Media Bias and Polarization through the Lens of a Markov Switching Latent Space Network Model

Roberto Casarin, **Antonio Peruzzi** & Mark Steel

Ca' Foscari University of Venice

Research Seminar, WU Vienna, Dec 17th 2025

This study was funded by the European Union - NextGenerationEU, in the framework of the GRINS - Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 - CUP H73C22000930001). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

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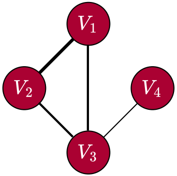
A Static Latent Space Model - An Illustration

Data



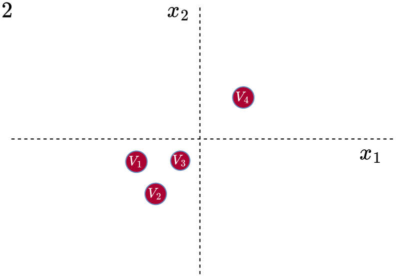
$$Y = [y_{ij}] = \begin{bmatrix} - & 3 & 2 & 0 \\ 3 & - & 2 & 0 \\ 2 & 2 & - & 1 \\ 0 & 0 & 1 & - \end{bmatrix}$$

Latent Space Model

$$y_{ij} \sim \mathcal{P}oi(\lambda_{ij})$$
$$\lambda_{ij} = g(\mu - ||\mathbf{x}_i - \mathbf{x}_j||)$$

Latent Space

$d = 2$



Latent Space Models: A Brief Overview

Common models

- **Binary networks**:

$$Y_{ij} \sim \mathcal{B}er(p_{ij}), \quad \text{logit}(p_{ij}) = \alpha_i + \alpha_j + \eta_{ij}$$

(Hoff, Raftery, and Handcock, 2002)

- **Count networks**:

$$Y_{ij} \sim Poi(\lambda_{ij}), \quad \log \lambda_{ij} = \alpha_i + \alpha_j + \eta_{ij}$$

(Sewell and Chen, 2015)

Latent interaction term η_{ij}

- **Distance-based**:

$$\eta_{ij} = -\|\mathbf{x}_i - \mathbf{x}_j\|^{\delta}$$

(Euclidean LS; Hoff, Raftery, and Handcock, 2002)

- **Inner-product / similarity**:

$$\eta_{ij} = \mathbf{x}_i' \Xi \mathbf{x}_j$$

(Eigenmodel; Hoff, 2008)

See Sosa and Buitrago (2021) for a comprehensive review of latent space models.

Common Issues with Latent Space Models

Latent Coordinates don't have a clear interpretation:

- We suggest a joint-inference scheme allowing for an interpretation of the latent coordinates via observable proxies that might be available.

Modelling a Dynamic LS model may be computationally intensive:

- We endow our LS model with a Markov-Switching component which is parsimonious compared to existing alternatives.

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Application to Media Bias and Polarization

Media Bias:

- A distortion in the news frame in favor of some individuals or groups with common interests;
- It entails a reduction in the informativeness of news pieces (Gentzkow, Shapiro, and Stone, 2015);
- It may cause distortions in political outcomes even if the evidence is mixed (Bernhardt, Krasa, and Polborn, 2008), (Prior, 2013).

Media Polarization:

- The emergence of more partisan media (Prior, 2013);
- Recently, attention has been shifting toward polarization online;
- Some suggested that incentivized homophilous behavior in Social Media may increase opinion polarization.

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Summary of the Work

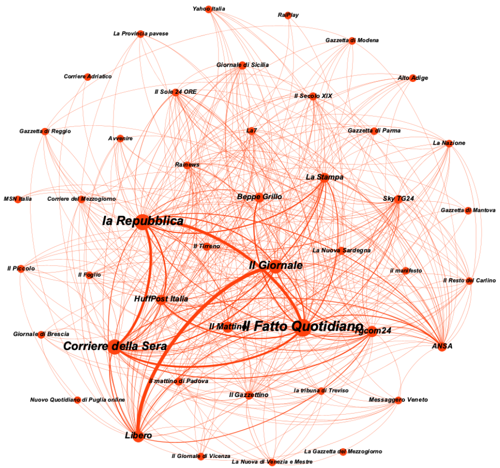
We propose a **dynamic Latent Space model** that provides insights on:

- **Media bias** of news outlets, leveraging both **user–article interactions** on Facebook and the **textual content of the articles** themselves;
- **Polarization regimes** through a **Markov-Switching** dynamic.

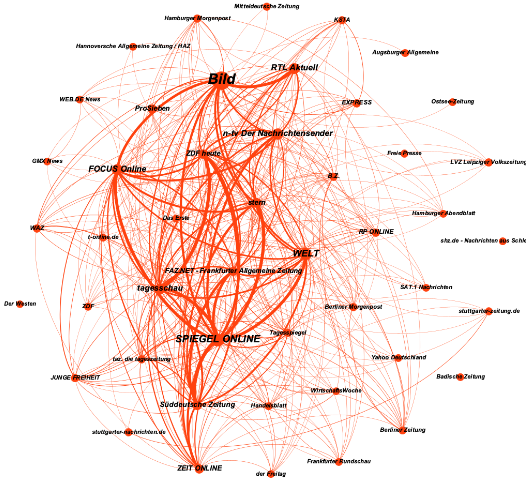
Relevant literature: Hoff, Raftery, and Handcock (2002), Friel et al. (2016), Barberá (2015) Rastelli, Friel, and Raftery (2016)

Data: Facebook dataset covering 1) user interactions with content published by the **main national and local newspapers in France, Germany, Italy, and Spain** (media networks), and 2) textual data from the published articles.

Media Networks on Facebook



Italy



Germany

The Model – Part 1

Let $\mathcal{G}_t = (V, E_t)$ be a network (e.g., a media network) at time t, where for each $(i, j) \in E_t$ we observe an edge weight y_{ijt}. We adopt a Poisson model for the edge weights with $j > i$ and for each i:

$$y_{ijt} | \lambda_{ijt} \overset{ind}{\sim} Poi(\lambda_{ijt}).$$

We model the intensity parameter $\lambda_{ijt} > 0$ as a function of the dynamic latent coordinate vectors $\boldsymbol{x}_{it} = (x_{1,it}, \ldots, x_{d,it})' \in \mathbb{R}^d$ for node i and $\boldsymbol{x}_{jt} \in \mathbb{R}^d$ for node j, using the squared Euclidean distance $\|\cdot\|^2$:

$$\log \lambda_{ijt} = \alpha_i + \alpha_j - \|\boldsymbol{x}_{it} - \boldsymbol{x}_{jt}\|^2.$$

Intuition: the smaller the squared distance between the latent characteristics of two nodes, the larger the Poisson intensity, and the stronger the relationship between nodes i and j.

Interpretation: one of the latent characteristics, $x_{1,it}$, can be viewed as the media bias of news outlet i at time t.

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The Model – Part 2: Interpretation of the Coordinates

In our application we employ an observable characteristic ℓ_{it} to provide an interpretation of the latent dimension.

In this case, $\ell_{it} \in [0, 1]$ is an observable proxy for *media bias*, obtained through text analysis techniques (Gentzkow and Shapiro, 2010; Garz, Sörensen, and Stone, 2020).

We assume that the observable proxy depends on the latent coordinate $x_{1,it}$ as follows:

$$\ell_{it} \sim \mathcal{B}e\Big(\varphi(\gamma_0 + \gamma_1 x_{1,it})\,\phi,\ \big[1 - \varphi(\gamma_0 + \gamma_1 x_{1,it})\big]\,\phi\Big)\,,$$

where $\varphi(x) = \dfrac{1}{1 + \exp(-x)}$.

The Model – Part 3: Markov–Switching Dynamics

We assume that the latent coordinates are jointly driven by a finite-state **Markov–Switching** process with states $s_t \in \{1, \ldots, K\}$, $K < \infty$:

$$\boldsymbol{x}_{it} = \sum_{k=1}^{K} \mathbb{I}(s_t = k)\, \zeta_{ik} \qquad \text{(equivalently: } \boldsymbol{x}_{it} = \zeta_{i\, s_t}\text{).}$$

where $\mathbb{I}(\cdot)$ denotes the indicator function.

The transition probabilities are given by

$$\mathbb{P}(s_t = l \mid s_{t-1} = k) = q_{lk}, \quad l, k = 1, \ldots, K,$$

with transition matrix $\boldsymbol{Q} = (q_{lk})$ (rows sum to 1).

Intuition: each state k represents a **regime** with latent positions ζ_{ik}; transitions between regimes are governed by $\boldsymbol{Q}$.

Identification of polarization regimes: we label them in increasing order of the median distance of the latent coordinate used as a measure of media bias,

$$\tilde{D}_k = \mathrm{med}_{j>i}\left(\|\zeta_{1,ik} - \zeta_{1,jk}\|\right).$$

Prior Choice

Parameter Priors

$$
\begin{aligned}
\alpha_i &\sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2),\\
\zeta_{ik} &\sim \mathcal{N}_d(\mu_k, \sigma_k^2 I_d),\\
\sigma_k^2 &\sim \mathcal{IG}(a_{\sigma^2}, b_{\sigma^2}),\\
\gamma_0 &\sim \mathcal{N}(\mu_{\gamma_0}, \sigma_{\gamma_0}^2),\\
\gamma_1 &\sim \mathcal{N}(\mu_{\gamma_1}, \sigma_{\gamma_1}^2),\\
\phi &\sim \mathcal{G}(a_\phi, b_\phi),\\
\boldsymbol{q}_k &\sim \mathcal{D}ir(\omega_1, \ldots, \omega_K).
\end{aligned}
$$

Note: I_d is the $d \times d$ identity matrix.

Choice (vague priors)

$$
\begin{aligned}
\alpha_i &\sim \mathcal{N}(0, 15^2),\\
\zeta_{ik} &\sim \mathcal{N}_d(\mathbf{0}, \sigma_k^2 I_d),\\
\sigma_k^2 &\sim \mathcal{IG}(0.1, 0.1),\\
\gamma_0 &\sim \mathcal{N}(0, 15^2),\\
\gamma_1 &\sim \mathcal{N}(0, 15^2),\\
\phi &\sim \mathcal{G}(0.01, 0.01),\\
\boldsymbol{q}_k &\sim \mathcal{D}ir(\underbrace{1/K, \ldots, 1/K}_{K}).
\end{aligned}
$$

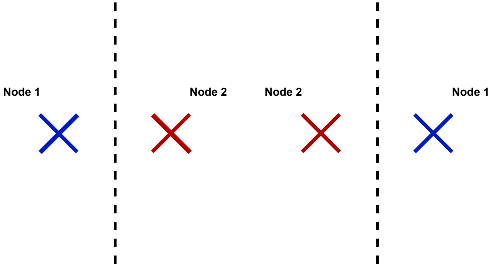
Identification Strategy: Latent Space Invariances

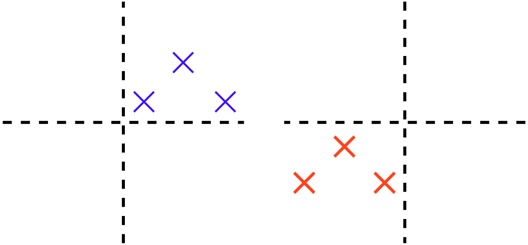
Latent coordinates ζ_{ik} enter the intensity parameter λ_{ijt} only through pairwise squared distances. As a consequence, the likelihood is invariant to:

- **Translation**: adding a constant vector to all latent positions;
- **Reflection**: mirroring coordinates around the origin, indeterminacy on the sign of γ_1;
- **Rotation** (for $d > 1$): orthogonal transformations of the latent space.

These invariances imply that multiple latent configurations are observationally equivalent (Hoff, Raftery, and Handcock, 2002, Friel et al., 2016).

To ensure interpretability and stable inference, we adopt a set of identifying restrictions tailored to the political–leaning interpretation of the latent space.





Identification Strategy: Practical Implementation

Translation. At each Gibbs iteration, latent coordinates are centered so that

$$\sum_i \zeta_{ik} = 0, \quad \forall k,$$

this is also known as *on-the-fly re-centering*.

Reflection ($d = 1$). When the latent dimension represents political leaning, reflection around the origin remains possible. We anchor the space by assuming that one outlet i^* has known orientation:

$$\zeta_{i^* k} < 0 \quad \text{(left-leaning)}, \ \forall k,$$

and apply a reflection whenever this constraint is violated, following Barberá, 2015.

Rotation ($d > 1$). For higher dimensions, rotation induces indeterminacy in the coefficient γ_1.
To fix orientation, we impose

$$\gamma_1 = (1, 0, \ldots, 0),$$

similarly to factor loading restrictions in factor models (Frühwirth-Schnatter, Hosszejni, and Lopes, 2024).

Remaining coordinates are aligned via **Procrustes transformation**, as standard in latent space models (Hoff, Raftery, and Handcock, 2002).

Model Properties - LS Model - Poisson Likelihood

Define the **average nodal strength** as:

$$\overline{Y}_t = \frac{1}{N}\sum_{j \neq i}\sum Y_{ijt}. \tag{1}$$

Then, the conditional **expected average strength** in our LS model is:

$$\mathbb{E}(\overline{Y}_t|\alpha, \sigma_1^2, \ldots, \sigma_K^2, Q, s_{t-1} = l) = (N-1)e^{\alpha}\sum_{k=1}^{K} q_{lk}\left(4\sigma_k^2 + 1\right)^{-\frac{d}{2}}. \tag{2}$$

Intuition:

- If α increases, then the expected average nodal strength increases.
- If σ_k^2 decreases, then the similarity among nodes decreases, and the connectivity level decreases.

We also provide an analytical expression for the **variance of the strength** and **Dispersion Index**.

Bayesian Estimation

The joint posterior distribution is not available in closed form. We adopt a *data augmentation* strategy and write the complete data likelihood as:

$$f(\mathbf{y}, \boldsymbol{\ell}, \xi \mid \theta) = \left[\prod_{t=1}^{T} \prod_{i=1}^{N} f_B(\ell_{it} \mid s_t, \theta) \prod_{j=i+1}^{N} f_P(y_{ijt} \mid s_t, \theta) \right] \times \left[\prod_{t=1}^{T} \prod_{l=1}^{K} \prod_{k=1}^{K} q_{lk}^{\xi_{l,t-1}\,\xi_{k,t}} \right].$$

- $f_P(y_{ijt} \mid s_t, \theta)$: Poisson density for edges (Latent Space model).
- $f_B(\ell_{it} \mid s_t, \theta)$: Beta density for the observable proxy of media bias.
- $\xi = \{\xi_{k,t}\}$ with $\xi_{k,t} \in \{0, 1\}$ state indicators; $s_t = \arg\max_k \xi_{k,t}$.
- θ: collection of model parameters $\{\alpha, \zeta, \gamma_0, \boldsymbol{\gamma}_1, \sigma_k^2, \phi, \boldsymbol{Q}\}$.

The posterior is approximated via **Metropolis within Gibbs**, using Gibbs steps where available and (Adaptive) Metropolis–Hastings otherwise.

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MCMC Algorithm

Gibbs sampler with MH/AMH steps. For each iteration h:

- Sample α_i from $\pi(\alpha_i \mid \cdot)$, $i = 1, \ldots, N$, using **Adaptive Metropolis–Hastings** (AMH);
- Sample ϕ from $\pi(\phi \mid \cdot)$ using **MH** with truncated normal proposal;
- Sample $(\gamma_0, \boldsymbol{\gamma}_1)$ from $\pi(\gamma_0, \boldsymbol{\gamma}_1 \mid \cdot)$ via **MH**;
- Sample ζ_{ik} from $\pi(\zeta_{ik} \mid \cdot)$, $i = 1, \ldots, N$, $k = 1, \ldots, K$, via **AMH**;
- Sample σ_k^2 from $\pi(\sigma_k^2 \mid \zeta_k)$, $k = 1, \ldots, K$ (*Gibbs*, prior $\mathcal{IG}$);
- Sample $\boldsymbol{q}_k$ from $\pi(\boldsymbol{q}_k \mid \xi)$, $k = 1, \ldots, K$ (*Gibbs*, prior $\mathcal{D}ir$);
- Sample $\boldsymbol{s}$ using **Forward–Filtering Backward–Sampling** (FFBS) (Frühwirth-Schnatter, 2006).

Implementation: algorithm written **entirely in C++**:

- `https://github.com/BayesianEcon/Dyn-MS-LS-Media`
- `https://codeocean.com/capsule/9380600/tree/v1`

Adaptive Metropolis–Hastings

In estimating the marginal distribution of the parameters α and ζ we rely on the Adaptive Metropolis algorithm with global adaptive scaling (Andrieu and Thoms, 2008).

1. Choose starting values for the parameter of interest θ_0 and for $(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0, \delta_0)$.
2. For each iteration $h = 1, 2, \ldots$, given $(\theta_{h-1}, \boldsymbol{\mu}_{h-1}, \boldsymbol{\Sigma}_{h-1}, \delta_{h-1})$:
   - 2.1 Propose $\widetilde{\theta}_h \sim \mathcal{N}\left(\theta_{h-1}, \delta_{h-1}\, \boldsymbol{\Sigma}_{h-1}\right)$ and set
   $$\theta_h = \begin{cases} \widetilde{\theta}_h, & \text{with prob. } \alpha\left(\theta_{h-1}, \widetilde{\theta}_h\right), \\ \theta_{h-1}, & \text{otherwise.} \end{cases}$$
   - 2.2 Update the global scale (Robbins–Monro):
   $$\log \delta_h = \log \delta_{h-1} + \gamma_h\left[\alpha\left(\theta_{h-1}, \widetilde{\theta}_h\right) - \alpha^\star\right].$$
   - 2.3 Update the running mean:
   $$\boldsymbol{\mu}_h = \boldsymbol{\mu}_{h-1} + \gamma_h\left(\theta_h - \boldsymbol{\mu}_{h-1}\right).$$
   - 2.4 Update the covariance (rank-1 update):
   $$\boldsymbol{\Sigma}_h = \boldsymbol{\Sigma}_{h-1} + \gamma_h\left[\left(\theta_h - \boldsymbol{\mu}_{h-1}\right)\left(\theta_h - \boldsymbol{\mu}_{h-1}\right)^\top - \boldsymbol{\Sigma}_{h-1}\right].$$

Where $\gamma_h = h^{-\psi}$ with $\psi \in (0, 1)$ and $\alpha(\cdot, \cdot)$ is the MH acceptance probability at iteration h; $\alpha^\star$ is the target acceptance rate (e.g., 0.234 for moderate dimension).

Simulation Study

Design (DGP)

- 20 fictitious news outlets observed over 100 periods: $N = 20$, $T = 100$, latent dimension $d = 1$.
- Two polarization regimes ($K = 2$): **L** = low, **H** = high.
- Latent positions: in **L**, the average political orientation distance is *lower*; in **H**, it is *higher*.
- Individual effects: vector α randomly initialized.
- Parameters: $\phi = 200$, $\gamma_0 = -0.1$, $\gamma_1 = 0.5$.

Regime Dynamics

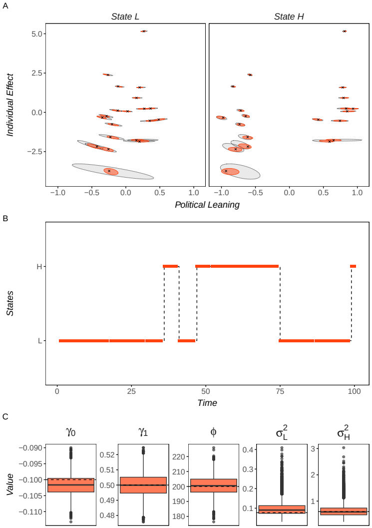
$$\mathbf{Q} = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}$$

- High persistence in both regimes.

Objective

Assess the model's ability to recover **media bias** and **polarization regimes** over time.

Simulation Results



Latent positions
Estimated coordinates in the *Latent Leaning–Individual Effect* plane with 99% credible ellipses and true values (crosses).

Latent states
Estimated vs. true latent leaning states. State L (H) corresponds to low (high) polarization and reflects a *low* (*high*) average distance between outlets' political positions.

Posterior distribution
Boxplots of the posterior distributions of selected parameters. Dashed lines indicate the true values in our simulation exercise.

Application

Data (Schmidt et al., 2018)

- Facebook data, *daily aggregation*, on national and local news outlets.
- Countries (total: **201** outlets):
  - France: 67 Germany: 47
  - Italy: 45 Spain: 42
- Time span: **Jan 2015 – Dec 2016**.
- Variables: *Posts*, *Likes*, *Comments*, *Shares*.

Model input

- Time series of **media networks** (by country) constructed from *user interactions via comments* (*audience duplication*).
- **Daily observable leaning** obtained with *text analysis* techniques following (Gentzkow and Shapiro, 2010; Garz, Sörensen, and Stone, 2020).

Empirical Application — Comparison with Pew Research

Pew Research Survey (2018) (Mitchell et al., 2018)

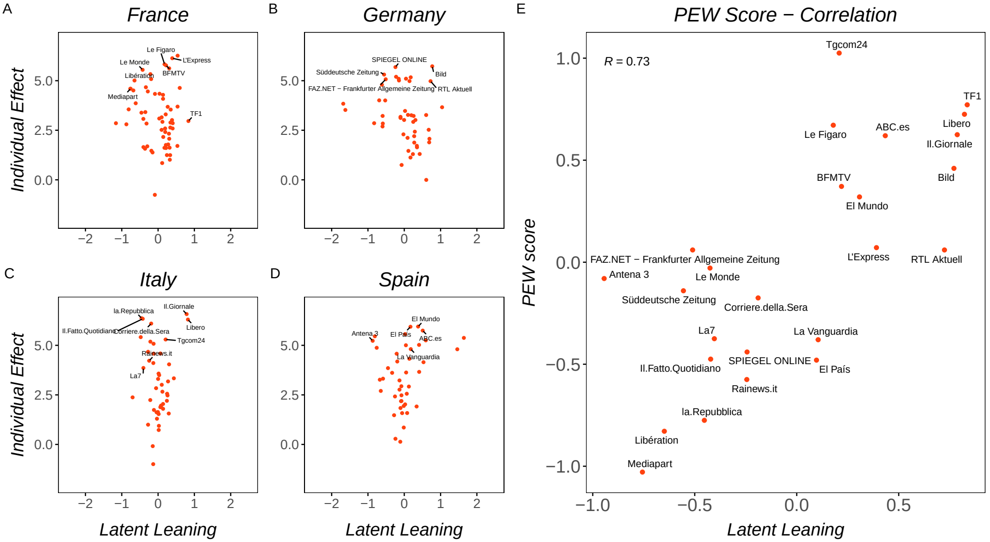
- Countries: France, Germany, Italy, Spain — *national* outlets.
- Sample: $\sim$ **2,000** respondents per country.
- Task: place each outlet on a **0–6** left–right scale.

In our study: we use the survey as an **external benchmark** to validate the latent coordinate (media bias).

PEW Survey Question

"Some people describe politics in terms of left, center, and right. Where would you place x on a left–right scale from 0 to 6, where 0 means far left and 6 means far right?"

Static Analysis



Model Selection - Dynamic Analysis

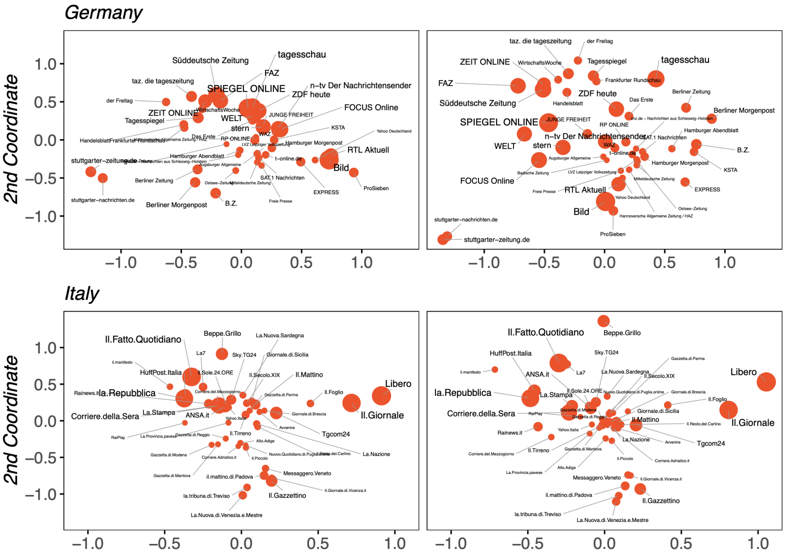
Model setup. We compare eight specifications: $\mathcal{M}_1$ (MS–LS, d=1, K=2, without textual proxy), $\mathcal{M}_2$ (static LS, d=1, K=1), $\mathcal{M}_3$ (MS–LS, d=1, K=2, full model), $\mathcal{M}_4$ (MS–LS, d=2, K=2), $\mathcal{M}_5$ (MS–LS, d=2, K=3), $\mathcal{M}_6$ (MS–LS, d=2, K=5), and two Poisson graphs: RG_1 (constant intensity) and RG_2 (individual effects + observed leaning distance).

Criteria. DIC (Spiegelhalter et al., 2002) and lppd (Gelman, Hwang, and Vehtari, 2014).

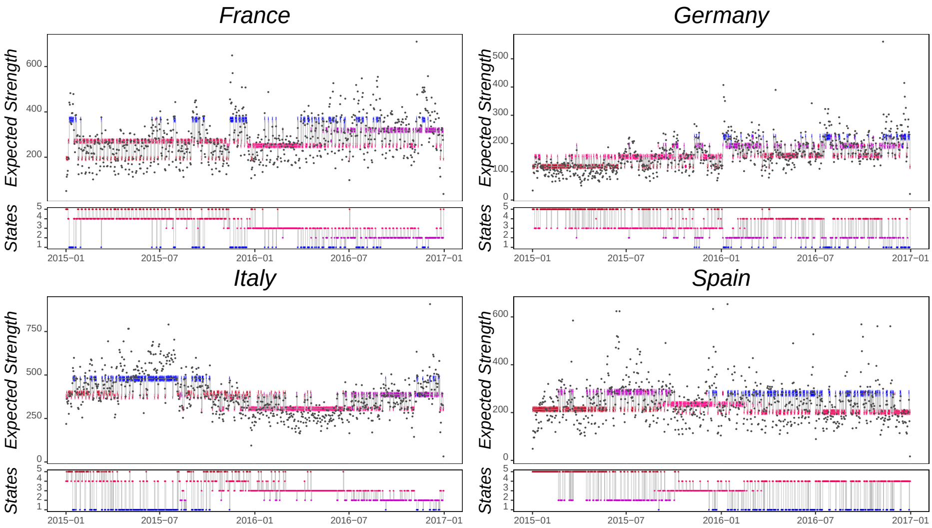
	(a) DIC $\times 10^{-6}$				(b) lppd $\times 10^{-6}$			
Model	France	Germany	Italy	Spain	France	Germany	Italy	Spain
$\mathcal{M}_1$	4.4698	2.3669	3.3066	4.6390	-2.2784	-1.2190	-1.6771	-2.3471
$\mathcal{M}_2$	4.6434	2.4766	3.4825	4.9049	-2.3597	-1.2702	-1.7657	-2.4511
$\mathcal{M}_3$	4.4696	2.3669	3.3049	4.6139	-2.2784	-1.2191	-1.6776	-2.3347
$\mathcal{M}_4$	4.2654	2.2582	2.9797	4.2796	-2.1697	-1.1500	-1.5171	-2.1576
$\mathcal{M}_5$	4.2533	2.2143	2.9766	4.1819	-2.1644	-1.1290	-1.5127	-2.1075
$\mathcal{M}_6$	**4.0949**	**2.1570**	**2.6588**	**3.9590**	**-2.0827**	**-1.1107**	**-1.4641**	**-2.0633**
RG_1	24.9489	9.6074	26.1551	15.1828	-12.5047	-4.8341	-13.1011	-7.6049
RG_2	5.1913	2.8212	4.4554	5.4713	-2.6153	-1.4121	-2.2424	-2.7350

Dynamic Analysis — Latent Space with $K = 2$ States

Low Polarization | High Polarization



Dynamic Analysis — States Dynamic



Temporal sequence of the latent states s_t; transistions governed by $\boldsymbol{Q}$.

Conclusion

What we did

- Proposed a **dynamic Latent Space** model with **Markov–Switching** for in–platform media bias and polarization.
- The latent dimension is **interpreted** through an **observable proxy** (text analysis).
- **Bayesian** inference via MCMC; **theoretical properties** derived and validated through simulations.

Empirical findings

- The **latent coordinate** is strongly **correlated** with the PEW index and consistently orders outlets (left/right).
- The **latent states** do not support a **unidirectional shift** towards higher polarization on Facebook (2015–2016).
- **Model selection**: the **dynamic** specification is preferred over the static; the text–analysis index **improves identification** of leaning.

Limitations

- Limited **longitudinal evidence** on polarization (esp. in Europe) $\mathbb{R}$*ightarrow* scarce *ground truth* for validating regime changes.
- **Identification** of latent factors and states is non-trivial.
- Lack of **shared information** *across countries* (no hierarchical prior).

Future developments

- More advanced **text analysis** indicators of bias.
- Finer–grained analysis **at the post level**.
- Alternative latent space **embeddings** (circular, **hyperbolic**).
- Alternative **identification constraints**.

Thank you for your time!

For further information and feedback:

antonio.peruzzi@unive.it

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The paper has been published in *The Annals of Applied Statistics*.

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