Pandemic Policymaking[†]

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Abstract: This study leverages a high dimensional manifold learning design to explore the latent structure of the pandemic policymaking space only based on bill-level characteristics of pandemic-focused bills from 1973 to 2020. Results indicate the COVID-19 era of policymaking maps extremely closely onto prior periods of related policymaking. This suggests that there is striking uniformity in Congressional policymaking related to these types of large-scale crises over time, despite currently operating in a unique era of hyperpolarization, division, and ineffective governance.

Key words: manifold learning; computational social science; congress; policymaking; COVID-19

1 Introduction

COVID-19 has rattled the world with far reaching consequences from social[1] and political[2], to epidemiological[3] and emotional[4]. Though unprecedented on a number of dimensions, such large-scale societal crises require formalized responses to protect the vulnerable and needy in society. In the American context when epidemics like COVID-19 occur, the clearest avenue for action that affects the broadest slice of the population is *governmental* action. The government, empowered by the constitution as well as the representational responsibility of political elites to respond to constituents[5], has the duty to act for the people by protecting, providing, and serving in some capacity, especially when the country is facing a common threat, which currently is COVID-19. Governmental action can take many forms, such as court rulings, resource provision to frontline workers, military intervention, or support to those who need it most. While manifestations of governmental action vary, the most common avenue through which such large-scale governmental action takes shape, or is possible, is through policymaking. That is, writing legislation and passing bills into law reflects the government's prime means of action, distribution of resources, and mobilization of a unified response[♮]. In sum, policymaking by elected officials in Congress is one of the clearest avenues for governmental action, and especially in times of crisis.

COVID-19 is not the first large-scale crisis in America requiring a consolidated governmental response. Indeed many crises, both public health related and otherwise, have littered America's past, from HIV/AIDS and the opioid epidemic, to urban crime, climate change, and public education. Yet, though the subject of the crisis might vary, there are several common threads underlying crises: (1) they affect a large portion of the population in some way (e.g., they are not geographically isolated), (2) the effects are negative in some measurable way, and (3) they require governmental policymaking to offer solutions, resources, and support to mitigate their effects. The result is that these large-scale crises rise to the level of an "epidemic" or "pandemic", depending on the scope of the issue[◇].

Yet, the current climate of policymaking is different today than it was even a few decades ago. Though government need and responsibility have remained unchanged, the context and institution allowing for action through policymaking have drastically changed in several ways. Of note, the major political parties

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[♮] This is most simply seen through the Constitutional provision for Congress to "hold the purse strings" as it relates to monetary appropriations for governmental action[6]. This monetary control and disbursement take shape through policymaking, e.g., passing the federal budget bill.

[◇] Use of these terms is discussed at length in Section 2.

are extremely polarized and ideologically distinct[7, 8]; the country, comprised of a voting electorate, is deeply politically fractured[9]; driven largely by political activism, the alignment between the two major American political parties (Democrat and Republican) and the two major political ideologies (liberal and conservative) is stronger now than ever before[10]; enactment of major rule changes has altered fundamental institutional processes, deepening elite political division[11]; and Congressional policymaking is increasingly negative and intense[12]. These recent developments suggest America is experiencing a unique political period, at both the elite and mass levels.

In light of the COVID-19 pandemic, the relatively common occurrence of epidemics throughout American history, and the current era of hyper-polarization and division, a question emerges: *Is policymaking in response to COVID-19, which is occurring in this divided era, substantively different from policymaking in response to similar epidemics in the past?* This question assumes that the occurrence of epidemics as well as the need for governmental response through policymaking are both constant. The question, then, centers on the *nature* of policymaking and how it is currently taking shape, compared to recent history. There are a couple of ways that one could approach addressing such a question: *causal*, requiring theoretical innovation and development of testable expectations; or *exploratory*, where nothing is assumed of the drivers of patterns in the data, seeking instead to learn from natural structure underlying the data.

In a recent paper, Ref. [12] addressed a similar question using an exploratory framework: *Has governmental policymaking in response to epidemics and pandemics evolved, or are we witnessing a unique period of policymaking in the era of COVID-19?* To explore this question, Ref. [12] built and mined a set of the text data comprised of long bill titles, which act as summaries and signals of the bill sponsor's intent. Results suggest that while the topics of epidemic-related bills historically remain focused on epidemics at respective moments in time (and are thus not "evolutionary"), the general sentiment, or the "how" of the bills has substantially evolved, growing in both positive and negative sentiment over time. The increasingly intense tone defining the policymaking approach on these consequential, yet apolitical issues suggests the current COVID-19 era is indeed a distinct period of policymaking. Intensity and extremism

are used to characterize proposed legislation in the current COVID-19 period, which is a marked shift from historical approaches to policymaking on similar issues.

Yet a limitation of Ref. [12] is in the unit of analysis. While bill titles are useful mechanisms for "bill branding", they are nonetheless a biased look at policymaking. In addition to numerous players contributing to crafting legislation (e.g., party leadership, multiple prime sponsors, and special interest groups), legislators themselves are inherently biased actors who have unique bases of support[13], political agendas to realize while in office[14], a party brand to maintain and support[15], party leadership to satisfy[16], and unique career concerns[17]. Further, legislators are ranked and rated by many special interest groups based on their policy portfolios[18, 19], suggesting they may be biased[20] or at least influenced to write a bill that does not purely address the epidemic or issue in question, while instead posturing to obtain a better rating. In short, while the bill title is a useful summary and signal of the policy, and thus a good starting place to explore the historical contours of pandemic policymaking, this approach remains a tainted signal of a broader pattern of Congressional policymaking.

Beyond picking up on the limitation of Ref. [12], though similarly motivated by the representational arrangement between policymakers and constituents[5, 21], this research is more broadly interested in placing COVID-19 policymaking into historical context. Indeed, citizens of a representative democracy rightly expect policymakers who have been elected to serve an electing population to respond to large-scale issues like COVID-19. And accordingly, one of the most common avenues for *responsiveness* by Congressional lawmakers is proposing and passing legislation, however tainted it may be, to address a problem from a variety of angles.

Building on the growing body of research on COVID-19 and policymaking[22–24], and specifically the evolutionary question of pandemic policymaking explored in Ref. [12], I approach this question from a different angle, but using the same dataset as Ref. [12]. I am interested in whether *patterns* of policymaking are distinct or not. Put differently, are characteristics of bills addressing epidemics throughout recent history similar or different in meaningful ways? "Meaningful ways" in this context refer to structural similarity between the pre-COVID and COVID periods, e.g., similar or different cosponsor configurations and committee paths. The goal here is to understand patterns of pandemic

policymaking, but from an institutional perspective, where characteristics of proposed bills without the text itself reveal structural characteristics of the institutions in which these actors are acting. By exploring these patterns, whether similar or not, a deeper understanding of pandemic policymaking is possible.

In this exploration, I leverage unsupervised manifold learning to uncover the structure of policymaking on all bills related to epidemics from the 93rd to the 116th Congress‡. To do so, I employ Uniform Manifold Approximation and Projection (UMAP) to explore pandemic policymaking, and so recover to the latent manifold of this space. As I am interested in the characteristics of the bills, rather than the text of the bill, I rely only on bill-level metadata (e.g., cosponsors, party of primary sponsor, committee assignments, etc.). My goal, then, is to understand whether characteristics of bills on similar topics are stable over time, or whether they shift in detectable ways. If stable, then this would suggest we are *not* witnessing a unique period in policymaking during COVID-19, as the manifolds would map well onto each other. On the other hand, if the structure is unstable and shifting over time, then this would suggest that the current era of COVID-19 policymaking is indeed *unique*, relative to historical policymaking on similar issues.

After several stages, final results point to remarkable stability in the pandemic policymaking space, such that the current COVID-19 era maps extremely closely onto prior periods. Indeed, the manifolds are nearly identical, based on bill characteristics after accounting for time. This suggests that there is less of an "evolutionary trend" in pandemic policymaking, where instead there is striking uniformity in this type of Congressional policymaking, despite currently operating an era of hyperpolarization[25], deepening mass political polarization[26], and ineffective governance[27]. Implications of these findings and next steps are discussed in the concluding remarks.

2 Empirical Strategy

As this project is interested in uncovering latent structure in a common space, but with no expected outcome, this is an unsupervised problem. Further, I assume that configurations of pandemic-related bill metadata should

reflect substantive patterns of *aggregate* policymaking, and thus point to institutional characteristics underlying pandemic policymaking. Such an assumption, in technical terms, is that these observations (bills) lie on a common manifold, and are thus structurally related. While this manifold need not be fully connected, such that each bill to every other bill along the manifold, the expectation rather is that the bills come from a common space, which mirrors reality. Put differently, there is a common data generating process, where all legislators whose author bills are acting in a common space, under common constraints, and on average, have a largely common set of goal as they author legislation[28]. Taken together, the unsupervised nature of the task and the assumption of a common manifold underlying these pandemic policies, the core assumption of this project is that there is latent, non-random underlying the pandemic policymaking space. The task, then, is to recover this manifold, and then compare versions of it over time, to address whether periods of pandemic policy are similar or different. As this is an exploratory project, results revealing either similarity in contours of pandemic policymaking or not, will nonetheless deepen an understanding on aggregate elite approaches to responding to major, national crises.

Importantly, the terms "pandemic" and "epidemic" often refer to instances of disease outbreak, with the former being widerly spread than the latter[29]. Yet, Ref. [12] demonstrated that when a wide array of problems, disease or otherwise, become widespread and capture national or international attention, these types of problems are often branded as "epidemics" by policymakers. As such, in this research I also use these terms as policy heuristics for widespread problems requiring governmental action at some level. Indeed, use of the word "pandemic" is largely unique to COVID-19 in the context of American policymaking, as politicians do not typically author legislation on international issues. Yet, the COVID-19 pandemic, though ultimately unparalleled in scope and impact, is related to other more commonly dubbed "epidemics" in America, such as the opioid epidemic or the HIV/AIDS epidemic in the 1980s, both affecting the nation and thus requiring governmental policymaking responses. As such, the loose definition of the terms found in Ref. [12] is based more on a policy-focused heuristic, rather than a formal public health definition. I follow the same logic in this research, and use "pandemic" and "epidemic" interchangeably to allow for a collection of a set of

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‡As addressed and justified below, and in line with Ref. [12], I use "epidemic" and "pandemic" as policy heuristics interchangeably throughout, allowing for cross-temporal comparability.

policies that are generally comparable over a long period of time.

2.1 Data

The data were scraped from congress.gov, and include all bills related to epidemics introduced in the American Congress from 1973 to May, 2020[12]. The data include several bill-level features: the chamber in which the bill was introduced (House or Senate), the canonical designation of the bill (e.g., resolution, joint resolution, bill, and concurrent resolution)§, the Congress (two-year period) in which the bill was introduced ranging from the 93rd (1973–1974) to the first half of the 116th (2019–2020), the date of bill introduction, long bill title, the party of the prime sponsor, the representing state of the prime sponsor, the representing district of the prime sponsor¶, number of cosponsors on the bill (non-negative integer), configuration of committees in which the bill was read‖, the date of last action, and finally the last action (e.g., read in committee or signed into law).

The data are split into two periods for exploration: pre-COVID (1973–2018) and COVID (2019–2020). Time is explicitly addressed in a later stage below.

Importantly, these features are included in the data set, and thus make sense for this type of exploration, as they comprise the information the modal member of Congress consumes as they pick up and read a bill. That is, they are able to see who sponsored a bill, their party, the bill's cosponsors, the committees of reference, the chamber, and district of the sponsor, when it was sponsored, and so on. And from a practical perspective, these features include all available metadata at the bill level. Thus, the goal here is to, as closely as possible, emulate and capture the process of filtering Congressional legislation for the purpose of *recovering the structure* of this process for comparative value. So, from this full feature space, I focus on the features that can be included in the specification, which is a subset (e.g., raw text cannot yet be reliably treated in UMAP applications): bill type, committee configuration for

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§ It is important to note that naming conventions vary by chamber. For example, a *resolution* might be a declaration of an idea, whereas a *bill* might be more substantive.

¶ dist $= 0 \forall$ Senate

‖ This could be a single committee or many. For example, HB 6311 in the 116th Congress, *Care for COVID-19 Act*, was read in three committees (Energy and Commerce, Ways and Means, Education and Labor), whereas HB 6623, *COVID-19 Language Access Act*, from the same Congress was only read in a single committee (Oversight and Reform).

each bill, state of prime sponsor, chamber of prime sponsor, date of introduction, and date of final action. Party of the prime sponsor is omitted to allow for conditioning visualizations of the lower dimensional space on party to understand whether the lower dimensional manifold finds any discernable differences between policymaking on a partisan basis. This decision makes results more substantively interpretable. For example, we can understand that Republican bills may be different Democratic bills, whereas bill-level differences represented by black dots in a two-dimensional setting are less clear.

2.2 UMAP

UMAP[30] is a recent approach to dimension reduction, which is particularly well suited for high dimensional contexts. As in other dimension reduction approaches, such as Principal Components Analysis (PCA), the goal is to make a complex, high dimensional space more interpretable and manageable by intentionally discarding some information for the benefit of homing in on the most interesting variation that characterizes the data well. UMAP, though, joins this common statistical learning approach to dimension reduction with a formal mathematical foundation based on topological data analysis/graph theory (e.g., simplicial subspaces) and manifold learning. The result is a scalable, computationally efficient (extremely fast), and mathematically grounded approach to dimension reduction. The goal of UMAP, then, is to learn a lower dimensional version of the data (i.e., low dimensional embedding, as in PCA), but it assumes the data exist along a common manifold. If the manifold is recovered, a better, but more parsimonious understanding of the data can also be recovered.

UMAP finds a lower dimensional manifold, w_{ij}, that captures both local structure in such a way that retains spatial relationships among observations i and j (via $d(i, j)$, where $d(\cdot)$ is some measure of distance) in the original high dimensional setting, v_{ij}. The goal is to do this, but while also retaining global structure to understand the full shape of the manifold. Compared to PCA, which seeks only to *maximize* variance in the raw data space to give a lower dimensional summary of that space, UMAP accomplishes retention of both global and local structure. UMAP does so by *minimizing* information loss across the high (v_{ij}) and low (w_{ij}) dimensional versions of the data by optimizing a cross-entropy cost function,

$$\sum_{i \neq j} v_{ij} \log\left(\frac{v_{ij}}{w_{ij}}\right) + (1 - v_{ij})\log\left(\frac{1 - v_{ij}}{1 - w_{ij}}\right) \quad (1)$$

The full cost function in Formula (1) can be rearranged into two components, which are typically optimized by stochastic gradient descent[30],

$$\sum_{i \neq j} v_{ij} \log(v_{ij}) + (1 - v_{ij})\log(1 - v_{ij}) - $$
$$v_{ij} \log(w_{ij}) - (1 - v_{ij})\log(1 - w_{ij}) \quad (2)$$

As such, the goal is to minimize the differences of local and global structure in the raw high-dimensional setting, v_{ij}, and the lower dimensional manifold, w_{ij}.

To underscore the graph-based approach of searching for an optimal manifold that underlies, and thus *connects* points that lie along it (i.e., a graph), the task can be reframed as one that searches at each point for the nearest neighbor. Once found, the neighbors are connected by an edge in a smooth way, such that the density of some region determines the decay, which moves outward from the observation, i. In other words, higher density regions in ambient (secondary) space have smaller radii around each point, compared to less dense regions, which have wider radii of decay. This fuzzy, secondary search (beyond the primary nearest neighbors search) is required for the manifold to connect. The secondary search satisfies a previously mentioned assumption that all points exist along a *common* manifold, though are not necessarily *locally* connected. For example, there could exist several locally-connected simplicies (connections between multiple vertices) found in the first nearest neighbors search, but not globally connected to each other. Thus, the secondary search region allowing varying radii $\forall i \in \{1, \ldots, N\}$, globally connects all points, which may or may not be fully connected after the first search. As such, the cost function can be re-written in graph notation as

$$\sum_{e \in G} w_h(e)\log\left(\frac{w_h(e)}{w_l(e)}\right)(1 - w_h(e))\log\left(\frac{1 - w_h(e)}{1 - w_l(e)}\right)$$
$$(3)$$

where e are the edges contained in graph G, $w_h(e)$ is the weighted edge in the high dimensional setting, and $w_l(e)$ is the weighted edge in the low dimensional setting. The first term, $\sum_{e \in G} w_h(e) \log\left(\frac{w_h(e)}{w_l(e)}\right)$, allows for optimal recovery of the local neighborhoods, and the second term, $(1 - w_h(e)) \log\left(\frac{1 - w_h(e)}{1 - w_l(e)}\right)$, allows for optimal recovery of the spacing between the local neighborhoods, thus allowing for consistent *global* structure, based on consistent *local* structure.

The term "consistent" points to vastly important aspect of UMAP, which is major improvement over t-distributed Stochastic Neighbor Embedding (t-SNE[31]). That is, the first term in Formula (3), $\sum_{e \in G} w_h(e) \log\left(\frac{w_h(e)}{w_l(e)}\right)$, is the goal of t-SNE, which is to capture local behavior to give a global representation of the data space. Yet, t-SNE does so in a probabilistic way, by drawing miniature t-distributions around each point, and calculating the probability that a certain number of points *should* be nearest neighbors, with some degree of uncertainty. Without the second term in Formula (3), $(1 - w_h(e)) \log\left(\frac{1 - w_h(e)}{1 - w_l(e)}\right)$, t-SNE is unable to project *new* data onto the lower dimensional embedding, as the lower dimensional embedding can change at each iteration, and is thus not reproducible.

As such, a major advantage of UMAP over t-SNE and other manifold-based dimension reduction techniques, is the ability to reproduce the same lower dimensional embedding, thereby opening up the possibility of *supervised* projection of new points onto the learned manifold. I take advantage of this feature in the second stage below, to directly compare pre-COVID policymaking with COVID-era policymaking.

It is important to note that while t-SNE finds nearest neighbors by calculating a series of N pointwise conditional probability distributions, similarity in the context of UMAP, thus defining nearest neighbor, $v_{j|i}$, is calculated by a measure of smoothed nearest neighbor distances based on spatial proximity to each other, e.g.,

$$v_{j|i} = \exp[(-d(i, j) - \rho_i)/\sigma_i] \quad (4)$$

where ρ_i is the minimum distance to the nearest point, and σ_i is a normalization factor controlling smoothness. These hyperparameters affect the smoothness of the solution[30]. In practice, tuning these hyperparameters affects the tradeoff between local and global structure, in addition to several other hyperparameters discussed more in the following subsection.

2.3 Hyperparameter tuning

There are five major hyperparameters that must be tuned when applying UMAP to a dimension reduction task of this sort: k (the number of neighbors considered in each neighborhood search), ρ_i (the minimum distance to the nearest point), number of epochs (number of times the algorithm sees the data), m (which is the number of dimensions (usually 2) constraining the lower dimensional embedding), and d (distance metric for

pairwise distance calculations).

As with many learning algorithms, a common approach to home in on final values for the hyperparameters is to conduct a grid search across some sequence of values of each hyperparameter for all unique hyperparameters associated with the given learning model. I take this approach in the research, but present the results across the two main hyperparameters, neighborhood size k and number of epochs in Fig. 1.

From Fig. 1, a few patterns stand out. Firstly, as expected, the more the algorithm sees the data (as the number of epochs increases), the clearer and more stable the patterns in the lower dimensional manifold become. Moving from left to right across the column facets in Fig. 1, the separation between smaller subgroups in the data becomes starker. This suggests that there may be differences in pandemic policymaking over the full study period, which are explored in the analysis that follows.

A second notable pattern in the grid search in Fig. 1 is that moving from top to bottom across the row facets as the size of the neighborhood increases from 5 (top row) to 45 (bottom row), additional clarity is gained.

Inspecting the highest values from each of these hyperparameter values in the lower right plot in Fig. 1, it becomes increasingly clear that two distinct groups of

pandemic-related policies take shape. Precisely, what these groups are and how they are comprised are the task of the later stages of analysis below.

It is worth pointing out that the features have been scaled and standardized, meaning the axis values have no substantive meaning, as in other similar dimension reduction techniques like Locally Linear Embedding (LLE) or t-SNE. Therefore, the greatest strength of these types of manifold-based dimension reduction techniques is to visualize the reduced data space, which allows for greater insight into substantive differences that naturally exist in the higher dimensional space. Here, the first conclusion we can draw from the single Fig. 1 is that there seem to be two groups of pandemic-policies characterizing this space. I transition now to pull this apart more overtly, by proceeding with hyperparameter values $k = 45$, number of epochs $= 450$, $d = 2$, dist $=$ Euclidean, and $\rho = 0.1$.

3 Learning Manifold of Pandemic Policymaking

I first present the results in Fig. 2 from fitting UMAP to the COVID period of policymaking. Point colors correspond with the party of the prime sponsor on the bill. This condition allows for understanding whether

Fig. 1 Grid search of UMAP hyperparameters. Here, columns represent number of epochs, and rows represent neighborhood sizes.
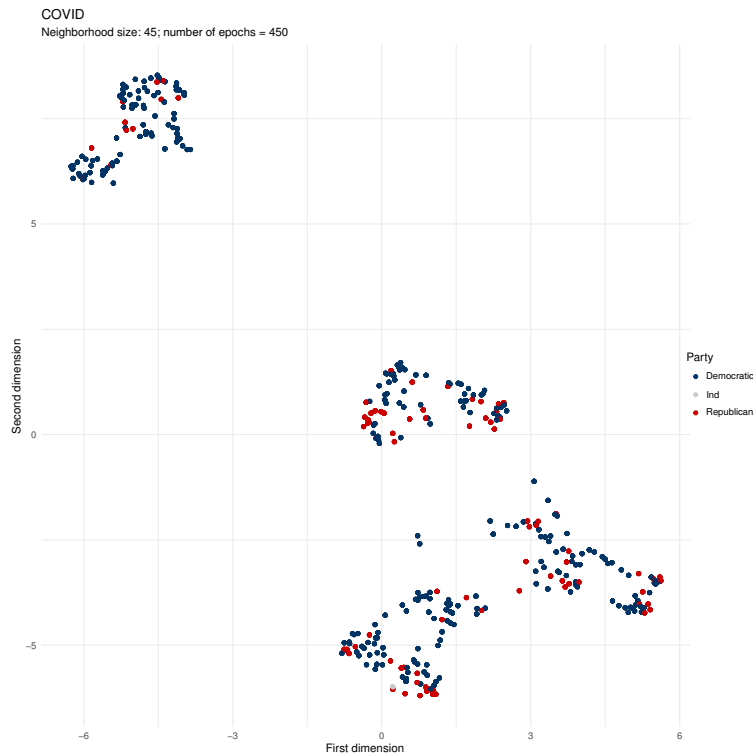
Fig. 2   COVID policymaking structure.

partisan differences exist in pandemic policymaking, in addition to the vector of additional features on which the UMAP fit is based.

Building on the patterns from the grid search in Fig. 1, it seems as though the distant cluster of points, apart from the "C"-shaped cluster, is the COVID period. As the key value of UMAP, and visualization of this sort is to observe where observations lie in high dimensional space, as recovered in a lower dimensional setting, the main takeaway from Fig. 2 is that there seems to be a distant pocket of Democratic (blue) bills, with only a few Republican bills in the upper left of the plot, which is distant from the remainder of the policies in the lower right of the plot. In the lower right, there is a blend of Democratic (blue) and Republican (red) bills mixed together, implying, for the most part, there are no major differences between the parties in the approach pandemic policymaking. While the distant group of mostly Democratic bills to the upper left is interesting, explicit probing of that group is beyond the scope of this analysis. Rather, I am interested in exploring whether differences exist across the two major time periods of pandemic policymaking. To this end, I turn now to present results from the UMAP fit on the pre-COVID set of policies, as shown in Fig. 3.

Here, we can confirm the "C"-shaped cluster of points is the pre-COVID era of policymaking. The distribution of political parties in this cluster over a long period of time is relatively uniform, with no major partisan differences emerging.

Of note, though, is the unique shape of the cluster, compared to the COVID period in Fig. 2. It seems as though the structure is more clearly segmented, with those existing in a given cluster (e.g., the first group in the lower left of the plot) being explicitly in that cluster, compared to the rest of the space, which is also clearly and explicitly grouped. In sum, this suggests that there is some aspect of this policymaking space that clearly sorts policies into bins that do not blend for the most part.

Stepping back and comparing trends across the COVID (Fig. 2) and pre-COVID (Fig. 3) periods, the patterns in the data seem to suggest that these periods of pandemic policymaking are indeed distinct. This gives credence to the notion that we are witnessing a truly unique moment in American policymaking, where political elites are engaging in policymaking in some fundamentally different way than ever before.

Pre-COVID
Neighborhood size: 45; number of epochs = 450
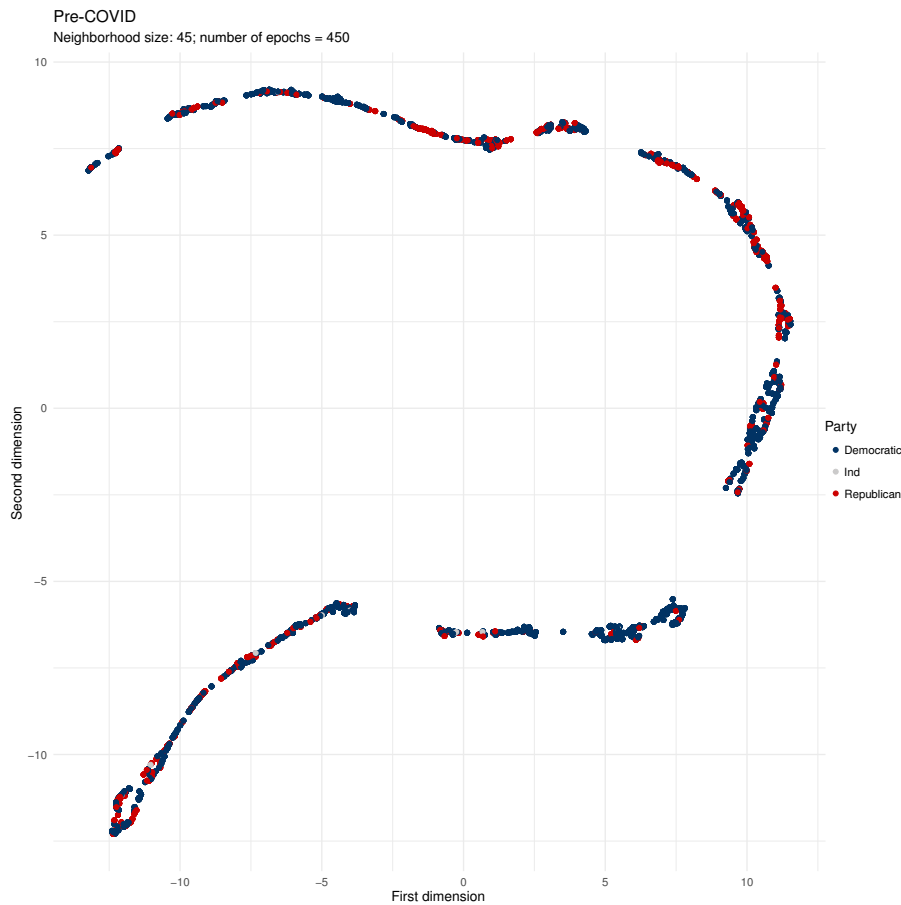
Fig. 3   Pre-COVID policymaking structure.

4 An Alternative Approach: Supervised Projection

At this point on visual inspection of the two periods of pandemic policymaking, it seems as though the periods are structurally distinct. Further, there seems to be a lack of clear partisan distinction between the periods, resulting in a lot of party overlap across both periods on average. Exploration has centered on observation and comparison of patterns in a descriptive way, given the nature (and limitations) of unsupervised dimension reduction.

Yet, recall that one of the prime benefits of UMAP is to learn a lower dimensional representation of the data that retains and balances global and local structure in a reproducible way given the lack of reliance on a probabilistic neighbor search. In practice, this feature of a reproducible solution from a UMAP fit allows for *supervised* dimension reduction, where new data can be projected onto the learned manifold, allowing for direct comparison between the two sets of data. If there is stability in the structure across the sets of data, then the

learned manifold is likely capturing true, unique features of the data, such that new, unseen data can be mapped closely onto that manifold. Yet, if there is a lack of structure in the space, then the learned manifold will be different from the manifold found when mapping new data to it.

For current purposes, this powerful benefit of UMAP allows for a direct comparison of the two eras of policymaking beyond simple visual exploration of two UMAP fits. As such, I turn now to fit UMAP on the pre-COVID era and learn the shape of the manifold. Then, I project the COVID era data onto the learned manifold from the pre-COVID era. In so doing, I treat the pre-COVID data as "training" data and the COVID data as "testing" data.

UMAP results on the full feature space are presented in Fig. 4. All features from the previous fits are included. "O" points represent the learned manifold from the training/pre-COVID set. "X" points represent the projection of the test/COVID period.

This view of the two periods is in line with findings to this point, where the COVID period (denoted by

Fig. 4   Projecting COVID onto pre-COVID period.

the green box) seems to be a very unique period of policymaking different from nearly every other period in pandemic policymaking. This is seen by the tiny position of COVID onto the full manifold, suggesting it projects very poorly onto this space.

If the COVID period were truly different from the pre-COVID period, then we might expect to see the COVID period project poorly onto the manifold from the pre-COVID period, e.g., a cluster of points distant from the main cluster of the pre-COVID period, which would be different from the pattern in the grid search in Fig. 1, as the grid search was *not* based on projection. Yet, we see the COVID period clearly projecting onto a very small, but specific part of the manifold learned from the pre-COVID era.

Note the spacing of the clusters of bills along the manifold in Fig. 4. There are explicit gaps in the manifold, suggesting clear separation in the projection space. Combined with the pattern in Fig. 3 that precise, but still distinct clusters of policies clearly spread out in the same space, the inclusion of time-dependent features seems to be influencing the structure of the manifold,

and thus projection of the distribution of points along it. This is likely the case, because for example, bills sponsored in 1980 will be treated very differently than bills sponsored in 2020 merely due to their different values along this feature. The same is true for other time-dependent features, like the Congressional period feature, which is treated as a non-negative integer (e.g., ranging from 93 to 116).

To explore whether this is the case and time is influencing the shape of the learned manifold, I turn now to fit a new version of UMAP on a subset of the feature space, *excluding* all time-dependent features. We are left with five features, still withholding party affiliation to allow for conditioning the color of points: bill type, cosponsors, committee configurations, state of primary sponsor, and the chamber of the primary sponsor. Though significantly pairing down the space, we are still left with a "high dimensional" problem, as we are considering a five-dimensional feature space, which on its own is substantively uninterpretable compared at least to a two-dimensional version of the same space.

Upon learning the lower dimensional manifold of

the pre-COVID period (this time minus time-dependent features), I project the COVID period onto the manifold to explore whether and to what degree the manifolds align. Results are presented in Fig. 5, where again, "O's" are pre-COVID bills, "X's" are COVID bills projected onto the space, and colors vary by party of the prime bill sponsor.

We now get a very different view of the pandemic policymaking space. Considering the role of time by dropping the time-dependent features from the fit, the patterns of pre-COVID and COVID map extremely closely on each other. Substantively, this suggests that the two periods, spanning a near 50-year period of Congressional policymaking, look very similar to each other. Further, the structure shrinks as well, with the "C"-shape of the manifold disappearing, and the precise grouping (presumably by time) from the earlier patterns in Figs. 3 and 4, now disappearing as well. If the COVID period of policymaking were truly unique, we might expect poor projection and no evidence of clear mapping across the periods, regardless of time. Yet, as shown in Fig. 5, the configuration of pandemic-sponsoring legislators look quite similar to each other over time where nearly all "X's" are plotted on top of nearly all

"O's."

From these results, as they are exploratory, it is impossible to say whether the patterns we see today *are a function* of the historical approach to pandemic policymaking. Target causal methods would be required for such a conclusion. But what is very clear from these results is that not much has changed over 50 years regarding how legislators approach pandemic policymaking, and thus how the institution processes pandemic-related legislation.

Even though the choice of setting the pre-COVID era as the training set and the COVID era as the testing set was substantively motivated, to directly compare the patterns of pandemic policymaking across the two periods, I offer a final check on these patterns in this section. To do so, and thus validate the patterns found thus far, particularly those in Fig. 5, I *randomly* split the full data space into training and testing sets, regardless of whether policies were from the COVID or pre-COVID periods. Note, I retain the same proportion of bills in each major period for direct comparison (≈ 0.66 in the training/pre-COVID set and $\approx 1 - 0.66$ in the testing/COVID set). Further, based on the findings showing striking similarity across the periods in Fig. 5,
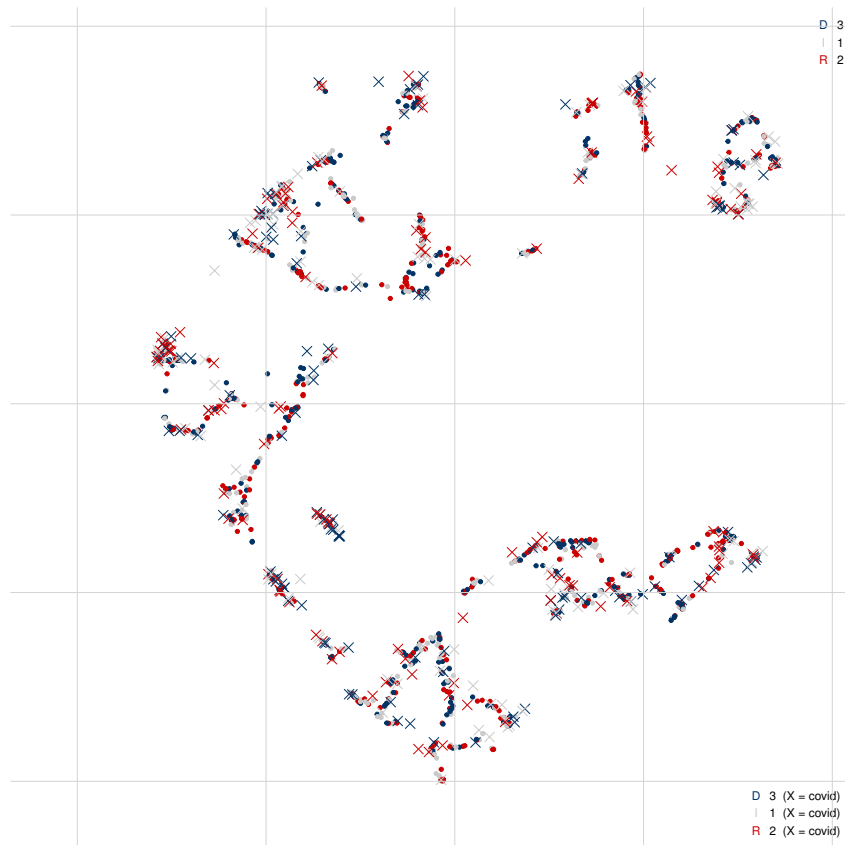

Fig. 5   Projecting COVID onto pre-COVID period: Addressing time-related features.

here I also exclude time-specific features (e.g., Congress period, date of introduction). Results are presented in Fig. 6.

In Fig. 6, as before, patterns are extremely similar with the projection of a random set of test points mapping closely onto the manifold learned from the training set. This strengthens the patterns from the previous section that the two periods of pandemic policymaking are virtually indistinguishable as it relates to partisan patterns, committee configurations of bills, cosponsorship, and so on for all features included in the model. Ultimately, this suggests that though we are in a current period of hyperpolarization and political division, institutional structure for processing policies in response to pandemics is a relatively stable phenomenon. This conclusion, though made on the basis of an exploratory study, provides a glimmer of hope in a current American political climate marked by bitter division and dislike for members of opposing political parties, such that when crisis strikes, politicians seem to have an informal code of policymaking. This code seems to be closely adhered to over a near 50-year period of pandemic policymaking. That is, these results suggest that perhaps

there is some evidence against polarization as it relates to this specific expression of policymaking. Regardless of the many legislators who have passed through the chamber and have been in charge over the years, the stability and consistency in how the institution as a whole handles policy of such a grave magnitude offers perhaps a glimmer of hope. Though implications are of course subject to interpretation, the stability in structure is noteworthy.

5 Concluding Remark

In this paper, I set out to explore and uncover the lower dimensional manifold of American policymaking related to epidemics and pandemics broadly defined. In so doing, a second order goal was to understand whether the unique institutional context of political division and polarization also influence the policies aimed at addressing COVID-19. By focusing on COVID-19 and institutional structure, the concept of pandemic policymaking places COVID-19 legislation into historical context. The result is a comparison of patterns of policymaking over time, to explore whether past approaches to epidemic-related policymaking
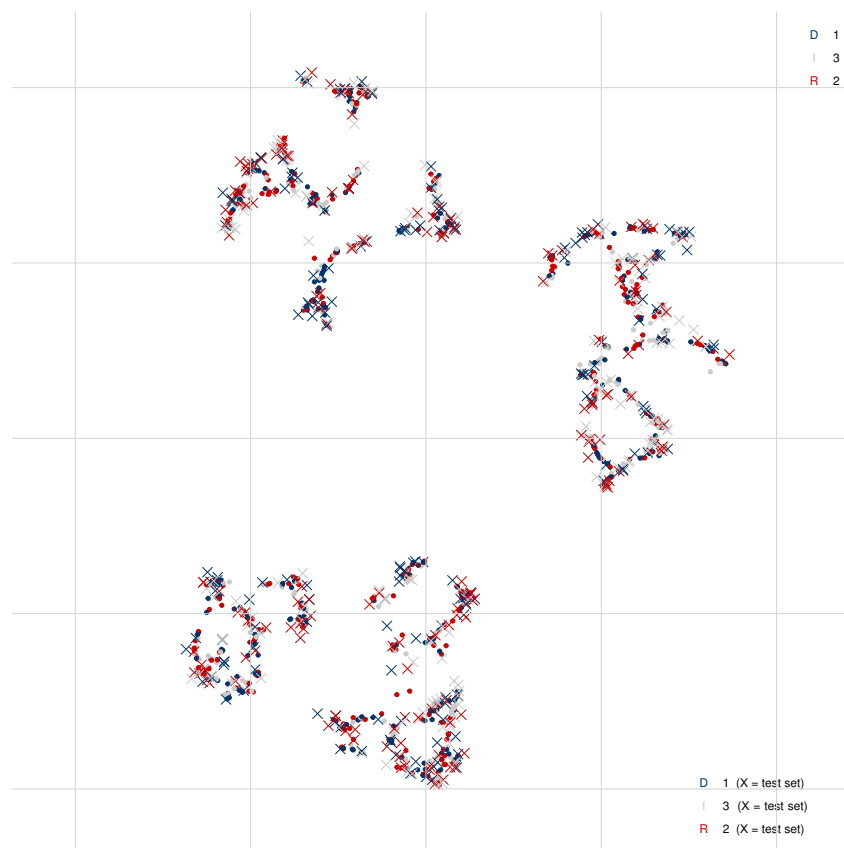
Fig. 6 Pandemic policymaking structure with random data split.

map onto the current approach of policymaking on COVID-19.

Though the initial stages of the exploration seemed to suggest that the current era of COVID-19 pandemic policymaking is distinct from prior periods, a more targeted exploration showed that once explicitly accounting for time, COVID-19 policymaking mapped extremely closely onto prior periods of pandemic and epidemic-related policymaking. This suggests, then, that though the political and institutional contexts have changed, becoming increasingly bitter and divided, the approaches and patterns of pandemic policymaking have remained largely stable over time. The substantive conclusion, then, is that the current era of COVID-19 policymaking looks very similar to prior eras of policymaking on a host of epidemics, all at varying scales, perhaps implying a degree of (restored) hope in the prime institution for policymaking in America. Indeed, a more stable, and perhaps even formulaic approach seems to characterize Congressional pandemic policymaking, regardless of the surrounding political and institutional context as well as the nature and scope of the epidemic(s) in question. These patterns were corroborated using random data splitting and then replicating the supervised projection task. Results remained strikingly similar across all periods, regardless of the cases ending up in the training or testing sets, thereby strengthening conclusions of uniformity in pandemic policymaking.

Though exploratory, and not confirmatory in motivation, the findings in this work could be explained, at least in part, by path dependency, which is a common feature of public and social institutions, such as policymaking institutions broadly defined[32], subnational policymaking[33], higher education[34], and even Congress[35]. Indeed, Ref. [35] demonstrated that political conflict can be an important driver in pushing institutions to break from path dependency. As such, and taken with the findings presented throughout this current work, the lack of political conflict surrounding at least the recognition of a need for policymaking at some level, regardless of the scope of that action, could be the driver behind the stability in patterns of legislating in response to COVID-19. Put differently, the ubiquitous presence of a common threat in COVID-19 may be resulting in unification, at least as a motivastor for policy and political mobilization. Thus, in the American context, Congress sees the threat, and on the basis of the representational arrangement, acts by leaning on

the historical safety and path dependence of processing similarly situated legislation. Though often cast in a negative light, such as an impediment to progress or needed policy change[36], perhaps path dependency in this unique historical moment presents an avenue to bypass polarized, ineffective policymaking that so often defines Congress.

To be sure, this targeted expectation was not explicitly tested in the current work. Yet, whether some event or context like COVID-19 can give rise to stable policymaking and so undermine the negative effects of polarization and ineffective governance is a question worth addressing in future research.

Future, future work might pick up on these results by considering either different periods of political history, different substantive topics (e.g., the economy, elections, and so on), as well as different governments around the world beyond the American case.

On the technical side, future work might pick up on the methodological approach (UMAP), but relaxing the strong assumption that all observations exist along a common manifold. A common manifold may not capture reality, where different data generating processes may result in actors in a common space acting fundamentally different from others. Such an extension of UMAP would be akin to anomaly detection, but in the context of, e.g., deriving *multiple* manifolds from a common space to explain such sparsity.

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