced effect on COVID-19 cases in selected European countries

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## Abstract

## Introduction

Growing levels of immunity against SARS-CoV-2 (through vaccination programs and post-infection [1, 2]) and potential effects of seasonality in the northern hemisphere [3, 4] promote a sustained re-opening in the COVID-19 pandemic. In the coming months, non-essential activities, such as sports events with spectators, are expected to increase [5]. However, social and economic pressure to restore a pre-COVID level of activities might lead to lifting restrictions too fast, thus risking further epidemic waves featuring variants of SARS-CoV-2 [1, 2, 6–8]. Consequently, it is critical to quantify the impact that these events might have on the spreading dynamics of COVID-19 [9, 10] and to detect subtle signatures of potential super-spreading events associated with them [11].

COVID-19 super-spreading events have been reported in different settings, mostly related to mass gatherings and closed settings [12–17]. Even though in-field and in-stadium preventive measures are in place for sports like football and rugby [18–20], popular matches that achieve country-scale engagement also influence uncontrolled settings (e.g., private gatherings, open-air bars, watching parties) to extents that are challenging to predict. Furthermore, the presence of in-stadium spectators (promoted mainly for economic reasons [5]) might have a synergistic effect on the engagement of TV watchers [21, 22] and on the peer pressure to participate in gatherings or watching parties [23]. Experiences of 2020, where some non-pharmaceutical interventions remained in place, pointed to a minor effect of local and country-scale matches on the community transmission

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of COVID-19 [24, 25]. However, international tournaments, such as the 2020 UEFA European Football Championship (EURO 2020, 11 June to 11 July 2021), might have a noticeable impact on the spreading dynamics of COVID-19 in the countries involved, especially in the context of restrictions being steadily lifted.

Here, we investigate the effect that independent matches of the EURO 2020 championship had on the spreading dynamics of COVID-19 across Europe, and quantify their contribution to spread in a Bayesian framework. We model the matches as singular interventions that affect the effective reproduction number. We compare the dynamics observed in every country after the match, using those eliminated in the qualifying tournament as control.

## Results

### Some countries show a significant effect of the championship on case numbers

Local news outlets and early reports alerted about increased COVID-19 incidence after EURO2020 matches [26–29]. This increased incidence was not only linked to in-stadium attendance, but also to public gatherings and mass celebrations [29]. To assess such effect, we analysed case numbers and the gender ratio among them for four European countries taking part in the EURO2020 championship: Germany, France, Scotland, and England (Fig. 1). We observe that not every country had an evident effect noticeable by naked-eye. However, countries like Scotland and England have marked deviations from the baseline trend in the gender ratio concurrent to EURO2020 matches in which they were involved, thus probably explained by them.

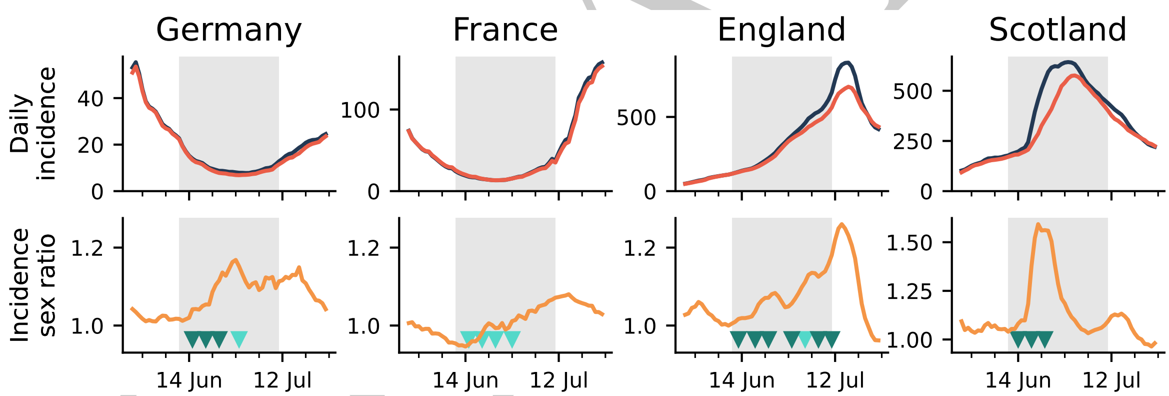


Figure 1: **UEFA 2020 football matches caused an increased COVID-19 incidence among men in several countries. A–D:** (upper) gender-resolved COVID-19 daily new cases per 1 million people and (lower) male/female gender ratio for Germany (A), France (B), England (C), and Scotland (D). The EURO2020 period is highlighted in grey, matches are marked with triangles. Trends have been averaged on a centered 7-day moving window to remove weekly modulation. On the one hand, countries as Germany, France and England show a slight —but notorious— trend shift in the gender ratio of COVID-19 incidence during the EURO2020 championship. On the other hand, there was a significant increase in the gender ratio of COVID-19 incidence upon single games as the finals in the English data and the away game versus England in the Scottish data.

### Gender-resolved Bayesian model quantifies EURO2020 impact on transmission

Aiming to quantify the impact of individual EURO 2020 matches on the country-level spread of COVID-19, we proposed a Bayesian model. Our model simulates the spread in each country using a discrete renewal process [30, 31], which has also a gender resolution for community contagion. The disease spreads with an

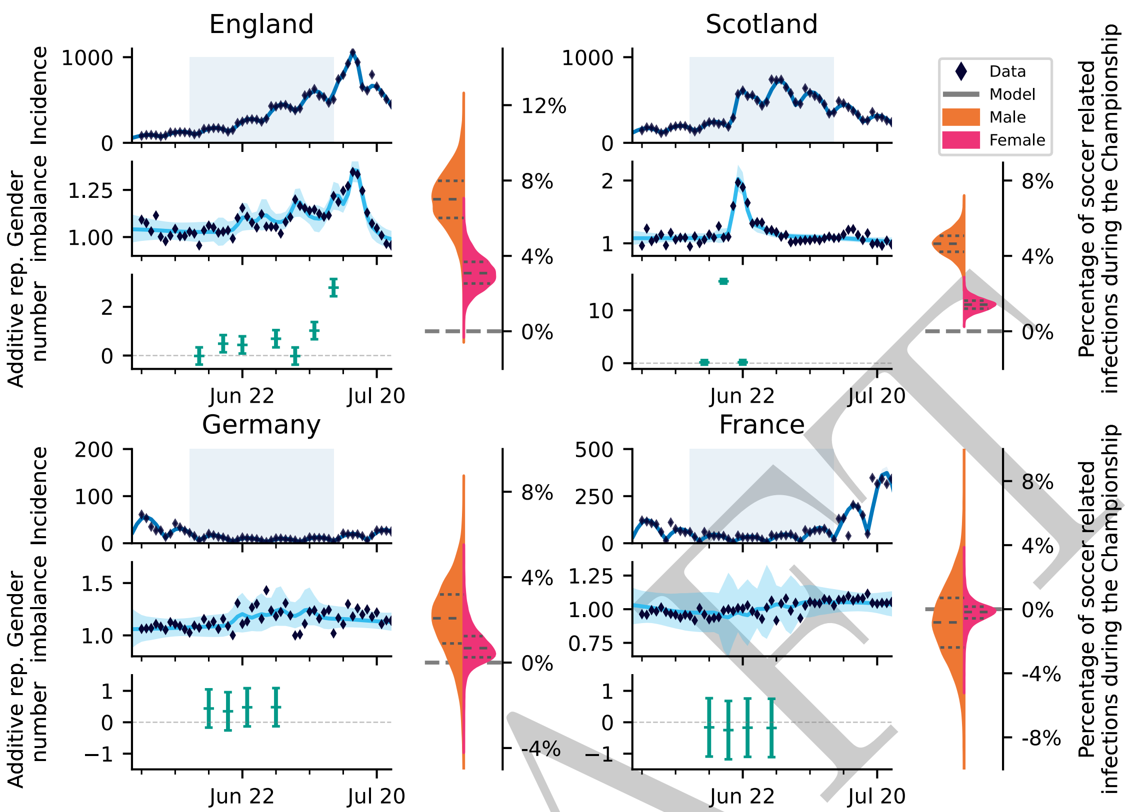


Figure 2: **Using a Bayesian model we can infer the effect size of the Championship in several countries.** The gender imbalance of the incidences (male incidence/female incidence) can be well explained by assuming that on the day of football matches, additional infections occurred mainly in the male population. This is here modelled by the additive reproduction number.

inferred time-dependent effective reproduction number $R_c$ [32], which was allowed to increase when matches took place. We then quantify the strength of the effect induced by the match, analyzing the gender-related difference in case numbers after the event, as men are likelier to attend the stadium and sport-related events [33]. We assumed that contagion can occur in two modii, depending on whether the contact was with peers of the same biological gender or not. Consistently, in football or football-induced events, contagion was more likely to occur between men, and the trend would be corrected with a delay as they subsequently interact with men and women more equally.

Under the assumption that changes in the incidence gender ratio was mainly driven by soccer games, even if the effect of individuals games are not significant, we find evidence in three out of 4 countries, that a significant proportion of the total infection during the UEFA cup was due to gatherings related to the games. In details, in our model we find that for England that 15% of the male infections during the duration of the UEFA cup [are likely due to the cup] (CI: [8%, 23%]), for Scotland 10% (CI: [6%, 15%]) and for Germany 15% (CI: [2%, 25%]). We find no effect for France (mean -5%, CI: [-23%, 8%]). Note that in England, Scotland and France the incidence of COVID-19 cases increased significantly over the course of the EURO 2020.

## Discussion

### Limitation of the chosen approach and model comparison

Our model allows us to decouple none-pharmaceutical interventions (NPIs), seasonality, vaccinations and other known or unknown effects from the effects of EURO 2020 single matches in the spreading dynamics of COVID-19. This is due to the use of the gender-ratio in the observed COVID-19 cases, and the separation of the modelling of gender-asymmetric transmission during championship-related fan gatherings from the subsequent gender-symmetric transmission in all other contact situations. This allows to model all EURO-2020 independent effects with an underlying slowly modifying base transmission dynamics, while the gender-asymmetry in the observed and modelled cases allows to extract both the gender asymmetry and a measure of COVID-19 transmission directly attributed to fan events. Furthermore, the known date of games allows to correlate spikes in the gender asymmetry of observed cases to inferred transmission dates. Mass events like this pose the unique opportunity to compare measurements of the overall average delay between infection and detection under the current testing and tracing regime from tracing of individual transmissions [] to an ensemble measurement.

Through the separation of the underlying gender-symmetric transmission dynamics from the gender-asymmetric fan events, our approach is insensitive to all other changes not directly attributed to fan events. Indirect effects like an average reduced self-imposed contact restriction through observation of game-related festivities would contribute to the base reproduction measurement of our model and not be attributed directly to the EURO 2020. Also, potentially increased travel between European countries is not explicitly modelled.

### Sensitivity and reliability of the results

We study the sensibility of our model to uncertainties in the parameters we explore, ...

### Discussion of results

Football matches in the EURO 2020 can be understood as singular perturbations to the dynamical state of the system. In that way, a stable (or meta-stable) system can see its stability compromised by the effect of the match, or case numbers would grow steeper if the system were already unstable. The dynamical state of the system, i.e., whether case numbers are controlled around a somewhat stable level or steadily growing, is determined by the balance between stabilising and destabilising contributions. In these endeavours, very strong contributions weigh each side of the balance, making it even more challenging to detect subtle, early hints of the effect of separate matches on COVID-19 dynamics [10]. Stabilising contributions are seasonality [3], the progress of vaccination [1], better hygiene and distancing concepts in stadiums and hospitality. The destabilising contributions of single matches of the EURO 2020 relate to the i) live audience and in-stadium spectators – which, besides exposing themselves, induce a larger engagement of people broadcasting the events [22, 23], ii) the broad international viewership of the contest, iii) the great heterogeneity among participant teams (in demographics, control of COVID-19, and culture), iv) incentives for going to the stadium or viewing parties among countries with low case numbers [34], and v) variants partially escaping immune response currently circulating. Furthermore, some of the factors act synergistically; a live audience in stadiums increases the interest among viewers and the total viewership [22] —which also increases the peer pressure for individuals to participate [23]—, and the referee decision bias, thus triggering emotional reactions that might endanger containment.

**Explicit comparison to other results not using observables optimised for the study target**

Previous studies aiming to evaluate the impact of football matches on the spread of COVID-19 were not conclusive on whether there was an effect. For instance, the study of Fischer [24] pointed to a minor impact of German premier league matches; only after three weeks, communities hosting a game would observe an increase in the daily incidence between 0.52 and 0.91 cases per 100.000 inhabitants — which could easily fall within the inherent noise in the observable. Furthermore, the weekly incidence on the day of the match (around 25 cases per week) modulates the match's impact on the community transmission. In contrast to ongoing premier league matches, the EURO 2020 is characterised by a significant increase of fan activity outside stadiums and an increase in international travel, which both are expected to boost the impact on COVID-19 transmission. In addition, the use of a more sensitive observable – the gender ratio – in addition to the overall case numbers allows to extract effects which otherwise are within statistical uncertainty.

In different settings at high COVID-19 incidence, large gatherings with poor preventive measures (as Trump rallies) were found to increase cumulative cases by 250 cases per 100.000 inhabitants ten weeks after the protest took place. Toumi et al. [25] studied the effect of matches of the US National Football League (NFL) on the increase of COVID-19 cases. The authors concluded no significant effect, as two weeks after the match, the county-level daily incidence did not increase more than 5 cases per 100.000 inhabitants, which would translate to a weekly incidence of 35 cases — a very generous upper bound when compared to the previously discussed studies. Furthermore, delays between contagion, testing, and identification of new cases within the community, can further delay the point when the effect would be noticeable.

Understanding how mass events with a high engagement and international viewership affect the spreading dynamics of COVID-19 can help us design better strategies for not endangering novel outbreaks. The general mechanisms reported in this article may help gain insights on the reasons why hygienic concepts proposed for the EURO2020 [29] and the Tokyo 2020 Summer Olympics [35] were not 100% effective.

## Methods

The methods might not be totally up to date but should still give you a rough overview of our model!

# 1 Model

## 1.1 Spreading dynamics including genders

To estimate the effect of the championship in different countries we build a hierarchical Bayesian model, which simulates the spread of COVID-19 in each country separately using a discrete renewal process [30, 31, 36]. We infer a time-dependent effective reproduction number $R(t)$ [32] for each country and gender.

Even though female participation in soccer has increased in the last decades [37], football (soccer) fans are predominantly male [33]. Integrating this information into the model together with gender separated case numbers, allows a better inference of the effect of the championship in individual countries. To this end, we model the spreading dynamics of COVID-19 in each country separately for males and females. Males and females are denoted by the subscript $\bullet_{f=1}$ and $\bullet_{f=2}$ respectively. Their interaction and reproduction number is modelled by the effective contact matrix $\mathbf{C}$.

Using the typical notation, i.e. susceptible pool $S$, infectious pool $E$, population size $N$ of the respective country the spreading dynamics then read as:

$$E_f(t) = \frac{S_f(t)}{N} \sum_{f'=1}^{2} \mathbf{C}_{f,f'}(t) \sum_{\tau=0}^{10} E_{f'}(t-1-\tau) g(\tau), \tag{1}$$

$$S_f(t) = S_f(t-1) - E_f(t-1), \tag{2}$$

$$g(\tau) = \text{Gamma}(\tau; \mu = 4, \sigma = 1.5), \tag{3}$$

$$\tag{4}$$

We apply a discrete convolution in (1) to account for the incubation period which we assume to be a Gamma distribution with a mean of four days [https://www.medrxiv.org/content/10.1101/2021.07.07.21260122v2.full-text].

The effective contact matrix is parameterized by: (I) a slowly changing base reproduction number $R_{\text{base}}$ (21) which has the same effect on both genders, representing the effect of NPIs and other changes to the transmission rate, (II) the reproduction number during soccer games $R_{\text{soccer}}(t)$ (10), which is only different from zero on days with soccer games and has a larger effect on men, and (III) a slowly changing noise term $R_{\text{noise}}(t)$ (29), which subsumes all additional effect which might change the incidence ratio between males and females.

The interaction between men and women is assumed to be symmetric, which can be seen by the symmetries of $\mathbf{C}_{\text{base}}$ and $\mathbf{C}_{\text{soccer}}$. For non-soccer related contacts, we assume as prior we assume that contacts between women-women and men-men are as probable as contacts between women-men ($c_{\text{off}}$). For soccer-related contacts during soccer games, we assume that women are only 20% as likely to get infected as men because of different transmission during soccer games:

$$\mathbf{C}_{f,f'} = R_{\text{base}} \mathbf{C}_{\text{base},f,f'} + (R_{\text{soccer}}(t) \mathbf{C}_{\text{soccer},f,f'} + R_{\text{noise}}(t)) \tag{5}$$

$$\mathbf{C}_{\text{base}} = \begin{pmatrix} 1 - c_{\text{off}} & c_{\text{off}} \\ c_{\text{off}} & 1 - c_{\text{off}} \end{pmatrix} \tag{6}$$

$$\mathbf{C}_{\text{soccer}} = \begin{pmatrix} 1 - \omega_{\text{female}} & \omega_{\text{female}} \\ \omega_{\text{female}} & \omega_{\text{female}}^2 \end{pmatrix}. \tag{7}$$

$$c_{\text{off}} \sim \text{Beta}(\alpha = 4, \beta = 4) \tag{8}$$

$$\omega_{\text{female}} \sim \text{Gamma}\left(\mu = 0.2, \sigma = 0.08165\right) \tag{9}$$

### 1.2 Soccer related effect

The soccer related infections can occur from public or private soccer viewing in the home country (parameterized by $\alpha^*$) or because of infections happening in stadiums (parameterized by $\beta^*$). Both of these can have different effects on each game $g$. To this end we further define the soccer related additive reproduction number:

$$R_{\text{soccer}}(t) = \sum_{g} (\alpha_g^* + \beta_g^*) \cdot \delta(t_g - t) \tag{10}$$

We assume the effect of each game to only be effective in a small timeframe centered around each game, thus we apply a delta function $\delta(t_g - t)$.

We distinguish between the effect size of each game and the overall effect of soccer games onto the spreading of COVID-19. For the effect associated to public or private soccer viewing in the home country $\alpha$ we introduce one base effect and differentiate their played games $\bullet_g$. We do this by a typical hierarchical modelling approach. As prior we assume that the effect is centered around zero, which means that in principle also a negative effect of the soccer games can be inferred. However, to make sure that the total reproduction number doesn't become negative, we apply a softplus transform to the effect $\alpha_g$. The subtraction of $\log(2)$ is required in order to map zero to zero, such that the prior effect on the reproduction number is zero:

$$\alpha_g^* = \text{softplus}(\alpha_g) - \log(2) \tag{11}$$
$$\alpha_g = \alpha_{\text{prior,g}}(\alpha_{\text{base}} + \Delta\alpha_g) \tag{12}$$
$$\alpha_{\text{base}} \sim \mathcal{N}(0,5), \tag{13}$$
$$\Delta\alpha_g \sim \mathcal{N}(0, \sigma_{\alpha,\text{g}}) \tag{14}$$
$$\sigma_{\alpha,g} \sim HalfNormal(5) \quad \forall g. \tag{15}$$

$\alpha_{\text{prior,g}}$ is the matrix that encodes the prior expectation of the effect of a game on the reproduction number. If a country participated in a game, the entry is 1 and otherwise 0.

The same applies to the effect $\beta$ induced by infections happening in stadiums. We apply the same hierarchy, but change the prior

$$\beta_g^* = \text{softplus}(\beta_g) - \log(2) \tag{16}$$
$$\beta_g = \beta_{\text{prior,g}}(\beta_{\text{base}} + \Delta\beta_g) \tag{17}$$
$$\beta_{\text{base}} \sim \mathcal{N}(0,2), \tag{18}$$
$$\Delta\beta_g \sim \mathcal{N}(0, \sigma_{\beta,\text{g}}) \tag{19}$$
$$\sigma_{\beta,g} \sim HalfNormal(2) \quad \forall g. \tag{20}$$

$\beta_{\text{prior},g}$ is matrix that encodes by ones where a game took place and otherwise contains only zeros.

### 1.3 Non-soccer related reproduction number

To account for effects not related to the soccer games, e.g. non-pharmaceutical interventions, vaccinations, seasonality or variants, we introduce a slowly changing reproduction number $R_{\text{base}}(t)$, which is identical for both genders and should map all other not specifically modelled gender independent effects.

$$R_{\text{base}}(t) = R_0 \exp\left(\sum_w \gamma_w(t)\right) \tag{21}$$
$$R_0 \sim LogNormal(\mu = 1, \sigma = 1) \tag{22}$$

This base reproduction number is modelled as a superposition of logistic change point $\gamma(t)$ every 10 days, which are parameterized by the transient length of the change points $l$, the date of the change point $d$ and the effectivity of the change point $\Delta\gamma^*$ . The subscripts $n$ denotes the discrete enumeration of the change points.

$$\gamma_n(t) = \frac{1}{1 + e^{-4/l_n \cdot (t-d_n)}} \cdot \Delta\gamma_n^* \tag{23}$$

$$\Delta\gamma_n^* = \Delta\gamma_n + \delta\gamma_n \tag{24}$$

$$\Delta\gamma_n \sim \mathcal{N}\left(0, \sigma_{\Delta\gamma}\right) \quad \forall n \tag{25}$$

$$\sigma_{\Delta\gamma} \sim \text{HalfNormal}\left(0.3\right) \tag{26}$$

$$\delta\gamma_n \sim \mathcal{N}\left(0, \sigma_{\delta\gamma}\right) \quad \forall n \tag{27}$$

$$\sigma_{\delta\gamma} \sim \text{HalfNormal}\left(0.05\right). \tag{28}$$

Similarly, to account for small changes in the gender imbalance, the noise on the ratio between male-female infections is modelled by slowly varying reproduction number, parameterized by series of change points every 20 days.

$$R_{\text{noise}}(t) = R_{0,\text{noise}} + \left(\sum_w \bar{\gamma}_w(t)\right) \tag{29}$$

$$R_{0,\text{noise}} \sim Normal\left(\mu = 0, \sigma = 0.1\right) \tag{30}$$

$$\bar{\gamma}_n(t) = \frac{1}{1 + e^{-4/l_n \cdot (t-d_n)}} \cdot \Delta\bar{\gamma}_n^* \tag{31}$$

$$\Delta\bar{\gamma}_n^* = \Delta\bar{\gamma}_n + \delta\bar{\gamma}_n \tag{32}$$

$$\Delta\bar{\gamma}_n \sim \mathcal{N}\left(0, \sigma_{\Delta\bar{\gamma}}\right) \quad \forall n \tag{33}$$

$$\sigma_{\Delta\bar{\gamma}} \sim Halfnormal\left(0.1\right) \tag{34}$$

$$\delta\bar{\gamma}_n \sim \mathcal{N}\left(0, \sigma_{\delta\bar{\gamma}}\right) \quad \forall n \tag{35}$$

$$\sigma_{\delta\bar{\gamma}} \sim Halfnormal\left(0.05\right). \tag{36}$$

## Author Contributions

## Data availability

The used data and source code are available online on GitHub `https://github.com/Priesemann-Group/covid19_soccer`. The daily case numbers stratified by age and gender were acquired from the local health authorities; in detail

- Germany: Robert Koch Institut
  `https://www.arcgis.com/home/item.html?id=f10774f1c63e40168479a1feb6c7ca74`
- France: Santé publique France
  `https://www.data.gouv.fr/fr/datasets/taux-dincidence-de-lepidemie-de-covid-19`
- England: National Health Service
  `https://coronavirus.data.gov.uk/details/download`
- Scotland: Public Health Scotland
  `https://www.opendata.nhs.scot/dataset/covid-19-in-scotland`

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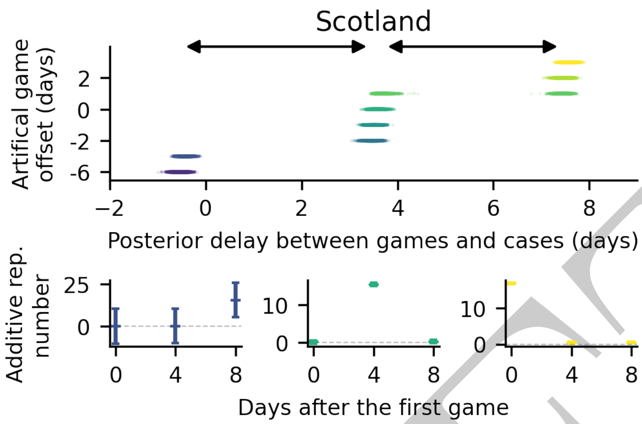
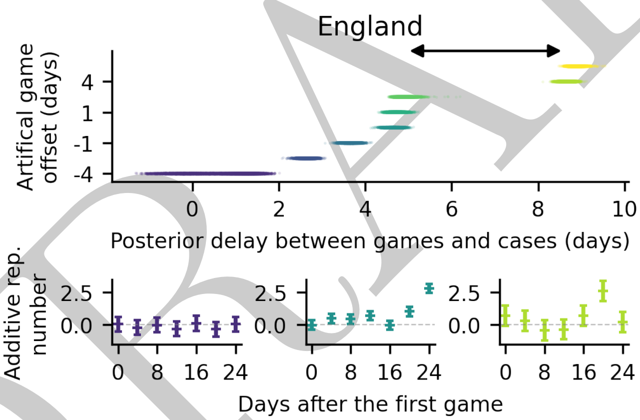
## Supplementary information

## S1 Delays




Supplementary Figure S1:




Supplementary Figure S2: