Modelling Mobility Data during COVID-19 in Portugal with `R-INLA`

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Introduction

Motivation

- **Human mobility was severely disrupted during the COVID-19 pandemic**, as restrictions and behavioural shifts led to unprecedented movement patterns [1].
- Mobility data can act as **a proxy for interpersonal contact and transmission risk**, supporting the design of adaptive mitigation measures. Yet, behavioural adaptations may weaken this proxy relationship [2].
- Regression analyses indicate that **mobility effectively predicted weekly COVID-19 infection rates during the first wave** [3], and that reduced mobility during the Omicron surge lowered peak incidence [4].
- Integrating mobility data into epidemic models—particularly in early pandemic stages—**improved predictive accuracy** and enhanced variant tracking, outperforming models that ignored travel or used lagged indicators [5].

Objectives

Aim: To model district-level mobility data from the COVID-19 Google Community Mobility Reports for Portugal [6].

Specific objectives:

1. **Describe** mobility patterns and the movement stringency dynamics during the COVID-19 pandemic in Portugal.
2. **Build** a comprehensive dataset with key predictors explaining mobility variability.
3. **Develop and evaluate** time series models to accurately capture mobility trends.
4. **Identify** significant predictors and characterize their effects across mobility categories and districts.
5. **Assess** the impact of stringency measures on observed mobility.

Data

Google's COVID-19 Community Mobility Reports (CMR) [6]

Derived from **Google Location Services** (e.g., Google Maps). covering multiple countries — including **Portugal** — and span from February 15, 2020 to October 15, 2022, across different spatial levels of detail.

- Data represent the **percentage change in mobility** relative to a pre-pandemic **baseline**, across six location categories:
  - `Retail and Recreation`
  - `Grocery and Pharmacy`
  - `Parks`
  - `Transit Stations`
  - `Workplaces`
  - `Residential`
- The **baseline** is defined as the median mobility value for each weekday during the period **January 3–February 6, 2020**, when mobility restrictions were not yet in place.

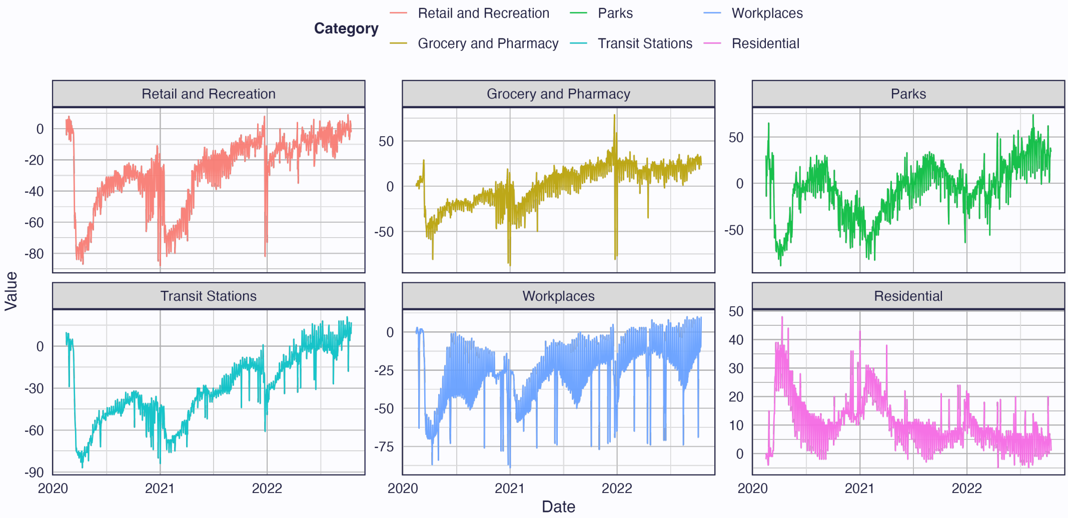

Figure 1: Overall mobility for mainland Portugal for all six categories.

During the COVID-19 pandemic, Portugal and other countries imposed movement restrictions, which were adjusted based on the evolving situation.

Movement Stringency Index [7]

Numerical score quantifying the effect of public health measures on movement restriction.

Based on nine metrics: school, workplace, and transport closures, public event cancellations, gathering restrictions, stay-at-home orders, public information campaigns, internal movement restrictions, and international travel controls.

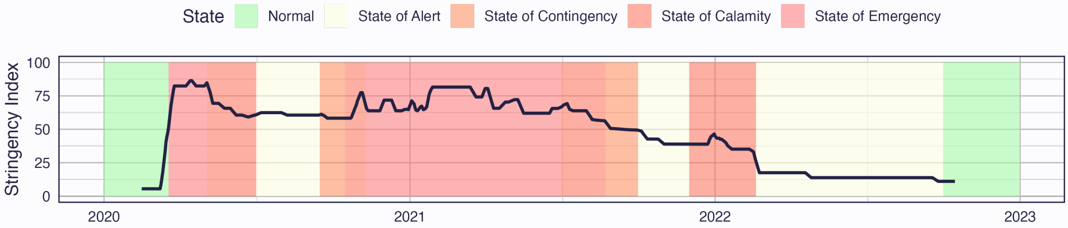

Figure 2: Movement stringency index overlaid on the Exceptional Legal Regime in force coded by colour.

Climate Data Store (CDS) [8]

Operated by the Copernicus Climate Change Service (C3S), provides **free and open access** to high-quality climate datasets — including daily gridded temperature observations across Europe.

- **Higher temperatures** have been associated with a lower incidence of COVID-19 [9].
- **Temperature variations** may also influence mobility patterns over time, serving as an important explanatory variable.

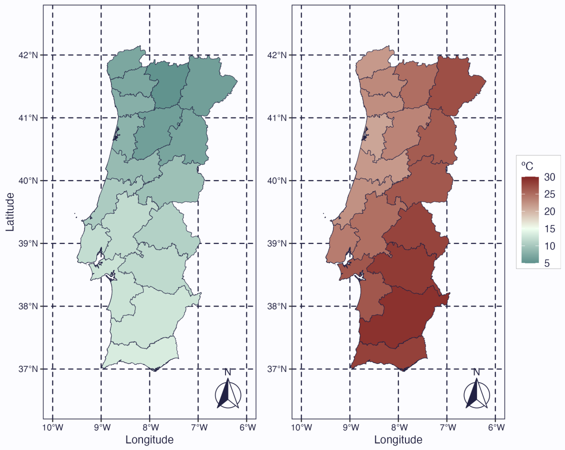

Figure 3: Mean temperature values on February 18th 2020 and August 15th 2021 per District.

- Clear **weekly patterns** emerge, particularly in:
  - `Workplaces`
  - `Transit Stations`
  - `Retail & Recreation`
- **National holidays** cause notable deviations in mobility, especially during weekdays.

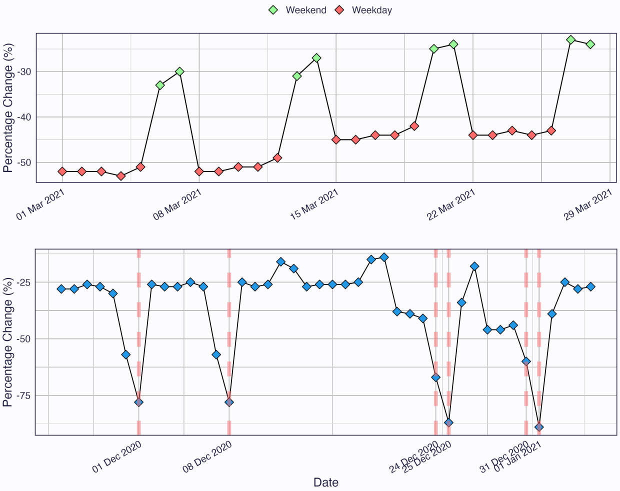

Figure 4: Percentage change in the Workplaces mobility category over time.

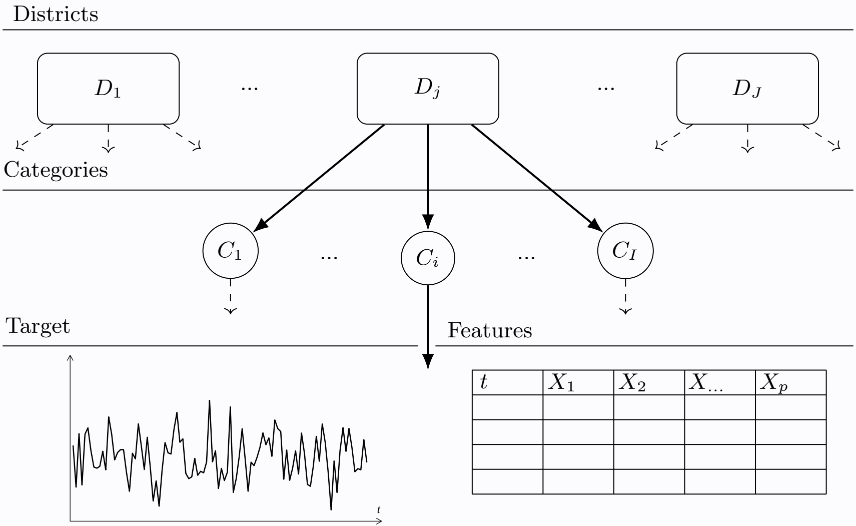

Figure 5: Schematic representation of the hierarchical dataset structure. For each District–Category pair (D_j, C_i), where $j = 1, \dots, J$ and $i = 1, \dots, I$, there is an associated distinct target time series and a set of features $X_1, \dots, X_p$, which may vary across time, space, or both. The representation is the same for each District-Category represented by the dashed lines.

Model

Hierarchical models break the modelling process into stages (1) *Observations*; (2) *Process*, and (3) *Parameters* [10].

Latent Gaussian Models (LGM) are **Bayesian hierarchical models** with a Gaussian assumption on the latent parameters. These include a wide and flexible class of models, namely, spatial and spatio-temporal models.

INLA (Integrated Nested Laplace Approximation) is a fast alternative for **LGM**.

Hierarchical Model Structure [11]:

$$(1)\ \boldsymbol{y} \mid \boldsymbol{x}, \boldsymbol{\theta} \sim \pi(y_i \mid x_i, \boldsymbol{\theta})\ (i = 1, \ldots, n), \quad (2)\ \boldsymbol{x} \mid \boldsymbol{\theta} \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}^{-1}(\boldsymbol{\theta})), \quad (3)\ \boldsymbol{\theta} \sim \pi(\boldsymbol{\theta})$$

- $\boldsymbol{y}$ is the vector containing the observations (response),
- $\boldsymbol{x}$ is the vector containing the latent parameters, i.e., represents the latent Gaussian field,
- $\boldsymbol{\theta}$ is a vector of hyperparameters,
- $\mathbf{Q}(\boldsymbol{\theta})$ is the precision matrix (*i.e.*, the inverse of the covariance matrix).

Model

The aim is to model mobility over three categories - Workplaces (C_1), Retail and Recreation (C_2), and Transit Stations (C_3) - across mainland Portugal using daily time data grouped per district.

$$\begin{aligned} Y_{j\,t\,c} = \beta_c + \texttt{temporal}_{j\,t\,c} + \texttt{lockdown}_{t\,c} + \texttt{stringency}_{t} + \texttt{temperature}_{j\,t} + \\ u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{j\,t\,|\,c} \end{aligned}$$

where,

- $Y_{j\,t\,c}$ is the percentage change in mobility for district j ($j = 1, \ldots, 18$) on day t for category c ($c = C_1, C_2, C_3$) and β_c represents a fixed effect per category.
- Random effects c,

$$\underbrace{u_j + v_j}_{\text{spatial effects}} + \underbrace{\gamma_{t|c} + \phi_{t|c}}_{\text{temporal effects}} + \underbrace{\delta_{jt|c}}_{\text{space-time interaction}} \quad [10]$$

Model

$$Y_{j\,t\,c} = \beta_c + \texttt{temporal}_{j\,t\,c} + \texttt{lockdown}_{t\,c} + \texttt{stringency}_t + \texttt{temperature}_{j\,t} + u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{j\,t\,|\,c}$$

- β_c — category-specific fixed effects $\beta_c = \sum_{i=1}^{3} \beta_{C_i} \mathbb{I}\,(c = C_i)$.
- $\texttt{temporal}j, t, c$ — category-specific linear trends, Fourier terms, day of the week and district holiday indicators.
- $\texttt{lockdown}t, c$ — full lockdown indicator with category-specific random effects.
- $\texttt{stringency}t$ — national movement stringency index [7]).
- $\texttt{temperature}j, t$ — daily mean temperature for district j on day t, with fixed and district-specific random effects.
- $u_j + v_j$ — spatial effects modeled using the Besag–York–Mollié (BYM) model [12, 11].
- $\gamma_{t,|,c}$ — correlated random temporal effect by mobility category c.
- $\phi_{t,|,c}$ — uncorrelated temporal effect by category c.
- $\delta_{j,t,|,c}$ — Type I space–time interaction, combining unstructured spatial and temporal effects.

Model

- Training set: Feb 20, 2020 – Feb 20, 2022; Testing set: Feb 21, 2022 – Oct 15, 2022 ($\approx$ 75–25% train-test split).
- Models were estimated using the `R-INLA` package [13].
- Model fit was evaluated with DIC and WAIC, while predictive performance was assessed using **MAE** and **RMSE** on both training and test sets [10, 14].

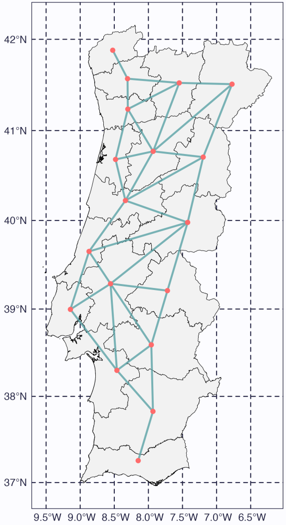

Figure 6: Geographical representation of mainland Portugal's districts with overimposed adjacency graph.

Results

Results

Table 1: Model specification and fit statistics

Model	DIC	WAIC	MSE (Train)	RMSE (Train)	MSE (Test)	RMSE (Test)
`model`	260647.71	278280.91	5.89	9.21	19.98	27.35

Table 2: Posterior estimates for the model, mean, standard deviation (SD), quantiles at 2.5%, 50% and 97.5%, and mode.

Covariate	Coefficient	Mean	SD	Q 2.5%	Q 50%	Q 97.5%	Mode
`category`	β_{c_1}	-15.76	5.46	-26.56	-15.73	-5.14	-15.73
`category`	β_{c_2}	22.38	5.39	11.84	22.36	33.03	22.36
`category`	β_{c_3}	15.52	5.28	5.26	15.49	25.97	15.49
`temporal features`	$\boldsymbol{\alpha}$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
`dow` [Saturday]	η_{d_2}	-0.30	1.19	-2.64	-0.30	2.05	-0.30
`dow` [Sunday]	η_{d_3}	-0.34	2.22	-4.71	-0.34	4.02	-0.34
`national holiday`	θ_1	-29.47	1.25	-31.92	-29.47	-27.01	-29.47
`regional holiday`	θ_2	-6.78	1.35	-9.44	-6.78	-4.13	-6.78
`commemorative holiday`	θ_3	-12.99	2.01	-16.94	-12.99	-9.05	-12.99
`lockdown`	ψ	-12.02	2.77	-17.49	-12.02	-6.56	-12.02
`stringency`	ζ	-0.77	0.03	-0.83	-0.77	-0.72	-0.77
`temperature`	ω	0.68	0.17	0.35	0.68	1.02	0.68

Results

Table 3: Posterior estimates for the model hyperparameters, posterior mean, posterior standard deviation (SD), quantiles at 2.5%, 50% and 97.5%, and Mode.

Covariate	Parameter	Mean	SD	Q 2.5%	Q 50%	Q 97.5%	Mode
`fixed effects`	τ	0.01	0.00	0.01	0.01	0.01	0.01
`dow`	τ_η	0.02	0.00	0.01	0.02	0.02	0.02
`lockdown`	τ_ψ	0.06	0.02	0.02	0.06	0.12	0.06
`temperature`	τ_ω	2.33	0.52	1.48	2.27	3.53	2.16
spatial comp.	τ_u	283.67	139.87	69.91	261.17	596.34	200.66
unstructured comp.	τ_v	0.01	0.00	0.01	0.01	0.02	0.01
AR time effect (AR1)	τ_γ	0.01	0.00	0.01	0.01	0.01	0.01
correlation term (AR1)	ρ	0.98	0.00	0.98	0.99	0.99	0.99
time effect	τ_ϕ	0.02	0.00	0.02	0.02	0.02	0.02
space-time interaction	τ_δ	2.06	3.13	0.38	1.16	9.61	0.54

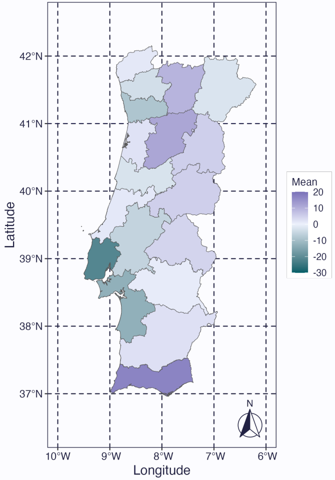

Figure 7: Posterior mean of the structured spatial main effect $u_j + v_j$.

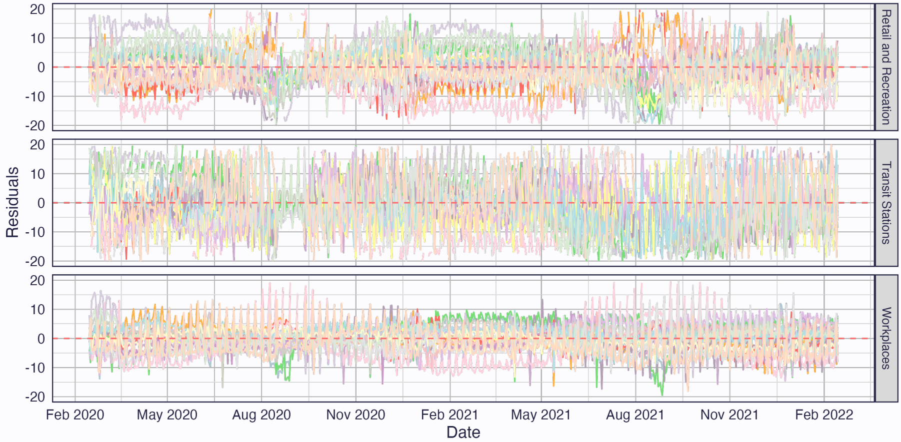

Figure 8: Time series of the residuals per category of mobility for training data coloured by district (each line).

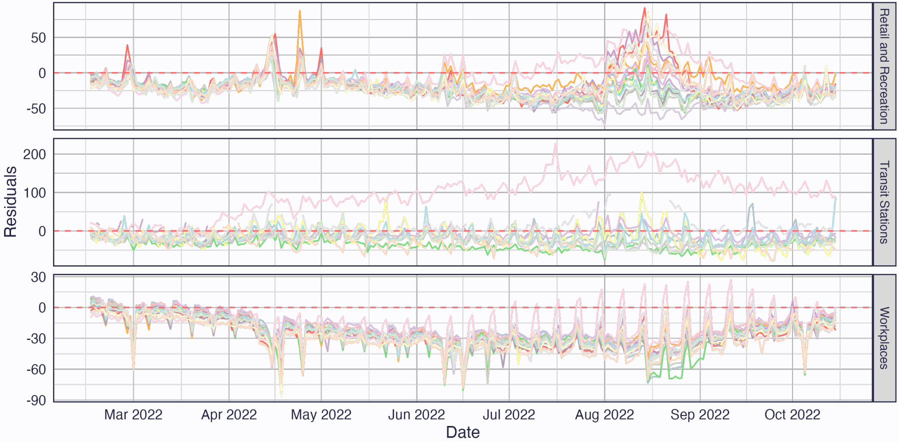

Figure 9: Time series of the residuals per category of mobility for testing data coloured by district (each line).

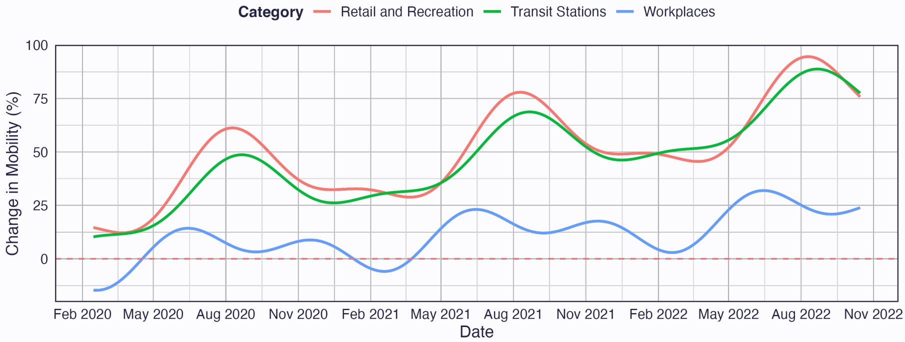

Figure 10: Time series of the underlying mobility seasonal patterns, baseline B_{C_i}, linear and Fourier terms, per category.

Results

- **Fourier terms** and **linear trends** significantly capture the seasonal patterns of each mobility category.
- **Holiday indicators** are highly significant, especially in the Workplace category, for capturing mobility disruptions.
- **Stringency** and **lockdown measures** jointly reduce mobility, with lockdowns amplifying the effects of stricter restrictions; however, the **stringency index alone** is insufficient to capture abrupt changes.
- Entering a full lockdown leads to an average **12% reduction** in mobility across all categories.
- **Temperature** has a small but significant positive effect, increasing mobility by approximately **0.68% per degree rise**.

Discussion

- Google mobility data reflects **percentage changes relative to a fixed baseline** from early 2020. This short, five-week winter period **does not represent typical annual mobility patterns**.
- Using an **annual average baseline** would better capture **seasonal fluctuations**.
- Ideally, mobility during COVID-19 would be compared to a **representative “normal” baseline**, such as average mobility from previous years.
- **Location category definitions** may change over time, but CMR documentation does not clarify the impact on reported values.
- Data may **not represent the entire population**, as it only includes users with location services enabled (e.g., Google Maps).

Thank you for your attention!

Any questions?

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Scan for the GitHub repository with slides, data and references.

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$$Y_{j\,t\,c} = \beta_c + \texttt{temporal}_{j\,t\,c} + \texttt{lockdown}_{t\,c} + \texttt{stringency}_t + \texttt{temperature}_{j\,t} + u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{j\,t\,|\,c}$$

Exploring each term in detail:

- β_c includes category fixed effect terms,

$$\beta_c = \sum_{i=1}^{3} \beta_{C_i} \mathbb{I}\left(c = C_i\right) \tag{1}$$

  where $\mathbb{I}\left(c = C_i\right)$ is the indicator function that takes the value 1 if c is the category C_i, and 0 otherwise.

$$Y_{j\,t\,c} = \beta_c + \texttt{temporal}_{j\,t\,c} + \texttt{lockdown}_{t\,c} + \texttt{stringency}_t + \texttt{temperature}_{j\,t} + u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{j\,t\,|\,c}$$

- The $\texttt{temporal}_{j\,t\,c}$ covariates include

$$\begin{aligned}\texttt{temporal}_{j\,t\,c} = \sum_{i=1}^{3} \Bigg[\mathbb{I}\left(c = C_i\right) \Bigg(\alpha_{C_i\,0}\, t + \quad \alpha_{C_i\,1} \cos\left(\frac{2\pi}{365.25}\, t\right) + \\ \alpha_{C_i\,2} \sin\left(\frac{2\pi}{365.25}\, t\right) + \alpha_{C_i\,3} \sin\left(\frac{4\pi}{365.25}\, t\right) + \alpha_{C_i\,4} \sin\left(\frac{4\pi}{365.25}\, t\right)\Bigg)\Bigg] + \\ \sum_{k=1}^{3} (\eta_{d_k} + \tilde{\eta}_{d_k\,j\,c})\, \mathbb{I}\left(\texttt{dow}_t = d_k\right) + \\ \theta_1\, \texttt{national holiday}_t + \theta_2\, \texttt{regional holiday}_{t\,j} + \theta_3\, \texttt{commemorative holiday}_t\end{aligned}$$

$$Y_{j\,t\,c} = \beta_c + \texttt{temporal}_{j\,t\,c} + \texttt{lockdown}_{t\,c} + \texttt{stringency}_t + \texttt{temperature}_{j\,t} + u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{j\,t\,|\,c}$$

- the $\texttt{lockdown}_{t\,c}$ term is an indicator variable to identify the periods under full lockdown. The term also includes category-specific random effects,

$$\texttt{lockdown}_{t\,c} = \left(\psi + \tilde{\psi}_c\right) \mathbb{I}(t \in L)$$

with L being the time intervals from March 18th to May 2nd 2020 and from January 14th to March 14th 2021.

$$Y_{j\,t\,c} = \beta_c + \texttt{temporal}_{j\,t\,c} + \texttt{lockdown}_{t\,c} + \texttt{stringency}_t + \texttt{temperature}_{j\,t} + u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{j\,t\,|\,c}$$

- the $\texttt{stringency}_t$ term is the national movement stringency index developed by Hale *et al.* [7] across all categories and districts,

$$\texttt{stringency}_t = \zeta\,\texttt{stringency}_t$$

$$Y_{jtc} = \beta_c + \texttt{temporal}_{jtc} + \texttt{lockdown}_{tc} + \texttt{stringency}_t + \texttt{temperature}_{jt} + u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{jt\,|\,c}$$

- the $\texttt{temperature}_{jt}$ term includes the daily mean temperature computed for the district j at day t. The mean temperature is used as it comprises the 24 hour exposure of the individuals. It includes a fixed effect combined with a district-specific random effects,

$$\texttt{temperature}_{jt} = \left(\omega + \tilde{\omega}_j\right)\ \texttt{temperature}_{jt} \tag{2}$$

$$Y_{j\,t\,c} = \beta_c + \texttt{temporal}_{j\,t\,c} + \texttt{lockdown}_{t\,c} + \texttt{stringency}_t + \texttt{temperature}_{j\,t} + u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{j\,t\,|\,c}$$

u_j represents the structured district-specific spatial effect, it is an intrinsic conditional autoregressive (iCAR) structure, which captures spatial dependences using the neighbourhood structure of the spatial units [10]. Assuming n areas, each having its own set of neighbours $\mathcal{N}(j)$, u_j is defined as,

$$u_j \mid \mathbf{u}_{-j} \sim N\left(\mu_j + \frac{1}{\mathcal{N}_j}\sum_{m=1}^{n} a_{mj}(u_m - \mu_m),\, s_j^2\right) \quad (j = 1, ..., 18)$$

where μ_j and $s_j^2 = \sigma_u^2/\mathcal{N}_j$ are the mean and variance for area j, respectively, and $\mathbf{u}_{-j} = \{u_1, ..., u_{j-1}\}$. The variance depends on the number neighbours for area j - the higher the number of neighbours the smaller the variance. The quantity a_{ij} takes value 1 if areas i and j are neighbours.

$$Y_{j\,t\,c} = \beta_c + \texttt{temporal}_{j\,t\,c} + \texttt{lockdown}_{t\,c} + \texttt{stringency}_t + \texttt{temperature}_{j\,t} + u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{j\,t\,|\,c}$$

- v_j represents an unstructured component that accounts for the residual spatial variation modelled by an a prior Normal distribution $v_j \sim N\left(0\,,1/\tau_v\right)$ with precision $\tau_v \sim \text{Gamma}(1, 0.001)$. The $u_j + v_j$ specification constitutes the Besag–York–Mollié (BYM) model [12, 11].

$$Y_{j\,t\,c} = \beta_c + \texttt{temporal}_{j\,t\,c} + \texttt{lockdown}_{t\,c} + \texttt{stringency}_t + \texttt{temperature}_{j\,t} + u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{j\,t\,|\,c}$$

- $\gamma_{t\,|\,c}$ represents a correlated random time effect given a category of mobility c, it accounts for time dependencies conditional on the category. This component assumes that the mobility for a given district in a given day depends on the mobility on the previous day. This is modelled as an autoregressive process such that

$$\gamma_{1\,|\,c} \sim N\left(0, \left(\tau_\gamma(1-\rho^2)\right)^{-1}\right)$$
$$\gamma_{t\,|\,c} = \rho\,\gamma_{t-1\,|\,c} + \epsilon_{t\,|\,c}$$
$$\epsilon_{t\,|\,c} \sim N\left(0, \frac{1}{\tau_\gamma}\right)$$

where the precision term $\tau_\gamma \sim \text{Gamma}(1, 0.001)$ and ρ represents a temporal correlation term.

$$Y_{j\,t\,c} = \beta_c + \texttt{temporal}_{j\,t\,c} + \texttt{lockdown}_{t\,c} + \texttt{stringency}_t + \texttt{temperature}_{j\,t} + u_j + v_j + \gamma_{t\,|\,c} + \phi_{t\,|\,c} + \delta_{j\,t\,|\,c}$$

- $\phi_{t\,|\,c}$ represents an uncorrelated time dependence given a category c that accounts for independent time effects. This uncorrelated time effect is modelled by a normal distribution with zero mean value and precision τ_ϕ,

$$\phi_{t\,|\,c} \sim N\left(0, \frac{1}{\tau_\phi}\right)$$

  where $\tau_\phi \sim \text{Gamma}(1, 0.001)$.
- $\delta_{j\,t\,|\,c}$ represents the space time interaction term, conditional to a category c. In this work, it is defined as a Type I space-time interaction - Type I assumes the two unstructured spatial and temporal effects interact.