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Trajectories and patterns of US counties' policy responses to the COVID-19 pandemic: A sequence analysis approach

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ABSTRACT

Background: It is increasingly recognized that policies played a role in mitigating or exacerbating health inequities during the COVID-19 pandemic. While US counties were particularly active in policymaking, limited work has characterized geographic and temporal variation in pandemic-era policymaking at the local level, a prerequisite for later studies examining the health effects of these policies. This paper fills this gap by characterizing county-level COVID-19-related policy trajectories over time using a novel national policy database and innovative methods.

Methods: Data came from the US COVID-19 County Policy (UCCP) Database, including 309 counties in 50 states plus Washington DC during January 2020 to December 2021. We examined measures of overall policy comprehensiveness, as well as three domains including containment and closure, economic response, and public health. We applied sequence analysis to characterize county-level trajectories overall and within each policy domain, and cluster analysis to group similar trajectories.

Results: There was wide variation in policymaking, with nearly half of counties demonstrating consistently comprehensive policymaking, about 15–20% with consistently low comprehensiveness, and the remainder exhibiting intermittent comprehensiveness. Economic policies were less comprehensive than containment/closure and public health policies. There was also substantial variation within and across states, and associations with county characteristics.

Conclusion: This study is among the first to document substantial geographic and temporal variation in a variety of US county-level COVID-19-related policies, which likely contributed to health disparities during and after the pandemic. Future work should evaluate how these different policy trajectories differentially affected health and social outcomes.

1. Introduction

The COVID-19 pandemic resulted in over a million deaths in the US and widespread economic hardship, especially among marginalized populations (Centers for Disease Control, 2024; Brown et al., 2022; Mooney et al., 2023; Hoskote et al., 2022). There was substantial local variation in COVID-19 infection and mortality, and other health and economic outcomes (Khan et al., 2022; Li et al., 2021). Since a federally coordinated policy response was often lacking, variations in local policy responses are increasingly recognized as potential contributors to pandemic-related health and socioeconomic disparities (Carter and May, 2020b).

Understanding geographic and temporal patterning of policy responses to the pandemic is a critical first step to social and legal epidemiology research in this area (Dawes et al., 2022). Prior work documented variation at national and state levels: the Oxford COVID-19 Government Response Tracker recorded policy responses across over 180 countries over time including the US. (Hale et al., 2021) It focused on containment and closure policies and showed substantial variation in timing of policy phase-in and phase-out across countries, as well as across states within the US. Likewise, the State Policy Response to COVID-19 (SPRC19) database tracked US state policy action in response to COVID-19 in several policy domains (Boehmke, Desmarais, & Eastman, 2023). The COVID-19 US State Policy database also documented state variation in COVID-19-related policies, including containment and closure policies and policies to reduce economic precarity (Raifman, Nocka, & Jones, 2020; Skinner et al., 2022). Subsequent studies have examined how temporal and geographic variation in federal and state policies like paid sick leave or eviction moratoria affected individual physical and mental health (Assaf et al., 2024; Batra et al., 2023; Jackson, Chiang, & Hamad, 2024; Leifheit et al., 2021; Raifman, Raderman, Skinner, & Hamad, 2021; Wells, Jackson, Leung, & Hamad, 2024). Yet few studies have examined county-level policymaking, despite preliminary evidence of substantial variation within and across

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states (Hamad et al., 2022a; Jackson et al., 2022). For example, one study examined county characteristics from a small subset of local areas but without specifically examining policies (Pan et al., 2020). Moreover, few have systematically captured longitudinal variation in these policies.

Another challenge in the existing literature on this topic is that studies often focus on examining the effects of a single pandemic-era policy—e.g., mask mandates (Guy et al., 2021)—without taking into consideration the broader policy landscape. As policies tend to bundle together, often associated with partisanship (Grumbach, 2018), more holistically and systematically characterizing the multitude and co-occurrence of policies is necessary to better adjust for confounding.

This study helps fill these knowledge gaps. We drew on data from the novel US COVID-19 County Policy Database (Hamad et al., 2022a; Hamad et al., 2022b), which includes data on a range of 26 county-level policy responses during 2020–2021. We employed a novel application of sequence analysis and cluster analysis to analyze sequences and trajectories of COVID-19 pandemic policies across policy domains and overall. This approach highlighted patterns and trajectories in timing of policy adoption and subsequent policy easing and reimposition. It sets the stage for future studies to explore determinants and consequences of these trajectories of policy comprehensiveness on health and social outcomes.

2. Methods

2.1. Data

We used nationwide data on county policies from the novel US COVID-19 County Policy (UCCP) Database. The Database and methodology for data collection have been described previously (Hamad et al., 2022a; Hamad et al., 2022b). Briefly, counties were selected for inclusion randomly using probability-proportional-to-size sampling, with the goal of including at least one county in all 50 states and Washington DC, and overrepresentation of counties ranked highly on the CDC's Social Vulnerability Index (Centers for Disease Control and Prevention, 2024). The UCCP Database includes weekly data on 26 policies in 309 US counties, and a total of 101 weeks during January 2020 to December 2021 (total county-week observations = 31,209). While the US has more than 3,000 counties, the present sample includes over half the US population. Additional details on sampling strategy and county list are included in the Supplement and Supplemental Table 1.

The 26 policy indicators include three policy domains: 1) containment and closure policies (e.g., school, bar, and restaurant closures); 2) economic response policies (e.g., income, housing, and nutrition support); and 3) public health policies (e.g., testing, mask mandates). These were selected because they are likely to affect health (Supplemental Table 2), and they were based in part on national policies collected in the Oxford COVID-19 Government Response Tracker (Hale et al., 2021). Data collectors searched the internet using standardized techniques, prioritizing information from government websites, to gather information retrospectively on selected 2020–2021 county policies on a week-by-week basis. For each policy in each county-week, the data collectors scored its comprehensiveness. For example, for restrictions on public events, categories included: minimal ($\geq$50% capacity) limitations, major (<50% capacity) limitations, recommended cancellation, and required cancellation. Data entry was conducted using REDCap (Patridge & Bardyn, 2018). Double-data entry was conducted on a sub-sample to ensure inter-rater reliability (Supplemental Tables 3–4). Additional details, including validation and inter-rater reliability of the data collection instruments, are provided in the online documentation of the UCCP Database (Hamad et al., 2022a; Hamad et al., 2022b).

2.2. Policy variables

We first constructed a composite measure of overall policy comprehensiveness across the 26 policy indicators as follows. For each policy, if there was no policy, this was coded as 0; the most comprehensive was coded as 1; and intermediate categories were fractions thereof. For instance, for public events, no restriction was coded as 0, minimal ($\geq$50% capacity) limitations was 0.25, major (<50% capacity) limitations was 0.50, recommended cancellation was 0.75, and required cancellation was 1. These individual policy variables were then summed to create the composite comprehensiveness index. We then categorized the comprehensiveness index into tertiles (low, medium, or high) for each week. Finally, we created additional composite measures of policy comprehensiveness for each of the three policy domains (containment/closure, economic response, and public health). More details are available in the Supplemental Methods and Supplemental Table 2.

2.3. Constructing Policy Trajectories

We applied sequence analysis and cluster analysis to characterize policy comprehensiveness trajectories. We then examined the association of the identified trajectory clusters with a range of county-level demographic characteristics (Table 1 for overall policy comprehensiveness and Supplemental Tables 5–7 by each policy domain).

2.3.1. Sequence analysis

To characterize the policy trajectory of each county across the study period, we used sequence analysis, a methodology first developed by biologists to compare DNA sequences (Abbott & Tsay, 2000; Kruskal, 1983). In recent years, sequence analysis has been applied in the social sciences (Halpin & Cban, 1998; Liao et al., 2022; Taylor et al., 2020; Vable et al., 2020). In this novel application, we treated counties as the unit of analysis (n = 309) and used sequence and cluster analysis to characterize and group similar patterns of county-level COVID-19 policy responses over time.

We characterized county-level trajectories by assigning a policy comprehensiveness "state" to each week based on the comprehensiveness score for that county-week (low, medium or high). We then visualized the heterogeneity over time using sequence index plots. To quantify differences between county-level trajectories, we then employed sequence analysis, which proceeds in several steps. First, we calculated the "costs" to transform each trajectory into every other trajectory in the data (Brzinsky et al., 2006). These costs reflect edit operations (substitution, insertion, or deletion of "states") needed to match trajectories across counties. Substitution costs were based on observed transition frequencies, where more frequent transitions (e.g., from low to medium) had lower costs than rarer transitions (e.g., from low to high). The maximum substitution cost was two, with a range of 0.27–1.85 in the data (see Supplemental Table 8 for the substitution cost matrix). Insertion and deletion costs were set to half of the maximum substitution cost (a cost of one), since a substitution can be thought of as one insertion and one deletion.

Using the example of overall policy comprehensiveness, the "cost" to move from low to medium comprehensiveness was 0.78, from low to high comprehensiveness was 1.76, and from medium to high comprehensiveness was 0.46 (Supplemental Table 8). Lower substitution costs represent more common transitions, suggesting that across the 309 county policy sequences, the transition from medium to high comprehensiveness was the most frequent, while the transition from low to high comprehensiveness was the least frequent, as reflected by the higher substitution costs.

We applied the Halpin duration-adjusted optimal matching algorithm (Halpin, 2010, 2017), which accounted for the amount of time spent in each "state" (Sankoff & Kruskal, 1983), to find the minimum total cost required to transform one sequence into another (Abbott & Tsay, 2000; MacIndoe & Abbott, 2004; Wu, 2000). The lower the costs, the more similar sequences were to each other. The result of the sequence analysis was a symmetric and square dissimilarity matrix (Abbott & Tsay, 2000), which represented the costs of transforming each sequence into all other sequences in the data.

Table 1
County characteristics, by cluster of overall policy comprehensiveness trajectory.

	Cluster of Overall Policy Comprehensiveness Trajectory				
	Mostly high, late predominantly medium (n = 102)	Mixed, but mostly medium (n = 24)	Mixed medium-high, late low (n = 91)	Early interrupted high, predominantly medium-low (n = 34)	Mixed low, interrupted medium-high (n = 58)
Characteristic	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
GDP (thousands of US$)	61,686.41 (107,018.92)	46,515.81 (53,380.94)	38,037.51 (61,659.37)	23,789.00 (28,195.39)	15,056.91 (27,309.78)
Poverty rate (%)	11.91 (4.39)	12.89 (6.02)	12.80 (4.78)	13.96 (4.72)	13.44 (4.56)
Population density (people per sq mi)	3129.61 (9054.23)	1085.21 (862.20)	1227.87 (2007.58)	590.81 (655.62)	364.53 (436.16)
Income (thousands of US$)	62,944.04 (24,857.51)	58,963.25 (19,654.02)	53,373.39 (12,643.78)	48,360.56 (9833.88)	46,484.02 (12,036.19)
Population in urban areas (%)	86.04 (16.62)	87.91 (15.41)	77.09 (27.96)	74.689 (25.81)	64.33 (28.09)
Racial segregation (%)	39.96 (11.97)	41.53 (10.69)	38.79 (12.32)	35.09 (10.36)	33.12 (11.03)
Democrat vote (%)	55.05 (15.65)	50.75 (16.46)	48.35 (16.12)	36.60 (14.77)	36.22 (14.60)
Race - White (%)	70.49 (16.35)	70.48 (19.04)	76.52 (16.30)	71.81 (14.49)	76.01 (17.07)
COVID-19 mortality rate (per 100,000 population)	2.02 (0.91)	2.59 (0.77)	2.39 (1.17)	2.81 (1.32)	2.71 (1.15)

Note: Data were drawn from the U.S. COVID-19 County Policy Database across 2020–2021, including 309 counties in 50 states and Washington D.C., linked with county characteristics from public sources. We categorized the overall policy comprehensiveness index into tertiles – low, medium, or high – and implemented sequence and cluster analysis to create clusters of counties with similar policy trajectories. Racial segregation was measured using the Black/White dissimilarity index. Abbreviation: GDP = real gross domestic product in thousands of chained (2012) dollars.

2.3.2. *Cluster analysis*

Next, we used cluster analysis to group similar county-level trajectories based on the dissimilarity matrix; this resulted in a set of distinct clusters, or groups of similar county-level trajectories (Halpin, 2016). We implemented agglomerative, hierarchical cluster analysis, which initially treated each unique trajectory as a separate cluster, and then serially combined clusters until only one cluster remained. Clusters were combined based on the Ward linkage (Ward, 1963), which maximized the similarities "within" clusters such that similar trajectories were sequentially clustered together (while maximizing the differences between clusters). We used cluster quality indicators to determine which cluster solutions best fit the observed data (Halpin, 2016). The Duda Hart cluster stopping rules and the Average Silhouette Widths were used to determine the right number of clusters (Supplemental Table 9) (Halpin, 2016; Rousseeuw, 1987). Average Silhouette Width is a measure of coherence, with high values indicating that observations are, on average, well matched to their own clusters compared with other clusters (Studer, 2013; Studer & Ritschard, 2016).

To interpret the identified clusters, we created chronograms, which showed the distribution of the policy comprehensiveness index for each cluster, and the proportion of individual counties in each. We further produced sequence nodal plots, which displayed the most common (or modal) "state" at each time point.

In our final visualization, we showed geographical variations by producing maps of several US states with the most counties included in the UCCP Database (Texas, California, Florida, Pennsylvania, and New Jersey) to illustrate county-level policy trajectory heterogeneities within states. These analyses were carried out for the overall comprehensiveness score MIT, 2023 and the three policy domains.

2.4. *Analyzing associations with county characteristics*

We linked the UCCP Database with county-level characteristics from publicly available data sources (U.S. Census Bureau, 2024a; 2024b; Federal Reserve Bank of St, 2023; MIT, 2023; Bureau of Economic, 2023). We extracted the county characteristic data either from the year 2019 or as close to 2019 as possible to ensure that they preceded the COVID-19 pandemic onset and would therefore be predictive of COVID-19-related policies, rather than consequential to them. These included gross domestic product (GDP) in thousands of USD in 2019, poverty rate (percent of people of all ages in poverty, 2019), population density (people per square mile), income in thousands of USD, percentage of population in urban area, racial segregation (measured using the racial dissimilarity index, 2015–2019), Democratic voter percentage (2016), and percentage White (2015–2019). Finally, we also included average COVID-19-related mortality rates per 100,000 population as a measure of COVID-19-related disease burden (Johns Hopkins University, 2023). We then merged these county-level characteristics into the UCCP Database using county Federal Information Processing System (FIPS) codes. We then examined the distribution of these characteristics among counties with differing policy trajectories.

2.5. *Sensitivity analysis*

We implemented an alternative costing approach—dynamic hamming—to produce the sequence analysis dissimilarity matrix to ensure the overall characteristics of the identified clusters were robust to different sequence analysis implementations (Supplemental Fig. 1) (Halpin, 2016). Dynamic hamming calculates time-varying substitution costs, prioritizing timing over duration of events (Halpin, 2016). It relies exclusively on substitutions in the comparison of sequences and did not account for either insertion or deletion costs (which tend to distort timing) (Lesnard, 2010).

All analyses were conducted in Stata SE 16 (College Station, Texas), and sequence analysis was implemented using the SADI package (Halpin, 2017; Ward, 1963). Maps were generated in R. All analyses were reviewed by a second coder (the second author) (Vable et al., 2021).

3. Results

3.1. *Individual county-level trajectories*

There was tremendous variation across counties in policy comprehensiveness over time (Fig. 1, Panel A–D). All 309 counties began with the same level of low overall comprehensiveness during January–February of 2020, prior to declaration of the national public health emergency in March 2020. About half of counties then gradually ramped up policy responses throughout 2020. Roughly 15–20% of counties maintained consistently low policy comprehensiveness, and the remainder exhibited intermittent comprehensiveness throughout the study period.

Policy comprehensiveness patterns for the containment/closure domain were similar to the overall index. Between March 2020 and December 2020, for instance, more than half of counties increased their

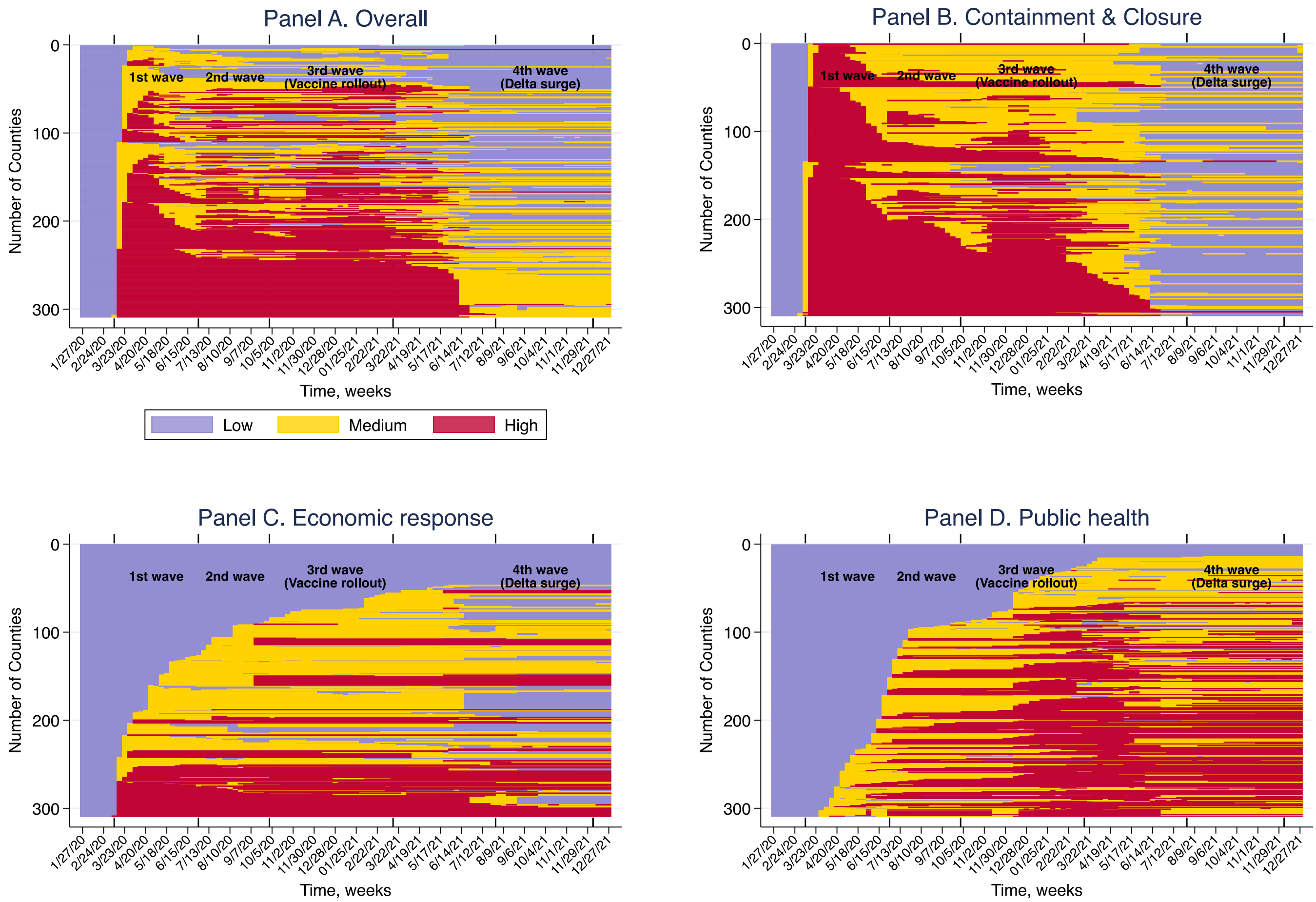

Fig. 1. Index plots representing individual county policy trajectories, for overall policy comprehensiveness index and three policy domains.
Note: Index plots illustrate changes in policy comprehensiveness across time for each policy domain. Each Panel represents a policy domain. Each horizontal line in each Panel represents a policy sequence for a particular county, with different colors indicating various policy "states" (i.e., low, medium, and high, based on tertile of policy comprehensiveness in a given week). The data used in this analysis came from the U.S. COVID-19 County Policy Database covering the years 2020–2021, which included 309 counties from all 50 states and Washington, D.C. Of a total 309 observed trajectories in the data, there were 259 unique policy trajectories for the overall policy comprehensive index, 238 for the containment and closure domain, 163 for the economic response domain, and 259 for the public health domain.

containment/closure policies and maintained them at the highest levels at least until the end of the 3rd wave (March 2021). In contrast, for economic response policies, roughly 15–20% of counties imposed more policies initially and maintained them throughout, while about a third remained in the lowest tertile throughout the study period. Additionally, economic support policies tended to be implemented later than containment/closure policies. For public health policies, most counties began with low levels of policy comprehensiveness, but gradually moved to higher comprehensiveness. There was also a near-uniform increase around December 2020, likely reflecting vaccine rollout.

3.2. *County-level trajectory clusters over time*

We identified five clusters for the overall policy comprehensiveness; for the three policy domains, we retained five clusters of containment/closure, 10 clusters for economic response, and six clusters for public health.

We assigned cluster labels based on prominent features of the timing and/or duration of sequences. For instance, "Mostly high, late predominantly medium" described counties that generally maintained high levels of policy comprehensiveness, but gradually decreased to medium levels of policy comprehensiveness at a later period. Visual representations of policy sequences included chronograms (Fig. 2, Panel A–D), and sequence modal plots (Supplemental Fig. 2).

Chronograms in Fig. 2 visualize policy sequences in wide format, helping to compare the timing, duration, and order of events across multiple counties over time. The most common trajectories for the overall policy index were "Mostly high, late predominantly medium" (33.0%) and "Mixed high-medium, late low" (30%). About 18.7% of counties had low levels of policy comprehensiveness during the entire period, with interrupted yet inconsistent medium and high policy comprehensiveness at some time points. For overall policy comprehensiveness, counties appeared to be characterized by a lot of transitions, with few counties staying in one policy response for a longer time.

For containment/closure policies, 39.5% of counties belonged to the most common cluster "Mostly high, late medium to low." The second most common cluster (34.6%) was "Early high, mainly medium, late low." Policies showed similar timing across counties (e.g., starting out with "high" policy response), but substantial differences in duration of "high" policy responses afterwards.

For economic response policies, there were 10 varying clusters with the most common clusters being "Predominantly low, sporadic medium" (18.5%) or "Early low, mainly medium, sporadic high" (17.1%).

Public health policies had the most similar order of policy responses

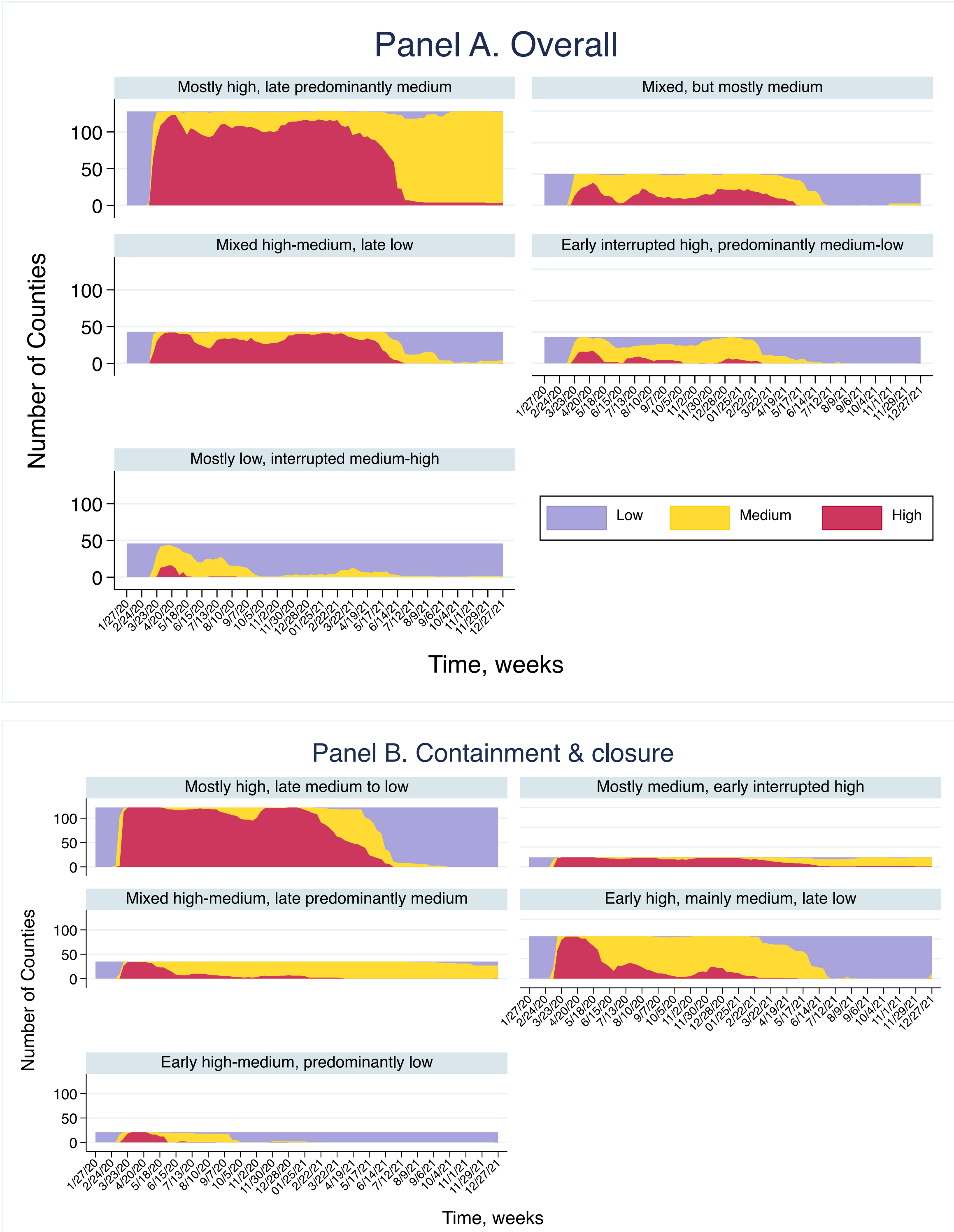

Fig. 2. Chronograms representing cluster types and frequencies, for overall policy comprehensiveness index and three policy domains.
Note: Chronograms illustrate changes in policy comprehensiveness across time within each cluster of counties. Each Panel represents a policy domain, and each sub-panel represents a cluster of counties with similar policy trajectories. Each horizontal line in each sub-panel represents a policy sequence for a particular county, with different colors indicating various policy "states" (i.e., low, medium, and high comprehensiveness). For example, in Panel A, 102 counties were classified under the "mostly high, late predominantly medium" cluster, where the first half of the timeline was dominated by high comprehensiveness, and the latter half by medium comprehensiveness. This enables comparisons of timing and policy transitions across counties. The data used in this analysis came from the U.S. COVID-19 County Policy Database covering the years 2020–2021, which included 309 counties from all 50 states and Washington, D.C.

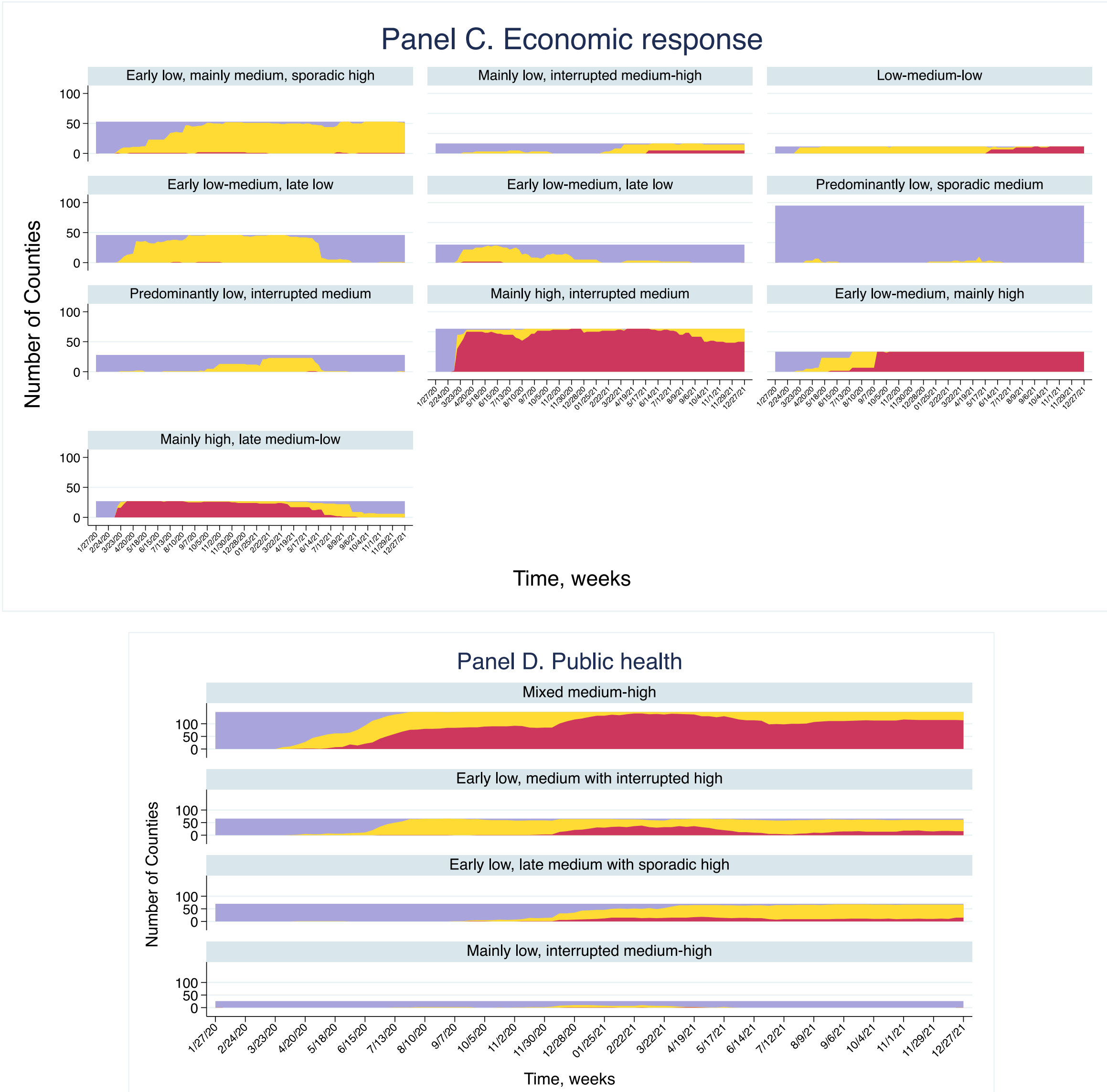

Fig. 2. (*continued*).

with 47.6% of counties falling into the "Mixed medium-high" cluster (with few interruptions) and 22.7% in the "Early low, late medium with sporadic high" cluster. Differences in policy responses between the two groups appeared at two time points: around week 20 (June 2020) and week 50 (January 2021). Specifically, counties in the "Mixed medium-high" cluster scaled up public health policies gradually and reached the highest comprehensiveness level around vaccine rollout in December 2020 and after. Meanwhile, counties in the "Early low, late medium with sporadic high" cluster similarly increased public health policy responses to the highest level coinciding with the vaccine rollout, but then gradually lessened to medium levels of public health policies. They also diverged as they initially maintained low levels of public health policies for a longer time before the policy changes.

3.3. Geographic variation

We then visualized distributions of policy clusters in Texas (25 counties), California (31 counties), Florida (17 counties), Pennsylvania (12 counties), and New Jersey (12 counties). Overall, policy comprehensiveness varied substantially between and within these states (Fig. 3). For the overall policy comprehensiveness index in Texas, for instance, El Paso and Dallas County had the most comprehensive policy responses to the pandemic; Harris County (which includes Houston) belonged to the "Mixed, but mostly medium" cluster; and Travis County (which includes the capital Austin) was in the "Mixed high-medium, late low" cluster. Overall, California counties had the most consistent/uniform high policy comprehensiveness across counties, in the "Mostly high, late predominantly medium" cluster.

In Florida, Hillsborough County (Tampa) and Dade County (Miami) had the most comprehensive policy responses, while other counties primarily fell into the "Mostly low, interrupted high-medium" cluster. Counties in Pennsylvania generally adopted a policy response in the "Early interrupted high, predominantly medium-low" cluster, except for the most populous Philadelphia County, which had a more comprehensive "Mixed, but mostly medium" policy response. Finally, in New Jersey, even the most populous counties, including Essex County (Newark) and Hudson County (Jersey City), adopted a less comprehensive policy response throughout, belonging to the "Mostly low, interrupted high-medium" cluster.

Policy responses also differed significantly across and within states by policy domain (Supplemental Figs. 3A–C). Counties in Texas and Florida, for instance, varied substantially on containment/closure

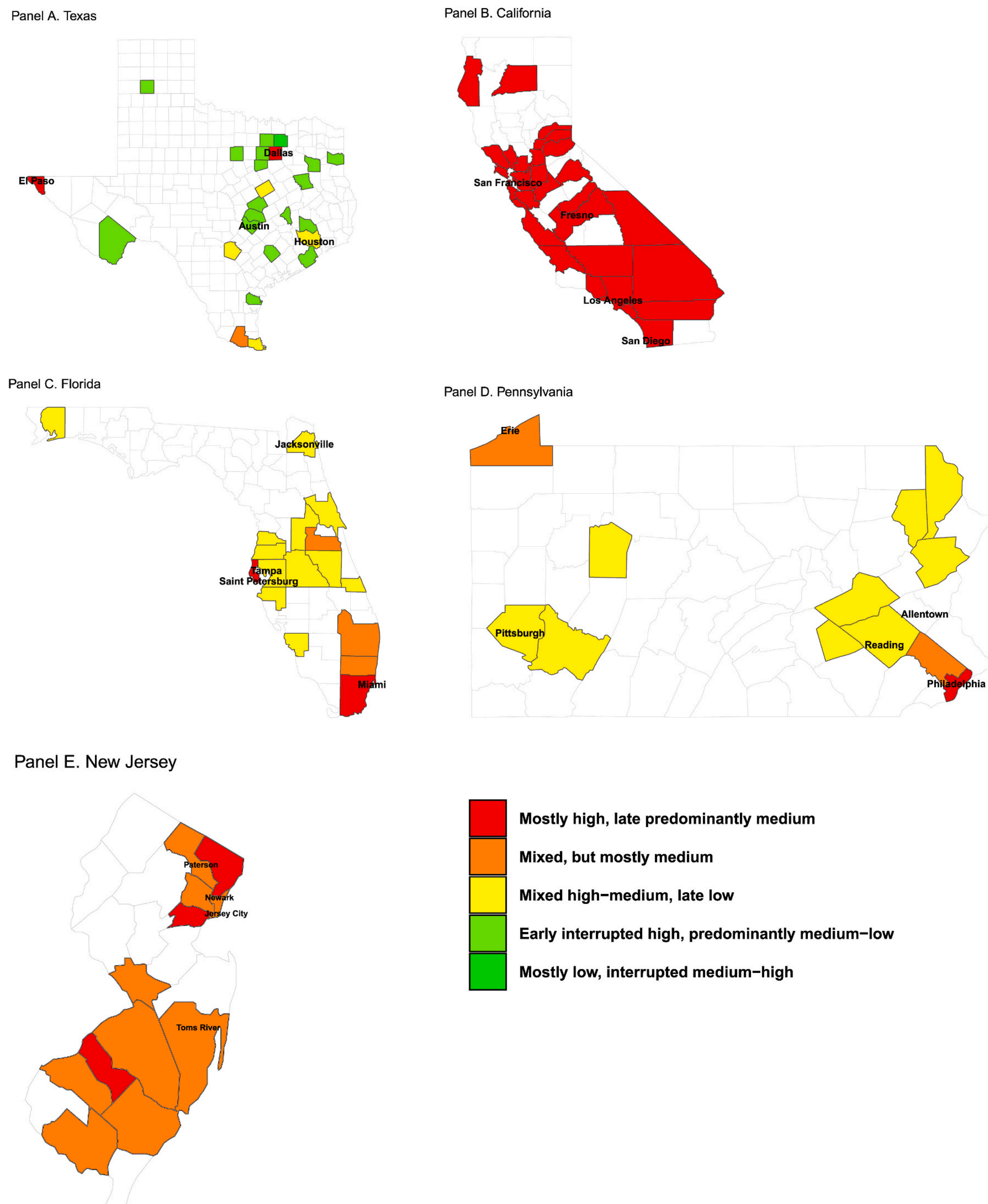

Fig. 3. County policy clusters for overall comprehensiveness index, by state.
Note: Data were drawn from the U.S. COVID-19 County Policy Database across 2020–2021, including 309 counties in 50 states and Washington D.C. These states are those in the Database that included the largest number of counties. We categorized the overall policy comprehensiveness index into tertiles – low, medium, or high – and implemented sequence and cluster analysis to create clusters of counties with similar policy trajectories. Counties without shading were not included in the data collection. Big cities are labelled for ease of interpretation.

policies, but were more similar for economic response policies. In California, except for San Francisco which belonged to "Early low-medium, late low" cluster, policy comprehensiveness was more similar for economic responses, as most counties were categorized as "Predominantly low, interrupted medium."

Geographical variation within states was substantial for public health policies. In Texas, for example, Travis and Dallas County belonged to the "Early low, medium with interrupted high" cluster, while Harris and El Peso County were both in the "Mixed medium-high" cluster, while other counties adopted more comprehensiveness with the "mixed medium-high" cluster or "Mainly low, interrupted medium-high." Similar variations were observed in California, Pennsylvania, New Jersey, and Florida.

3.4. County demographics by trajectory cluster

We then examined descriptive social, economic, and demographic characteristics of the identified policy trajectories clusters for the overall comprehensiveness index (Table 1) and three domains (Supplemental Tables 5–7). Of note, counties in the "Mostly high, late predominantly medium" cluster had higher average GDP, population density, income, and percentage of vote Democratic. We also found that counties in this cluster were more likely to have lower COVID-19-related mortality. With decreasing levels of policy comprehensiveness, we observed lower GDP, population density, income, urbanicity, Democratic voter share, and racial segregation, yet higher mortality. Patterns were similar for each policy domain.

3.5. Sensitivity analysis

Results using cluster analysis with the dynamic hamming approach to calculate costs produced five clusters for the overall policy comprehensiveness (Supplemental Fig. 1), the same number of clusters as in the main analysis using the Halpin optimal matching approach. Generally, the results were similar to the primary approach.

4. Discussion

This study is among the first to systematically characterize patterns of US COVID-19-related local policymaking longitudinally. We leveraged the novel UCCP Database and used sequence and cluster analysis to summarize policy trajectories across 2020–2021 for 309 counties nationwide.

Existing research has examined variation in COVID-19 policies and how policies shaped health at the national and state levels (Assaf et al., 2024; Boehmke, Desmarais, & Eastman, 2023; Carter and May, 2020; Hale et al., 2021; Patterson, 2022; Skinner et al., 2022), and the more granular units of analysis included in the present study provide a more local picture of policy variation. One prior study examined county policy heterogeneity across a few states (Hamad et al., 2022a), although it focused on a single time point, while our study examines longitudinal variation. Others examined longitudinal variation in local policies (Guy et al., 2021; Lasry et al., 2020), but focused primarily on a single policy (e.g., mask mandates). The data in the present study are freely available online, allowing follow-up studies to examine how different policy patterns impacted disparities in health and other outcomes.

Almost all counties implemented at least one policy in each of the three policy domains, albeit with differences in timing and duration. Sequence analysis captured substantial heterogeneities with respect to timing, order, and duration of policy responses across multiple policy domains, reflecting a highly dynamic policy environment.

There was particularly low comprehensiveness for economic policies. While economic support may be seen as the responsibility of federal and state governments, about 25% of counties gradually scaled up economic support. Yet the majority either sustained low policy comprehensiveness or switched between low and medium policy comprehensiveness. This local variation may have exacerbated racial/ethnic and socioeconomic disparities and contributed to health inequities. This variation in trajectories also highlights the possible need for nationwide policy advances that may contribute to fewer geographic disparities, such as the vaccine rollout in December 2020. Sequence analysis also helped to identify substantial differences in the timing of implementation of containment/closure (earlier) versus public health policies (later). For example, for containment/closure domains, almost all counties passed through all three policy states (low, medium, and high), but with differences in timing and duration.

We also found substantial geographical variation in COVID-19-related county policy comprehensiveness. These variations are consistent with the fact that different regions have distinct political, social, and economic conditions that shape their responses to policies. For example, they may have differing local needs, political ideologies, or resource availability. By comparing sequences of policy comprehensiveness with and across states, it allows us to understand how trajectories vary and diverge as well. For instance, we found that counties in California—a state that was among the first to impose stay-at-home mandates (Carter and May, 2020)—had the most consistent/uniform policies throughout the study period. Conversely, policy trajectories in other states varied between counties; e.g., major cities in Texas implemented varying levels of policy comprehensiveness.

Relatedly, differences in policy implementation likely also affected geographic differences in health and social outcomes. Counties with older populations or higher rates of underlying health conditions such as diabetes or heart disease are more vulnerable to severe outcomes from COVID-19. For instance, a study found that COVID-19 initially spread in heavy populated region and over time moved to more distant areas and rural counties (Kim & Castro, 2020). COVID-19 containment policies were associated with lower crime in Los Angeles (Campedelli et al., 2021). Business closures were associated with reduced COVID-19 transmission in Pennsylvania (Song et al., 2021), while state-level shelter-in-place policies were associated with increased domestic violence calls and decreased sharing of cannabis during 2020 (Assaf et al., 2024; Leslie & Wilson, 2020).

One key question is which upstream factors contributed to the differences in county-level policymaking observed here (Williams). Here we explored correlates of the county policy trajectories, and found that more comprehensive policymaking over the entire period was more common in counties with higher GDP and Democratic lean and lower COVID-19 mortality rates. This is similar to other studies that have examined different aspects of this research question. For example, studies at the state level have found that Democratic governors were faster and more likely to adopt containment/closure policies such as stay-at-home orders than Republican counterparts, perhaps due to partisan beliefs about the role of government (Patterson, 2022). In our analysis, nearly all county demographic variables are strongly correlated with policy clusters. We found counties with lower GDP and income had lower policy comprehensiveness. Mortality rates, a measure of COVID burden, are highly associated with clusters with higher levels of policy comprehensiveness. Such variation may reflect differences in the resources of local public health departments. However, it is worth noting that our analysis is a correlational and not causal analysis. That is, counties could have increased/decreased policy based on their COVID burden, and COVID burden could have changed in response to these policies. Future work can address this further.

One key drawback of many prior studies is confounding, namely the inability to account for other co-occurring policies that may have also contributed to the outcomes of interest. For example, attributing changes in COVID-19 transmission to stricter containment/closure policies may not account for the effects of contemporaneous changes in economic response policies that may help low-income families stay healthy at home. The present study informs future work to more rigorously account for a fuller policy landscape.

This study has several strengths. It is among the first analyses to examine the trajectories of multiple COVID-19-related policies at the county level across different domains and across time on a weekly basis, using sequence analysis to provide a robust characterization of this variation. The identified clusters reveal variations in policy patterns that would not have been captured by looking at single time points or summary measures. It also characterizes policy trajectories using sequence analysis, an innovative approach that allows reducing the complexity of policy variation across a two-year period to capture heterogeneity in the timing, duration, and order of implemented policies.

This study also has limitations. Counties in the UCCP Database were selected based on the criteria of this project, and therefore may not constitute a representative sample, nor do they cover the whole country or the period after 2021. Nevertheless, while the present data set contains about 10% of US counties, it represents over half the US population. Moreover, researchers and policymakers may be interested in policies that are not covered in this database. The study also covers only implementation of policies, rather than actual enforcement, which was not included in the UCCP Database. Also, because sequence analysis requires categorical variables, we categorized the continuous policy index into tertiles, which may result in a loss of information.

5. Conclusion

This study used innovative data and methods to provide among the first evidence of longitudinal and geographic variation in local pandemic-era US policies, where there was tremendous heterogeneity that may have contributed to inequities in health and social outcomes. The dynamic and heterogeneous nature of local COVID-19 policy responses may have been motivated by a need for tailored, context-specific interventions, but may also imply the potential benefits of more uniform federal guidelines to reduce geographic disparities. Future studies should examine how these policy trajectories impacted health and disparities to inform policymaking during future public health crises.

CRediT authorship contribution statement

Yunyu Amy Chiang: Writing – original draft, Formal analysis, Data curation. **Lucia Pacca:** Writing – review & editing, Methodology, Formal analysis. **Anusha Vable:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Thomas Carton:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Mark J. Pletcher:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Rita Hamad:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Ethical statement

This analysis did not involve the use of human subjects data, and therefore no ethical review was required.

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Declaration of interests

The authors have no competing interests to report.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2024.101734.

Data availability

The U.S. COVID-19 County Policy (UCCP) Database is publicly and freely available in the data repository of the Inter-university Consortium for Political and Social Research: https://doi.org/10.3886/ICPSR39109.v1.

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