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Research paper

The role of populations' behavioral traits in policy-making during a global crisis: Worldwide evidence[☆]

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A B S T R A C T

Substantial heterogeneity in behavioral traits has been observed across human societies, which have been linked to important differences in individual as well as societal outcomes. In this paper, we complement the existing literature by investigating the role of key behavioral traits, i.e. risk-taking, patience, altruism, and trust, at the population level in the design of new policies and institutions during an unexpected global crisis. Combining granular data on policy responses to the COVID-19 crisis with several pre-pandemic survey measures of behavioral traits in 109 countries, we observe robust relationships of significant magnitude. In particular, our findings underline that countries with higher levels of trust tended to respond later to the crisis; while populations that are patient, altruistic, and trusting are more likely to implement stringent policies in the medium and long-term. These results improve our understanding of how countries deal with global crises. They also supply an explanation for the lack of coordinated response at the international level during such events.

1. Introduction

People's willingness to take risks, stay patient, behave altruistically and trust strangers are fundamental characteristics of human societies. These behavioral traits affect a wide range of personal decisions (Barsky et al., 1997; Heckman et al., 2006; Becker et al., 2012; Åkerlund et al., 2016; Kosse and Tincani, 2020) and vary considerably across societies (Henrich et al., 2010; Rieger et al., 2015; Falk et al., 2018), leading to substantial differences in societal outcomes (Fehr and Gächter, 2002; Aghion et al., 2010; Algan and Cahuc, 2013; Falk et al., 2018; Sunde et al., 2022). Subsequently, behavioral decision models are increasingly considered by scholars and policy-makers when designing new policies (Chetty, 2015; Matjasko et al., 2016; van Bavel et al., 2020). However, still little is known about the influence of populations' behavioral traits on the way societies tackle societal challenges through policy-making, especially in the event of an unexpected global crisis.

In this study, we examine the role of behavioral traits at the population level in explaining national policy decisions during a global crisis. Our analysis examines the relationship between two key factors: (i) population-level behavioral traits, i.e. willingness to take risks, patience, altruism and trust, and (ii) the timing (henceforth government *Responsiveness*) and the intensity (henceforth policy *Stringency*) of countries' policy responses to the COVID-19, an event involving substantial uncertainty in terms of public

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health consequences and efficacy of policy interventions. We extract individual measures of behavioral traits from large-scale cross-cultural surveys that were conducted prior to the pandemic outbreak, and aggregate these measures at the population level. As for policy responses, we use daily information on policy-making during the COVID-19 pandemic to obtain detailed measures of government *Responsiveness* and policy *Stringency*. Our analysis ultimately provides a nearly comprehensive description of the relationships between population-level behavioral traits and policy responses to a global crisis, by focusing not only on governments' initial reaction but also on policy changes over time in a total of 109 countries.

From a theoretical perspective, policy-making can be rationalized as a reaction to citizens' policy demands. Governments are expected to be particularly responsive to such demands when highly mediatized events emerge unexpectedly, thus providing a stress test of their ruling abilities (Besley and Burgess, 2002; Ashworth et al., 2018). Within this framework, policy responses to an unexpected event are driven by citizens' willingness to protect themselves and others. Such willingness is directly influenced by individuals' behavioral traits: a large body of evidence highlights that adopting health-enhancing behaviors correlate positively with risk-aversion, patience, altruism and trust (Anderson and Mellor, 2008; Suzuki et al., 2010; Kim et al., 2012; Sutter et al., 2013; Li et al., 2016; Betsch et al., 2017), which was also observed during the coronavirus crisis (Chan et al., 2020; Barrios et al., 2021; Campos-Mercade et al., 2021; Jordan et al., 2021; Thunström et al., 2021; Alfaro et al., 2022). Furthermore, all four behavioral traits were identified as important drivers of the support for and compliance with COVID-related restrictions (Müller and Rau, 2021; Campos-Mercade et al., 2021; Siegrist and Bearth, 2021; Alfaro et al., 2022; Fang et al., 2022). Consequently, governments of risk-averse, patient, altruistic or trusting populations could be incentivized to address an unexpected global event early and swiftly to match populations' policy demands. However, citizens' demands are not the only factor considered in policy decisions.

When addressing a policy issue, governments are also attentive to the effectiveness of implemented policies, especially when they come at substantial economic and social costs, as in the case of COVID-19 (Witteveen and Velthorst, 2020; Brodeur et al., 2021). Such effectiveness crucially relies on how citizens spontaneously react to the event and on how they comply with implemented policies, both of which are influenced by behavioral traits. Failure to correctly anticipate citizens' behavior is likely to cause inefficient policy decisions (Chang and Velasco, 2020; Alfaro et al., 2022). This applies particularly to the COVID-19 crisis as the absence of effective drugs or vaccines to "flatten the curve" led governments to rely on behavior-dependant interventions (e.g: stay-at-home or mask-wearing requirements) (van Bavel et al., 2020; West et al., 2020). In other words, because risk-averse, patient, altruistic and trusting populations spontaneously adopt health-enhancing behavior and adhere to public policies, their governments could be given the opportunity to delay their intervention or implement soft restrictions. Acting hastily or imposing overly stringent restrictions can even prove counterproductive because otherwise compliant actors may then perceive enforcement as a sign that the government distrusts them, which ultimately undermines their initial motivations to abide by the restrictions (Bowles and Polania-Reyes, 2012; Schmelz, 2021; Algan et al., 2021). Therefore, an intricate interplay appears to exist between policy responses to a global crisis and population-level behavioral traits, which thus merits an empirical investigation.

The COVID-19 pandemic outbreak offers a unique opportunity to investigate the relationship between populations' behavioral traits and policy decisions. It was a highly exogenous and mostly unexpected event that rapidly spread internationally. Consequently, it exposed governments from all over the world to the same unanticipated issue at approximately the same time. This feature facilitates international comparisons and mitigates endogeneity issues. The extreme nature of the crisis also increases the saliency of the behavioral traits under scrutiny. Handling extreme events indeed requires pondering risks, comparing outcomes over time, and infringing upon individual behaviors to protect the collective interest. At the same time, the crisis's duration allows us to track policy-making changes over time, during the waxing and waning phases of the pandemic. Finally, ample granular data are available on both populations' behavioral characteristics and policy responses to the crisis. Prior to the pandemic, representative surveys measured people's willingness to take risks, patience, altruism, and trust, which can reduce reverse causation interpretation. Additionally, detailed data on policies implemented during the crisis were quickly gathered by the scientific community, hence providing a comprehensive view of the policies enacted in most countries.

Our research identifies significant and consistent patterns between population-level behavioral traits and policy-making during a global crisis. We find that countries with higher levels of trust tend to respond to the crisis later than other countries, even after controlling for a range of country characteristics such as GDP, population characteristics, COVID-19 spread, and democratic governance. This effect is also robust to a variety of robustness checks, including changes in the definition of *Responsiveness* and continent-based analyses. Furthermore, we find that populations that exhibit patience, altruism, and trust are more likely to adopt stringent policies in the medium-term (100 days after the first policy response) and in the long-term (220 days). These findings underscore the importance of average behavioral traits within a population in the making of new policies when human societies are exposed to a highly unexpected global challenge. Subsequently, they supply an explanation for the lack of coordinated response at the international level during global crises, hence the need to better anticipate and prepare future crises.

The remainder of this paper is structured as follows: Section 2 describes the data and methods we use, Section 3 presents the results from our analyses and Section 4 offers a discussion and concludes.

2. Data & methods

2.1. Data

Measuring government policy responses to the pandemic

The information on the policy responses of governments begins the 1st of January 2020 and is recorded by the Oxford COVID-19 Government Response Tracker (OxCGRT, Hale et al., 2021a). The OxCGRT is a comprehensive source of information that reports on

19 indicators of government responses in over 180 countries, using publicly-available data. It is meticulously compiled by a team of more than 400 volunteers (see Hale et al., 2021a, for details). The dataset categorizes the indicators into three categories: (*i*) containment and closure, (*ii*) economic response, and (*iii*) health systems. The information for each indicator comprises formal laws, executive orders, policies issued by regulatory authorities, as well as recommendations and guidance. The database assigns a value $v^i_{k,t}$ to quantify the intensity of each indicator k at a given date t. For instance, the "stay-at-home requirements" indicator is coded as follows: 0 = no measures, 1 = recommendation not to leave the house, 2 = requirement with exceptions for essential trips, and 3 = strict requirement with minimal exceptions. In this study, we focus on policies that directly impact citizens, because our aim is to study the relationship between policy responses and aggregated measures of individual behavioral traits. As a consequence, we restrict our attention to the nine indicators that entail legal restrictions on individual behavior: school closures, workplace closures, cancellation of public events, restrictions on social gatherings, public transportation closures, stay-at-home requirements, travel bans (domestic and international), and facial coverings.[1] This approach minimizes potential measurement errors and comparability concerns across countries.

This study focuses on two dimensions of governments' policy responses to the pandemic: (i) *Responsiveness*, i.e. how quickly a given country responded to the spread of the virus; and (ii) *Stringency*, i.e. how strongly the country responded.

To define our measure of government *Responsiveness*, we focus on mandatory policies that have a significant impact on individuals' well-being, excluding recommendations that may only have an announcement effect. "Restrictive policies" are defined as those with values $v^i_{k,t}$ above 2, except for restrictions on gatherings and international travel controls, which are already restricting individual behavior with a value of 1. We identify the day of the first implementation of a restrictive policy in a country as D_0. Our primary measure for *Responsiveness* uses the negative logarithm of the number of COVID-19 cases recorded in the country on D_0 (Definition R_1). A higher number of cases implies a lower government responsiveness. Such a metric takes into account both the local dynamics of the pandemic and the fact that the number of reported COVID cases was one major piece of information scrutinized by governments at the beginning of the sanitary crisis (Doornik et al., 2021). For countries that reacted before their first recorded case, we assign a value of 0. However, we acknowledge that this metric may overlook differences in testing strategies and possible errors in case records. It also does not account for the size of the underlying population. To overcome these limitations, we consider alternative measures: the number of days between the first recorded case and the implementation of the first restrictive policy (Definition R_2), and the negative logarithm of the number of recorded cases per million inhabitants on the day of implementing the first restrictive policy (Definition R_3). These alternative measures provide different perspectives on government *Responsiveness*, considering factors such as the time elapsed since the start of the epidemic at the local level and the proportion of recorded cases within the population.

To measure the *Stringency* of implemented policies, we follow the methodology proposed by Hale et al. (2021a). We apply this procedure to our set of indicators to calculate a Stringency Index for each country at a given date t. The process involves two steps. First, we flag the indicators to account for policies targeting specific areas, reducing the indicator value by half a rank if the policy is not applied nationally. Second, we normalize the indicators to address differences in range. The flagged value of each indicator is divided by its maximal possible value and multiplied by 100, resulting in a score between 0 and 100 for each indicator. The Stringency Index is then computed as the unweighted average of the scores of all nine indicators. The formula for the Stringency Index for country i at date t is given by:

$$SI_{it} = (1/K).\sum_{k=1}^{K} 100.((v^i_{k,t} - 0.5 f^i_{k,t})/N^i_k)$$

K represents the number of indicators (9), $v^i_{k,t}$ denotes the value of indicator k at date t, $f^i_{k,t}$ represents the flag value for indicator k at date t (1 for targeted policies, 0 otherwise), and N^i_k is the maximal value of indicator k. The Stringency Index ranges from 0 (no response) to 100 (highly-coercive response) and is calculated daily in each country over the year following the implementation of the first restrictive policy (D_0). Indeed, the relationship between behavioral traits and policy stringency is expected to change over time due to people and governments updating their behavior as the pandemic evolves (e.g., norm compliance fatigue, arising socioeconomic emergencies, crisis habituation, etc.). Consequently, our analysis is not restricted to immediate policy responses but instead focuses on correlations over the year following the implementation of the first restrictive policy.[2] The relative date t corresponds to the number of days since a country reacted to the local dynamics of the pandemic and implemented its first restrictive policy. D_0 varies across countries, ranging from mid-January to early March. D_{90} falls between mid-April and early June, representing a time when pandemic-induced pressure began to decline overall. Similarly, D_{210} falls between mid-August and early October, when the number of cases worldwide started to rapidly increase again.

Measuring population-level behavioral traits

Our empirical strategy builds on measures of risk-taking, patience, altruism and interpersonal trust taken from different sources in order to achieve extensive external validity thanks to: (*i*) including a large number of countries from all continents; and (*ii*) having obtained representative samples from the national populations aged 15+ through probability-based sampling. Furthermore,

[1] We exclude indicators such as testing policies and contact tracing due to their subjective interpretation and varying enforcement capacities across countries (see Hale et al., 2021a, for details).

[2] We focus on pre-vaccine policies by considering only the first year, as vaccination policies significantly impacted the dynamics of the pandemic. Additionally, the emergence of new COVID variants and their influence on the worldwide spread of the virus became prominent in late 2020.

all our measures were collected prior to the COVID-19 outbreak, minimizing the potential for reverse causation bias. Indeed, it is well-documented that the COVID-19 crisis has influenced individual preferences (Cappelen et al., 2021; Shachat et al., 2021; Branas-Garza et al., 2022). Therefore, using data from surveys conducted during the health crisis would have increased the risk of misinterpretation.

Our main measures are taken from the Global Preferences Survey (GPS, Falk et al., 2022), which covers 76 countries and accounts for about 90% of both the world population and the world GDP in 2012.[3] The GPS employs an innovative *ex-ante* validation procedure that selects survey questions based on incentivized experimental economic games. Consequently, the GPS exhibits internal validity due to its link with lab-environment behaviors and substantial external validity as a representative survey. We also extract information from the 6th wave of the World Values Survey (WVS, Inglehart et al., 2014), conducted in 60 countries from 2010 to 2014 (henceforth WVS6). In addition to expanding the geographical scope of our study, the WVS also includes various components of interpersonal and institutional trust, allowing us to refine our analysis of interpersonal trust. To this end, we utilize the survey questions that assess trust in different groups of people, ranging from family to foreigners. *Narrow* trust is the score related to strangers and is likely closest to the GPS measure. *Global* trust adds up the scores from all the survey questions on trust in others. Furthermore, the WVS enables us to examine trust in governments as an additional variable of interest. Several studies indeed document that trust in governments is critical to the effectiveness of public interventions during an epidemic (Blair et al., 2017; Aassve et al., 2021).

As an additional robustness check, we also use the joint WVS (7th wave)/EVS (European Values Survey) dataset (EVS/WVS, 2021), which covers 79 countries (2017–2021). The main advantage of the joint dataset over the WVS6 is its larger number of surveyed countries, providing stronger external validity. However, the WVS/EVS dataset has two limitations: (*i*) it lacks information on willingness to take risks, and (*ii*) some countries were surveyed after the onset of the pandemic. This exposure potentially introduces biases into the measures of behavioral traits due to the influence of the health crisis in the surveyed countries. Accordingly, we present the results using the complete dataset (79 countries) as well as a restricted dataset comprising only the countries surveyed before the start of the pandemic (65 countries).

For all measures of behavioral traits, we aggregate observations at the national level and standardize the result at the international level. A more detailed presentation of the variables and a description of the underlying data sources are reported in the online appendix (see Data & Methods (detailed)). Fig. A-1 maps all countries that have been included in our dataset (that is surveyed at least once). Table A-3 exposes the number of participants per country per survey.

2.2. Empirical approach

Our empirical approach involves conducting a cross-sectional analysis to examine the determinants of government *Responsiveness*, followed by a panel analysis to analyze the determinants of policy *Stringency* during the first year of the pandemic.

Model specification for Responsiveness

$$Y_i = \alpha + \beta^1 Risk_i + \beta^2 Patience_i + \beta^3 Altruism_i + \beta^4 Trust_i + \theta \times Controls + \epsilon_i \tag{1}$$

Y_i represents the outcome variable for country i, which we define as *Responsiveness* (measured as the negative logarithm of the number of cases on the day the first restriction was implemented in the main results). We acknowledge that considering only the raw number of cases without accounting for the population size of countries may seem trivial at first glance. However, we argue that the number of reported COVID cases played a crucial role in government scrutiny during the early stages of the sanitary crisis. Indeed, it took some time for policymakers and the media to acknowledge that the size of the population inflates the number of cases. Nevertheless, we examine alternative measures of *Responsiveness*: (i) the number of days between the country's first recorded case and the implementation of the initial required policy (Definition R_2) and (*ii*) replacing the absolute number of cases with the number of cases per 1000 inhabitants in R_1 (Definition R_3). Notably, definition R_2 also accounts for the possibility that the behavioral characteristics examined in this study might be correlated with testing capacities, potentially biasing our other findings. However it does not account for the local dynamics of the pandemic, contrary to definitions R_1 and R_3. We estimate all models using Ordinary Least Squares (OLS) with robust standard errors.

Our primary focus is on the behavioral traits of the population, which include $Risk_i$, $Patience_i$, $Altruism_i$, and $Trust_i$, along with their corresponding regression coefficients β^k. We first define trust as the interpersonal aspect of trust, specifically the level of trust individuals have in random people. This is captured both by the GPS and the WVS. As an alternative measure of trust, we compute an aggregate trust score by averaging the trust-related questions in the WVS (*Global* trust, as opposed to *Narrow* trust). In addition, when analyzing the data from WVS6, we introduce the variable $Trust\ gov_i$, i.e. the trust in government.

We proceed by incorporating several variables to control for the possible impact of country and population characteristics, which have been documented to have an impact on country's reaction to the COVID pandemic (Jinjarak et al., 2020; Brodeur

[3] In addition to risk-taking, patience, altruism and interpersonal trust, the GPS contains measures of positive and negative reciprocity. These measures are excluded from our analysis, considering that they are much less documented in the literature as key drivers of health decisions. Moreover, they are highly-correlated with the other behavioral traits which we focus on, leading to power issues in the statistical models.

et al., 2021). Specifically, we consider five key characteristics: *population's density*, *median age*, *log(GDP per capita)*, indicators of democratic governance, and *worldwide COVID spread*. The first two variables importantly determine the need for early and stringent policy intervention in the face of COVID-19, as older persons are more likely endangered by the disease and denser social networks facilitate the virus's dissemination. GDP per capita is also a proxy for different variables that affect the ability of a given country to deal with the epidemic, such as the quality of the healthcare system, the education level in the population, or the country's budgetary constraints. Besides, all three variables are correlated with the behavioral traits under scrutiny (see Fig A-9), so that their omission has the potential to bias our estimates. The indicators of governance account for the fact that the nature of the political regime has been identified as an important driver of country's reactions to the COVID crisis (Sebhatu et al., 2020; Chen et al., 2023). In particular, the responsiveness of governments to population demands and more generally to population well-being is likely different between democratic and non-democratic regimes. For this purpose, we utilize the Worldwide Governance Indicators.[4] Finally, COVID's worldwide spread is the difference in days between the first worldwide case in our dataset and the first case within the country. This accounts for the non-random spatial spread of the virus, which may have caused countries impacted later to benefit from the experience of those impacted earlier, specifically in dealing with the pandemic.

As a supplemental robustness check, we also consider two additional control variables: *political color*, the political inclination of the ruling party (on a left–right scale), and *connectivity*, an indication of how connected a country is to other countries based on airline distance. *Political color* is constructed as the score on the "economic left–right scale" for the party with the highest number of seats in the parliament in 2019 from the V-party dataset.[5] Governments with different ideological stances may for instance be differently sensible to infringing on citizens' liberties or have different opinions with respect to the urgency of addressing a global health issue. *Connectivity* comes from Meslé et al. (2022): it is defined as the normalized index of airline connectivity and computed from the estimation of a network percolation model using global airline passenger data. This variable serves as another way to capture the route of spread of the virus, given that our *worldwide COVID spread* variable may suffer from some weaknesses (e.g: since it relies on recorded cases for which the measurement accuracy is debatable). However, considering that the inclusion of both *political color* and *connectivity* implies the exclusion of 5 (resp. 8) countries in the GPS (resp. VWS6) dataset, which correspond to about 7% (resp. 14%) of included countries, we decided not to include these additional controls in our main analyses and expose the corresponding results only in the appendix.

While many other variables could be relevant in explaining countries' policy reactions, we believe that our analysis accounts for the main confounders given the limited number of observations. In comparison, Falk et al. (2018) examined the relationship between preferences from the GPS survey and a country's GDP per capita. Their set of controls includes variables such as distance to the Equator, average temperature, average precipitation, the share of the population living in (sub)tropical zones, terrain ruggedness, average distance to the nearest waterway, and an island dummy. They find that their set of controls reduces their initial estimates by a third for the relationship between trust and their main outcome. On the contrary, and despite our dependent variables provide a more refined measure of outcomes as compared to GDP per capita, our controls do have a limited impact on our main results.

2.2.1. Model specification for *Stringency*

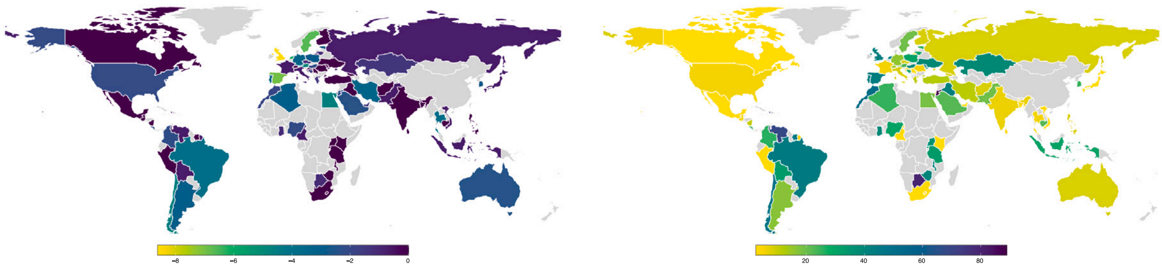
We now shift our focus to the relationship between population-level behavioral traits and the dynamics of policy-making during the sanitary crisis. The underlying concept behind this approach is the idea that the trade-off between policy implementation and subsequent behavioral traits changes over the course of the pandemic. Several indications support this idea. First, citizens' demands may evolve over time (fatigue, crisis habituation, etc.). For instance, a patient population might be more inclined to durably accept stringent policies even in the absence of a significant spread of the pandemic. Second, behavioral traits can influence the spread of the virus, and thus indirectly affect policies tailored to them. We are thus primarily interested in the time-changing relationship between population-level behavioral traits and the policy-making process. We therefore rely on a panel data analysis that allows us to account for the evolution of the stringency index over time as well as time and country unobserved characteristics.

$$Y_{it} = \sum_{k=1}^{K} \sum_{t=1}^{365} \beta_t^k \times (Trait_i^k \times D_t) + \theta \times \log(Cases_{it}) + \alpha_i + D_t + \epsilon_{it} \tag{2}$$

The outcome variable Y_{it} represents the Stringency Index for country i at date t. The behavioral trait measures, denoted as $Trait_i^k$, capture various behavioral traits such as willingness to take risks, patience, altruism, trust (for GPS, $K = 4$), or willingness to take risks, patience, altruism, trust, and trust in government (for WVS6, $K = 5$). The associated regression coefficients, $\beta_1^k \cdots \beta_{365}^k$, account for the relationship between behavioral traits and the outcome variable over all dates t. This approach enables us to analyze the statistical significance of each interaction term of interest, but also to compare estimates over time. Additionally, we incorporate the number of recorded cases, $Casesit$, to account for the impact of the dynamics of the epidemic. We include relative date fixed effects, D_t, as well as country fixed effects, α_i. Both parameters aim to account for (*i*) the specific response structure of policy stringency following D_0 (*e.g.* an experience effect), and (*ii*) country time-invariant factors (*e.g.* an endowment effect). Finally, the error term ϵ_{it} captures unobserved factors.

[4] The Worldwide Governance Indicators are *Government Effectiveness*, *Voice and Accountability*, *Political Stability and Absence of Violence/Terrorism*, *Regulatory Quality*, *Rule of Law*, and *Control of Corruption*. They can be found at https://www.govindicators.org/.

[5] The V-party Dataset from the Varieties of Democracy (V-dem) project (https://v-dem.net/data/v-party-dataset/) offers several pieces of information about all known political parties, such as policy positions and organizational structures, from a large number of countries. More specifically, each variable in the dataset is constructed from a model-based aggregation of a pool of about 3700 expert answers to a series of questions. Notably, the dataset currently does not cover 2020 and beyond, so that if a country's ruling party changed in the early days of the pandemic we may have a biased measure of its political inclination. However, we also note that the likelihood of such an event is low, and even more so considering that countries for which elections had to be held in 2020 usually decided to postpone it because of the pandemic.



(a) *Responsiveness* (b) *Stringency* at D_3

Fig. 1. Worldwide policy responses. *Responsiveness* is computed as the negative of the log number of recorded cases on the day when the first restrictive policy is implemented (D_0). E.g.: a value of −4 corresponds to approximately 55 recorded cases. *Stringency* is an index ranging from 0 (absence of response) to 100 (highly-coercive response). It is measured every day following D_0 (e.g., D_3 is D_0 plus 3, hence the third day). Only countries surveyed in the GPS are included.

3. Results

Fig. 1 depicts substantial international heterogeneity in terms of both *Responsiveness* (Fig. 1(a)) and *Stringency* (Fig. 1(b)) in the GPS dataset. The United Kingdom, Spain, Sweden, the Netherlands, and Austria waited the longest before implementing their first restrictive policies, whereas many other countries around the globe reacted as soon as or even before they recorded their first case (e.g., Finland, India, Mexico, Kenya or Croatia.). Although the majority of countries first restricted international travel, we also observe some variations in the nature of the first restrictive policy around the globe (Fig. A-2). Similarly, countries from very diverse locations adopted policies of comparable intensity: On the third day following D_0, Jordan, Botswana, Haiti, Venezuela, and Morocco implemented the most stringent policies, whereas South Africa, Canada, Sri Lanka, Croatia, and Japan were among the countries implementing the least stringent. Similar maps for the other datasets, for alternative definitions of *Responsiveness*, and for various time spans (*Stringency*) can be found in Figs. A-3, A-4, A-5. Consequently, the heterogeneity in policy responses to the pandemic does not appear to be geographically concentrated, suggesting that the international spread of the virus may not entirely explain cross-country differences in COVID-related restrictions.

3.1. Government Responsiveness

Fig. 2 reports estimated coefficients and corresponding 95% confidence intervals in OLS regressions of government *Responsiveness* on nationally-aggregated behavioral traits using data from either the GPS (top panel) or the WVS6 (bottom panel). The precise OLS specification is described in the Data & Methods section. All models include all four behavioral traits. For each trait, the first model (orange triangle) includes the four traits as explanatory variables, while the second (blue circle) adds the country-level control variables. The results remain, however, unchanged when the correlations are scrutinized separately (Tables A-4 and A-5).

Most notably, we observe in the GPS a negative and highly significant correlation between *Responsiveness* and trust. For instance, following the definition R_1, a one standard deviation (0.271) in the population's level of trust corresponds to a 290% increase in the number of cases at D_0 ($p < 0.01$). Upon introducing control variables or varying the definition of *Responsiveness*, this relationship remains remarkably stable in both its magnitude and statistical significance. Similarly, we obtain virtually the same results when adding *political color* and *connectivity* alongside our main controls (Fig. A-6). The governments of populations with higher levels of trust thus appear more willing to wait before implementing COVID-related policies.[6] We also observe a similar though slightly weaker relationship with patience, which is no longer significant after including controls. At the same time, altruism and willingness to take risk do not strongly relate to *Responsiveness*. Finally, we observe that the model with all behavioral traits accounts for approximately 21% of the variance in government *Responsiveness* (23% when controls are added, Table A-4). Consequently, a population's behavioral traits (and, foremost, trust) appear strongly related to its government's eagerness to address the pandemic.[7]

We recover the negative relationship between trust and Responsiveness (R_1) in the WVS6 (first column of bottom panel), although it is slightly reduced in terms of both magnitude and significance.[8] The direction of the correlation remains similar when varying

[6] Accounting for data concentration at 0 with a Tobit specification also yields qualitatively similar results.

[7] Because we run several statistical tests simultaneously (four tests on three dependent variables), there is an inflated risk of false positive results that is not accounted for in the regression model. We thus computed adjusted p-values to control the family-wise error rate at the 5% threshold following Clarke et al. (2020), and report the results in Table A-6. Overall, correcting for multiple hypothesis testing only induces little changes for the statistical significance of the correlations between *Responsiveness* and trust.

[8] Apart for altruism, we observe that the different datasets measure similar behavioral traits: although not always significant, the correlations between datasets for risk-taking, patience, and interpersonal trust are positive (Fig. A-8). Interestingly, we observe a negative correlation for altruism in both comparisons, a finding that may indicate that the surveys ultimately quantify different notions of "selfishness".

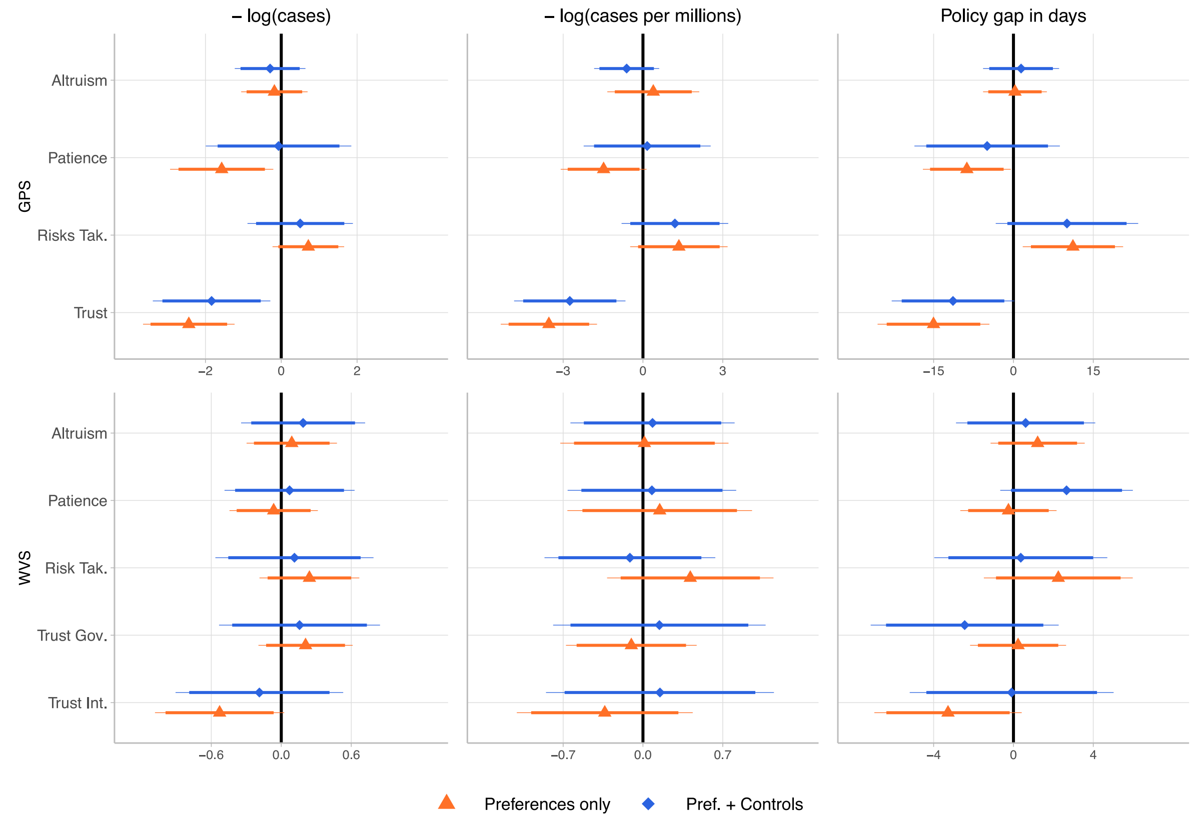


Fig. 2. *Responsiveness* and behavioral traits. Dots correspond to estimated coefficients in OLS regressions of government *Responsiveness* on nationally-aggregated behavioral traits. Bars correspond to 90% (smaller) and 95% (larger) confidence intervals, computed with robust standard errors. Regressions either include only the behavioral measures or they control for *population density*, *median age*, *log(GDP)$_{pc}$*, the indicators of democratic governance, and the *worldwide COVID spread*. The figure is organized as follows. Each column represents a given measure of *Responsiveness*: column 1 is the -log(number of cases); 2 is the -log(number of cases/per million inhabitants); and 3 is the number of days between the first case and the first implemented policy. Each row gathers estimates for each measure of *Responsiveness* for a given dataset: GPS (top, 75 countries) or WVS6 (bottom, 59 countries).

the definition of *Responsiveness* (second and third columns), but it is no longer statistically significant at conventional significance thresholds. Similarly, introducing control variables decreases both the strength and statistical significance of the relationship. At the same time, all other correlations between *Responsiveness* and behavioral traits are small and non-significant, including trust in the government. However, these results may originate from a lower statistical power due to the lower number of observations in the WVS6 than in the GPS (16 less countries).

As a robustness check, we run the same analysis on the WVS/EVS dataset in Fig. A-7. The results on trust strikes a balance between the GPS and the WVS6: regressions without control variables show a highly significant relationship that vanishes upon the introduction of the control variables. Nonetheless, we also observe that the correlation between trust and *Responsiveness* is systematically negative. In addition, these results are sensitive to the inclusion of the indicators of democratic governance: adding only one indicator at a time instead of considering all six indicators (which are highly correlated, see Fig A-9) often results in a statistically highly significant relationship, depending on the democratic indicator and definition of *Responsiveness* under consideration.[9] Moreover, the Adjusted R-square from the regression is usually higher in the models with only one indicator as opposed to the models with all six indicators. In other words, we believe that the exposed results are rather conservative. At the same time, the relationships with the other behavioral measures remain virtually unchanged. Also, substituting the “Narrow” with the “Global” version of trust provides consistent results (Table A-7 and Fig. A-11), and so does restricting the EVS/WVS to the countries that were surveyed before 2020 (Fig. A-7 and A-11).

We also verify that the observed relationships are not driven by some geographical imbalances by considering continents separately (Fig. A-12). We find that the coefficient signs are relatively consistent throughout: Though our results do not remain invariably consistent for all continents taken separately, we do not observe significant contradictory relationships across continents.

[9] For instance, we systematically observe a negative and significant relationship between trust and definitions R_1 or R_2 of *Responsiveness* in the EVS/WVS when only one democratic governance indicator is accounted for at a time.

Overall, our results are thus very robust in our primary database of interest (the GPS), which contains more observations and more precise measures of behavioral traits, whereas the evidence is weaker from a statistical perspective in the alternative databases. In particular, our findings emphasize the robustness of the negative relationship between interpersonal trust and governments' eagerness to address the COVID-19 crisis.

3.2. Stringency of policy responses

Our analysis of the *Stringency* of policy responses employs a fixed-effect panel regression model, with the Stringency Index as dependent variable. The independent variables of interest are interaction terms between each of the four behavioral traits and the day dummies D_t: $Trait \times D_t$, with $t \in [1, 365]$ (see Data & Methods section). This specification allows us to study how the relationships have evolved throughout the year since the day when the country implemented its first restrictive policy (D_0). We include dates and countries fixed effects to account for unobserved heterogeneity. We also systematically control for the (log) number of recorded cases at date t to account for the within-country pandemic dynamics.

The results are depicted in Figs. 3(a) and 3(b). Each horizontal panel plots the magnitude and the statistical significance of the relationship between the Stringency Index and one behavioral trait. Our goal is to assess whether clear correlation patterns emerge over time, rather than to focus on specific point estimates. In addition, our graphical approach avoids the issues that usually arise when presenting regression results (e.g. p-hacking), because we neither select a specific (arbitrary) date nor report only the standard thresholds on statistical significance.

Fig. 3(a) plots the regressions for countries surveyed in the GPS. Most notably, we find differentiated patterns over time for all behavioral traits. Overall, altruism and trust are similarly related to *Stringency*: Governments of altruistic and trusting populations implement stricter restrictions than the governments of self-interested and defiant populations. A standard deviation in the level of altruism or trust increases the Stringency Index by up to 20 points. However, the statistical significance of such patterns varies importantly with time. First, the relationships are not statistically different from 0 until approximately three months following D_0. Second, the evolution over time of the relationships' statistical significance is inversely related to altruism and trust. Altruism has a highly significant relationship with Stringency during the three- to seven-month period following D_0 and in the last month; whereas the relationship is much less significant otherwise. The converse is observed with trust. Concerning patience, an apparently dual relationship appears as the coefficient increases over time. For a short period after D_0, the governments of patient populations implement looser restrictions than governments of impatient populations. However, this relationship reverses in the long-term, particularly around seven months after D_0.[10] Finally, we find a weaker relationship between a population's willingness to take risk and the Stringency Index, with a weakly-significant positive relationship beginning three months after D_0 and lasting over two months, meaning that governments implement stricter restrictions on risk-loving populations than on risk-averse populations during this period.[11]

Fig. 3(b) plots the regressions for countries surveyed in the WVS6. We observe globally consistent patterns with the results on the GPS. Overall, we observe that both the magnitude and statistical significance of the coefficients are lower than in the GPS. Again, this could relate to power issues due to the lower number of observations in the WVS6. The patterns for risk-taking and patience are similar to previous observations: We observe a positive relationship with willingness to take risks in the short-term and both a negative (in the short-term) and a positive (in the long-term) relationship with patience. However, the correlation with risk-taking is much more significant, whereas the long-term correlation with patience is much less significant.[12] Concerning altruism, the correlation is not significant at any point in time. Finally, the correlation with trust is significantly negative in the short-term but non-significant otherwise. As a consequence, the results on both altruism and trust appears different between GPS data and WVS6 data. However, when we compare all patterns over time, we observe that shifting the GPS patterns downwards approximates the WVS patterns. Interestingly, substituting the "Narrow" with the "Global" version of trust yields a pattern closer to our GPS findings, while the patterns for the other behavioral traits remain virtually unchanged (Fig. A-13). The results over time are thus consistent across the two datasets, though the interpretations differ slightly. These discrepancies may thus originate from differing sample sizes or compositions of the country pools across datasets, or different ways to measure behavioral traits across surveys.

Running the analysis on WVS/EVS consolidates this view of overall consistent results: We obtain positive correlations with both altruism and trust for the same periods as in the GPS (Fig. A-14). We also observe a significant negative relationship with patience, although the period differs (mid-term instead of short-term), and we find no positive relationship in the long-term. Additionally, when we correlate the Stringency Index with trust in the government in the WVS6 and the WVS/EVS, we observe a consistent pattern over time across the two datasets. However, the coefficients are significantly different from zero at different periods. Specifically, the correlation is negative in the early weeks (WVS/EVS) and positive for sixty days, beginning about three months after D_0.

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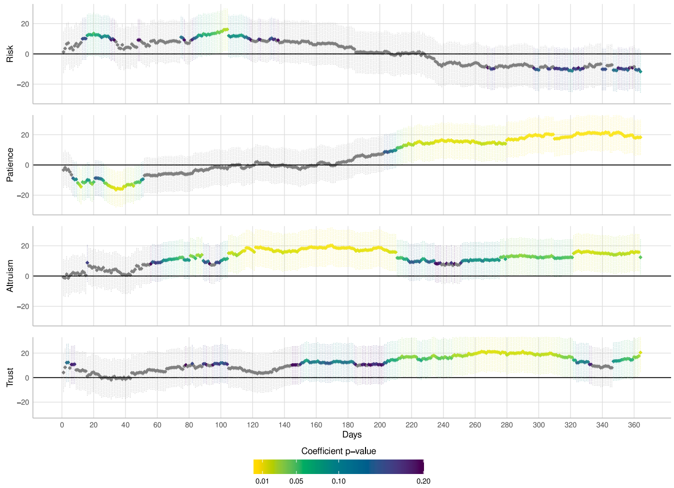
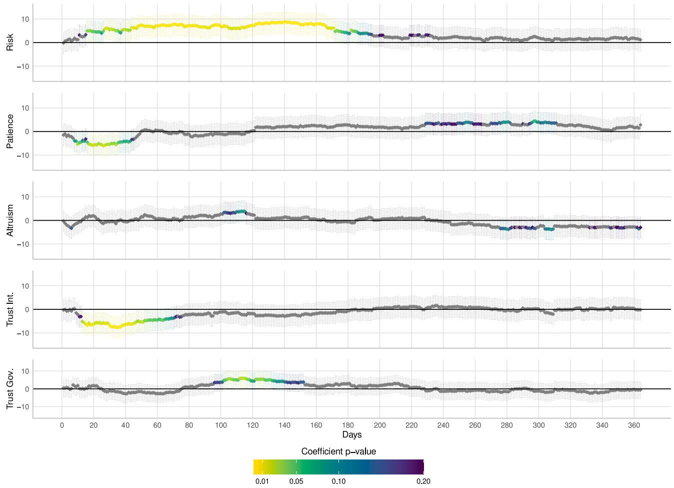
[10] Admittedly, a fixed-effects estimation accounts for invariant country characteristics, which may still correlate with the differentiated impact of behavioral traits over time. Thus, we cannot rule out that the changes observed in the coefficients are driven by temporal changes in the impact of invariant characteristics. In particular, the long-term impact of patience may originate from a policy change in wealthier countries, which also happen to be more patient (Fig. A6).

[11] Given the number of tests involved in our analysis, that is one per date over a year for each behavioral trait under scrutiny, one concern is that an important number of them might be false positives. To shed light on this issue, we followed the procedure advocated by Storey and Tibshirani (2003) to control the false discovery rate. The results are reported in Fig. A-10. From such an analysis, we conclude that the likelihood that this issue is important in our dataset is very small for most of the observed correlations, as the probability that the test yields a false positive result is very small for most tests.

[12] It is also possible that the difference we observe between the GPS and the WVS6 with respect to risk-taking stems from the willingness to take risk evaluating different dimensions of risk across surveys.



(a) Global Preferences Survey



(b) World Values Survey

Fig. 3. *Stringency* and behavioral traits. Figs. 3(a) and 3(b) illustrate 364 coefficients from panel regressions of behavioral traits on the Stringency Index at day D_t ($t \in [1, 365]$). Each sub-graph in Fig. 3(a) (3(b)) displays estimates for each of the four (five) behavioral traits obtained from the 75 (59) countries included in the GPS (WVS). Each regression includes all behavioral traits that interact with the day dummies D_t, the (log)number of cases at date t, the day dummies, and country-level fixed effects. The position indicates the sign and magnitude of the coefficient associated with *Trait* $\times D_t$ while the color indicates the statistical significance of the coefficient (p-value from two-sided t-test with heteroskedasticity-robust standard errors). The lighter the color, the closer the p-value is to zero. Gray indicates a p-value greater than 0.2. Bars correspond to the 95% confidence intervals.

For all datasets, we also run the same regressions on a standardized version of the Stringency Index to check whether the results are similar when considering the relative intensity of implemented policies as compared to the absolute intensity (Fig. A-15). Specifically, we compute at each date D_t the standardized index as the difference between the Stringency Index and the average Stringency Index divided by the standard deviation of the index in the sample at date D_t. Most interestingly, the results on both the GPS and the WVS6 are very close: apart from some differences in the range of the patterns over time, the same behavioral traits are similarly correlated with the *Stringency* of policies at approximately the same (relative) time. In addition, the correlations are more clear-cut in the WVS6 than they were with the absolute Stringency Index. Specifically, we recover the positive relationship with willingness to take risks and altruism as well as the negative relationship with patience and trust, all globally in the short to mid-term. Moreover, despite the absence of positive relationships with trust and patience in the long-term, we again observe that the patterns of correlations evolve over time and in the same direction as in the above analyses.[13]

[13] As for the same analysis on the EVS/WVS dataset, the results are very similar to the one with the absolute value of the Stringency Index, see Fig. A-14.

We also conduct additional robustness checks that vary the way we define the starting date D_0 of our analysis. Using a relative instead of the calendar date accounts for the local dynamics of the epidemic (no matter when a country is affected) and improves, therefore, our interpretation of short, medium and long term relationships. However, because the starting point of analysis is observation-dependent, this strategy also means comparing countries at possibly very different points in time, which may cause interpretation issues. As a consequence, we alternatively defined D_0 as either the date when a country reaches a certain level of exposure to the pandemic (whether it has already responded or not) or as the simple calendar date (starting 01/01/2020).

The Figs. A-16 and A-17 expose the results in both the GPS and the WVS6 when D_0 corresponds to the date when there are 50 (resp. 100) recorded cases in the country.[14] First, we observe that the patterns are very close across both the GPS and the WVS6 and across the baseline number of cases. Second, we observe in all cases a highly significant positive relationship between *Stringency* and both trust and patience which lasts over almost the whole period. These patterns are consistent with what we observed in the GPS in the long-term.[15] Regarding altruism, most correlations are not statistically significant but the estimates are globally positive and sometimes weakly significant over a similar period of time. Regarding risk-taking, though we do not find a positive relationship in the short-term, we find a consistent decreasing correlational pattern over time.

The Fig. A-18 expose the results when relying on the calendar dates. We observe mostly consistent results with all previous analyses, as well as very similar patterns across datasets. Notably, we do not observe much correlation with trust in the GPS when relying on the calendar date, which contrasts with the significant negative (short-term) and positive (long-term) relationship that we observe with the relative dates. However, using calendar dates implies that we compare on the same day countries whose governments possibly responded very differently to the pandemic, which is precisely correlated with interpersonal trust (see the results on *Responsiveness*). Additionally, these analyses reveal a positive correlation between *Stringency* and trust in the government that is weakly significant over several weeks in the mid-term (roughly: from June to August). This relationship also appeared in the main analysis (Fig. 3(b)) and in all robustness checks for the WVS6, although its significance is less marked. It may thus indicate that governments whose action benefited from a high level of trust within the population could maintain more stringent restrictions when the pandemic receded.

We also replicate our main analysis on each continent separately. We observe important variability both within and between continents (Figs. A-19 and A-20). The relationships for Europe (resp. Asia) are the closest to the aggregate relationships in the GPS (resp. WVS6). Notably, Europe and Asia represent a third of, respectively, the GPS and the WVS6. The findings on other continents are less clear-cut, but we still observe consistent patterns. We notice only one important contradictory pattern: The European countries surveyed in the WVS6 show a negative correlation between *Stringency* and patience in the long-term. Otherwise, all the remaining analyses yield either consistent or at worst non-significant relationships between the behavioral traits and *Stringency*. Ultimately, despite some heterogeneity across continents and variations in countries across datasets, we still observe coherent patterns overall.

3.3. Secondary analyses: distribution of population-level behavioral traits

Focusing on average measures of behavioral traits at the population level overlooks the diversity in such traits within the population. Indeed, the degree of heterogeneity across individuals may determine different policy responses to a global crisis. For instance, an homogeneous population may provide a rather uniform support for/compliance with a given policy or adopt a collective behavior that may be more easily predicted. Moreover, if the (nationally-aggregated) level of a behavioral trait is related to the shape of its distribution, the previously observed relationships may be biased. To explore further the link between population-level behavioral traits and policy-making during the COVID pandemic, we nationally aggregate and standardize the information about the standard deviations in all four behavioral traits for all countries in both the GPS and the WVS6. Then, we run similar models to (1) (*Responsiveness*) and (2) (*Stringency*) using these variables.

Tables A-8 and A-9 expose the results from both substituting levels of behavioral traits with standard deviations and introducing both moments in the regression model for *Responsiveness*. First, we observe that introducing the standard deviations has little impact on either the magnitude or the significance of our main variables of interest (average behavioral traits). Second, we observe no simple correlation between either one of the standard deviations of the behavioral traits and *Responsiveness* (R_1), no matter the dataset under scrutiny. When controlling for the (national) level of behavioral traits, we observe virtually the same results except for a (mild) negative relationship with the standard deviation in altruism in the GPS. Interestingly, this relationship strengthens when adding our set of control variables. It is also consistent with the results from the WVS6. In other words, countries that are more heterogeneous in terms of altruism also appear slower in their reaction to the pandemic. On the contrary, we observe a positive relationship between *Responsiveness* and the heterogeneity in patience and trust once we control for all variables under scrutiny, though only in the GPS.[16]

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[14] These numbers correspond to the average number of cases when governments in our samples decided to implement their first restrictive policies: 50 cases in the WVS6 and 100 cases in the GPS. As another robustness check we considered 2 cases (that is the median number of cases when first restrictive policy in both datasets) but we do not report the results in the appendix given that they are virtually identical to the ones exposed in Figs. 3(a) and 3(b).

[15] We also do not observe the negative relationship between *Stringency* and trust or patience in the short-term. However, this may be partly due to the fact that we lost some information regarding what happens across countries before all countries reach the targeted number of cases.

[16] However, we believe that the latter results should be interpreted with care. First, the heterogeneity in patience strongly correlates with almost all our control variables as well as with the average level of patience (see Fig A-9), so that the resulting significant correlation may only be spurious. Second, the heterogeneity in trust is negatively related to the level of trust and positively related to the spread of the virus, so that it may capture part of the variance that could be attributed to these variables. Third, the correlations are not significant on their own or when only the average level of behavioral traits are accounted for.

Figs. A-21 and A-22 report the results from a model for *Stringency* that adds coefficients for the interactions between each date D_t and the (standardized) population-level standard deviations for each of the four behavioral traits under scrutiny. First, accounting for the within-country distributions of behavioral traits yield similar patterns of correlation with the averages of behavioral traits. Specifically, we observe only two changes: the relationship with patience is no longer significant in the short-term in both datasets, and the relationship with interpersonal trust gets closer across datasets (positive and significant in the long-term). Second, we observe some relationships between *Stringency* and the standard deviations of behavioral traits. In particular, we observe that countries that experience a greater diversity in willingness to take risks (resp. interpersonal trust) implement stricter (resp. looser) restrictions. These correlations are consistent over the whole period and increasing over time. Although it may not be simple to elaborate on the possible mechanisms behind these findings, they minimally suggest that a more thorough and theory-based examination of the relationship between policy-making and population-level behavioral traits should go beyond mean effects to account for within-country heterogeneity.

4. Discussion

Our analysis emphasizes the importance of population-level behavioral traits to explain policy-making during a worldwide crisis. We identify robust correlations between nationally-aggregated measures of willingness to take risks, patience, altruism and trust within the population, and both governments' responsiveness to the COVID crisis and the evolution of policy stringency over time.

In particular, we observe that countries with high levels of trust addressed the crisis later than other countries. One possible interpretation is that citizens in high-trust countries believed others would behave responsibly during the pandemic, hence a lower demand for early and stringent policy interventions. This interpretation is indeed consistent with previous evidence that rampant distrust generates an increased demand for regulation, even in the presence of corruption or failure of democratic institutions (Aghion et al., 2010; Schmelz, 2021; Algan et al., 2021). However, we also observe a robust positive relationship between interpersonal trust and the stringency of COVID-related restrictions starting several months after the initial reaction. This observation contradicts the existing theory (Aghion et al., 2010), which suggests a self-sustaining dynamic where distrust and regulation co-evolve in the same direction. This discrepancy between the short-term and the long-term impact of interpersonal trust on policy-making may reflect a learning process: populations in high-trust countries may have subsequently faced worse health outcomes than populations in low-trust countries, which may have increased the demand for more stringent policies in the long-term. An alternative supply-based explanation is also possible: policy-makers in high-trust countries initially trusted citizens to behave responsibly but later updated their beliefs due to the long-term persistence of the sanitary crisis.

We also observe important relationships between policy stringency and the other behavioral traits under scrutiny (willingness to take risks, patience and altruism), both in terms of magnitude and in terms of statistical significance. Similar to the correlations with interpersonal trust, governments of patient populations respond more mildly in the short-term and more strictly in the long-term. Altruistic and risk-willing populations are also exposed to more stringent restrictions, but at different points in time. Finally, secondary analyses also highlight that the distributions of behavioral traits within the population matter for policy-making during a worldwide crisis alongside the levels: the intensity of policies also seems to vary with the population's behavioral heterogeneity.

Altogether, these results may suggest that different channels exist that link population-level behavioral traits to policy-making during a worldwide crisis. However, there seems to be one coherent pattern overall with governments enacting stringent policies in the short-term on populations that are predominantly risk-taking, impatient and distrustful, all of which correlate at the individual level with a tendency to refrain from adopting health-enhancing behaviors during the COVID crisis (see e.g: Chan et al., 2020; Barrios et al., 2021; Campos-Mercade et al., 2021; Alfaro et al., 2022), while the relationship reverses in the mid and long-term. One mechanism for this reversal could be that in the short-term populations' demands are not well-defined in front of a new phenomenon, while some learning occurs after a few months and spur policy demands that match citizens' behavior. At the same time, the changes over time in the correlations may also suggest a non-linear relationship between behavioral traits and policy responses that may rest upon exogenous time-varying factors. For instance, Andersson et al. (2021) emphasize that people modified their behavior in response to vaccine-related news, which could have led governments to do the same. This rationale may supply an explanation for the long-term relationships with trust and patience: since distrusting and impatient individuals are less likely to support/comply with COVID-related restrictions, good news from vaccines may have led governments in low-trust and low-patience countries to loosen their policies. In addition, some of our results may also be explained by policy-makers own behavioral traits, for which population-level behavioral traits may act as a proxy. This interpretation may for instance explain the correlations with risk-taking (implementing stringent restrictions may indeed be perceived as politically risky) or with altruism (a positive weight placed on others' well-being could lead policy-makers to implement protective measures).

Like similar studies (Becker et al., 2012; Kosse and Tincani, 2020; Sunde et al., 2022), ours is ill-suited to claim causality or disentangle the possible mechanisms at play. The cross-country scope of our data indeed limits investigations on issues of reverse causality or omitted variables. Moreover, the number of observations in this study is ultimately limited, so that we may have failed to detect possibly meaningful correlations due to low statistical power. In other words, though we can say that we observe correlations of different magnitude (hence importance), it would likely be a mistake to interpret non-significant relationships as truly null. Given these limitations, our study is meant to highlight that robust associations exist between population-level behavioral traits and policy-making during an unexpected event. Specifically our results suggest that different countries react differently to the same crisis not only because of different demographic, economic or social conditions, but because their populations hold different behavioral traits (on average). This may supply an explanation for the observed difficulties in coordinating policies at the international level, despite the importance of coordination for the global effectiveness of policy responses, as advocated by the World Health Organization.

Obviously, any interpretation of our findings must account for the context of the analysis. The COVID crisis supplies an interesting background because of its unforeseen, unprecedented impact worldwide and because all governments had to come up with policy instruments that were mostly novel. Yet, we ultimately cannot rule out that we observe only stand-alone correlations. One possible extension to our work would then be to run a similar analysis in other policy contexts: for other exogenous events, for policy issues that all governments must consider (e.g: fighting climate change), for policy-making at sub-national levels, etc. In addition, our methodology relies on cross-validated measures of behavioral traits that are unaffected by the pandemic. Yet, policy-making, behavioral traits and the local dynamic of the pandemic may also all be endogenously determined. Future research may thus focus on this co-evolution by combining survey measures before, during, and after the pandemic (such as those from Jørgensen et al., 2022; Azevedo et al., 2023).

Understanding the drivers of policy responses to worldwide crises is crucial. First, they have substantial impacts on populations' well-being both in the short-term and in the long-term. For instance, early and stringent interventions had a strong impact on COVID-related cases and deaths (Hale et al., 2021b), but also caused important and durable changes in social organization (e.g: remote work). Second, the likelihood that such global events happen again in the future is increasing, mostly due to global warming. Yet, despite the increasing use of behavioral models of decisions in policy design (Chetty, 2015; Matjasko et al., 2016; van Bavel et al., 2020), our understanding of the behavioral drivers of political decisions currently remains limited (Schnellenbach and Schubert, 2015; DeAngelo and McCannon, 2022). More research, both theoretical and empirical, on such issues would thus be warranted. Finally, by showing how experiment-based behavioral characteristics aggregated at the population level correlate with national policy responses to a worldwide crisis, our study informs the ongoing debate on the generalizability of results in the behavioral sciences (Henrich et al., 2010). In particular, our results underline that behavioral traits do not only matter for individual or societal outcomes: they also matter for political decisions.

CRediT authorship contribution statement

Etienne Dagorn: Performed research, Analyzed data, Writing – original draft. **Martina Dattilo:** Performed research, Analyzed data. **Matthieu Pourieux:** Performed research, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2024.06.040.

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