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Simulation-Derived Cognitive Hierarchy and COVID-19 Policy-Related Behavior: A State-Level Ecological Study of U.S. Mobility and Vaccination Data

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Abstract

Regional differences in behavioral responses to COVID-19 policies are not fully explained by demographic, socioeconomic, political, or psychological factors. This study examined whether a simulation-derived Cognitive Hierarchy (CH) parameter provides complementary information for explaining COVID-19-related behavior across 48 U.S. states and the District of Columbia. CH parameters were estimated from Google Community Mobility Reports using an agent-based simulation of recursive reasoning and incorporated into empirical models with conventional regional characteristics and Big Five personality traits. The CH parameter was positively associated with voluntary mobility reduction and remained statistically significant across alternative specifications, heteroskedasticity-consistent estimation, and spatial robustness analyses. The CH parameter also provided explanatory information beyond conventional regional characteristics and Big Five personality traits. External validation using COVID-19 vaccination uptake showed that CH remained positively associated with vaccination after accounting for personality, policy, and political factors. These findings suggest that simulation-derived behavioral parameters can complement conventional empirical measures in explaining heterogeneous COVID-19-related behavior.

Keywords: COVID-19; Cognitive Hierarchy; human mobility; vaccination uptake; policy-related behavior; agent-based simulation; behavioral modeling

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1. Introduction

1.1. Background

The COVID-19 pandemic revealed substantial regional differences in behavioral responses to public health policies and recommendations. During the early phase of the pandemic, non-pharmaceutical interventions, including stay-at-home orders and recommendations, were widely introduced to reduce mobility and limit infection. However, mobility reduction varied considerably across regions. Previous studies have associated this variation with political, demographic, socioeconomic, and institutional characteristics [1–4].

Conventional empirical analyses are useful for identifying associations between observable regional characteristics and pandemic-related behavior, but they may not fully represent the behavioral processes through which individuals respond to information, anticipate others' behavior, and adjust their own decisions. Such interactive processes are difficult to observe directly using regional datasets.

Agent-based simulation provides a complementary approach by representing how heterogeneous individuals make decisions and interact with others [5–7]. Cognitive Hierarchy (CH) theory is particularly relevant because it models differences in the extent to which individuals recursively anticipate the behavior and reasoning of others [8]. When incorporated into an agent-based simulation, CH theory allows a behavioral parameter related to recursive reasoning to be inferred from observed collective behavior.

In the context of COVID-19, a simulation-derived CH parameter can be interpreted as a model-based representation of the degree of recursive reasoning required to reproduce observed mobility patterns. It is not a direct psychological measure of individuals, but a parameter inferred from a computational model fitted to population-level behavior.

Despite the extensive use of agent-based models during the COVID-19 pandemic, simulation-derived behavioral parameters have rarely been evaluated alongside conventional variables in empirical statistical models. It therefore remains unclear whether such parameters provide complementary information for explaining regional differences in COVID-19-related behavior beyond demographic, socioeconomic, political, institutional, and psychological characteristics.

1.2. Research Gap

Previous studies have identified demographic, socioeconomic, political, institutional, and psychological factors associated with regional differences in COVID-19-related behavior. However, these observable characteristics provide limited information about interactive processes through which individuals respond to information, form expectations about others, and adjust their own behavior.

Agent-based simulation offers a way to represent such processes. In particular, Cognitive Hierarchy (CH) theory can be used to infer model-based behavioral parameters related to recursive reasoning from observed collective behavior. However, simulation-derived parameters are more commonly used within simulation environments than evaluated as explanatory variables in empirical statistical models. Previous methodological studies have therefore emphasized the importance of linking simulation models with observational data and assessing their empirical validity [9,10].

For COVID-19 research, it remains unclear whether a simulation-derived CH parameter provides complementary explanatory information beyond conventional regional characteristics when applied to real-world behavioral data. A further concern is that a parameter estimated from mobility trajectories may primarily reflect the same data used for its estimation. Association with the original mobility outcome alone therefore provides limited evidence of external validity.

This study addresses these gaps by examining whether a simulation-derived CH parameter contributes explanatory information beyond conventional demographic, socioeconomic, political, institutional, and psychological variables, and whether its association extends to an independent COVID-19-related outcome, namely vaccination uptake observed during a later phase of the pandemic.

1.3. Objective

This study examines whether a simulation-derived Cognitive Hierarchy (CH) parameter provides complementary explanatory information for COVID-19-related behavior beyond conventional regional characteristics.

Using an agent-based simulation implemented in NetLogo 6.2.1, state-level CH parameters were estimated by reproducing observed mobility trajectories during the first wave of the COVID-19 pandemic. The CH parameter represents a model-based measure of the degree of recursive reasoning required to reproduce the observed collective mobility trajectory in each jurisdiction. These parameters were then incorporated into regression models together with demographic, socioeconomic, political, institutional, social, and personality variables.

The analysis comprised three components: (i) estimation of CH from observed mobility trajectories, (ii) evaluation of its association with voluntary mobility reduction alongside conventional regional characteristics, and (iii) external validation using COVID-19 vaccination uptake as an independent behavioral outcome. Robustness was assessed using alternative model specifications, heteroskedasticity-consistent estimation, and spatial analyses.

Overall, the study evaluates whether simulation-derived behavioral information can complement conventional empirical measures in explaining heterogeneous COVID-19-related behavior.

2. Literature Review

2.1. Heterogeneity in COVID-19 Policy-Related Behavior

Behavioral responses to COVID-19 policies varied substantially across regions. Although governments introduced non-pharmaceutical interventions such as stay-at-home orders and recommendations, reductions in mobility were not uniform. Smartphone-based mobility studies documented marked geographic variation during the pandemic [11].

Previous research has associated differences in social distancing and mobility with political, demographic, socioeconomic, and population characteristics [1–3]. Parker and Mejia [4] further showed that regional mobility patterns reflected broader sociopolitical contexts as well as policy conditions. These studies demonstrate that COVID-19-related mobility behavior was shaped by multiple regional characteristics. A recent systematic review of COVID-19 distancing behavior identified associations with attitudes, perceived social norms, perceived behavioral control, and worry, although the strength of these associations varied across studies [12]. These findings suggest that pandemic-related behavioral responses also involve psychosocial processes that may not be fully represented by conventional demographic or political indicators.

However, most empirical studies focus on directly observed characteristics and outcomes, providing less information about interactive processes through which individuals respond to information and anticipate others' behavior. Simulation-derived behavioral parameters may complement conventional variables by representing aspects of collective decision-making that are difficult to observe directly. Evaluating such parameters alongside established regional characteristics may therefore provide additional insight into heterogeneous mobility responses during the pandemic.

2.2. Personality Traits and COVID-19-Related Behavior

Personality traits have been widely examined as predictors of health-related and policy-related behavior during the COVID-19 pandemic. The Big Five model—Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness—has been used to study preventive behavior, risk perception, and vaccination uptake.

Among these traits, Openness is particularly relevant because it is associated with receptiveness to new information and cognitive flexibility. Recent studies have reported associations between Openness and COVID-19 vaccination uptake [13,14].

Personality traits also provide a useful benchmark for evaluating simulation-derived behavioral information. Big Five traits represent relatively stable psychological dispositions, whereas the Cognitive Hierarchy (CH) parameter used in this study is a model-based representation of recursive decision-making inferred from collective behavior. Examining both together therefore allows an assessment of whether simulation-derived behavioral information contributes explanatory value beyond established personality characteristics.

2.3. Cognitive Hierarchy Theory and Behavioral Responses to COVID-19

Cognitive Hierarchy (CH) theory represents heterogeneity in recursive reasoning by assuming that individuals differ in the extent to which they anticipate the behavior and reasoning of others [8]. These differences are represented through cognitive levels ranging from simple behavioral responses to deeper levels of recursive reasoning. For example, in the context of stay-at-home orders and recommendations, individuals may respond not only to these interventions themselves but also to their expectations about how others will respond; higher cognitive levels represent progressively deeper consideration of such anticipated responses.

Such reasoning may be relevant to COVID-19-related behavior, where individuals repeatedly responded to changing epidemiological conditions, public health recommendations, and the observed behavior of others. When CH theory is incorporated into an agent-based simulation fitted to observed mobility data, the resulting CH parameter represents the degree of recursive reasoning required to reproduce collective mobility patterns. It should therefore be interpreted as a simulation-derived, model-based parameter rather than as a direct psychological measure of individuals.

A key question is whether this parameter contains behavioral information beyond the mobility data used for its estimation. If CH captures aspects of behavioral responsiveness not fully represented by conventional demographic, socioeconomic, political, institutional, or personality variables, it may provide complementary explanatory information in empirical models. Recent research in simulation-based social science has emphasized the importance of grounding agent-based models in empirical behavioral data. Karic et al. (2024) calibrated an agent-based model of responses to COVID-19 distancing interventions using behavioral data collected in an immersive video environment [15]. Collins et al. (2024) reviewed methods for validating agent-based models and emphasized the importance of evaluating models in relation to their intended purposes [16]. These studies highlight the need to distinguish goodness of fit to calibration data from evidence supporting the broader behavioral relevance of simulation-derived parameters.

To examine this issue, the present study also evaluates CH against COVID-19 vaccination uptake, a distinct behavioral outcome observed during a later phase of the pandemic. This provides an external test of whether the relevance of the mobility-derived CH parameter extends beyond the original mobility outcome.

2.4. Research Framework

This study examines whether a simulation-derived Cognitive Hierarchy (CH) parameter provides complementary information for explaining regional variation in COVID-19-related behavior. The framework combines agent-based simulation with empirical statistical analysis and distinguishes between the mobility data used to estimate CH and an independent outcome used for external validation.

As shown in Figure 1, observed mobility trajectories from the Google Community Mobility Reports are first used to estimate state-level CH parameters through an agent-based simulation. The estimated CH parameter represents the degree of recursive reasoning required to reproduce the observed collective mobility trajectory.

The CH parameter is then incorporated into regression models together with demographic, socioeconomic, political, institutional, social, and Big Five personality variables to examine its association with voluntary mobility reduction. Robustness is assessed using alternative model specifications, heteroskedasticity-consistent estimation, and spatial analyses. Finally, COVID-19 vaccination uptake is used as an independent behavioral outcome to assess whether the association of CH extends beyond the mobility data used for its estimation.

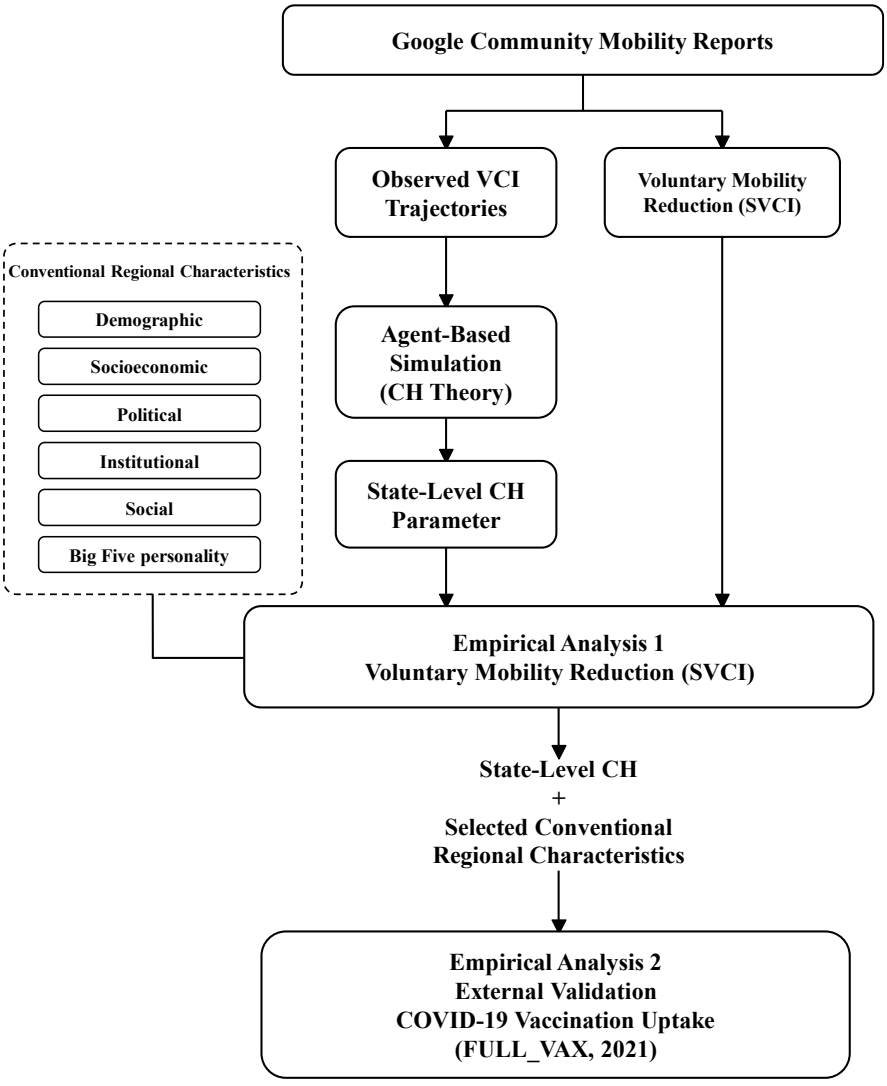


Figure 1. Research framework linking the simulation-derived Cognitive Hierarchy parameter to COVID-19 mobility reduction and vaccination uptake.

3. Materials and Methods

3.1. Data Sources and Study Sample

This study combined a state-level ecological observational analysis of publicly available aggregated data with agent-based simulation for estimating the Cognitive Hierarchy (CH) parameter. The unit of analysis in the observational component was the U.S. state or the District of Columbia. The final sample included 48 states and the District of Columbia (n = 49); Alaska and Hawaii were excluded because state-level Big Five personality data were unavailable [17]. The sample size was therefore determined by the availability of the required state-level data rather than by a power-based sampling design. For simplicity,

the term "state-level" is used throughout this study to describe variables measured for these 49 units, while "jurisdiction" refers to an individual state or the District of Columbia.

Human mobility data were obtained from the Google Community Mobility Reports [18], which report daily percentage changes relative to a pre-pandemic baseline defined as the median value for the corresponding day of the week from 3 January to 6 February 2020. The transit stations category was used to measure changes in visits to locations classified by Google as transit stations. The transit-stations category was selected as an operational indicator of changes in travel-related, out-of-home activity during the stay-at-home period. It captures visits to transport-related locations, such as bus and train stations, whereas other Google mobility categories focus on different types of activities or locations, including workplaces, residential settings, and retail or recreational destinations [18]. A reduction in transit-station visits may therefore serve as an indirect indicator of reduced out-of-home activity associated with stay-at-home behavior, particularly in areas where public transportation is commonly used. Using the same transit-stations series for VCI construction and CH calibration also maintains consistency within the simulation framework. However, this choice does not imply that transit-station visits represent all forms of mobility or directly measure voluntary compliance with public health policies.

Let $Transit_t$ denote the daily percentage change in visits to these locations relative to the baseline. Because negative values indicate reduced visits relative to the baseline, the sign was reversed to define the daily Voluntary Curfew Index (VCI),

$$VCI_t = -Transit_t$$

Higher *VCI* values indicate greater mobility reduction, as captured by decreased visits to locations included in Google's transit stations category, and are interpreted here as a mobility-based indicator of voluntary behavioral restraint. VCI should therefore be interpreted as a mobility-based behavioral indicator rather than as a direct measure of legal or policy compliance.

Daily *VCI* values were aggregated over the 30-week period from 16 February to 13 September 2020 to calculate the Summation of the Voluntary Curfew Index (SVCI):

$$SVCI = \sum_{t=1}^{210} V\,CI_t$$

SVCI was the dependent variable in the primary analysis, with higher values indicating greater cumulative reductions in visits to transit-station locations. In this study, "mobility" refers specifically to changes in visits to locations included in Google's transit stations category, rather than to point-to-point travel between stations or total travel distance.

The explanatory variables included demographic, epidemiological, socioeconomic, political, institutional, social, and Big Five personality characteristics. The principal explanatory variable was the simulation-derived Cognitive Hierarchy (CH) parameter described in Section 3.2. CH was estimated as the parameter value that best reproduced the observed mobility trajectory for each jurisdiction and should be interpreted as a model-based representation of the degree of recursive reasoning required to reproduce collective mobility patterns, rather than as a directly measured psychological characteristic. State-level COVID-19 case data were obtained from The New York Times [19]. The epidemiological variable was calculated as the cumulative number of reported COVID-19 cases through 13 September 2020, divided by the corresponding state population from the 2020 U.S. Census Bureau population data and multiplied by 100,000. This measure characterizes regional differences in the epidemiological conditions during the mobility analysis period. For descriptive purposes, Supplementary Table S6 also reports cumulative COVID-19 cases through 31 December 2020 and the corresponding reported cases per

100,000 population for all 49 jurisdictions, using the same population denominators. These full-year figures were not included in the regression analyses because they include cases reported after the mobility analysis period.

Table 1 summarizes the variables and data sources, and Table 2 presents descriptive statistics. The state-level analytical dataset and additional robustness results are provided in the Supplementary Materials, while the mathematical formulation and CH estimation procedure are presented in Appendix A. Missing daily observations in the Google Community Mobility Reports were imputed using the available observations immediately before and after the missing dates. The resulting state-level analytical dataset contained complete observations for all variables reported in Table 2 (n = 49 for each variable). The reporting of the ecological observational component was reviewed with reference to the relevant items of the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) checklist for cross-sectional studies, as provided through the EQUATOR Network. Because this study combines state-level ecological analysis with agent-based simulation, the checklist was used as a reporting framework while considering the specific study design and unit of analysis. Items concerning individual participant recruitment and follow-up were not applicable.

Table 1. Variables used in the primary analysis of voluntary mobility reduction.

Category	Variable	Description	Source
Outcome	SVCI	Cumulative voluntary mobility reduction based on the Summation of the Voluntary Curfew Index	Google LLC [18]
Simulation-derived behavioral measure	CH	Estimated state-level Cognitive Hierarchy parameter	Agent-based simulation
Demographic/epidemiological	COVID-19 cases	Cumulative reported COVID-19 cases through 13 September 2020 per 100,000 population, using 2020 U.S. Census Bureau population data as the denominator.	The New York Times [19]
Demographic	Population density	Persons per km²	U.S. Census Bureau [20]
Demographic	Average age	Mean age	U.S. Census Bureau [20]
Socioeconomic	Household income	Median household income	U.S. Census Bureau [20]
Political	Republican vote share	Republican vote share in the 2016 U.S. presidential election	MIT Election Data and Science Lab [21]
Institutional	Stay-at-home order	Presence of a statewide stay-at-home order	Moreland et al. [22]
Institutional	Penalty provision	Presence of an associated legal penalty	Mazziotta [23]
Social	Religious attendance	Weekly religious attendance	Pew Research Center [24]
Personality	Extraversion	Big Five personality score	Rentfrow et al. [17]
	Agreeableness	Big Five personality score	Rentfrow et al. [17]
	Conscientiousness	Big Five personality score	Rentfrow et al. [17]
	Neuroticism	Big Five personality score	Rentfrow et al. [17]
	Openness	Big Five personality score	Rentfrow et al. [17]

Table 2. Descriptive statistics for variables used in the primary mobility analysis.

Variable	N	Mean	SD	Min	Max
SVCI	49	522.84	515.57	−528.0	1658.0
COVID-19 cases	49	1774.79	720.77	261.7	3400.5
Population density	49	436.28	1605.31	5.9	11,280.0
Average age	49	38.82	2.29	31.5	44.8
Median household income	49	57,604.57	9561.91	42,129	86,567
Stay-at-home order	49	0.857	0.354	0	1

Penalty provision	49	0.408	0.497	0	1
Republican vote share	49	48.28	12.06	4.1	68.6
Religious attendance	49	35.86	7.61	21.0	53.0
Cognitive Hierarchy (CH)	49	0.839	0.787	0.10	2.00
Extraversion	49	50.00	10.00	26.5	69.8
Agreeableness	49	50.00	10.01	21.4	69.4
Conscientiousness	49	50.00	10.00	24.0	69.6
Neuroticism	49	50.01	10.00	30.4	79.2
Openness	49	50.00	10.01	21.8	77.5

3.2. Agent-Based Simulation

An agent-based simulation was implemented in NetLogo 6.2.1 to estimate a behavioral parameter representing recursive decision-making during the COVID-19 pandemic. The model combined Cognitive Hierarchy (CH) theory with observed Voluntary Curfew Index (VCI) trajectories derived from the Google Community Mobility Reports.

Figure 2 summarizes the CH estimation procedure. Both the simulation model and the CH estimation procedure were based on Matsui and Hashimoto [25]. Following their approach, for each jurisdiction, the simulation was fitted to the observed VCI trajectory by systematically varying the CH parameter and selecting the value that produced the closest correspondence between simulated and observed mobility patterns. Following Camerer et al. [8], heterogeneity in cognitive levels was represented by a Poisson distribution, with the CH parameter corresponding to its mean. Level-0 agents do not strategically anticipate others' behavior, whereas higher-level agents recursively form expectations about lower-level agents.

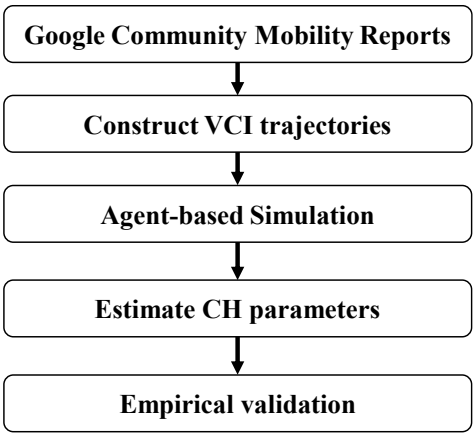


Figure 2. Computational procedure for estimating the simulation-derived Cognitive Hierarchy (CH) parameter from observed COVID-19 mobility trajectories.

Figure 3 illustrates the recursive decision-making process represented in the simulation. Agents update their behavioral decisions in response to information and their expectations regarding the behavior of others. During the COVID-19 pandemic, for example, an agent may initially reduce mobility after observing or anticipating that others are restricting their activities. As additional information becomes available through public communication and other information channels, the agent may update expectations regarding how others are likely to respond and subsequently revise its own behavioral decision. Repeated interactions of this type generate the collective behavioral dynamics represented by the simulated VCI trajectories.

The simulation included 1000 agents. Parameters governing information dissemination and behavioral updating were held constant, whereas CH was varied. Public

attention to stay-at-home recommendations was represented using the Google Trends topic "stay at home," following previous research on COVID-19-related information-seeking behavior [26].

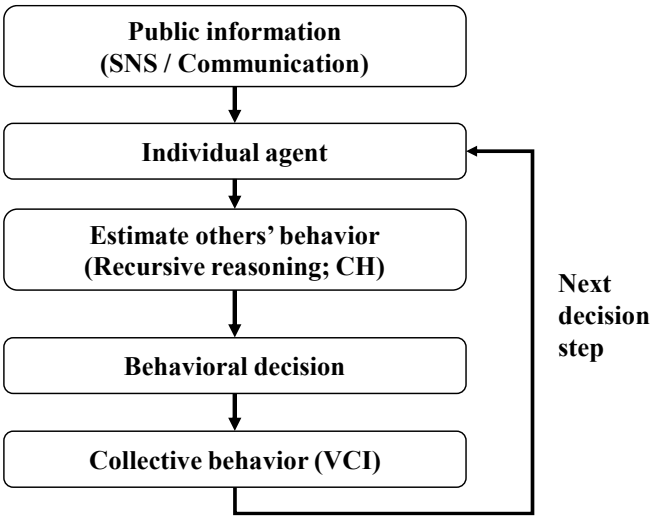


Figure 3. Recursive decision-making process represented in the agent-based simulation.

For each jurisdiction, CH was estimated by minimizing the Root Mean Square Error (RMSE) between observed and simulated VCI trajectories:

$$CH_i^* = \arg\min_{CH} RMSE_i(CH)$$

where CH_i^* denotes the estimated CH parameter for jurisdiction i. The detailed RMSE formulation and the Poisson specification of cognitive levels are provided in Appendix A. The corresponding estimation procedure is presented as Algorithm A1, and the fixed simulation parameters are summarized in Supplementary Table S4.

The estimated CH parameter represents the mean of the Poisson distribution of recursive reasoning levels assumed in the simulation. A higher estimated CH value indicates that a distribution assigning relatively greater weight to higher reasoning levels was selected as the best-fitting specification for that jurisdiction, given the model structure and other fixed parameters. Thus, CH should be interpreted as a model-dependent parameter characterizing collective mobility dynamics, rather than as a directly measured psychological characteristic or cognitive ability of individuals.

3.3. Empirical Analysis of Voluntary Mobility Reduction

Five ordinary least squares (OLS) regression models were estimated with the Summation of the Voluntary Curfew Index (SVCI) as the dependent variable to examine whether the simulation-derived Cognitive Hierarchy (CH) parameter provided complementary explanatory information beyond conventional regional characteristics. General model formulations are provided in Appendix A.

Because the CH parameter was estimated by fitting the observed VCI trajectories, whereas SVCI was calculated from the same mobility data, the two measures are not statistically independent. Consequently, the association between CH and SVCI may partly reflect their shared data source. The primary regression analysis is therefore interpreted as an in-sample association rather than as independent validation of the CH parameter.

Model (1) included demographic, socioeconomic, and institutional variables. Model (2) added Republican vote share, religious attendance, and CH. Model (3) replaced CH with the five Big Five personality traits. Model (4) included both CH and the Big Five traits together with Republican vote share and religious attendance. Model (5) retained CH and

the Big Five traits but excluded Republican vote share to examine the CH association without explicitly adjusting for political context.

The incremental contribution of CH was evaluated using nested F-tests. An intermediate model containing Republican vote share and religious attendance but excluding CH was compared with Model (2), while Models (3) and (4) were compared to assess whether CH added explanatory information beyond the Big Five traits. Potential spatial dependence was examined using spatial autocorrelation diagnostics and spatial regression models. All analyses were conducted in R version 4.5.2.

3.4. Spatial Analysis

Spatial analyses were conducted to assess whether geographic dependence affected the estimated relationships between the explanatory variables and voluntary mobility reduction. Neighboring jurisdictions may share similar demographic, socioeconomic, political, institutional, and behavioral characteristics, potentially violating the independence assumption underlying ordinary least squares regression.

Spatial autocorrelation was evaluated using Global Moran's I and Local Moran's I (LISA). Two row-standardized spatial weights matrices were considered. The primary specification used queen contiguity, in which jurisdictions sharing a common boundary or vertex were treated as neighbors. As a sensitivity analysis, a distance-based matrix was also constructed by connecting jurisdictions whose geometric centroids were within 800 km. The specifications of the spatial weights matrices are provided in Appendix A.

Global Moran's I was first calculated for SVCI to determine whether voluntary mobility reduction exhibited spatial clustering across U.S. jurisdictions. Global Moran's I was then calculated for the residuals of the regression models to assess whether spatial dependence remained after accounting for the included explanatory variables. Local Moran's I was used to identify significant High–High and Low–Low spatial clusters, as well as High–Low and Low–High spatial outliers.

To further examine the robustness of the association between CH and SVCI, Spatial Lag and Spatial Error Models were estimated using the same explanatory variables as Model (5). The queen-contiguity matrix was used for the primary spatial regression analyses, and the distance-based matrix was used as an alternative specification. These analyses assessed whether the estimated association between the simulation-derived CH parameter and voluntary mobility reduction remained stable after accounting for potential spatial dependence.

3.5. Robustness Analysis Methods

Several additional analyses were conducted to assess the stability of the association between the simulation-derived CH parameter and voluntary mobility reduction. First, nested model comparisons were used to evaluate whether the inclusion of CH significantly improved model fit beyond conventional political, social, and personality variables. Second, multicollinearity was assessed using Variance Inflation Factors (VIFs). Third, HC3 heteroskedasticity-consistent standard errors were estimated to examine whether the statistical inference for the CH parameter was sensitive to potential heteroskedasticity. Fourth, a Leave-One-State-Out (LOSO) sensitivity analysis was performed for Model (5), in which the model was re-estimated 49 times, omitting one jurisdiction in each iteration to assess the sensitivity of the CH coefficient to individual observations.

Spatial robustness was evaluated using residual spatial autocorrelation diagnostics, Spatial Lag and Spatial Error Models, and alternative spatial weights matrices. Together, these analyses were used to determine whether the direction and statistical significance of the association between CH and SVCI remained stable across alternative statistical specifications and assumptions.

The external validity of the CH parameter was evaluated separately using COVID-19 vaccination uptake as an independent behavioral outcome, as described in Section 3.6.

3.6. External Validation Methods Using COVID-19 Vaccination Uptake

Because the simulation-derived Cognitive Hierarchy (CH) parameter was estimated from mobility data, external validation was conducted using COVID-19 vaccination uptake, a distinct behavioral outcome observed during a later phase of the pandemic and not used to estimate CH.

The dependent variable was the full COVID-19 vaccination rate (FULL_VAX) in 2021, based on the dataset used by Webster et al. [27]. The analysis included the same 48 U.S. states and the District of Columbia as the primary mobility analysis.

Four ordinary least squares models were estimated. Model V1 included the five Big Five personality traits, and Model V2 added CH. Model V3 further included COVID-19 policy-related variables, while Model V4 additionally included Republican vote share. These specifications assessed whether the association between CH and vaccination uptake remained evident after accounting for personality, policy, and political factors.

A Leave-One-State-Out sensitivity analysis was also conducted to assess whether the association was driven by any single state-level observation; detailed results are reported in Supplementary Table S2.

Unlike RMSE-based trajectory fitting, which evaluates the agreement between simulated and observed mobility data used for parameter estimation, the vaccination analysis examines the association of CH with a distinct behavioral outcome that was not used to estimate CH. The Leave-One-State-Out analysis further assesses whether this association is driven by individual jurisdictions. These analyses provide complementary evidence beyond trajectory fitting, although they do not directly validate the underlying cognitive mechanisms assumed in the simulation or establish a causal relationship.

4. Results

4.1. Estimation of the Simulation-Derived Cognitive Hierarchy Parameter

The agent-based simulation was used to reproduce observed Voluntary Curfew Index (VCI) trajectories for the 48 U.S. states and the District of Columbia. For each jurisdiction, the simulation-derived Cognitive Hierarchy (CH) parameter was estimated by minimizing the Root Mean Square Error (RMSE) between simulated and observed VCI trajectories.

Figure 4 illustrates the observed and simulated Voluntary Curfew Index (VCI) trajectories for eight illustrative jurisdictions, one selected from each of the eight BEA regions. The complete trajectories for all 48 U.S. states and the District of Columbia are provided in Supplementary Figures S1–S10. Overall, the simulation reproduced the broad temporal patterns of voluntary mobility reduction, although model fit varied across jurisdictions. Figure 5 presents the jurisdiction-specific RMSE values. Among the 48 U.S. states and the District of Columbia, 40 had an average daily RMSE below 10 VCI points, indicating relatively close correspondence between observed and simulated trajectories in most cases. However, variation in RMSE indicates that simulation fit was not uniform and should be considered when interpreting the estimated CH parameters.

The estimated CH parameters were subsequently incorporated into the empirical regression models to examine their association with cumulative voluntary mobility reduction.

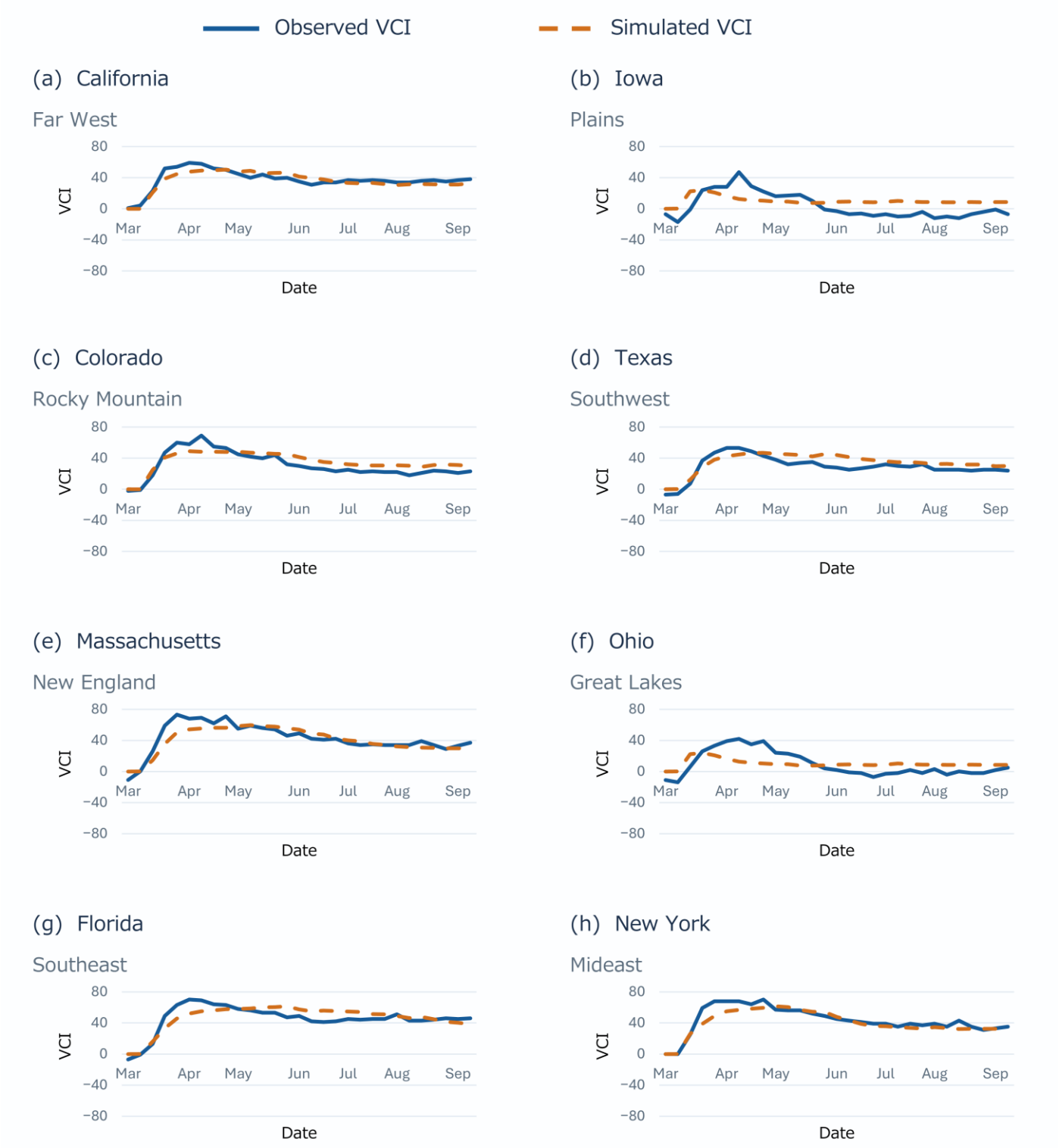


Figure 4. Comparison of observed and simulated Voluntary Curfew Index (VCI) trajectories for eight illustrative jurisdictions, one from each BEA region: (**a**) California (Far West), (**b**) Iowa (Plains), (**c**) Colorado (Rocky Mountain), (**d**) Texas (Southwest), (**e**) Massachusetts (New England), (**f**) Ohio (Great Lakes), (**g**) Florida (Southeast), and (**h**) New York (Mideast). Blue solid lines indicate observed VCI, and orange dashed lines indicate simulated VCI. All panels use the same vertical scale (−80 to 80 VCI points). Trajectories for all 49 jurisdictions are provided in Supplementary Figures S1–S10.

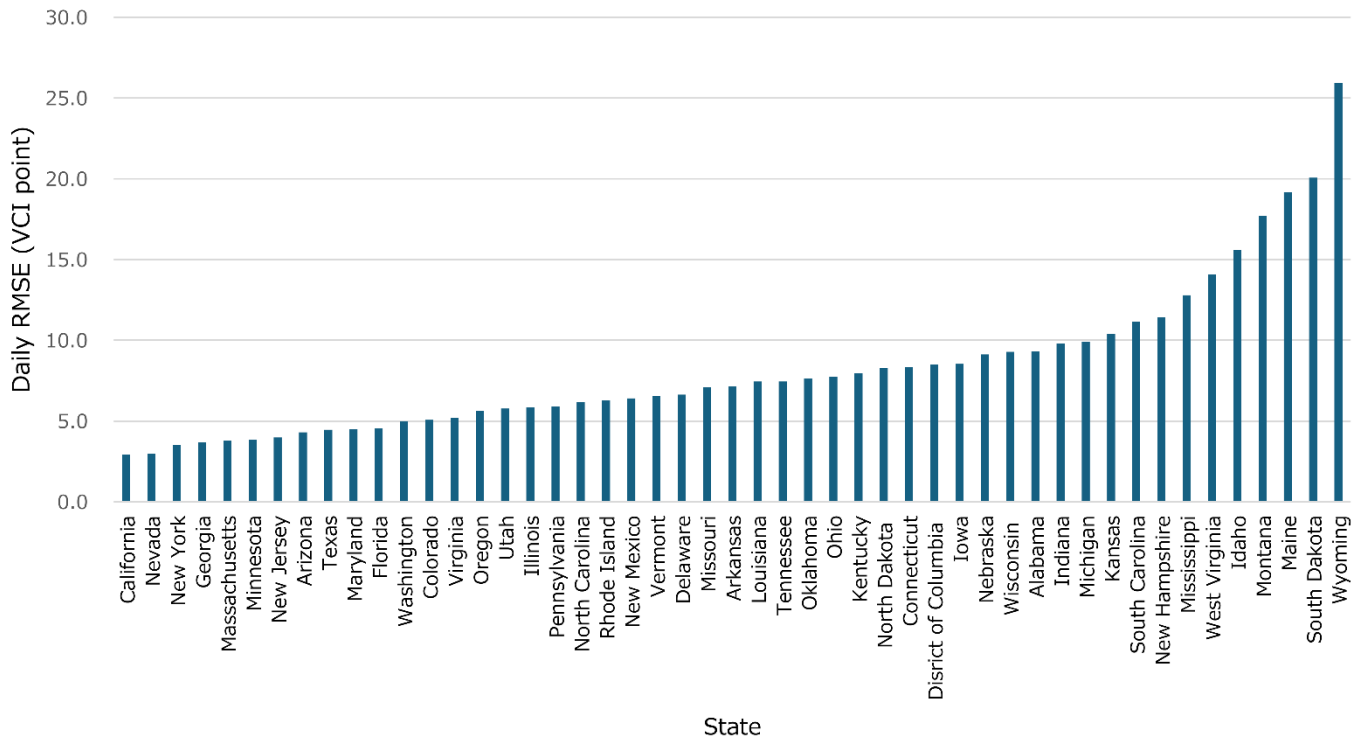


Figure 5. State-level root mean square error (RMSE) between observed and simulated Voluntary Curfew Index (VCI) trajectories.

4.2. Association Between Cognitive Hierarchy and Voluntary Mobility Reduction

Table 3 presents the ordinary least squares regression results for cumulative voluntary mobility reduction, measured by the Summation of the Voluntary Curfew Index (SVCI).

Model (1), which included demographic, socioeconomic, and institutional characteristics, had an adjusted R^2 of 0.525. COVID-19 case counts, median household income, and the presence of a statewide stay-at-home order were positively associated with SVCI.

After Republican vote share, religious attendance, and the simulation-derived Cognitive Hierarchy (CH) parameter were added in Model (2), adjusted R^2 increased to 0.798. Republican vote share was negatively associated with SVCI, whereas CH showed a positive and statistically significant association with voluntary mobility reduction ($\beta = 289.099$, SE = 64.888, $p < 0.001$).

Model (3), which replaced CH with the Big Five personality traits, yielded an adjusted R^2 of 0.689, with none of the personality traits reaching statistical significance. When CH and the Big Five traits were included together in Model (4), CH remained positively associated with SVCI ($\beta = 280.938$, SE = 68.167, $p < 0.001$), while none of the Big Five traits was statistically significant.

In Model (5), which retained CH and the Big Five traits but excluded Republican vote share, CH remained positively associated with SVCI ($\beta = 333.362$, SE = 77.133, 95% CI: 176.77–489.95, $p < 0.001$). Openness was positively associated with SVCI, whereas average age showed a negative association.

Overall, CH showed a positive and statistically significant association with voluntary mobility reduction across all specifications in which it was included. Subsequent robustness analyses examined the stability of this association.

Table 3. Associations between the simulation-derived Cognitive Hierarchy parameter and cumulative voluntary mobility reduction (SVCI).

Dependent Variable: Summation of the Voluntary Curfew Index (SVCI)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5) †
COVID-19 cases	0.235 ***	0.164 ***	0.239 ***	0.163 **	0.134
	(0.079)	(0.059)	(0.086)	(0.074)	(0.085)
Population density	−0.006	−0.042	−0.072 *	−0.045	−0.003
	(0.040)	(0.029)	(0.040)	(0.034)	(0.037)
Average age	−19.418	−16.947	−9.678	−27.388	−52.950 *
	(27.754)	(19.784)	(31.939)	(26.810)	(29.944)
Median household income	0.031 ***	0.001	0.019 **	0.005	0.005
	(0.007)	(0.006)	(0.008)	(0.008)	(0.009)
Stay-at-home order	547.809 ***	150.475	171.576	98.721	104.564
	(168.892)	(122.071)	(174.296)	(145.489)	(168.506)
Penalty provision	108.099	72.363	67.174	87.379	156.519
	(115.350)	(77.393)	(101.134)	(83.936)	(94.642)
Republican vote share		−23.466 ***	−30.271 ***	−24.321 ***	
		(5.303)	(7.967)	(6.757)	
Religious attendance		3.956	2.435	−0.244	−14.077
		(7.654)	(10.663)	(8.859)	(9.245)
Cognitive Hierarchy (CH)		289.099 ***		280.938 ***	333.362 ***
		(64.888)		(68.167)	(77.133)
Extraversion			−0.857	0.090	3.760
			(6.313)	(5.235)	(5.948)
Agreeableness			5.146	4.612	10.582
			(7.195)	(5.963)	(6.634)
Conscientiousness			10.584	7.553	1.474
			(7.647)	(6.378)	(7.124)
Neuroticism			8.631	8.648	10.537
			(7.854)	(6.507)	(7.513)
Openness			4.873	2.252	18.000 **
			(9.543)	(7.933)	(7.664)
Constant	−1445.623	1411.562	−832.265	696.552	−66.655
	(1150.774)	(1032.417)	(1511.611)	(1306.205)	(1492.883)
Observations	49	49	49	49	49
R^2	0.585	0.836	0.773	0.849	0.791
Adjusted R^2	0.525	0.798	0.689	0.787	0.714
F statistic	9.854 ***	22.042 ***	9.185 ***	13.637 ***	10.204 ***
	(df = 6, 42)	(df = 9, 39)	(df = 13, 35)	(df = 14, 34)	(df = 13, 35)

Note: Standard errors are reported in parentheses. † Model (5) was used for the subsequent spatial robustness analyses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Spatial Patterns of Voluntary Mobility Reduction

Using the queen-contiguity spatial weights matrix, cumulative voluntary mobility reduction (SVCI) showed significant positive spatial autocorrelation across the 48 U.S. states and the District of Columbia (Global Moran's I = 0.308, $p < 0.001$), indicating that neighboring jurisdictions tended to exhibit similar levels of mobility reduction.

Local Moran's I (LISA) further identified significant High–High and Low–Low clusters, together with fewer High–Low and Low–High spatial outliers (Figure 6). These findings indicate that voluntary mobility reduction was geographically clustered. Whether spatial dependence remained after accounting for the explanatory variables was examined in the subsequent robustness analyses.

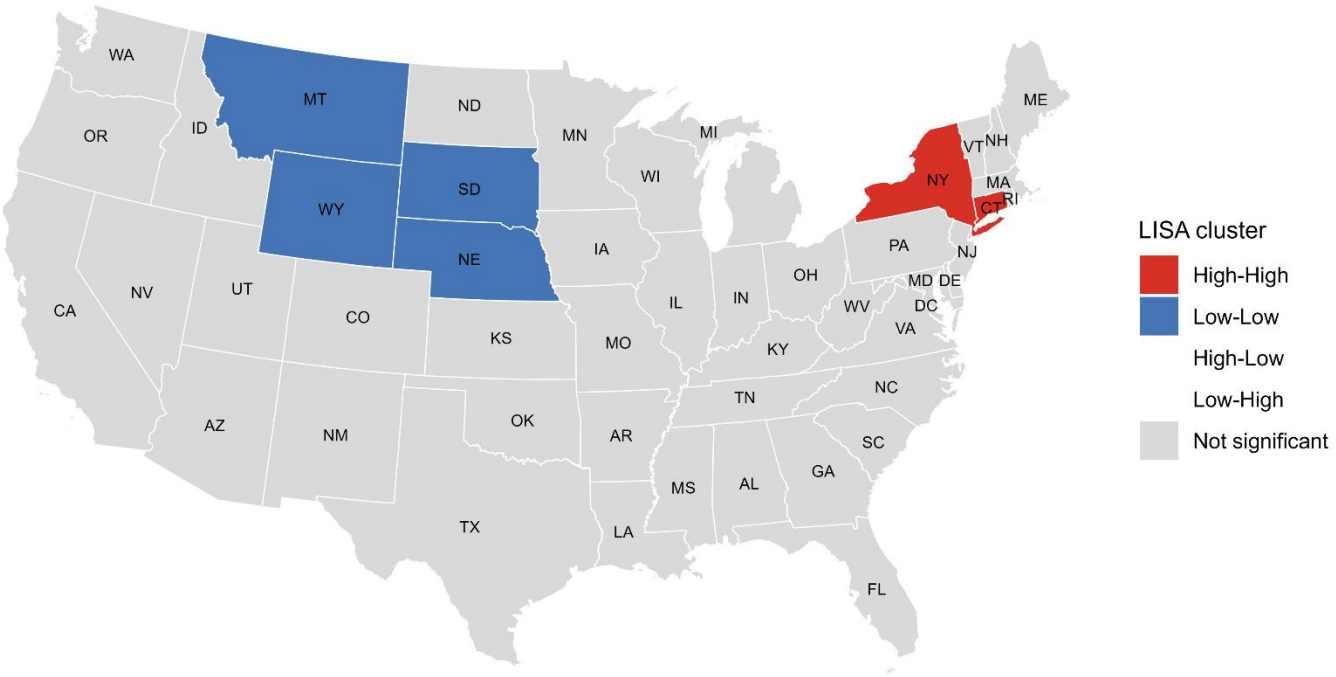


Figure 6. Local Moran's *I* (LISA) cluster map of cumulative voluntary mobility reduction (SVCI).

4.4. External Validation Using COVID-19 Vaccination Uptake

Because the simulation-derived Cognitive Hierarchy (CH) parameter was estimated from the mobility data used in the primary analysis, external validation was conducted using the full COVID-19 vaccination rate (FULL_VAX) in 2021 as an independent behavioral outcome. The analysis covered the same 48 U.S. states and the District of Columbia and used the vaccination dataset of Webster et al. [27].

As shown in Table 4, adding CH to the Big Five personality model increased the adjusted R^2 from 0.412 to 0.508, with CH positively associated with vaccination uptake ($p < 0.01$). The association remained significant after adding COVID-19 policy-related variables (adjusted $R^2 = 0.538$, $p < 0.01$) and Republican vote share (adjusted $R^2 = 0.666$, $p < 0.05$). Although the CH association was attenuated after political context was included, it remained statistically significant.

A Leave-One-State-Out sensitivity analysis showed that the positive CH association remained significant across all iterations (Supplementary Table S2). These results indicate that the association of CH extended beyond the mobility data used for its estimation. However, the findings represent associations and do not establish a causal effect of CH on vaccination behavior.

Table 4. External validation using state-level COVID-19 vaccination uptake.

Model	Additional Explanatory Variables	Adjusted R^2	CH Coefficient (SE)
V1	Big Five	0.412	—
V2	Big Five + CH	0.508	4.382 *** (1.427)
V3	+Policy variables	0.538	4.276 *** (1.395)
V4	+Republican vote share	0.666	3.136 ** (1.218)

Note: The dependent variable is the state-level full COVID-19 vaccination rate (FULL_VAX) in 2021. CH = Cognitive Hierarchy. Standard errors are reported in parentheses. ** $p < 0.05$, *** $p < 0.01$.

5. Robustness Analyses

5.1. Model Specification and Statistical Robustness

A series of robustness analyses was conducted to assess whether the positive association between the simulation-derived Cognitive Hierarchy (CH) parameter and cumulative voluntary mobility reduction was sensitive to model specification, multicollinearity, or heteroskedasticity. The principal results are summarized in Table 5.

Nested model comparisons showed that adding Republican vote share, religious attendance, and CH to Model (1) significantly improved model fit ($F(3, 39) = 19.863$, $p < 0.001$). To isolate the contribution of CH, an intermediate model containing Republican vote share and religious attendance but excluding CH was compared with Model (2). Adding CH significantly improved model fit ($F(1, 39) = 19.851$, $p < 0.001$). Similarly, comparing Models (3) and (4) showed that adding CH to the Big Five personality specification significantly improved model fit ($F(1, 34) = 16.985$, $p < 0.001$).

Multicollinearity diagnostics showed a maximum Variance Inflation Factor (VIF) of 4.39 in Model (5), indicating no severe multicollinearity in the specification used for subsequent spatial analyses. HC3 heteroskedasticity-consistent standard errors also left the direction and statistical significance of the CH coefficient unchanged. To assess sensitivity to individual observations, a Leave-One-State-Out (LOSO) analysis was additionally conducted for Model (5). Across the 49 iterations, the estimated CH coefficient ranged from 287.73 to 370.93 and remained positive and statistically significant in all cases ($p < 0.05$). These results suggest that the positive association between CH and SVCI was not driven by any single jurisdiction, although they do not eliminate concerns regarding the limited sample size. Detailed jurisdiction-specific results are reported in Supplementary Table S5.

Taken together, these analyses suggest that the positive association between CH and voluntary mobility reduction was stable across alternative model specifications, heteroskedasticity-consistent estimation, and the LOSO sensitivity analysis, with no evidence of severe multicollinearity. Spatial robustness is examined separately in Section 5.2.

Table 5. Summary of robustness analyses for the association between CH and voluntary mobility reduction.

Diagnostic	Comparison/Model	Result	Interpretation
Nested F-test	Model (1) → Model (2)	$F(3, 39) = 19.863$, $p < 0.001$	Republican vote share, religious attendance, and CH jointly improved model fit
Nested F-test	Intermediate model → Model (2)	$F(1, 39) = 19.851$, $p < 0.001$	Addition of CH improved model fit beyond Republican vote share and religious attendance
Nested F-test	Model (3) → Model (4)	$F(1, 34) = 16.985$, $p < 0.001$	Addition of CH improved model fit beyond the Big Five personality traits
Maximum VIF	Model (5)	4.39	No indication of severe multicollinearity in the specification used for spatial robustness analyses
HC3 robust SE	Model (5)	CH remained statistically significant	Association between CH and SVCI was robust to heteroskedasticity-consistent inference
Global Moran's I	SVCI	0.308 ($p < 0.001$)	Significant spatial clustering in cumulative voluntary mobility reduction
Residual Moran's I	Model (5)	−0.085 ($p = 0.746$)	Little evidence of residual spatial autocorrelation

Note: The Model (1)–Model (2) comparison evaluates the joint contribution of Republican vote share, religious attendance, and CH. The intermediate-model comparison isolates the incremental contribution of CH. VIF = Variance Inflation Factor; HC3 = heteroskedasticity-consistent covariance estimator; SVCI = Summation of the Voluntary Curfew Index; CH = Cognitive Hierarchy.

5.2. Spatial Robustness

Spatial robustness analyses were conducted to assess whether geographic dependence affected the association between the simulation-derived Cognitive Hierarchy (CH) parameter and cumulative voluntary mobility reduction. Although SVCI exhibited significant positive spatial autocorrelation (Global Moran's I = 0.308, $p < 0.001$), the residuals from Model (5) showed little evidence of remaining spatial dependence (Moran's I = −0.085, $p = 0.746$).

The CH coefficient remained positive and statistically significant in both Spatial Lag and Spatial Error Models. Similar results were obtained using an alternative distance-based spatial weights matrix based on an 800-km threshold between jurisdictional geometric centroids.

These findings indicate that the positive association between CH and voluntary mobility reduction was not substantially altered after accounting for spatial dependence. Detailed results for the spatial specifications are provided in Supplementary Tables S1 and S3.

6. Discussion

6.1. Simulation-Derived Cognitive Hierarchy and COVID-19-Related Behavior

The primary mobility analysis showed that the simulation-derived Cognitive Hierarchy (CH) parameter was positively associated with voluntary mobility reduction during the COVID-19 pandemic after accounting for demographic, socioeconomic, political, institutional, social, and personality characteristics. This association remained statistically significant across alternative model specifications, heteroskedasticity-consistent estimation, and spatial robustness analyses, suggesting that CH provides complementary information beyond conventional regional characteristics.

The CH parameter should be interpreted as a model-dependent measure of recursive reasoning represented in the simulation. For example, individuals may adjust their mobility decisions not only in response to public health recommendations but also according to their expectations about how others will behave. A higher estimated CH value indicates that the simulation required relatively greater weight on higher levels of such recursive reasoning to reproduce the observed mobility pattern. It does not imply that individuals in a jurisdiction possess greater cognitive ability or necessarily exhibit stronger compliance with public health policies.

The CH association also remained positive when Big Five personality traits were included, indicating that the behavioral information represented by CH was not fully captured by conventional psychological measures. Its stability across heteroskedasticity-consistent and spatial analyses further supports the robustness of this association.

External validation using COVID-19 vaccination uptake provided an additional test because vaccination represented a distinct behavioral outcome observed during a later phase of the pandemic and was not used to estimate CH. The positive association between CH and vaccination uptake remained statistically significant after accounting for personality, policy-related, and political variables, suggesting that the association extended beyond the mobility trajectories used for parameter estimation.

An important limitation of the primary analysis is that CH was estimated from VCI trajectories, whereas SVCI was constructed from the same underlying mobility data. Therefore, the observed CH–SVCI association may partly reflect this shared information and should not be interpreted as independent predictive evidence. The vaccination analysis provides complementary evidence because vaccination uptake was not used to estimate CH. Nevertheless, this cross-outcome association does not establish that CH directly measures recursive reasoning or causally determines mobility or vaccination behavior.

Unobserved regional factors and model assumptions may also contribute to the observed associations.

More broadly, these findings illustrate how agent-based simulation can complement empirical analysis by generating interpretable behavioral parameters that can be evaluated against observed outcomes.

6.2. Personality Traits and Political Context

The findings suggest that personality traits, political context, and the simulation-derived Cognitive Hierarchy (CH) parameter represent distinct sources of information about regional variation in COVID-19-related behavior. Among the Big Five traits, Openness was positively associated with voluntary mobility reduction in Model (5), consistent with previous research linking personality characteristics to COVID-19-related health behavior.

Openness and CH should nevertheless be interpreted differently. Openness represents a relatively stable psychological disposition, whereas CH is a simulation-derived, model-based parameter representing the degree of recursive reasoning required to reproduce observed collective mobility trajectories.

Republican vote share was also associated with voluntary mobility reduction in several model specifications, but CH is not intended to represent political orientation. The CH association remained statistically significant when Republican vote share was included, indicating that it was not fully accounted for by this political measure.

The attenuation of the stay-at-home order and COVID-19 case coefficients after additional variables were introduced suggests some overlap with broader regional characteristics. These changes should be interpreted cautiously because they do not establish causal mediation.

6.3. Methodological Implications

The methodological contribution of this study lies in linking simulation-derived behavioral parameter estimation with empirical analysis of COVID-19-related behavior. Rather than using agent-based simulation only to reproduce collective dynamics, the approach estimates an interpretable behavioral parameter and evaluates its association with observed outcomes alongside conventional regional characteristics.

In this study, CH was estimated from mobility trajectories and evaluated in models of voluntary mobility reduction, followed by external validation using COVID-19 vaccination uptake. This approach provides a means of assessing whether behavioral information inferred through simulation extends beyond the data used for parameter estimation.

More generally, simulation-derived behavioral parameters may complement conventional empirical variables when they are substantively interpretable and evaluated against observational data. The CH framework can also be distinguished from established models of health-related decision-making. The Theory of Planned Behavior emphasizes attitudes, subjective norms, and perceived behavioral control as determinants of behavioral intentions [28], whereas the Health Belief Model focuses on perceived susceptibility, severity, benefits, and barriers [29]. In contrast, CH represents heterogeneity in recursive expectations about others' decisions within the simulation rather than directly measuring individual beliefs or intentions. These frameworks are conceptually complementary, although the present study does not directly test their constructs or compare their predictive performance with CH.

The present findings can also be compared with studies conducted in other countries. Matsui and Hashimoto [25] applied a simulation-based approach incorporating Cognitive Hierarchy theory to examine responses to stay-at-home requests across Japanese prefectures. The present study extends this approach to U.S. jurisdictions and further examines

its association with subsequent vaccination uptake as a distinct behavioral outcome. Roelofs et al. [11] examined the relationship between regional mobility patterns and COVID-19 incidence in the Netherlands, highlighting the importance of spatial and temporal heterogeneity. Although these studies differ in their research objectives, outcome measures, and analytical frameworks, they underscore the importance of regional characteristics in understanding pandemic-related behavior and its public health context. Direct quantitative comparisons remain limited by differences in institutional settings, policy responses, and data structures.

From a public health perspective, understanding regional differences in behavioral responses to health-related policies may help inform risk communication strategies and the design of context-sensitive preventive interventions during future infectious disease outbreaks. Simulation-derived behavioral parameters may provide complementary information about collective responses that is not fully captured by conventional regional characteristics. However, the present study does not directly measure individual exposure to SARS-CoV-2, clinical outcomes, or the effectiveness of specific medical interventions. Therefore, its findings should not be interpreted as evidence that higher CH values reduce infection risk or improve clinical outcomes. From an ethical perspective, particular caution is required to avoid attributing individual cognitive abilities or moral qualities to populations based on aggregate, simulation-derived parameters.

6.4. Limitations

Several limitations should be acknowledged. First, the analysis was based on 48 U.S. states and the District of Columbia (n = 49), with Alaska and Hawaii excluded because state-level personality data were unavailable. The relatively small sample size, particularly in relation to the number of explanatory variables included in the regression models, may reduce statistical power to detect smaller associations and increase uncertainty in coefficient estimates and the risk of overfitting. Although the Leave-One-State-Out sensitivity analysis indicated that the positive association between CH and SVCI was not driven by any single jurisdiction, this does not fully resolve concerns regarding model stability and statistical power. The findings may therefore not generalize directly to regions with different geographical, institutional, or cultural contexts. Because the analysis was conducted at the state level, the observed associations should also not be interpreted as individual-level relationships.

Second, the mobility and vaccination datasets have potential measurement limitations. Google mobility data are based on users who enabled Location History and may not fully represent the broader population [18]. Moreover, transit-station visits are influenced not only by voluntary behavioral restraint but also by regional differences in public transportation infrastructure, service availability, and transportation choices. Differences in location classification and data coverage may also affect comparisons across jurisdictions. The direction and magnitude of these potential measurement biases cannot be reliably quantified from the available aggregated data. The sensitivity of CH estimates to the choice of Google mobility category was not examined in this study. Similarly, state-level vaccination rates may be affected by differences in reporting practices, vaccination eligibility, access to vaccines, and healthcare infrastructure. Consequently, the association between CH and vaccination uptake should not be interpreted as direct evidence of individual-level behavioral mechanisms. Further validation using alternative mobility indicators and independent behavioral outcomes is warranted.

Third, the agent-based model relies on several simplifying assumptions that may influence the estimated CH parameters. Cognitive reasoning levels are assumed to follow a Poisson distribution, and the simulation uses 1000 agents with fixed parameters governing information dissemination and behavioral updating. Only the CH parameter was

varied to fit the observed mobility trajectories. Consequently, unmodeled differences in information exposure, social interactions, or behavioral responses across jurisdictions may be reflected in the estimated CH values. The estimates may also depend on the assumed model structure and fixed parameter settings. Therefore, CH should be interpreted as a model-dependent representation of collective behavioral dynamics rather than as a direct measure of individual cognitive ability. Future studies should evaluate the sensitivity of CH estimates to alternative model assumptions and parameter settings.

Fourth, CH and SVCI were derived from overlapping mobility data, which limits the independence of the primary empirical analysis. Although vaccination uptake provides a distinct outcome for assessing the relevance of CH beyond the original mobility trajectories, it does not independently confirm the cognitive mechanisms represented by the simulation. Future research should examine the stability of CH estimates across different calibration periods and model assumptions and evaluate their predictive performance using independent behavioral data.

7. Conclusions

This study examined whether a simulation-derived Cognitive Hierarchy (CH) parameter provides complementary information for explaining regional differences in COVID-19-related behavior. CH was estimated from observed mobility trajectories using an agent-based simulation and incorporated into empirical models alongside conventional regional characteristics.

CH was positively associated with voluntary mobility reduction and remained statistically significant across alternative model specifications, heteroskedasticity-consistent estimation, and spatial robustness analyses. External validation further showed a positive association between CH and COVID-19 vaccination uptake, an independent outcome not used to estimate CH. These associations should not, however, be interpreted as evidence of causal effects on mobility or vaccination behavior.

Overall, the findings indicate that simulation-derived behavioral parameters can complement conventional regional characteristics in empirical analyses of COVID-19-related behavior and illustrate an approach for linking agent-based behavioral modeling with observational data.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/covid6110194/s1: Table S1: Spatial regression results comparing OLS, Spatial Lag, and Spatial Error Models; Table S2: Leave-One-State-Out (LOSO) sensitivity analysis for the association between the simulation-derived Cognitive Hierarchy (CH) parameter and state-level COVID-19 vaccination uptake; Table S3: Sensitivity analysis using alternative spatial weights matrices (Model (5)); Table S4: Fixed simulation parameters used in the CH parameter estimation procedure; Table S5: Leave-One-State-Out sensitivity analysis for Model (5); Table S6: Cumulative reported COVID-19 cases in 2020 across the 49 study jurisdictions; Figure S1: Observed and simulated VCI trajectories for Far West: California, Nevada, Washington, and Oregon; Figure S2: Observed and simulated VCI trajectories for Mideast: Delaware, Maryland, New Jersey, New York, Pennsylvania, and the District of Columbia; Figure S3: Observed and simulated VCI trajectories for New England: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont; Figure S4: Observed and simulated VCI trajectories for Plains (part 1 of 2): Iowa, Kansas, Minnesota, and Missouri; Figure S5: Observed and simulated VCI trajectories for Plains (part 2 of 2): Nebraska, North Dakota, and South Dakota; Figure S6: Observed and simulated VCI trajectories for Rocky Mountain: Idaho, Colorado, Montana, Utah, and Wyoming; Figure S7: Observed and simulated VCI trajectories for Southeast (part 1 of 2): Alabama, Arkansas, Florida, Georgia, Kentucky, and Louisiana; Figure S8: Observed and simulated VCI trajectories for Southeast (part 2 of 2): Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia; Figure S9:

Observed and simulated VCI trajectories for Southwest: Arizona, New Mexico, Oklahoma, and Texas; Figure S10: Observed and simulated VCI trajectories for Great Lakes: Illinois, Indiana, Michigan, Ohio, and Wisconsin. For Figures S1–S10, blue solid lines indicate observed VCI, and orange dashed lines indicate simulated VCI. All panels use the same vertical scale (−80 to 80 VCI points). Supplementary Dataset S1, state-level analytical dataset used in the empirical analyses; STROBE Checklist, completed reporting checklist for the ecological observational component.

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Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets analyzed in this study were obtained from publicly available sources cited in the References. The state-level analytical dataset used in the primary mobility analyses, including the estimated Cognitive Hierarchy (CH) parameters, is provided as a supplementary CSV file. The COVID-19 vaccination data used for external validation were obtained from the dataset reported by Webster et al. [27] and are not redistributed with this article. The R scripts (R version 4.5.2) used for statistical analyses and the NetLogo model (NetLogo version 6.2.1) used for the agent-based simulation are not publicly available. The analytical procedures, model specifications, pseudocode, and fixed simulation parameters are described in the manuscript and Supplementary Materials.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Mathematical Formulation of the Proposed Methodological Framework

Appendix A.1. Regression Model

$$SVCI_i = \beta_0 + \beta_1 CH_i + \sum_{k=2}^{K} \beta_k X_{ki} + \varepsilon_i$$

where $SVCI_i$ denotes the Summation of the Voluntary Curfew Index for state i, CH_i denotes the simulation-derived Cognitive Hierarchy parameter, $X_k i$ denotes the conventional regional explanatory variables, and ε_i is the random error term.

Appendix A.2. Spatial Lag Model

$$y = \rho W y + X\beta + \varepsilon$$

where W is the spatial weights matrix and ϱ is the spatial autoregressive coefficient.

Appendix A.3. Spatial Error Model

$$y = X\beta + u$$

$$u = \lambda W u + \varepsilon$$

where λ denotes the spatial error coefficient.

Appendix A.4. Estimation of the Cognitive Hierarchy Parameter

$$RMSE = sqrt\left[(1/T)\Sigma_t\left(VCI_t^{obs} - VCI_t^{sim}\right)^2\right]$$

where

- VCI_t^{obs} denotes the observed Voluntary Curfew Index,
- VCI_t^{sim} denotes the simulated Voluntary Curfew Index.

The CH parameter for each state was estimated by minimizing the RMSE between the observed and simulated VCI trajectories.

Appendix A.5. Cognitive Hierarchy Distribution

$$P(L = k) = exp(-\tau)\tau^k/k!$$

Following Camerer et al. [8], the proportions of Cognitive Hierarchy levels were assumed to follow a Poisson distribution, where L denotes the reasoning level and τ is the mean Cognitive Hierarchy parameter.

Appendix A.6. Spatial Weights Matrices

Two row-standardized spatial weights matrices were examined:

- Queen-contiguity matrix
- Distance-based matrix connecting states whose geometric centroids were within 800 km.

The robustness analyses reported in Supplementary Table S3 confirmed that the principal findings were robust to alternative specifications of the spatial weights matrix.

Appendix A.7. Algorithm A1: Pseudo-Code for the CH Parameter Estimation Procedure

Algorithm A1 presents the pseudocode for the CH parameter estimation procedure described analytically in Appendix A, Sections A.4 and A.5. For each state, the algorithm performs a grid search over candidate CH values, simulates the corresponding Voluntary Curfew Index (VCI) trajectory, and selects the value that minimizes the RMSE between the simulated and observed trajectories. The fixed simulation parameters used in this procedure are reported in Supplementary Table S4. The full mathematical formulation is provided in Appendix A, whereas the complete specification of the underlying agent-based sub-models is described in Matsui and Hashimoto [25].

Algorithm A1 Estimation of the state-level Cognitive Hierarchy (CH) parameter

Input: Observed VCI trajectory $\{VCI_{\text{obs},s}(t)\}$, $t = 1, \ldots, 210$, for jurisdiction s

Input: Candidate CH grid: $CH \in \{0.10, 0.15, \ldots, 2.00\}$

Input: Fixed simulation parameters (Supplementary Table S4): N, S_1, S_2, S_3, S_4, b_1–b_4

1: **procedure ESTIMATE-CH**(s)

2: **for** each candidate value CH_k in the grid **do**

3: initialize $N = 1{,}000$ agents

4: assign each agent a cognitive level drawn from $\text{Poisson}(\lambda = CH_k)$ [8]

for $tick = 1$ to 210 **do**

run sub-models Y_1–Y_4 to update agent states
See [25], Appendix A, for full specifications of the sub-models.

end for

record simulated trajectory $VCI_{\mathrm{sim},s}(t; CH_k)$

$$\mathrm{RMSE}_s(CH_k) \leftarrow \sqrt{\frac{1}{210}\sum_t (VCI_{\mathrm{obs},s}(t) - VCI_{\mathrm{sim},s}(t; CH_k))^2}$$

end for

$$CH_s^* \leftarrow \underset{CH_k}{\mathrm{argmin}}\ \mathrm{RMSE}_s(CH_k)$$

return CH_s^*

end procedure

Output: Estimated CH parameter CH_s^* for each of the 49 jurisdictions (48 U.S. states and the District of Columbia).

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