GeoHealth

Supporting Information for

Evolving Drivers of Brazilian SARS-CoV-2 Transmission: A Spatiotemporally Disaggregated Time Series Analysis of Meteorology, Policy, and Human Mobility

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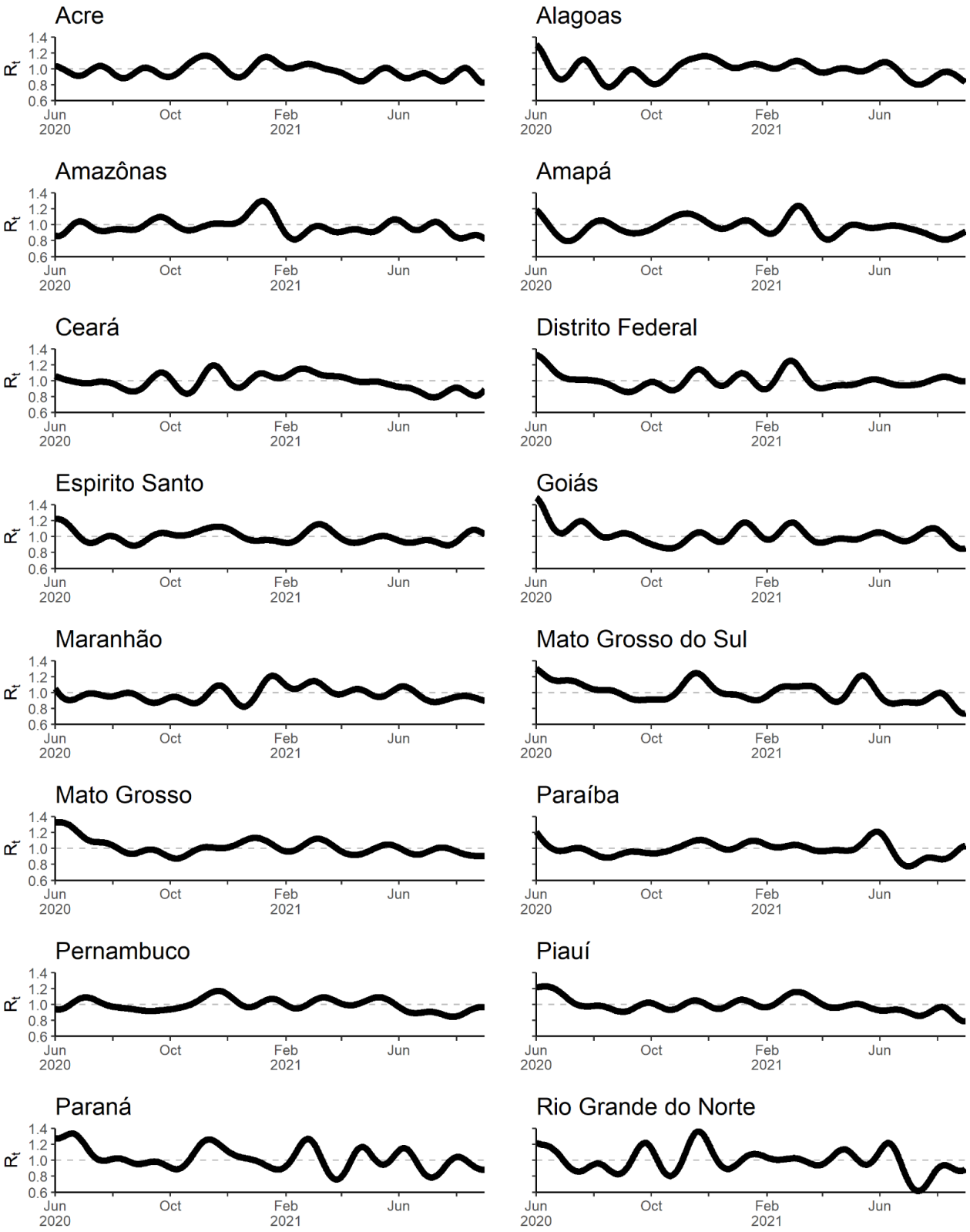

Figure S1. Same as Figure 1B-G in the main text but showing time series of R_t for other Brazilian states and the federal district.

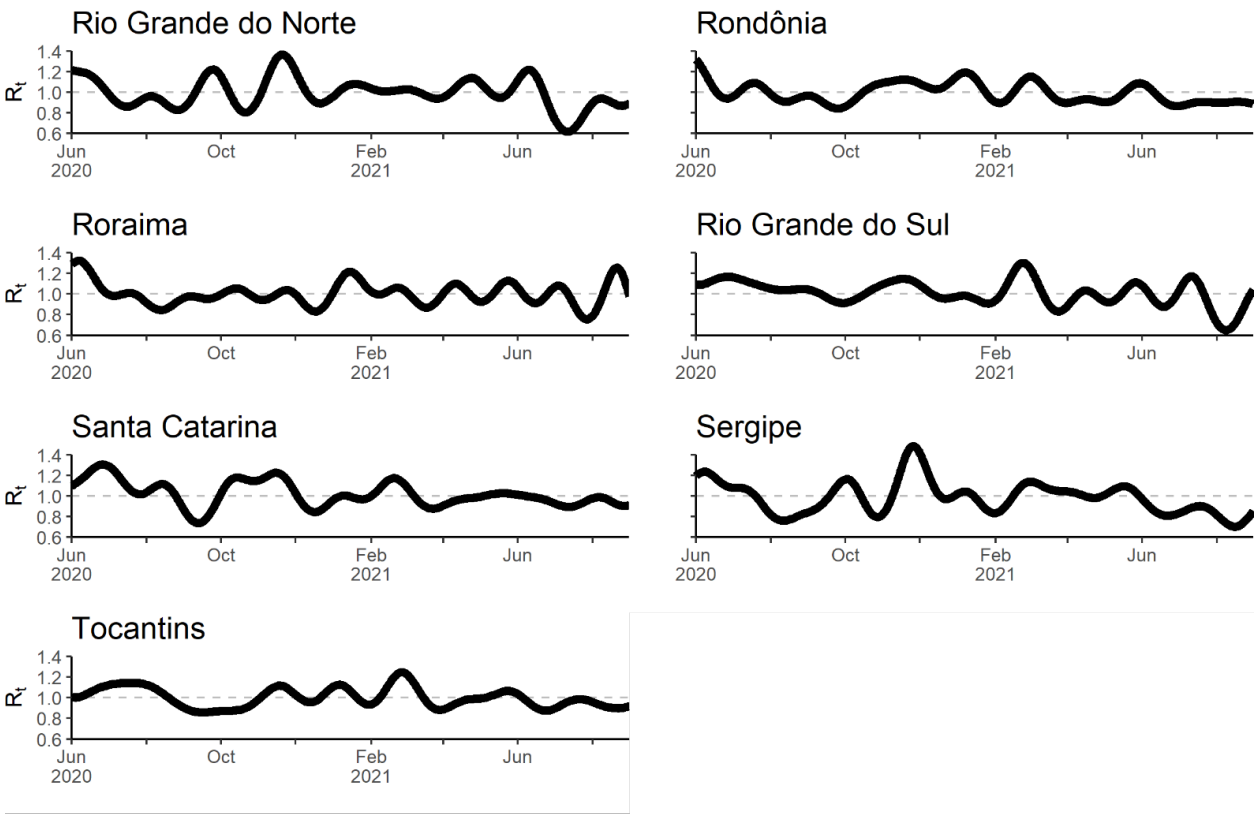

Figure S1 (continued).

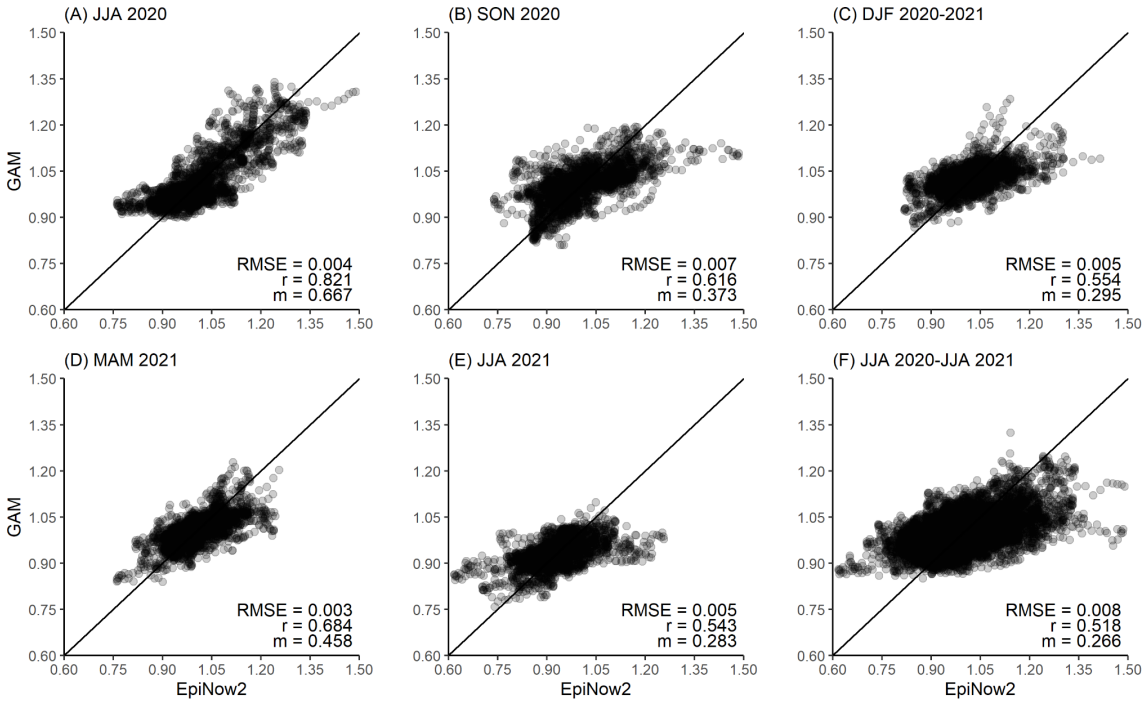

Figure S2. Scatter plot showing GAM-predicted versus EpiNow2-estimated R_t for different periods of interest. The solid line shows the 1:1 line. Inset text denotes the root mean square error (RMSE), Pearson correlation coefficient (r), and the slope of the linear regression fit (m), where GAM R_t is the dependent variable and EpiNow2 R_t is the explanatory variable.

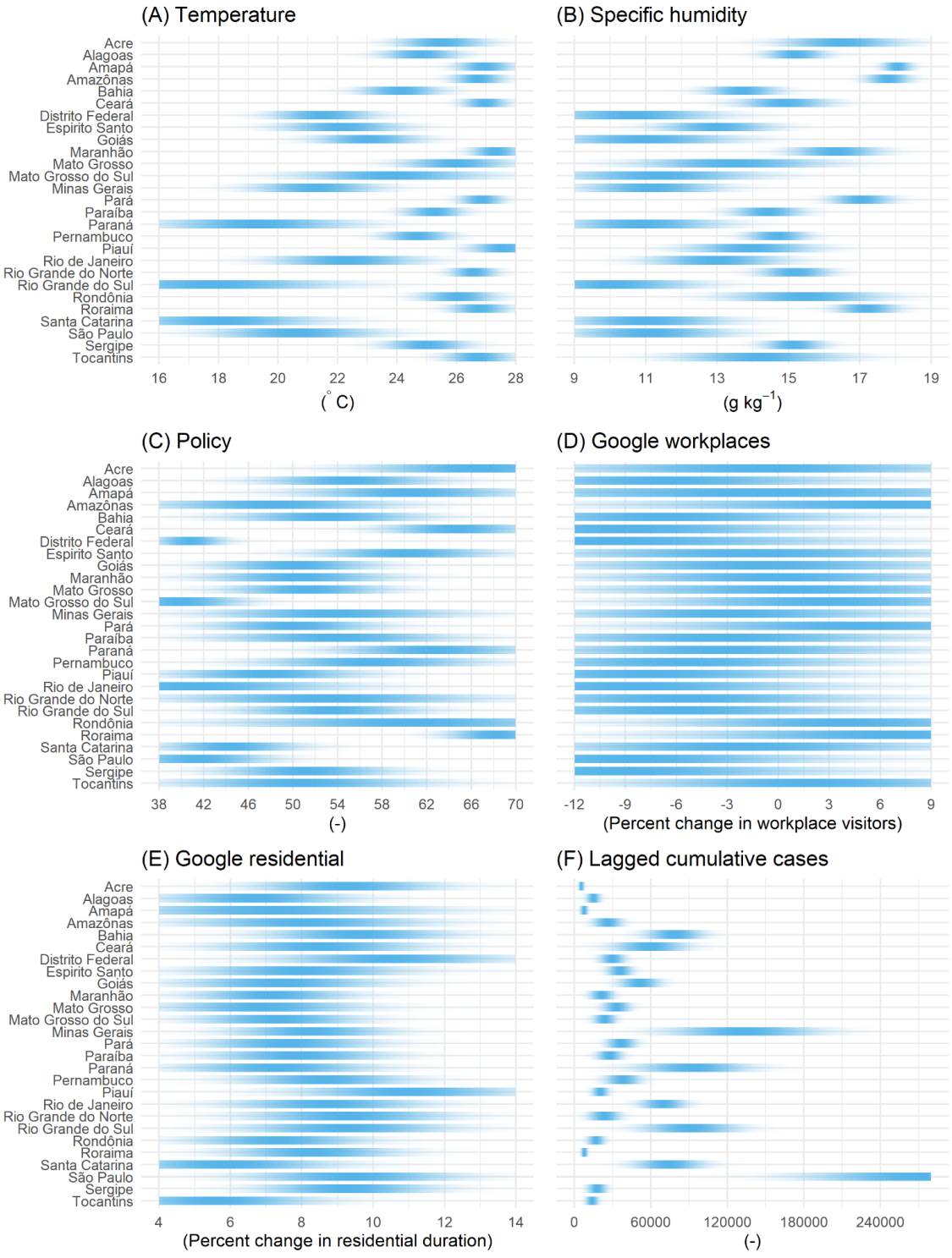

Figure S3. Distribution of state-level GAM model terms for the full study period, JJA 2020-JJA 2021. Bands show the 95% confidence interval generated from each model term and its margin of error.

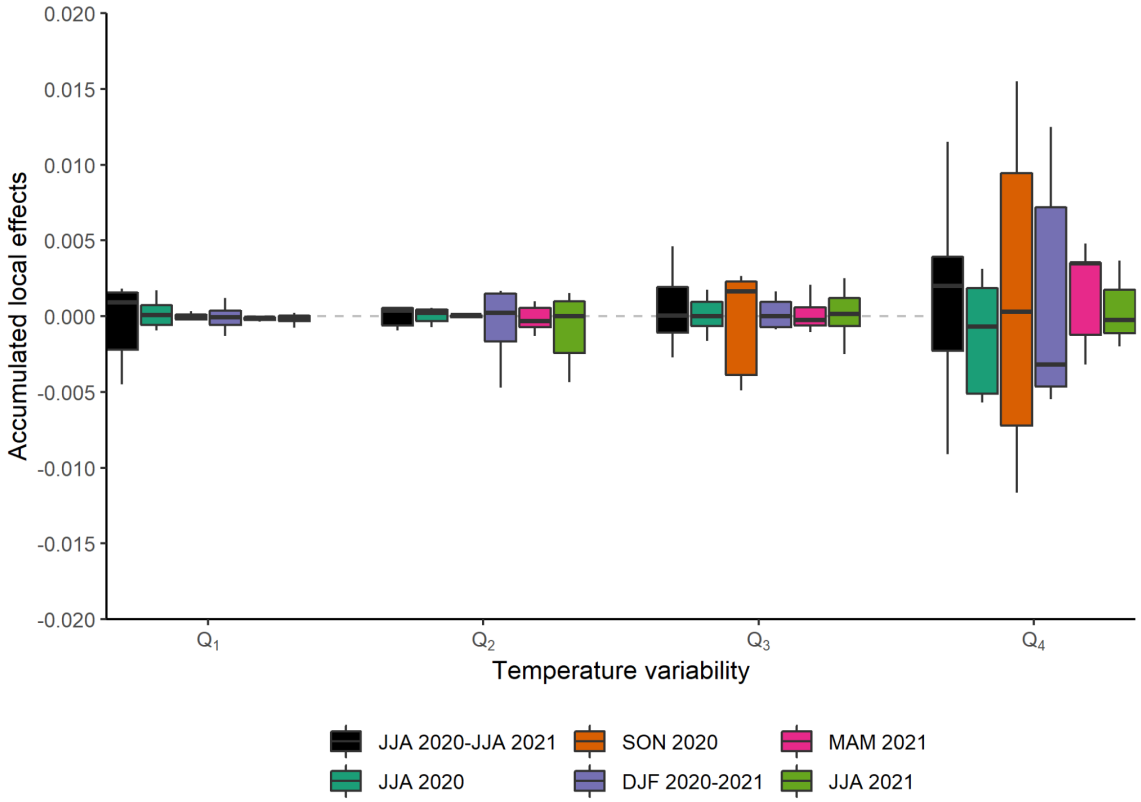

Figure S4. Distribution of the ALE for state-level temperature variability ($\sigma(\text{temperature})_s$ in Equation 2 in the main text). Different groups of boxes represent different quartiles of temperature variability: Q_1 represents states with temperature variability in the 0-25th percentile, Q_2 in the 25-50th percentile, Q_3 in the 50-75th percentile, and Q_4 in the 75-100th percentile. Individual box features, from bottom to top, denote the first quartile, the median, and the third quartile. Whiskers extend to ±1.5 times the interquartile range.

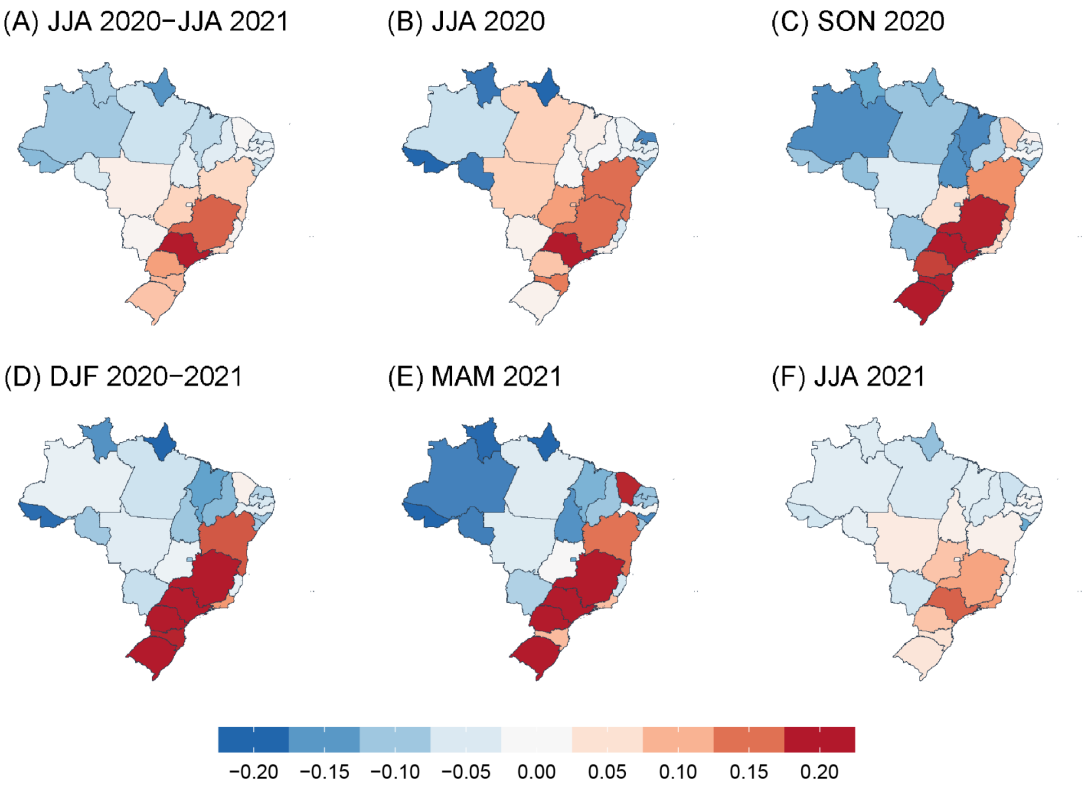

Figure S5. ALE of the state-level random effects. States with ALE>0 can be interpreted as states with higher propensity for transmission.

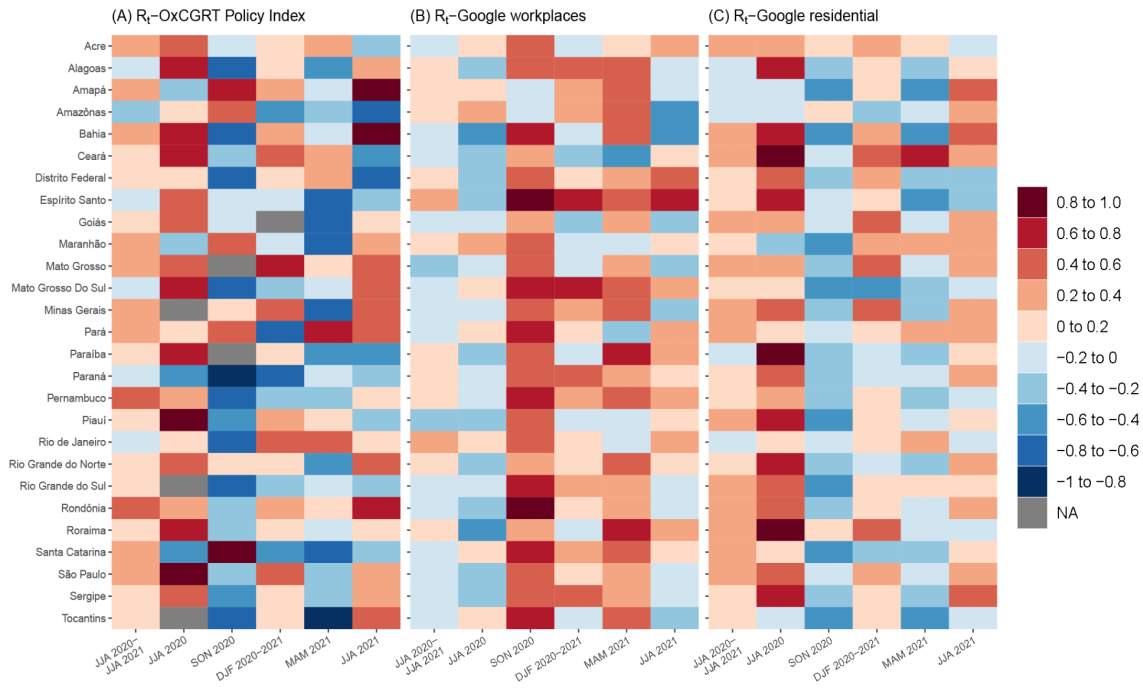

Figure S6. Spearman's rank correlation coefficient measuring the relationship between state-level R_t and (A) the OxCGRT policy, (B) Google workplaces, and (C) Google residential model terms for each study time period. States where the OxCGRT policy term has no daily variations for a particular period are denoted with the NA value.

Period	Deviance explained (%)	*p*-value								
		f(temperature)	f(specific humidity)	f(Temperature, Specific humidity)	f(Temperature variability, Specific humidity)	f(OxCGRT Policy Index)	f(Google workplaces)	f(Google residential)	f(Lagged cumulative cases)	f(state)
JJA 2020-JJA 2021	26.8	0.0025	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
JJA 2020	67.4	< 0.0001	< 0.0001	< 0.0001	0.0008	< 0.0001	0.0995	< 0.0001	< 0.0001	< 0.0001
SON 2020	37.9	0.0015	< 0.0001	0.5377	< 0.0001	< 0.0001	0.0075	< 0.0001	< 0.0001	< 0.0001
DJF 2020-2021	30.6	< 0.0001	0.0001	0.7890	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
MAM 2021	46.8	< 0.0001	0.1721	< 0.0001	0.1475	< 0.0001	0.0795	0.0842	< 0.0001	< 0.0001
JJA 2021	29.5	0.7750	0.0001	< 0.0001	0.0183	< 0.0001	0.0009	0.0003	< 0.0001	< 0.0001

Table S1. Generalized additive model (GAM) deviance explained and significance of smoothing parameters for each study period and terms. Here, JJA = June-July, SON = September-November, DJF = December-February, and MAM = March-May.