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Global analysis of the COVID-19 policy activity levels and evolution patterns: A cross-sectional study

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Abstract

Background and Aims: Since the beginning of the coronavirus disease 2019 (COVID-19), a large number of government policies have been implemented worldwide in response to the global spread of COVID-19. This paper aims at developing a data-driven analysis to answer the three research questions: (a) Compared to the pandemic development, are the global government COVID-19 policies sufficiently active? (b) What are the differences and characteristics in the policy activity levels at the country level? (c) What types of COVID-19 policy patterns are forming?

Methods: Using the Oxford COVID-19 Government Response Tracker data set, we present a global analysis of the COVID-19 policy activity levels and evolution patterns from January 1, 2020 to June 30, 2022, based on the differential expression-sliding window analysis (DE-SWAN) algorithm and the clustering ensemble algorithm.

Results: Within the period under study, the results indicate that (a) the global government policy responses to COVID-19 are very active, and the policy activity levels are significantly higher than those of global pandemic developments; (b) a high activity of policy is positively correlated to pandemic prevention at the country level; and (c) a high human development index (HDI) score is negatively correlated to the country policy activity level. Furthermore, we propose to categorize the global policy evolution patterns into three categories: (i) Mainstream (152 countries); (ii) China; and (iii) Others (34 countries).

Conclusion: This work is one of the few studies that quantitatively explores the evolutionary characteristics of global government policies on COVID-19, and our results provide some new perspectives on global policy activity levels and evolution patterns.

KEYWORDS

activity level, COVID-19, government policy, policy pattern

1 | INTRODUCTION

Since the beginning of coronavirus disease 2019 (COVID-19), an extraordinary variety of government policies have been implemented worldwide in response to the global spread of COVID-19, and these policies vary in space and time. Government policies have been shown to be effective in reducing COVID-19 transmission.[1–4] In addition, Sebhatu et al.[5] and Chen et al.[6] highlighted the important role of behavioral and cultural elements in government COVID-19 policies. Robinson et al.[7] analyzed the trade-off between the benefits and costs of government COVID-19 policies. Furthermore, some decision problems under government COVID-19 policies, such as medical capacity investment, counterterrorism resource allocation, and psychological health impacts, have been studied.[8–10]

One of the most important factors determining the development of the pandemic is the proactivity of the government response to the pandemic, which is called the activity level of the government COVID-19 policies in this paper. A high policy activity level can be interpreted as policy responses that are faster than the level of pandemic development, while on the contrary, it is a low policy activity level. However, there exist some debates about the activity level of the government's COVID-19 policies.[11,12] Some see the government responses as weak,[13,14] while others argue that the pandemic prevention measures are excessive.[15,16] Furthermore, the government COVID-19 policies vary in space and time, and there exist conflicting directions of the policy patterns (e.g., "Living with COVID-19" and "Dynamic zero-COVID-19"),[17,18] which also lead to some debates of policy patterns.[19] According to the literature survey, few studies have systematically quantified these debates. Therefore, this paper addresses the following three under-studied questions using a quantitative data analysis:

1. Compared to the pandemic development, are the global government COVID-19 policies sufficiently active?
2. What are the differences and characteristics in the policy activity levels at the country level?
3. What types of COVID-19 policy patterns are forming?

The Oxford COVID-19 Government Response Tracker (OxCGRT) data set provides a systematic way to track government policies on COVID-19 containing 21 indicators and recording daily strictness scores (ordinal scales) for each indicator in 187 countries from January 1, 2020.[20] The OxCGRT data set provides an opportunity to analyze the global government COVID-19 policies.

In this paper, to address the research gap, we aim at developing a data-driven analysis based on the OxCGRT data set to answer the above three research questions. For this purpose, based on the DE-SWAN algorithm, we provide a comparison of the activity levels between government policies and pandemic developments at the global level (answering question 1), and analyze the policy activity levels at the country level (answering question 2). Then, we analyze the dynamic evolution of global policy patterns using a clustering ensemble algorithm (answering question 3).

2 | METHODS

2.1 | Data overview

The OxCGRT data set contains data from January 1, 2020, and provides a systematic cross-national, cross-temporal measure of government policies, which are related to containment and closure, economic, health system, and vaccination for 187 countries. This data set tracks government policies across a standardized 21 indicators (for more details see Supporting Information: Appendix A), and provides open-access, near-real-time data of policy strictness scores in a time-series format. For more descriptions and statistics of the OxCGRT data set see Hale et al.[20]

In this paper, we use 16 indicators, provided in the OxCGRT data set, to measure the government COVID-19 policies (see Table 1). Specifically, we use 187 countries' time series of strictness scores for the 16 government policy indicators from January 1, 2020 to June

TABLE 1 Overview of the 16 government policies indicators.

Indicators	Score range	Indicators	Score range
Containment and closure (C1–C8)		*Economic (E1–E2)*	
C1: School closing	0, 1, 2, 3	E1: Income support	0, 1, 2
C2: Workplace closing	0, 1, 2, 3	E2: Debt/contract relief for households	0, 1, 2
C3: Cancel public events	0, 1, 2	*Health (H1–H3, H6–H8)*	
C4: Restrictions on gatherings	0, 1, 2, 3, 4	H1: Public information campaign	0, 1, 2
C5: Close public transport	0, 1, 2	H2: Testing policy	0, 1, 2, 3
C6: Stay-at-home requirements	0, 1, 2, 3	H3: Contact tracing	0, 1, 2
C7: Restrictions on internal movement	0, 1, 2	H6: Facial coverings	0, 1, 2, 3, 4
C8: International travel controls	0, 1, 2, 3, 4	H7: Vaccination policy	0, 1, 2, 3, 4, 5
		H8: Protection of elderly people	0, 1, 2, 3

30, 2022. Note that we do not use indicators "H5: Investment in vaccines," "V1: Vaccine prioritization," "V2: Vaccine eligibility/availability," "V3: Vaccine financial support," and "V4: Mandatory vaccination" in the OxCGRT data set, because the data set does not provide time series of strictness scores of these indicators.[21]

Notably, the OxCGRT data set mainly shows the time series of government policies over the established indicators, confirmed COVID-19 cases, and deaths at the national scale. We complete the missing data in the time series by using the previous period data, if it exists; otherwise, we replace missing early data with zero (no previous period data).

2.2 | Study design

The framework of the used methods is summarized in Figure 1.

This paper follows the STROBE (Strengthening the Reporting of Observational studies in Epidemiology) reporting guidelines to ensure the results can be understood and replicated, and the quality of observational research. This study has been carried out in an ethical and responsible way, with no research misconduct. The data that support the findings of this study are openly available in the OxCGRT data set at https://github.com/OxCGRT/covid-policy-tracker.[20]

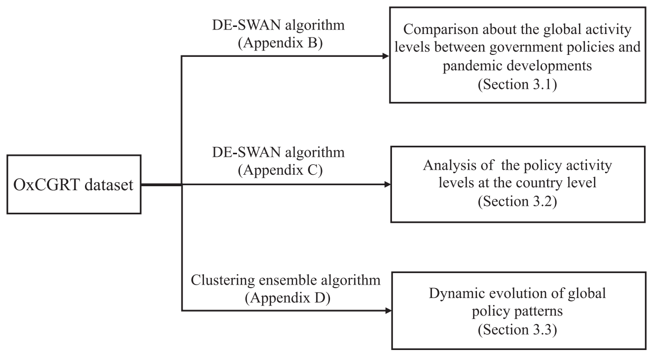

FIGURE 1 Framework of the used methods. DE-SWAN, differential expression-sliding window analysis; OxCGRT, Oxford COVID-19 Government Response Tracker.

2.3 | Global policy activity level

The global policy activity level at time t is measured by the number of countries with significant changes in government policies at time t

$$\text{global policy activity level}_t = \#\left(\text{Coun}_t^{\text{policy}}\right), \tag{1}$$

where # is a counter and $\text{Coun}_t^{\text{policy}}$ is the set of the countries with significant changes in government policies at time t, which are measured by the differential expression-sliding window analysis (DE-SWAN) algorithm within a 20-day window at a specific confidence level (F-test in generalized linear models: $q < 0.05$).[22] The q value is an adjusted p value and stricter than p value in statistical hypothesis testing. We use the same algorithm and calculate the number of countries with significant changes in new confirmed cases at time t (i.e., $\#(\text{Coun}_t^{\text{confirmed}})$) and new deaths at time t (i.e., $\#(\text{Coun}_t^{\text{deaths}})$) to measure the global activity level of pandemic development at time t, respectively. The detailed DE-SWAN algorithms are provided in Supporting Information: Appendix B, and the comparison results about the global activity levels between government policies and pandemic developments will be included in Section 3.1.

2.4 | Country policy activity level

Based on the use of DE-SWAN algorithm (Supporting Information: Appendix B), we further define a set of policy-active countries C_t^{active} as those countries in which there is no significant change in the number of new confirmed cases but a significant change in policies at time t. We then measure the policy activity level of country j by calculating how often country j belongs to the set of policy-active countries C_t^{active} from January 11, 2020 to June 20, 2022

$$\text{country policy activity level}_j = \sum_t \left(\#\left(c_j \cap C_t^{\text{active}}\right)\right), \tag{2}$$

where # is a counter, and $\{c_j | 1 \leq j \leq 187\}$ denotes the set of selected countries. For further details about the calculation of the country policy activity levels, please see Supporting Information: Appendix C. The policy activity levels at the country level will be analyzed in Section 3.2 in detail.

2.5 | Policy density

In Section 3.3, we analyze the government policies based on the clustering method, where countries in the same cluster are considered to have the same policy pattern. Specifically, we analyze how global policy patterns have dynamically evolved and what the main policy patterns are. First, as for each of the 187 countries, we define a policy density measurement of policy indicator m at time t to analyze the per confirmed case cumulative strictness score of policy indicator m at time t

$$\text{policy density}_{t,m} = \frac{\text{cumulative strictness score}_{t,m} \times \text{population}}{\text{cumulative confirmed cases}_t}. \tag{3}$$

Then, we cluster all the 187 countries based on the policy densities associated with the 16 government policy indicators at each time point using the clustering ensemble algorithm from March 1, 2020 to June 30, 2022.[23] Then, we extract the information from the daily clustering results from March 1, 2020 to June 30, 2022 to explore the main categories of global policy patterns based on the co–association matrix method.[24] For further details refer to Supporting Information: Appendix D.

Notably, DE-SWAN algorithms mainly use the generalized linear models, and the p values are derived from two-sided F-tests. We obtain the q values (an adjusted p value) using the

Benjamini–Hochberg method[25] and calculate the type II sum of squares using the analysis of variance (ANOVA) function implemented in the R "car" package.[26] All the analyses were produced in the R statistics software (version 4.2.2).[27]

3 | RESULTS

3.1 | Global activity levels: Government policies versus pandemic developments

We use the DE-SWAN algorithm (Supporting Information: Appendix B) to calculate the time series of the number of countries with significant changes ($q < 0.05$) in government policies (i.e., $\#(\mathrm{Coun}_t^{\mathrm{policy}})$), new confirmed cases (i.e., $\#(\mathrm{Coun}_t^{\mathrm{confirmed}})$), and new deaths (i.e., $\#(\mathrm{Coun}_t^{\mathrm{deaths}})$) from January 11, 2020 to June 20, 2022 (Figure 2). We infer that the global activity level in government policies follows a four-phase process based on the two-stage multiple change point detection method,[28] with change points detected on February 14, 2020, April 28, 2020, and January 8, 2022. In the first phase, there is no global outbreak, but more than 100 countries reacted defensively. In the second phase, as the pandemic expanded to a global scale, the policy activity level reached its peak. In the third phase, the policy activity level plateaued. In the last phase, both the activity levels of government policies and pandemic developments show a decreasing trend. Taking this a step further, we discover that the policy activity levels in terms of the number of countries with significant changes are significantly higher than pandemic activity levels over time, regardless of whether we express the pandemic development in terms of the new confirmed cases or new deaths. (The red curve in Figure 2 is much taller than the blue or green one.) We call this phenomenon "policy's high activity," which can be explained by the fact that some countries frequently adjust their government policies while their own pandemic developments remain unchanged due to a lack of confidence in pandemic prevention, the influence of neighboring countries, high-risk perception, a belief in prevention myths, and so on.[5] This high level of concern and tension about the pandemic has contributed to the phenomenon of the policy's high activity. In addition, the new confirmed case activity levels are higher than the new death activity levels over time (i.e., the blue curve in Figure 2 is taller than the green one), which may be because the number of new confirmed cases is more influenced by government policies (e.g., contact tracing and case testing).

3.2 | Policy activity levels at the country level

Based on the use of DE-SWAN algorithm (Supporting Information: Appendix B), we measure the country policy activity levels by calculating how often a country belongs to the set of policy-active countries (i.e., C_t^{active}) over time (Supporting Information: Appendix C). Because the values of policy activity levels vary too much between countries, we use *z*-scores[29] to normalize country policy activity levels, which improves the comparability and eliminates the effect of data magnitude. In Figure 3A, we show the *z*-scores of country policy activity levels of all 187 countries. In addition, we collect the HDI[30] scores for 170 countries in 2017 from the "Our World in Data" online data set,[31] which measures the average achievement in key dimensions of human development: having a long and healthy life, being knowledgeable, and having a decent standard of living. From Figure 3B, we can know that the *z*-scores of policy activity levels and human development index (HDI) scores are almost evenly distributed above and below the mean value across 187 countries. However, for the *z*-scores of total confirmed cases, there are many outliers much higher than the mean value. Figure 3C examines the relationship between the *z*-scores of country policy activity levels and the *z*-scores of total confirmed cases until June 30, 2022, and finds a negative correlation between them under a simple linear model (*F*-test: $p < 0.05$). That is, higher country policy activity levels are associated with fewer total confirmed cases, implying that a high policy activity level has a positive effect on the pandemic development. Then, we explore the relationship between the *z*-scores of country policy activity levels and the *z*-scores of the HDI scores in Figure 3D and find a negative correlation between them under a simple linear model (*F*-test: $p < 0.05$). We argue that countries with higher HDI scores are more confident in their ability to deal with the epidemic and thus have lower levels of the country policy activity.

3.3 | Dynamic evolution of global policy patterns

We cluster all 187 countries based on the policy densities associated with the 16 government policy indicators at each time point using a clustering ensemble algorithm (Supporting Information: Appendix D) to capture the global policy evolution patterns. In our study, countries clustered in a category are assumed to share a similar policy pattern over the selected time period. Figure 4A

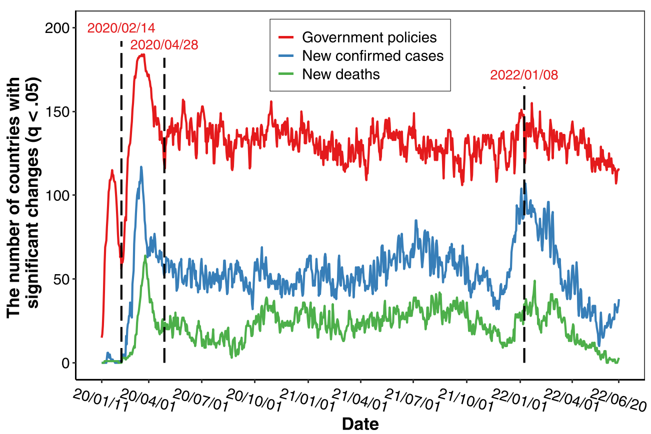

FIGURE 2 The number of countries with significant changes ($q < 0.05$) in government policies (red curve), new confirmed cases (blue curve), and new deaths (green curve) from January 11, 2020 to June 20, 2022.

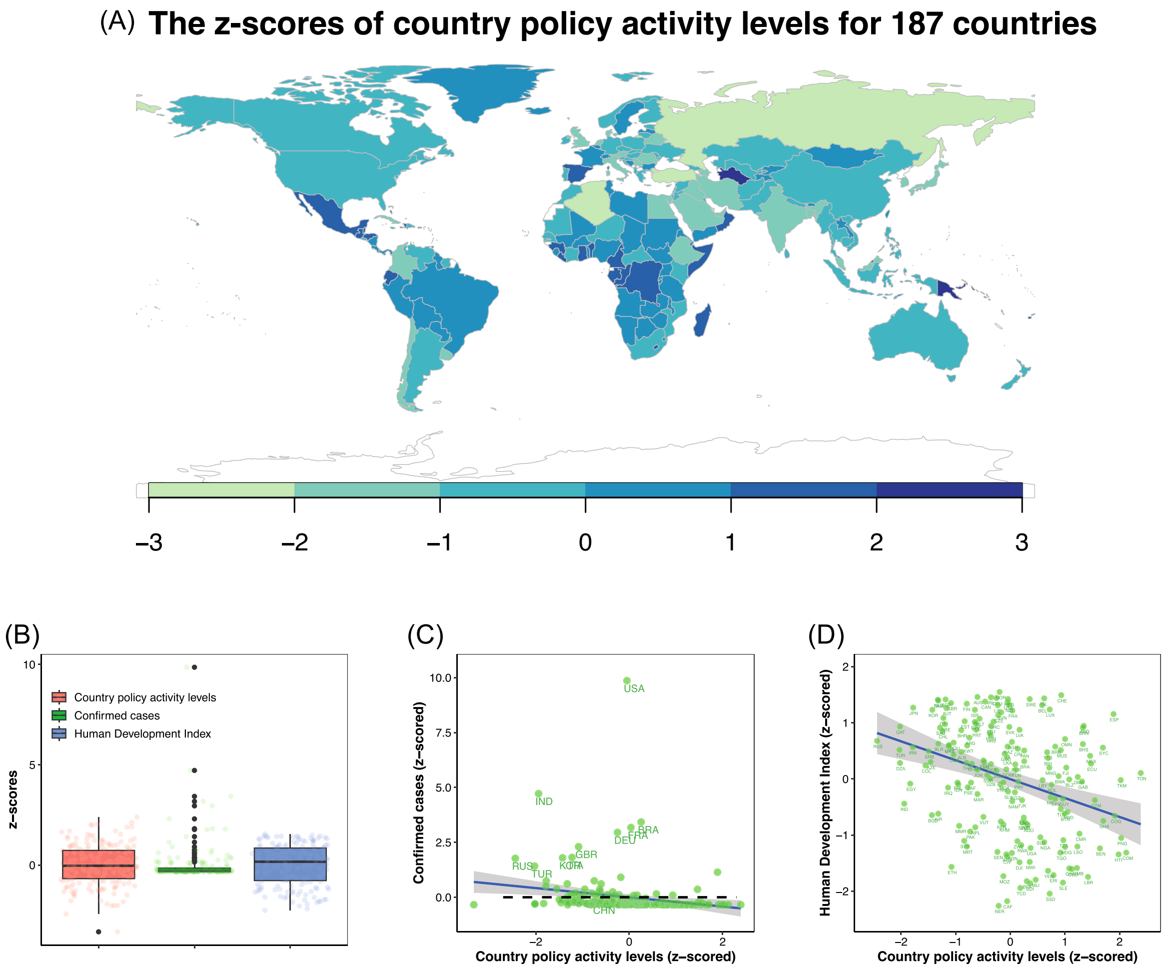

FIGURE 3 (A) The *z*-scores of country policy activity levels for 187 countries. (B) Boxplots plot the distribution of the *z*-scores of country policy activity levels, confirmed cases, and human development index (HDI) for 187 countries. (C) The changes in *z*-scores of total confirmed cases versus *z*-scores of country policy activity levels. The fitting curve in blue is estimated by the linear model. (D) The changes in *z*-scores of HDI versus *z*-scores of country policy activity levels. The fitting curve in blue is estimated by the linear model.

shows the results of global policy patterns with 3-month intervals: Almost all countries share one policy pattern except for a few African and Asian countries in the first half of 2020, and then China broke away from the policy pattern shared by most countries to form a separate policy pattern.

Furthermore, we merge together the daily policy clustering results from March 1, 2020 to June 30, 2022 based on the co–association matrix method (please see Supporting Information: Appendix D) to explore the main categories of global policy patterns, which are depicted in the left panel of Figure 4B. We can find that (1) 152 countries share one policy pattern, and these countries account for about 80% (6.47E+13/8.07E+13) of the global gross domestic product (GDP) and about 70% (5.4E+9/7.7E+9) of the global population (based on the 2020 national GDP and 2021 national population data from the “Our World in Data” online data set); (2) China has a separate policy pattern; (3) the rest 34 countries have different policy patterns. These countries are mainly distributed in Africa and cover about 1.7% (1.37E+12/8.07E+13) of the global GDP and about 11% (8.7E+8/7.7E+9) of the global population. Given the small influence of the rest 34 countries on the development of the global pandemic in terms of GDP and population, we approximately group the rest 34 countries into one category. Therefore, we divide the global policy patterns into 3 categories: (i) Mainstream (152 countries); (ii) China; (iii) Others (34 countries), which are depicted in the right panel of Figure 4B.

We further show the time series of average policy densities of the three global policy patterns (i.e., Mainstream, China, and Others) and the average global levels in 16 policy indicators (see Supporting Information: Figure S2 in Appendix E). We have the following observations: (1) the policy densities of the “Mainstream” policy pattern are slightly below the average global levels, with decreasing trends; (2) China's policy densities are well above the average global levels, and have been increasing until March 2022 when there are significant declines. China continues to have strong policies in pandemic prevention after March 2022, and the declines in policy densities in March 2022 are due to a sharp increase in the cumulative confirmed cases according to the definition of policy density (i.e., Equation 3); (3) the policy densities of the “Others” policy pattern are

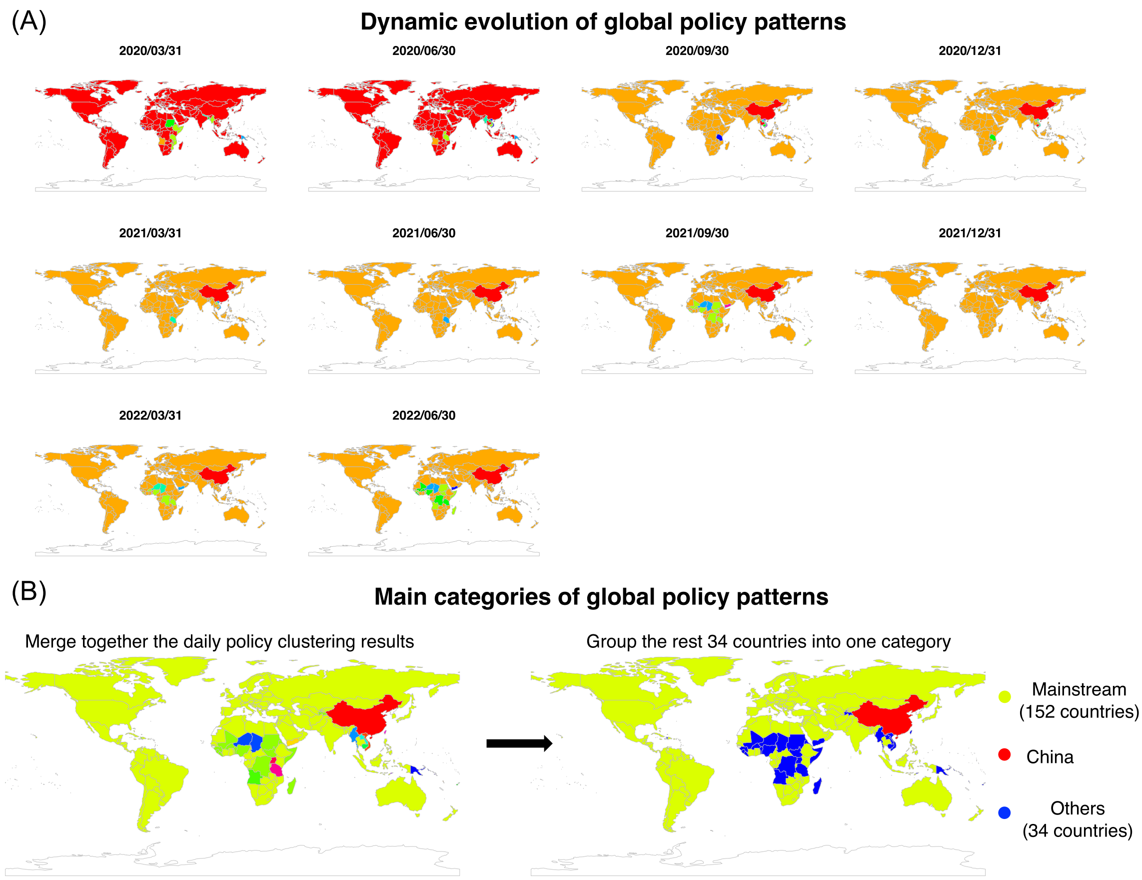

FIGURE 4 (A) Plots of the evolution of global policy patterns with 3-month intervals based on the clustering ensemble algorithm. (B) The left panel shows the fusion of daily policy clustering results from March 1, 2020 to June 30, 2022 based on the co–association matrix method; the right panel shows the three global policy patterns. Countries with the same color share the same policy pattern.

lower than China and higher than the average global level, showing decreasing trends.

4 | CONCLUSION AND DISCUSSION

COVID-19 pandemic has lasted for 3 years, and it is the right time to provide a retrospective study about global government COVID-19 policies based on a quantitative data analysis. With the support of OxCGRT data set covering 187 countries, this paper develops a global analysis of COVID-19 policy activity levels and evolution patterns from January 1, 2020 to June 30, 2022.

Within the period under study, we show that the global government policy responses to COVID-19 are significantly more active than the pandemic developments. Furthermore, we analyze the policy activity levels at the country level, showing that a higher country policy activity level positively contributes to the pandemic prevention and a high HDI score has a negative effect on the country policy activity level. Furthermore, we analyze the dynamic evolution of global policy patterns based on the policy densities, which are divided into three policy patterns: (i) Mainstream (152 countries); (ii) China; (iii) Others (34 countries). The "Mainstream" policy pattern exhibits the policy densities below the average global levels with decreasing trends in all policy indicators. China demonstrates a policy pattern well above the average global levels in most policy indicators, and the policy densities are on the rise until March 2022.

In this paper, we set multiple groups of parameters, such as the time window and confidence level in DE-SWAN algorithm, for the experiments to test the effect of some parameter settings on the results. We find that the related results are consistent with the above section, further details refer to Supporting Information: Appendix F.

This paper is one of the few retrospective studies that quantitatively explores the evolutionary characteristics of global government policies on COVID-19. For conventional crises, governments may have established ways of responding. But the COVID-19 pandemic was a "novel"[32] and serious crisis that most countries have not experienced. An important policy implication from our study is that we provide a new perspective on the government's understanding of its own policies and provide a reference for the government policies on "novel" crises.

Governments were faced with a difficult trade-off between the benefits and costs of government COVID-19 policies: excessive pandemic prevention measures will inevitably have a negative impact on the economy, freedom, and so on, and weak pandemic prevention measures will bring about widespread deaths. Our analysis indicates that the activities of global government policy responses to COVID-19 have shown above-pandemic developments. Therefore, we suggest that governments with high policy activity levels can consider enhancing the flexibility of policies, that is, strengthening policies that are appropriate to their national conditions, and relaxing policies that are less effective. In addition, the negative correlation between the HDI score and the policy activity level has a significant predictive power for the government's response in the face of a crisis.

There is heterogeneity in policy evaluation across countries because the national conditions and the state of pandemic development vary from country and country. There are some existing indexes that have been used to evaluate the government policies, such as the Stringency index,[20] Government response index,[33] and Economic support index.[34] However, these indexes focus only on the policy itself and ignore the national conditions, which may lead to inaccurate results when comparing the policies between countries. The policy activity level proposed in this paper evaluates the proactivity of the government policies considering the level of pandemic development. Therefore, from a methodological point of view, this paper provides a new option for defining the proactivity level of government policies during a crisis.

There are still many questions left, such as reasons for the differences between policy patterns. A limitation of our paper lies in the cross-sectional design, which poses difficulties in determining the causal influence of factors such as culture and politics in each country on the formation of policy patterns, and these questions deserve further study.

AUTHOR CONTRIBUTIONS

Meiqian Chen: Conceptualization; formal analysis; methodology; writing—original draft; writing—review and editing. **Yucheng Dong**: Conceptualization; methodology; writing—original draft; writing—review and editing. **Xiaoping Shi**: Conceptualization; methodology; writing—original draft; writing—review and editing. **Jun Zhuang**: Conceptualization; writing—original draft; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in OxCGRT data set at https://github.com/OxCGRT/covid-policy-tracker.

ETHICS STATEMENT

This study does not contain any studies with human or animal subjects. There are no human subjects in this study and informed consent is not applicable.

TRANSPARENCY STATEMENT

The lead author Yucheng Dong affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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