S1 Appendix

A Example of Revision Behavior and Target Lag Selection

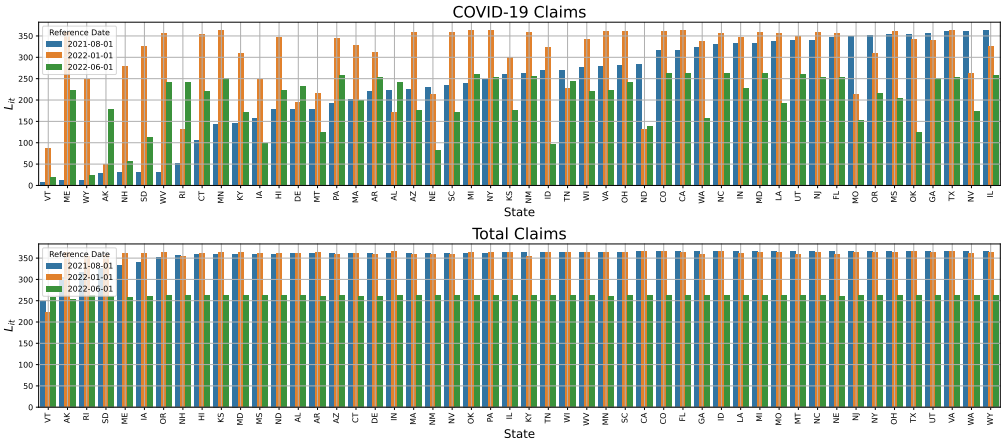

Fig S1. ***Lag convergence patterns across states.*** *Top: Comparison of the lags required for convergence across states, shown for a sample of different reference dates based on CHNG outpatient COVID-19 insurance claims. Bottom: Same as the top panel, but based on CHNG outpatient total insurance claims data.*

B Computational Cost of Training Window Variation for Daily Data

Computing Time (s) (per location per report date)		**Model**		
Training Window (days)	**Data**	Delphi-RF Training (once/week or month)	Epinowcast	NobBS
180	Confirmed Cases (Daily, State, MA only)	6.773 ± 0.018	406.097 ± 16.190	24.220 ± 0.675
	Insurance Claims (Daily, State, All states)	23.712 ± 0.029	2386.512 ± 230.895	96.012 ± 0.453
365	Confirmed Cases (Daily, State, MA only)	7.348 ± 0.024	1289.363 ± 79.974	59.549 ± 1.011
	Insurance Claims (Daily, State, All states)	37.389 ± 0.042	-	297.092 ± 1.709

Table 1. ***Runtime comparison across methods for daily data at different training windows.*** *This table presents the mean and standard error of the mean (SEM) for computing time (in seconds) required by different forecasting methods, applied to daily COVID-19 datasets. Results are reported per reference date and location. Models are trained and used to generate forecasts every 30 days for CHNG insurance claims data and every 7 days for MA-DPH confirmed case data. The comparison is performed under two training window settings (180 and 365 days), with all other configurations held constant to ensure a fair evaluation of runtime differences across methods.*

C Complete Set of DelphiRF Revision Forecasts by Reference Date

Figures S2–S51 present DelphiRF revision forecasts for CHNG-provided insurance claims data at lag 7 across all 50 U.S. states. The model is re-trained every 30 days using training windows of 180 and 365 days, respectively. The format follows that of Figures 5 and 6 in the main text.

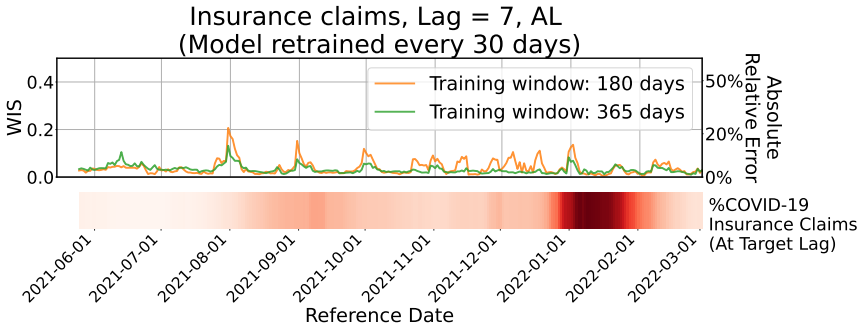

Fig S2. *Forecast Accuracy for AL.*

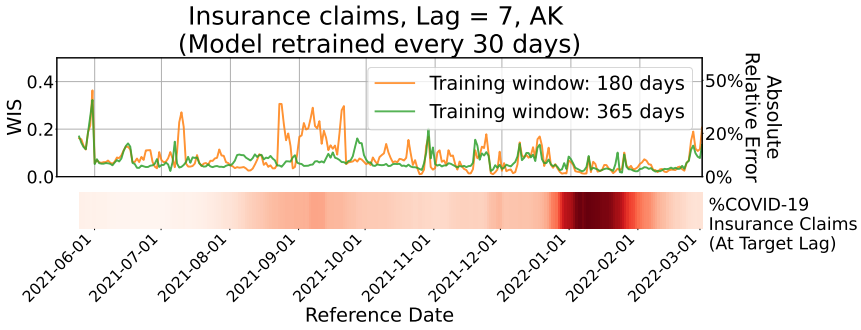

Fig S3. *Forecast Accuracy for AK.*

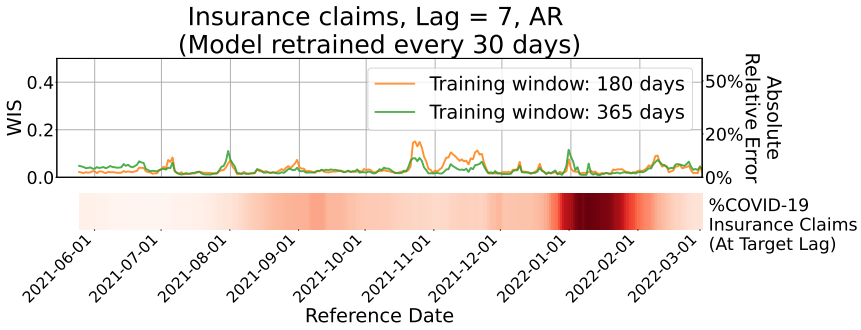

Fig S4. *Forecast Accuracy for AR.*

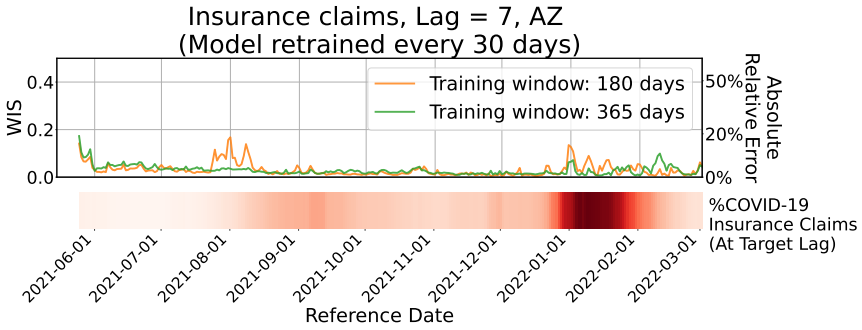

Fig S5. *Forecast Accuracy for AZ.*

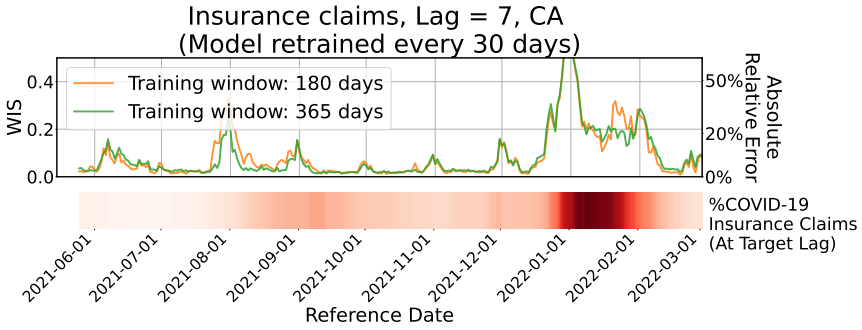

Fig S6. *Forecast Accuracy for CA.*

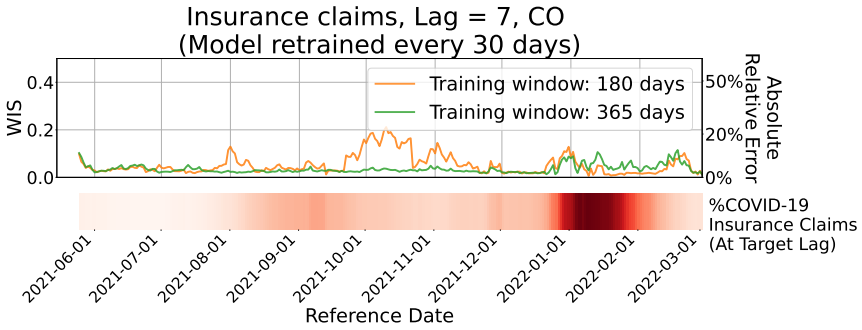

Fig S7. *Forecast Accuracy for CO.*

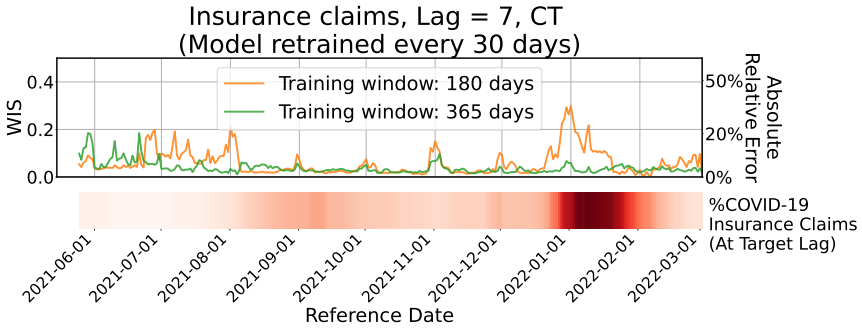

Fig S8. *Forecast Accuracy for CT.*

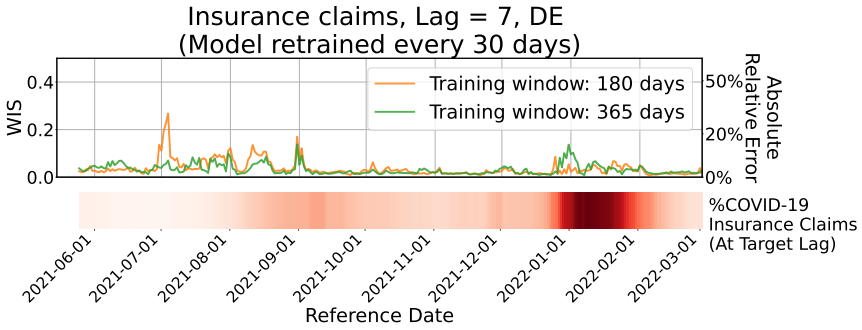

Fig S9. *Forecast Accuracy for DE.*

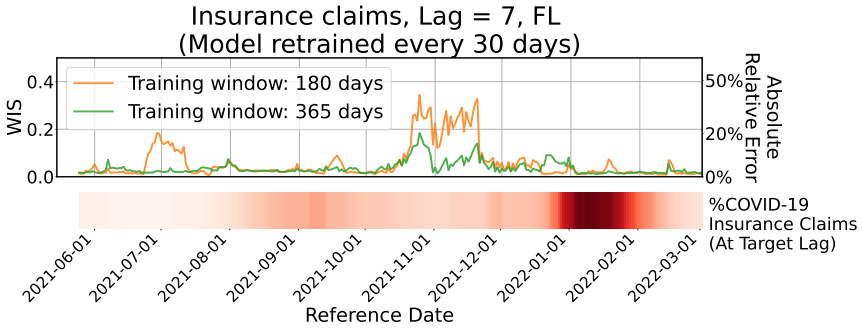

Fig S10. *Forecast Accuracy for FL.*

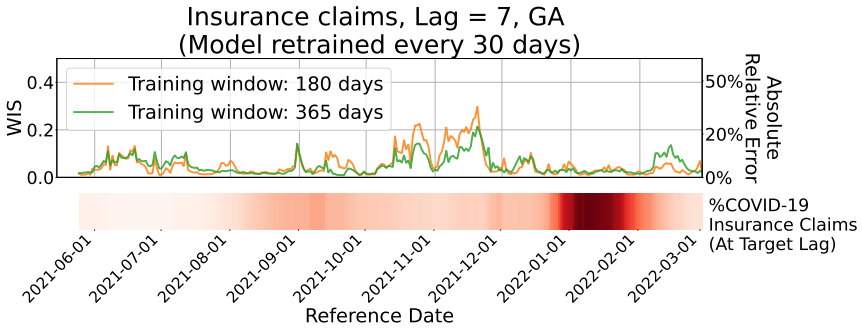

Fig S11. *Forecast Accuracy for GA.*

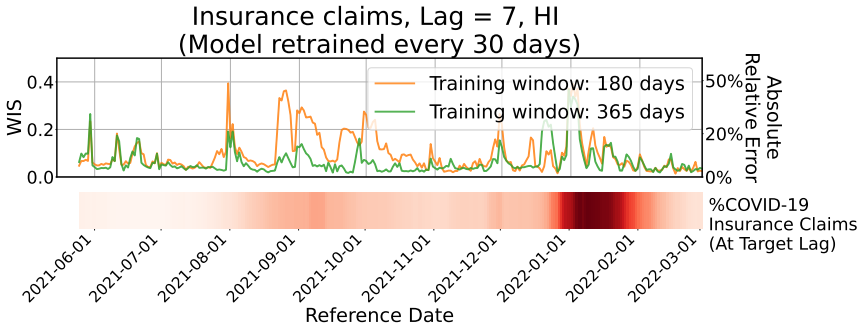

Fig S12. *Forecast Accuracy for HI.*

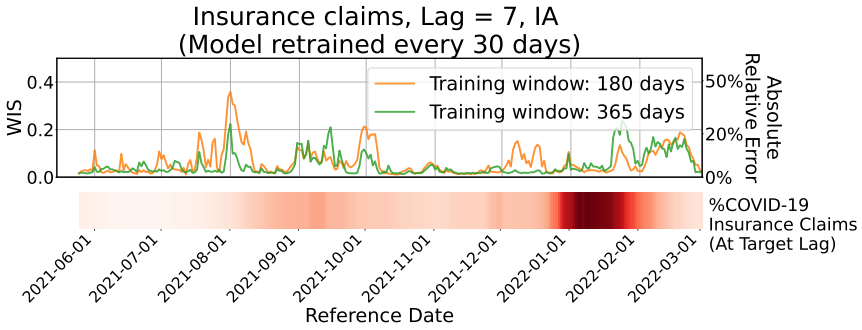

Fig S13. *Forecast Accuracy for IA.*

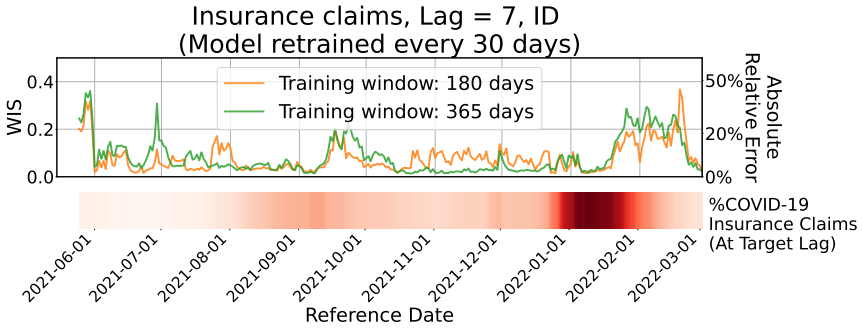

Fig S14. *Forecast Accuracy for ID.*

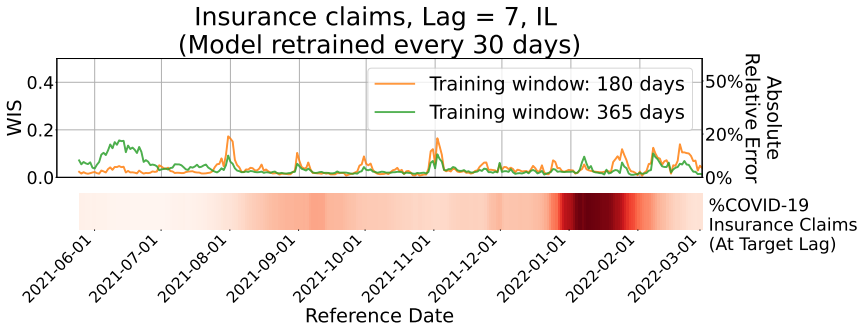

Fig S15. *Forecast Accuracy for IL.*

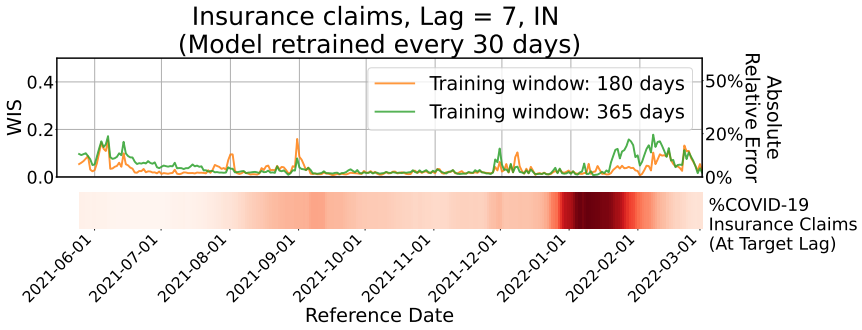

Fig S16. *Forecast Accuracy for IN.*

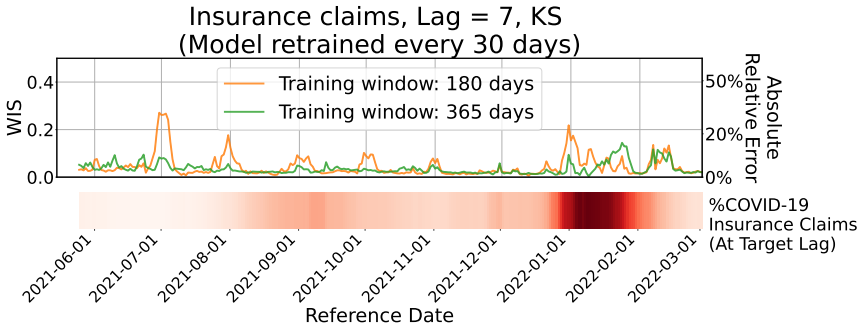

Fig S17. *Forecast Accuracy for KS.*

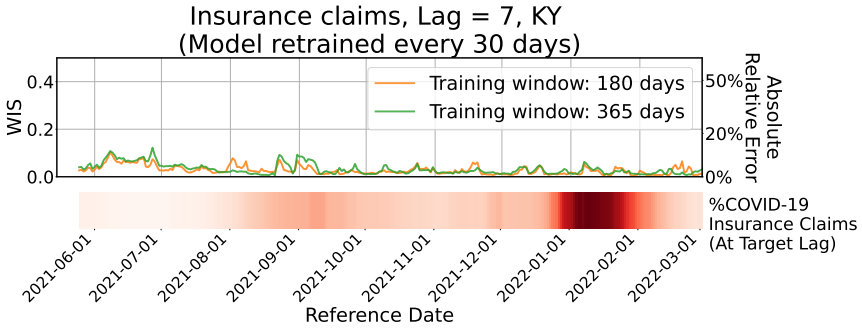

Fig S18. *Forecast Accuracy for KY.*

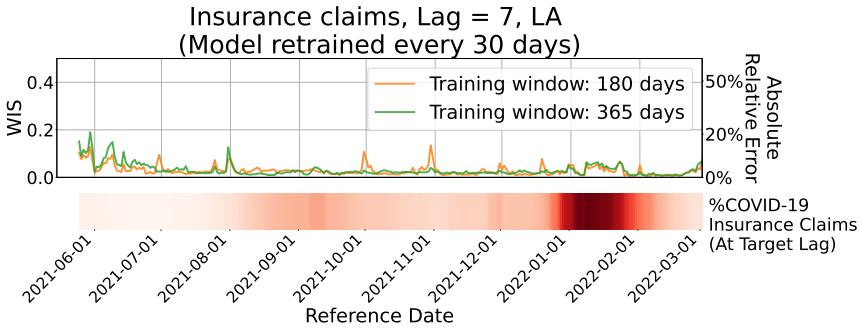

Fig S19. *Forecast Accuracy for LA.*

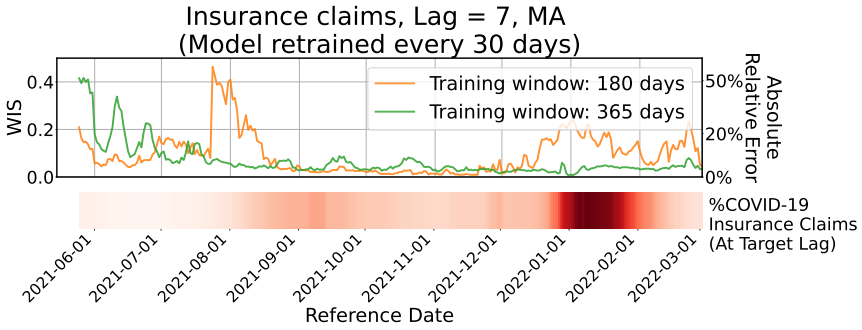

Fig S20. *Forecast Accuracy for MA.*

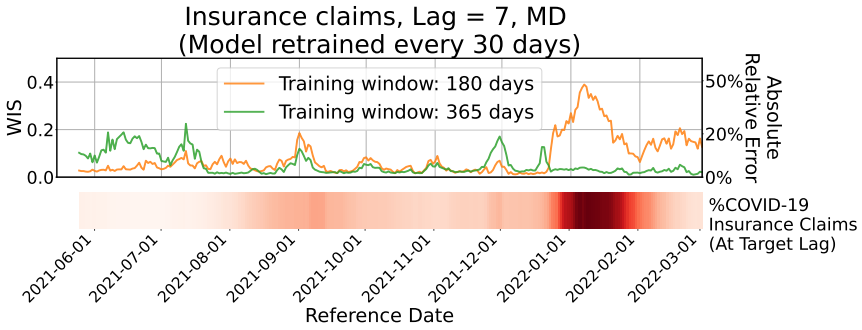

Fig S21. *Forecast Accuracy for MD.*

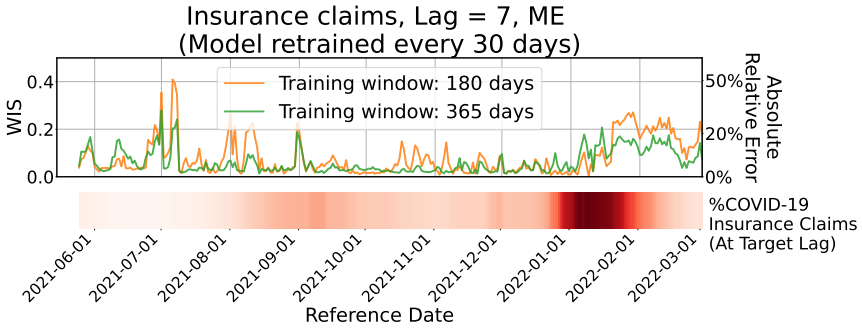

Fig S22. *Forecast Accuracy for ME.*

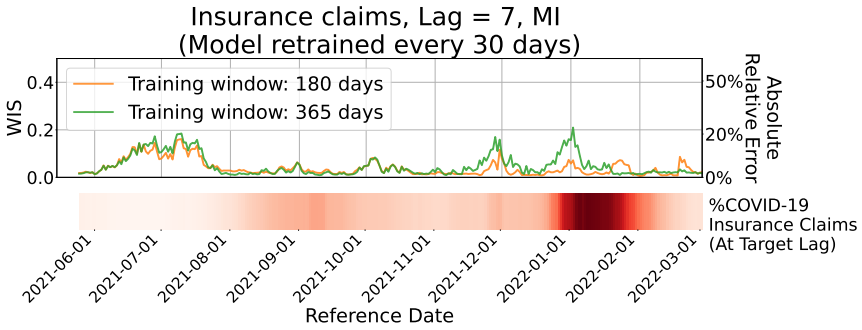

Fig S23. *Forecast Accuracy for MI.*

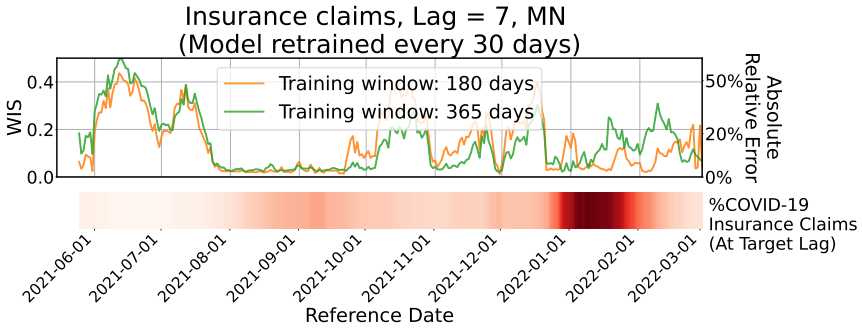

Fig S24. *Forecast Accuracy for MN.*

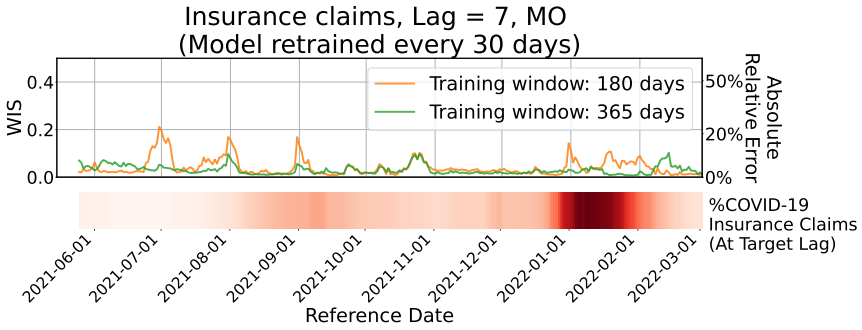

Fig S25. *Forecast Accuracy for MO.*

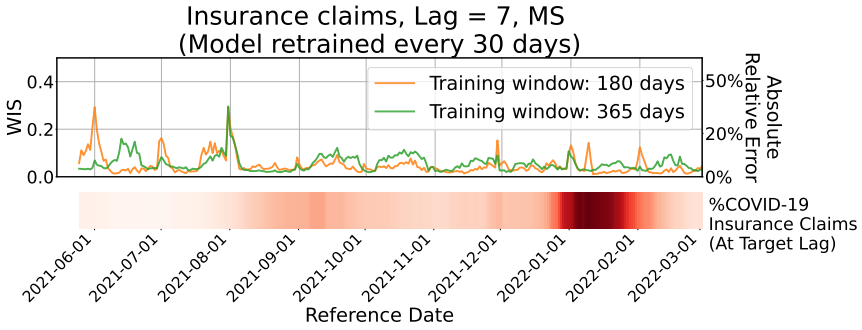

Fig S26. *Forecast Accuracy for MS.*

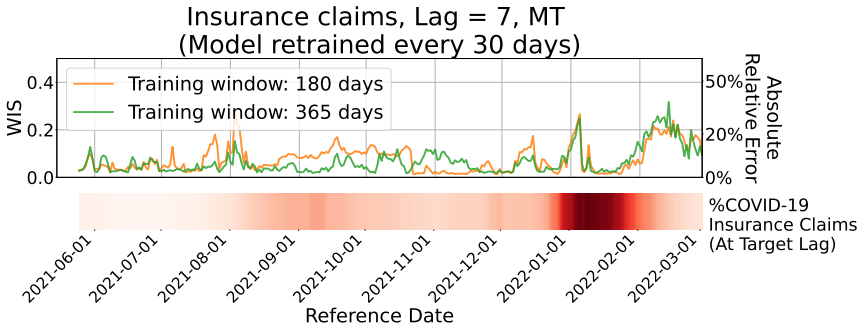

Fig S27. *Forecast Accuracy for MT.*

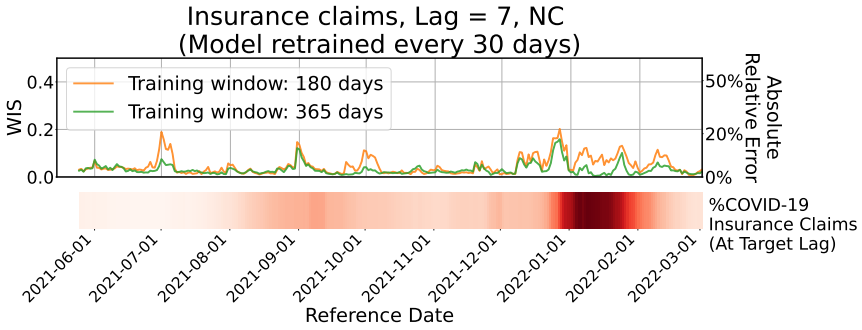

Fig S28. *Forecast Accuracy for NC.*

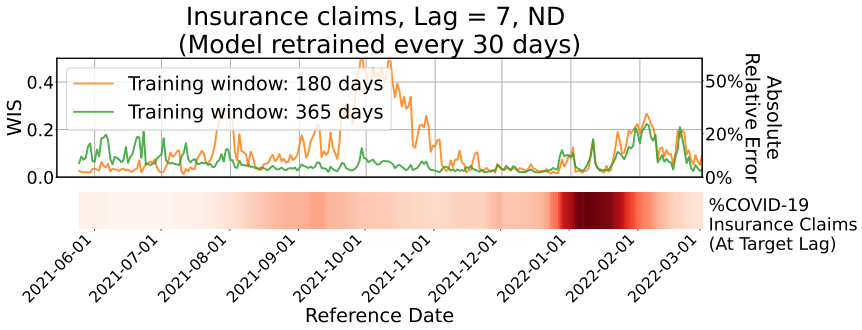

Fig S29. *Forecast Accuracy for ND.*

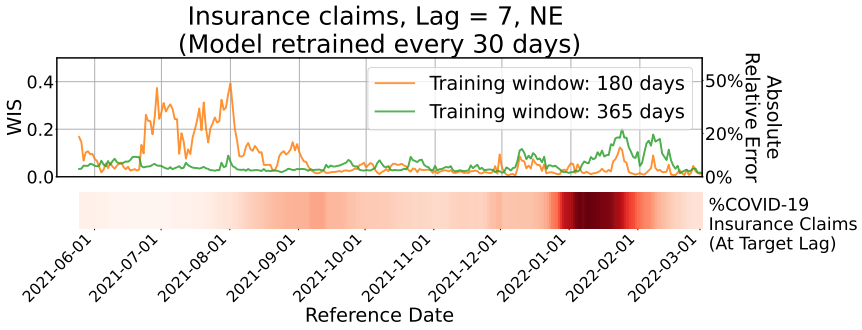

Fig S30. *Forecast Accuracy for NE.*

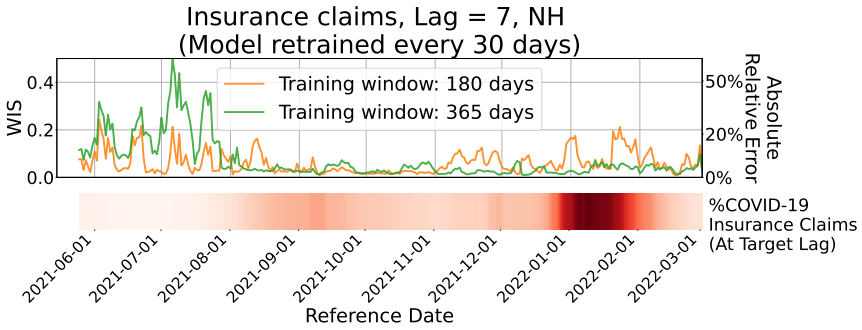

Fig S31. *Forecast Accuracy for NH.*

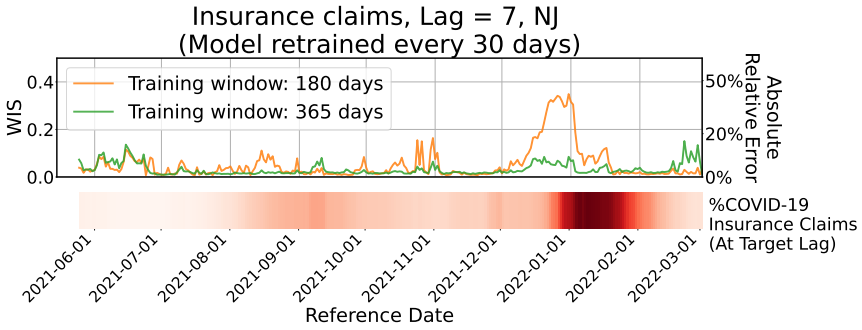

Fig S32. *Forecast Accuracy for NJ.*

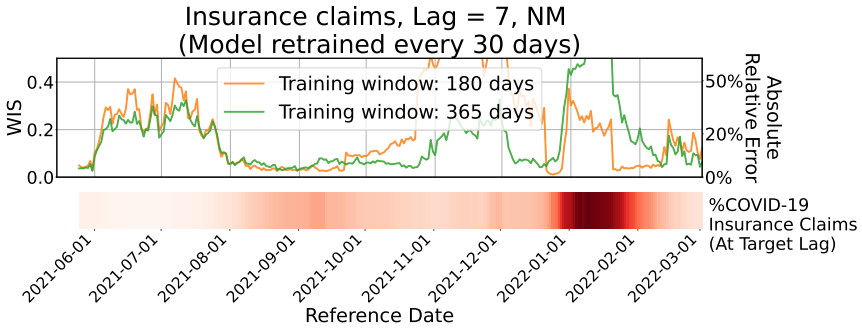

Fig S33. *Forecast Accuracy for NM.*

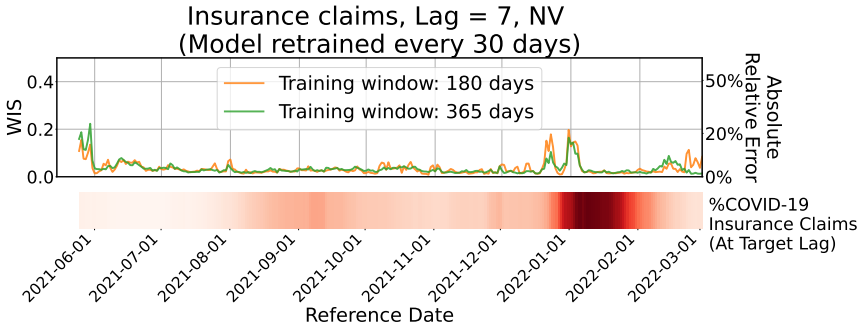

Fig S34. *Forecast Accuracy for NV.*

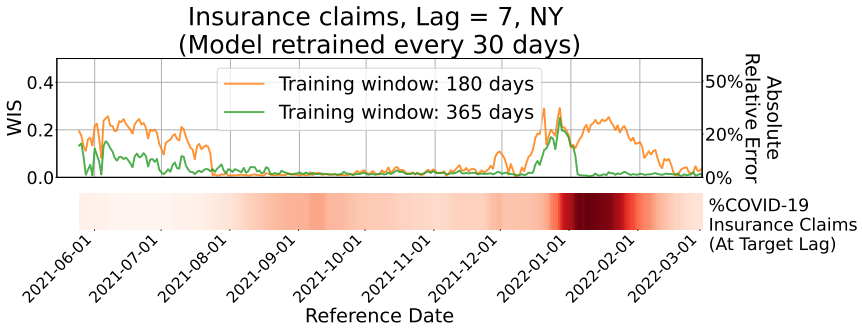

Fig S35. *Forecast Accuracy for NY.*

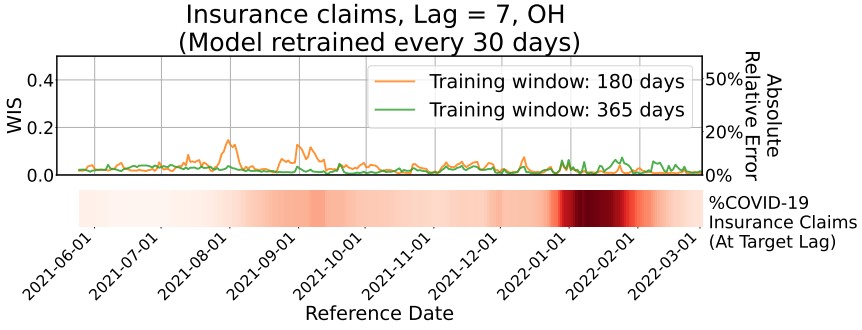

Fig S36. *Forecast Accuracy for OH.*

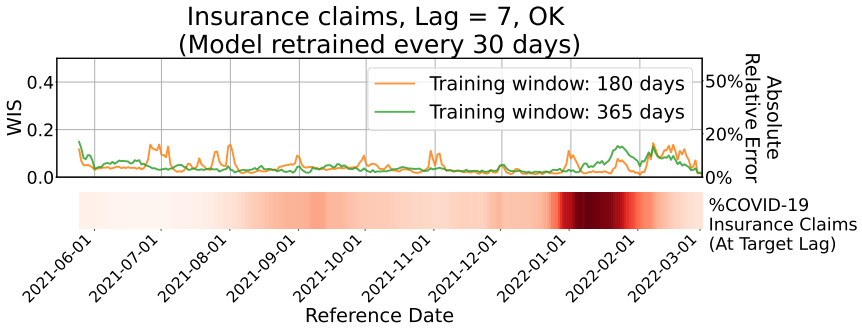

Fig S37. *Forecast Accuracy for OK.*

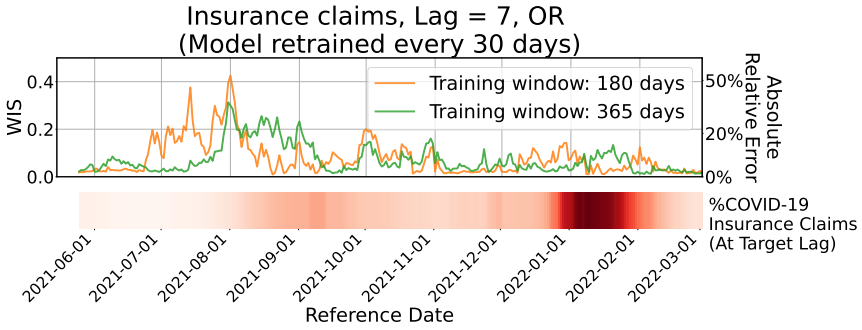

Fig S38. *Forecast Accuracy for OR.*

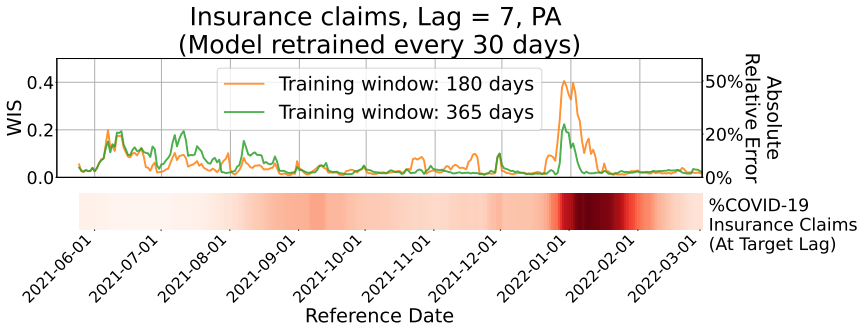

Fig S39. *Forecast Accuracy for PA.*

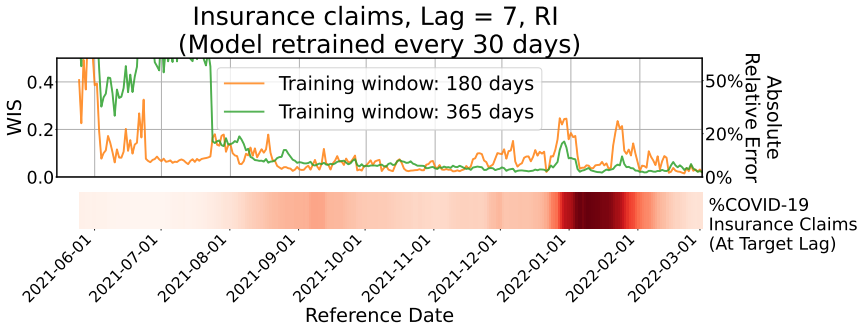

Fig S40. *Forecast Accuracy for RI.*

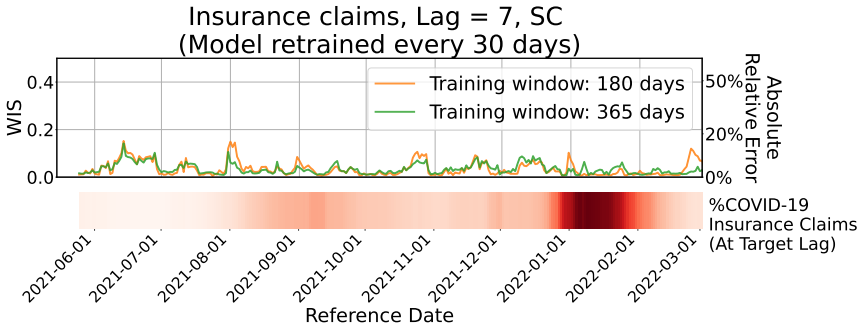

Fig S41. *Forecast Accuracy for SC.*

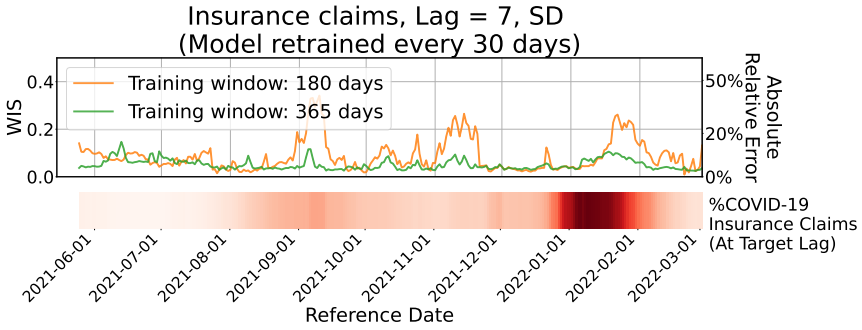

Fig S42. *Forecast Accuracy for SD.*

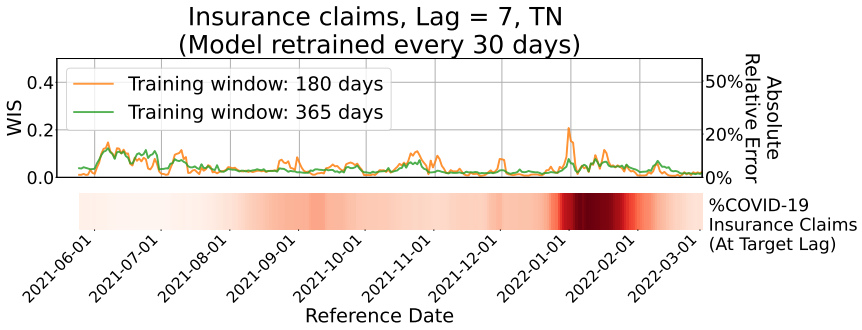

Fig S43. *Forecast Accuracy for TN.*

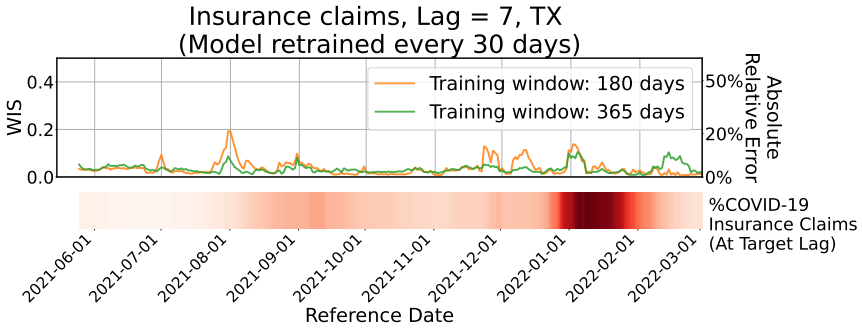

Fig S44. *Forecast Accuracy for TX.*

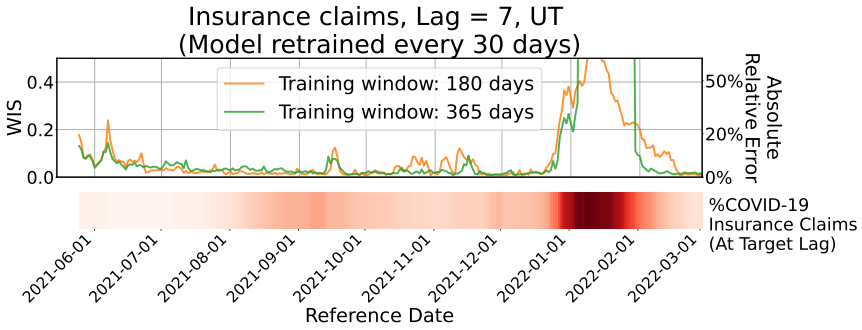

Fig S45. *Forecast Accuracy for UT.*

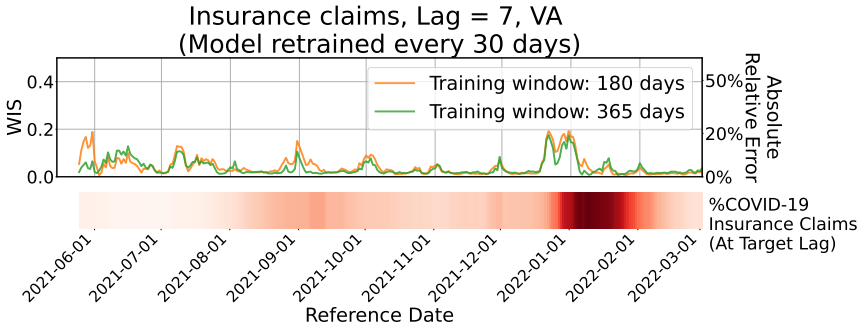

Fig S46. *Forecast Accuracy for VA.*

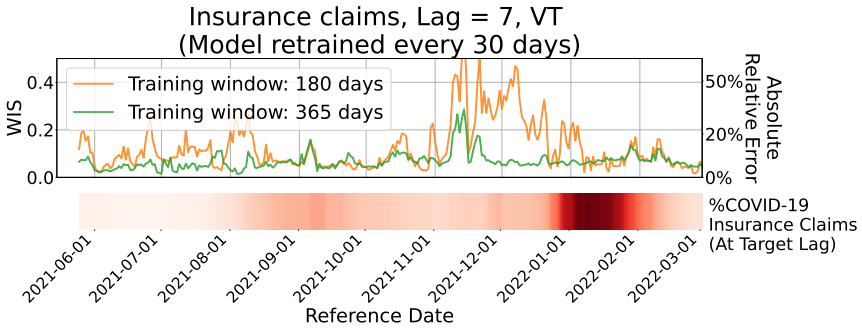

Fig S47. *Forecast Accuracy for VT.*

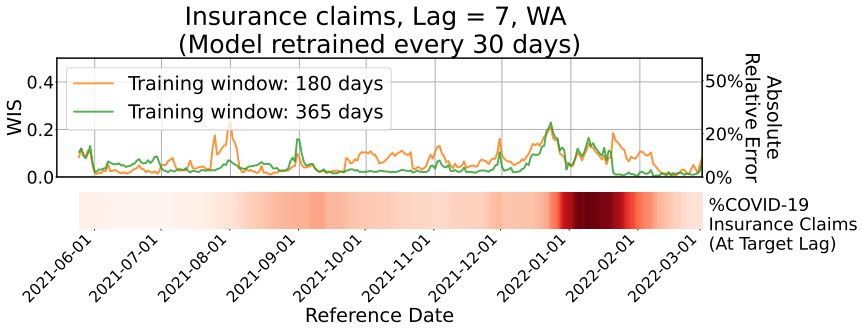

Fig S48. *Forecast Accuracy for WA.*

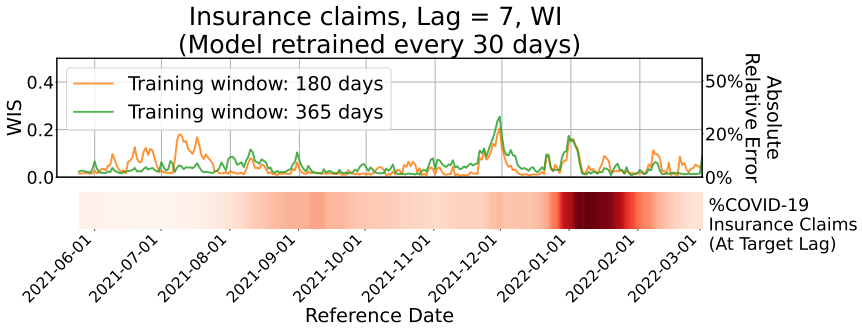

Fig S49. *Forecast Accuracy for WI.*

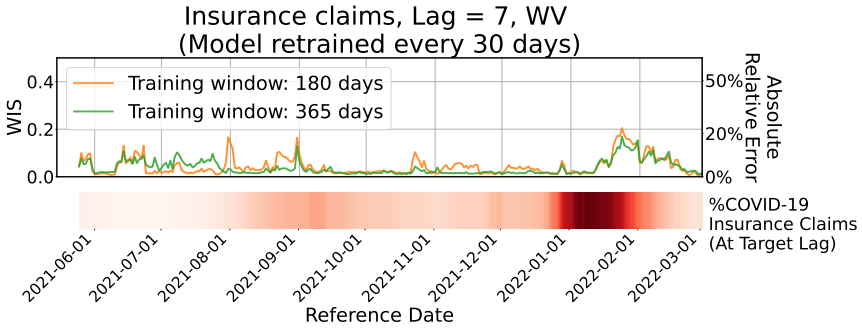

Fig S50. *Forecast Accuracy for WV.*

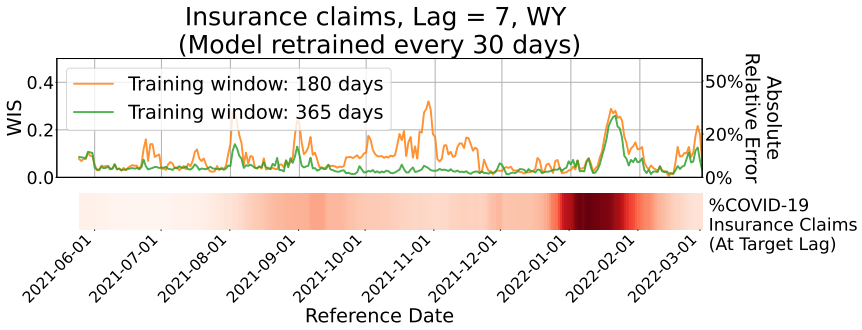

Fig S51. *Forecast Accuracy for WY.*

D Annotated Trend Categories in Target Values Across States

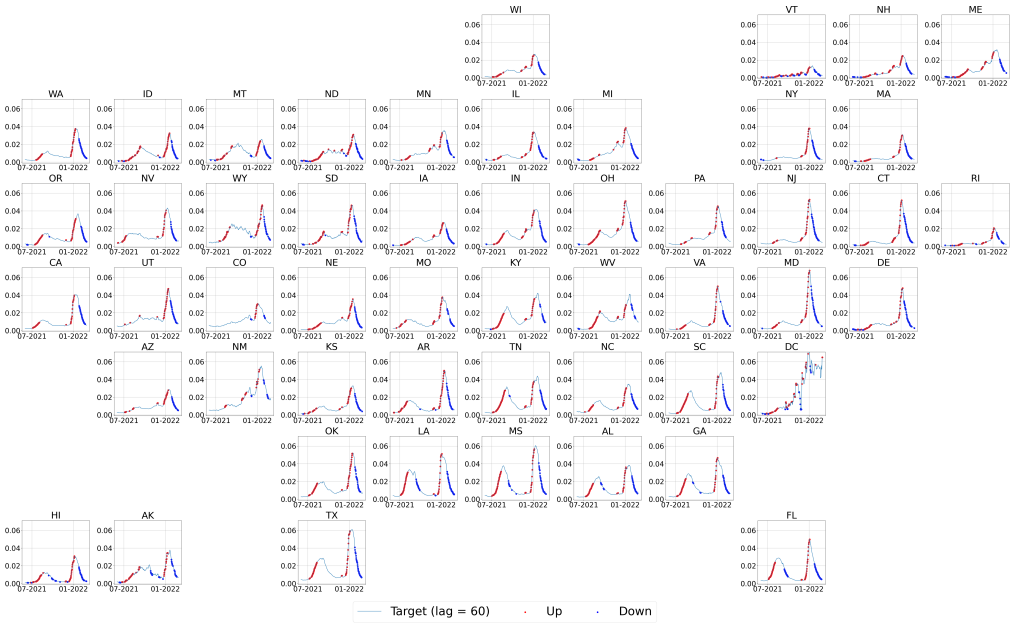

Fig S52. *Temporal Annotation of Trend Categories*