The irrational interplay between partisanship, beliefs about the severity of the COVID-19 pandemic, and support for policy interventions

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Abstract

The COVID-19 pandemic is a global crisis that has forced governments around the world to implement large-scale interventions such as school closures and national lockdowns. Previous research has shown that partisanship plays a major role in explaining public attitudes towards these policies and beliefs about the severity of the crisis. However, the cognitive roots of this phenomenon remain poorly understood. In principle, partisan gaps in policy support could emerge from cost-benefit analyses from individuals with dissimilar perceptions about the severity of the pandemic, as proposed by rational models of partisan behavior. Alternatively, polarized responses may be driven by social identity motives that are unrelated to individual beliefs, as predicted by theories of tribal partisanship. Here, we tested the predictions of these two models across four experiments (N=1980) performed in four different countries (Argentina, Uruguay, Brazil, and the United States). Participants forecasted the number of COVID-19 deaths in their country after considering either a high or low number. Then, they rated their agreement with a series of interventions. This anchoring procedure, which experimentally induced a large variability in the forecasted number of deaths, did not modify policy preferences. Instead, we observed that partisanship independently modulated the optimism of forecasts and participants' support for COVID-19 policies. These results, which are against the predictions of the rational partisanship model, have strong policy implications. In particular, our findings suggest that communication strategies aimed at informing the public about the severity of the pandemic will not substantially change levels of support for COVID-19 interventions.

Introduction

The COVID-19 pandemic is a global emergency that has posed complex challenges to modern societies (1). In response to this formidable crisis, governments around the world have designed, implemented, and communicated unprecedentedly strong public policies aimed at mitigating the impact of the epidemic (2-4). These policies have included large-scale non-pharmaceutical interventions such as the closure of schools (2), the implementation of national lockdowns (3), and the use of virus-tracking procedures with varying degrees of technological sophistication (4), among others. Despite their effectiveness at controlling the spread of the virus (3), some of these interventions have yielded large negative side effects such as sharp reductions in economic activity (5) and public mental health (6).

This critical context, along with the inherent uncertainty about the ultimate impact of the crisis (7), has left people susceptible to cues sent by political leaders, who are known shape public opinion in the midst of national crises (8, 9). For example, research has shown that political polarization in elite discussions in the United States (10) was followed by a partisan divide in policy preferences (11-13) and behavioral responses to the COVID-19 crisis (14-18). However, while several studies have reported the existence of polarized attitudes and reactions to the pandemic, the cognitive roots of this phenomenon remain less understood. The aim of this work is to shed light on the psychological processes underlying partisan responses to the pandemic by testing the predictions of two competing models.

The *rational partisanship model* posits that polarized attitudes towards COVID-19 policies result from dissimilar perceptions about the severity of the pandemic (**Figure 1A**). For example, previous research has shown that Republicans, when compared to Democrats, are relatively less concerned about the severity of the crisis and about the contagiousness and mortality of the virus (18-21). Given that most interventions to address the COVID-19 pandemic have large negative side effects, particularly in the economy (5), this would explain why they show greater opposition to those policies. According to this model, partisan differences should emerge from cost-benefit analyses and

the optimization of utility functions with heterogeneous risk perceptions, as proposed by previous theoretical research (22). The main prediction of this account, which remains untested, is that partisanship should correlate with perceived individual differences about the severity of the crisis, and those perceptions should causally shape support for non-pharmaceutical interventions.

The *tribal partisanship model* postulates that polarized reactions to collective threats (23) result from social identity motives (24, 25), which are unrelated to individual beliefs about the intensity of the crisis (**Figure 1B**). This idea is consistent with research showing that policy preferences may be more strongly influenced by partisanship than individual beliefs (26, 27). For example, previous research found that, in the United States, individuals might support welfare policies that contradict their own ideology if they believe that those policies are endorsed by their own party (26). Similarly, an experiment in Argentina has shown that policy sponsorship by political leaders polarize public opinion over ex-ante non-divisive issues (27). Summarizing, this model predicts that partisanship should independently modulate support for COVID-19 policies and expectations about the severity of the pandemic. The key prediction of the tribal partisanship hypothesis is that policy preferences should not depend on individual beliefs about the intensity of the crisis.

To unfold the relationship between partisanship, beliefs, and policy preferences during the COVID-19 pandemic, we empirically tested the predictions of these two accounts across four experiments, each one in a different country in the Americas: Argentina, Uruguay, Brazil, and the United States. To distinguish between models, we studied the causal relationship between individual beliefs and policy preferences. To anticipate our results, which were consistent across experiments, we found robust evidence that perceptions about the severity of the crisis do not drive policy preferences, and that both variables independently correlate with support to the ruling party, as predicted by the tribal partisanship model.

Figure 1. Predictions of two alternative models of partisan differences in support for COVID-19 policies. A) The rational partisanship model postulates that polarized attitudes towards COVID-19 interventions emerge from cost-benefit analyses performed by individuals with dissimilar perceptions about the intensity of the crisis. The key prediction of this model is that the effect of partisanship on policy preferences should be strongly mediated by individual beliefs about the severity of the pandemic. **B)** The tribal partisanship model posits that partisan differences are due to social identity motives that are unrelated to individual beliefs about the intensity of the crisis. The main prediction of this account is that partisanship should independently modulate perceptions about the severity of the crisis and support for COVID-19 policies. Importantly, this model predicts that there should be no direct association between individual beliefs and policy preferences.

Results

We performed four online survey experiments (total sample size, $N=1980$) to test for a causal relationship between beliefs about the severity of the pandemic and policy preferences. In all cases, participants first provided demographic data and rated their affiliation to the two main political parties in their country. To experimentally manipulate beliefs, we used the anchoring effect (28): participants were asked to forecast the number of COVID-19 deaths in their country after considering either an extremely low or high number. Then, they rated their degree of agreement with a set of interventions including closing schools, restricting freedom of movement across their country, and allowing their government to collect geolocation data from COVID-19 patients, among others (see **Materials and Methods** for details). This setup allowed us evaluating whether participants' support for COVID-19 interventions were influenced by our experimental manipulation on beliefs about the severity of the pandemic.

Experiments in South America

Experiment 1 (N=640) was performed in Argentina during May 2020, when the cumulated number of COVID-19 deaths in that country was between 382 and 589. Participants were asked to forecast the total number of COVID-19 deaths by 31 December 2020 in two steps. First, we asked them to report if they believed that such number will be higher or lower than a target value, randomly selected between two options. In the “low anchor” condition, the target was 600, and in the “high anchor” condition, the number was 60,000. Then, participants estimated the exact number of COVID-19 deaths by the end of 2020. This experimental manipulation produced a significant modulation on forecasts, with a very large effect size (**Figure 2A**, mean $\pm$ SD in log₁₀ units, low anchor: $3.3 \pm .4$, high anchor: $4.1 \pm .5$, Cohen's $d=1.55$, $t(638)=19.7$, $p=1 \times 10^{-67}$). To illustrate the magnitude of the effect, the anchoring procedure led to a five-fold difference in the median number of forecasted deaths across conditions (i.e., 2000 in the “low anchor” condition and 10000 in the “high anchor” condition). In contrast to the predictions of the rational partisanship model, this difference of expectations did not translate to a sizeable effect in participants' mean agreement with COVID-19 policies (**Figure 2B**, mean $\pm$ SD, low anchor: 3.54 ± 1.50 , high anchor: 3.45 ± 1.40 , Cohen's $d=.06$, $t(638)=.87$, $p=.39$). In line with this result, we observed a non-significant correlation, with a negligible effect size, between the forecasted number of deaths and ratings of agreement (**Figure 2C**, $r=-.05$, $p=.19$). In other words, participants who forecasted a more pessimistic scenario (i.e., higher number of COVID-19 deaths) did not show significantly greater support for non-pharmaceutical interventions compared to those who were relatively more optimistic.

To test the robustness of these findings we performed two direct replication experiments in two different countries. We recruited participants from Uruguay (Experiment 2, N=372, **Figures 2D**, **2E** and **2F**) and Brazil (Experiment 3, N=353, **Figures 2G**, **2H** and **2I**) in June 2020. During this time window, the range of total COVID-19 deaths was between 25 and 27 in Uruguay and between 51,271 and 58,314 in Brazil. As in Experiment 1, participants estimated the total number of COVID-19 deaths in their country by the end of 2020. The low and high anchors were respectively set to 40 and 4,000 deaths in Uruguay and 80,000 and 8,000,000 deaths in Brazil. We found that the anchoring

manipulation produced a strong and significant effect on the forecasts collected in both experiments (Experiment 2: **Figures 2D**, mean $\pm$ SD in log10 units, low anchor: $1.7 \pm .3$, high anchor: $2.2 \pm .6$, Cohen's $d = .94$, $t(370) = 9.1$, $p = 8 \times 10^{-18}$; Experiment 3: **Figures 2G**, mean $\pm$ SD in log10 units, low anchor: $5.0 \pm .5$, high anchor: 5.3 ± 1.0 , Cohen's $d = .43$, $t(351) = 4.1$, $p = 6 \times 10^{-5}$). Once again, against the predictions of the rational partisanship model, we observed that the experimental treatment yielded a non-significant effect in participants' support for COVID-19 policies (Experiment 2: **Figure 2E**, mean $\pm$ SD, low anchor: 3.81 ± 1.22 , high anchor: 3.60 ± 1.23 , Cohen's $d = .17$, $t(370) = 1.61$, $p = .11$; Experiment 3: **Figure 2H**, mean $\pm$ SD, low anchor: 4.80 ± 1.13 , high anchor: 4.87 ± 1.24 , Cohen's $d = .06$, $t(351) = .54$, $p = .59$). As in Experiment 1, the correlation between the forecasted number of deaths and policy support was also non-significant, with small effect sizes, in both experiments (Experiment 2: **Figure 2F**, $r = .08$, $p = .09$; Experiment 3: **Figure 2I**, $r = .10$, $p = .06$).

Given that the anchoring procedure strongly modulated expectations but did not induce any meaningful effect on policy preferences, these empirical observations appear to be in conflict with the predictions of the rational partisanship model. However, the analyses presented so far do not allow distinguishing between absent evidence (i.e., no evidence for any of the two models) versus evidence of an absent effect (i.e., as predicted by the tribal partisanship model). We addressed this limitation by performing three separate statistical analyses.

First, Monte Carlo simulations (29) revealed that our experimental setup was adequately powered to detect small differences between conditions (**Figure S1**, small effect size with $d = .2$, 92.0% power in Experiment 1, 73.5% in Experiment 2, and 69.8% in Experiment 3). Therefore, this analysis suggests that, if the anchoring manipulation produced a small effect on policy preferences, the probability to have missed it in all three experiments is lower than .01%. Similarly, our experiments were sufficiently powered to detect a small correlation between forecasts and agreement with COVID-19 policies (**Figure S1**, $r = .15$, 97.2% power in Experiment 1, 84.3% in Experiment 2, and 81.1% in Experiment 3). If there was a weak association between these two variables, the probability to have observed three non-significant results with 5% significance level is lower than .001%.

Figure 2. Experiments in South America. A-C) Experiment in Argentina (N=640). **A)** The forecasted number of COVID-19 deaths was smaller in the “low anchor” condition (blue) than in the “high anchor” condition (red). Squares show mean forecasted number of deaths (in log-10 units), vertical bars depict SEM, and we display the p-value of the two-sample t-test. **B)** The mean agreement with COVID-19 policies was not significantly different across conditions. **C)** We observed a negligible association between forecasted deaths and agreement with COVID-19 policies. Dots show data from all participants, the solid black line show the best-fitting linear regression, and the dotted lines depict 95% confidence intervals. We also display the correlation coefficient and the p-value for correlation. **D-F)** Same as A-C for Experiment 2 in Uruguay (N=372). **G-I)** Same as A-C for Experiment 3 in Brazil (N=353).

Second, we performed equivalence tests to probe the hypothesis that the difference between conditions was within a small interval against the null hypothesis of a meaningful difference between them (30). To this end, we ran two one-sided tests (TOST) for equivalence. Assuming that differences smaller than half a Likert point are deemed irrelevant from a practical point of view, these tests rejected the null hypothesis of a relevant difference between conditions for the three experiments (95% CI and p-value for TOST, Experiment 1: [-.13, .32], $p=3\times 10^{-4}$; Experiment 2: [-.05, .45], $p=.01$; Experiment 3: [-.31, .18], $p=4\times 10^{-4}$; for a sensitivity analysis, see **Figure S2**).

Third, we quantified the relative strength of evidence for each hypothesis using Bayes factor analyses (31). This revealed that our data is 146 times more likely under an absent effect (as predicted by the tribal model) than under the effect predicted by the rational model (Bayes Factor BF_{01} , Experiment 1: $BF_{01} = 7.8$; Experiment 2: $BF_{01} = 2.5$; Experiment 3: $BF_{01} = 7.4$; aggregate $BF_{01} = 146.6$). The same Bayesian analysis applied on the observed correlation between forecasts and agreement ratings suggests that an absent association between those variables is 290 times more likely than its presence (Bayes Factor BF_{01} , Experiment 1: $BF_{01} = 13.2$; Experiment 2: $BF_{01} = 5.8$; Experiment 3: $BF_{01} = 3.8$; aggregate $BF_{01} = 290.9$). Summarizing, the data collected in Experiments 1, 2, and 3 clearly reject the rational partisanship hypothesis and supports the key prediction of the tribal partisanship model: policy preferences do not depend on individual beliefs about the severity of the pandemic.

Experiment in the United States

Our study was inspired by the observation that Republicans and Democrats have different perceptions about the severity of the pandemic (18). Previous research suggested that this variability in risk perceptions could explain partisan differences in their support for COVID-19 interventions (22). Therefore, we tested this idea in a pre-registered experiment in the United States ($N=615$, 312 female, aged 45.8 ± 15.9 , representative sample in terms of age, gender, and ethnicity). The experiment was launched on 23 July 2020 and finished on 25 July 2020, when the cumulative number of COVID-19 deaths in the United States was 145,546. The experimental design had two main differences compared to the ones performed in South America. First, participants were asked to forecast the

number of COVID-19 deaths and cases in the week following the experiment and were economically incentivized for accuracy. Second, the experimental treatments included anchors on deaths (low anchor: 40; high anchor: 400,000), anchors on cases (low anchor: 8,000; high anchor: 8,000,000), and two control conditions with no anchors (see **Materials and Methods** for details about the experimental design).

As per our pre-registration, we first studied the effects given by the anchoring manipulations. Setting anchors on deaths significantly modulated the forecasted number of deaths (**Figure 3A**, mean $\pm$ SD in log10 units, low anchor: $3.0 \pm .8$, control: $3.6 \pm .8$, high anchor: $4.1 \pm .9$, low vs. high: Cohen's $d=1.32$, $t(223)=9.8$, $p=2 \times 10^{-19}$) and cases (**Figure 3B**, mean $\pm$ SD in log10 units, low anchor: 4.4 ± 1.1 , control: $4.8 \pm .9$, high anchor: $5.0 \pm .8$, low vs. high: Cohen's $d=.70$, $t(223)=5.3$, $p=4 \times 10^{-7}$) but did not significantly change participants' agreement with policy interventions (**Figure 3C**, mean $\pm$ SD, low anchor: 3.72 ± 1.50 , control: 3.68 ± 1.67 , high anchor: 3.60 ± 1.36 , low vs. high: Cohen's $d=.09$, $t(223)=.64$, $p=.52$). As predicted, and consistent with the three previous experiments, we observed a non-significant correlation between the forecasted number of COVID-19 deaths and participants' degree of support for COVID-19 interventions (**Figure 3D**, $r=.03$, $p=.57$).

Similarly, setting anchors on cases significantly influenced forecasted deaths (**Figure 3E**, mean $\pm$ SD in log10 units, low anchor: $3.2 \pm .6$, control: $3.5 \pm .7$, high anchor: $3.7 \pm .7$, low vs. high: Cohen's $d=.64$, $t(186)=4.4$, $p=2 \times 10^{-5}$) and cases (**Figure 3F**, mean $\pm$ SD in log10 units, low anchor: $4.5 \pm .9$, control: $4.8 \pm .9$, high anchor: $5.3 \pm .8$, low vs. high: Cohen's $d=1.03$, $t(186)=7.1$, $p=3 \times 10^{-11}$) but did not modulate policy preferences (**Figure 3G**, mean $\pm$ SD, low anchor: 3.86 ± 1.47 , control: 3.71 ± 1.88 , high anchor: 3.54 ± 1.56 , low vs. high: Cohen's $d=.21$, $t(186)=1.5$, $p=.13$). We also observed that the forecasted number of cases did not correlate significantly with participants' support for COVID-19 policies (**Figure 3H**, $r=-.04$, $p=.41$).

Experiment 4 - United States (N=615)

Figure 3. Experiment in the United States. A-D) In two experimental conditions, we set anchors on the number of COVID-19 deaths, as in Experiments 1-3. **A)** The forecasted number of COVID-19 deaths in the “low anchor” condition (blue) was smaller than in the “control” condition (gray). The forecasted number of COVID-19 deaths in the “high anchor” condition (red) was larger than in the “control” condition (gray). Squares show mean (in log-10 units), vertical bars depict SEM, and we display the p-value of the two-sample t-test. **B)** Same as A but for the forecasted number of COVID-19 cases. **C)** The mean agreement with COVID-19 policies was not significantly different across conditions. **D)** We observed a negligible association between forecasted deaths and agreement with COVID-19 policies. Dots show data from all participants, the solid black line show the best-fitting linear regression and the dotted lines depict 95% confidence intervals. We also display the correlation coefficient and the p-value for correlation. **E-G)** Same as A-C for the conditions where we set anchors on cases. **H)** Same as D but for the forecasted number of COVID-19 cases.

Following our pre-registered protocol, we estimated the relative strength of evidence for each hypothesis through Bayes factor analysis (31). This indicated that agreement ratings measured in Experiment 4 are approximately 5 times more likely under the tribal hypothesis (i.e., policy preferences are constant across anchoring treatments) than under the rational model (Bayes Factor BF_{01} ; anchor on deaths, low vs. control: $BF_{01} = 6.4$, high vs. control: $BF_{01} = 6.1$; anchor on cases, low vs. control: $BF_{01} = 5.0$, high vs. control: $BF_{01} = 4.7$). Replicating our previous analyses, and using the posteriors of Experiments 1-3 as priors for Experiment 4, we found that the difference across conditions in the entire dataset is 835 times more likely under the tribal model than under the rational model (comparison between low versus high anchors on deaths, Experiments 1-3: $BF_{01} = 146.6$, Experiment 4: $BF_{01} = 5.7$, aggregate $BF_{01} = 835.6$). Similarly, the forecasts and policy ratings obtained in the four experiments are over 5,000 times more likely under the hypothesis of an absent correlation than under its presence (Experiments 1-3: $BF_{01} = 290.9$, Experiment 4: $BF_{01} = 19.9$, aggregate $BF_{01} = 5556.2$). To sum up, the results of this pre-registered replication in the United States provide further evidence that individual beliefs about the severity of the pandemic do not modulate support for COVID-19 policies.

Partisanship effects and formal model comparison

To unravel the relationship between partisanship, beliefs, and policy preferences, we estimated a structural equation model for each experiment (**Figure 4A**, see Equations 1-3 in Materials and Methods for details and **Tables S1 to S4**). More specifically, we performed path analyses (32) by fitting three simultaneous equations. First, we modeled participants' support to the ruling party as a function of three demographic variables: age, gender, and years of education. Second, we explained the forecasted number of deaths as a linear combination of participants' support for the ruling party and the experimental treatment (i.e., using a dummy variable referenced to the "low anchor" condition). Lastly, we modeled ratings of agreement with COVID-19 policies as a function of the forecasted number of deaths and participants' support for the ruling party.

This analysis revealed that support to the ruling party correlated negatively with the number of forecasted COVID-19 deaths (Experiment 1: $\beta = -.08 \pm .02$, $p = 3 \times 10^{-4}$; Experiment 2: $\beta = -.08 \pm .03$, $p = .002$; Experiment 3: $\beta = -.13 \pm .03$, $p = 3 \times 10^{-5}$, Experiment 4: $\beta = -.06 \pm .02$, $p = .006$). This effect, by which pro-government partisans were more optimistic about the severity of the crisis than people against the ruling party, was significant on each individual experiment (**Figure 4B**, forecasted deaths in log10 units; Experiment 1: mean $\pm$ SD, strongly against: $3.75 \pm .60$, neutral: $3.66 \pm .60$, strongly support: $3.51 \pm .54$, against vs. support: Cohen's $d = .41$, $t(392) = 3.1$, $p = .002$; Experiment 2: mean $\pm$ SD, strongly against: $2.08 \pm .54$, neutral: $2.03 \pm .59$, strongly support: $1.89 \pm .47$, against vs. support: Cohen's $d = .38$, $t(249) = 2.8$, $p = .005$; Experiment 3: mean $\pm$ SD, strongly against: $5.30 \pm .80$, neutral: $5.23 \pm .78$, strongly support: $4.84 \pm .75$, against vs. support: Cohen's $d = .59$, $t(195) = 4.1$, $p = 5 \times 10^{-5}$; Experiment 4: mean $\pm$ SD, strongly against: $3.62 \pm .80$, neutral: $3.50 \pm .84$, strongly support: $3.20 \pm .81$, against vs. support: Cohen's $d = .53$, $t(301) = 4.0$, $p = 7 \times 10^{-5}$).

In line with previous literature (11-13), we observed that partisanship strongly correlated with agreement ratings (Experiment 1: $\beta = .38 \pm .04$, $p \sim 0$; Experiment 2: $\beta = .12 \pm .04$, $p = .003$; Experiment 3: $\beta = -.21 \pm .05$, $p = 7 \times 10^{-6}$, Experiment 4: $\beta = -.10 \pm .03$, $p = 4 \times 10^{-4}$). The sign of this effect, however, was not the same in all countries. In Argentina and Uruguay, more support to the ruling party correlated with greater support for COVID-19 policies (**Figure 4C**, mean agreement ratings; Experiment 1: mean $\pm$ SD, strongly against: 3.08 ± 1.49 , neutral: 3.73 ± 1.27 , strongly support: 4.55 ± 1.15 , against vs. support: Cohen's $d = 1.0$, $t(392) = 7.9$, $p = 3 \times 10^{-14}$; Experiment 2: mean $\pm$ SD, strongly against: 3.55 ± 1.46 , neutral: 3.53 ± 1.11 , strongly support: 3.90 ± 1.16 , against vs. support: Cohen's $d = .27$, $t(249) = 2.0$, $p = .04$). In Brazil and the United States, i.e. two countries where the presidents publicly dismissed the risks associated with the pandemic (21, 33), the effect manifested as a negative correlation between pro-government partisanship and agreement with COVID-19 policies (**Figure 4C**, Experiment 3: mean $\pm$ SD, strongly against: 5.31 ± 1.15 , neutral: 4.68 ± 1.09 , strongly support: 4.51 ± 1.22 , against vs. support: Cohen's $d = .68$, $t(195) = 4.7$, $p = 4 \times 10^{-6}$; Experiment 4: mean $\pm$ SD, strongly against: 4.03 ± 1.09 , neutral: 3.64 ± 1.51 , strongly support: 2.86 ± 1.96 , against vs. support: Cohen's $d = .86$, $t(301) = 6.5$, $p = 3 \times 10^{-10}$).

A

B

C

Figure 4. Partisan effects across all experiments. A-C) Across all panels, light blue codes for Experiment 1 (Argentina), purple codes for Experiment 2 (Uruguay), green codes for Experiment 3 (Brazil) and red codes for Experiment 4 (United States). **A)** We estimated a path analysis model by fitting three simultaneous equations (see **Tables S1 to S4**). First, we explained support to the ruling party as a function of demographic variables (age, gender, and years of education). Second, we explained the forecasted number of deaths as a function of the experimental treatment and participants' support for the ruling party. Third, we modeled agreement ratings with COVID-19 policies as a function of the forecasted number of deaths and support for the ruling party. We display the best fitting estimates and standard error for all pairwise connections between partisanship, forecasts and policy support (*: $p < .05$, **: $p < .01$, ***: $p < .001$). **B)** Dots show the mean forecasted number of deaths for people who are strongly against, who are neutral, and who strongly support the ruling party. Vertical lines depict SEM and we display the p-value of pairwise two-sample t-tests. **C)** Same as B but for mean ratings of agreement with COVID-19 policies.

Lastly, the best-fitting structural equation models showed that the forecasted number of deaths did not significantly modulate support for COVID-19 policies in any experiment (Experiment 1: $\beta = -.01 \pm .05$, $p = .72$; Experiment 2: $\beta = .13 \pm .07$, $p = .06$; Experiment 3: $\beta = .08 \pm .08$, $p = .29$, Experiment 4: $\beta = -.11 \pm .08$, $p = .15$). In line with this observation, quantitative model comparison analyses suggested that the tribal partisanship model (**Figure 1B**, i.e. wherein partisanship independently modulates forecasts and agreement ratings, and there is no association between those two variables) provided better fits to the data than the rational partisanship model (**Figure 1A**, Experiment 1: $\Delta BIC = 90$; Experiment 2: $\Delta BIC = 5$; Experiment 3: $\Delta BIC = 19$; Experiment 4: $\Delta BIC = 10$). The tribal partisanship model was also better than a full model allowing for both direct and indirect partisan effects on agreement ratings (as the one estimated in **Figure 4A**, Experiment 1: $\Delta BIC = 7$; Experiment 2: $\Delta BIC = 2$; Experiment 3: $\Delta BIC = 4$; Experiment 4: $\Delta BIC = 3$). Overall, this model comparison analysis suggests that partisanship independently modulated support for COVID-19 policies and beliefs about the severity of the pandemic.

Discussion

Political parties are essential components of modern democracies and the key mechanism by which the preferences of social groups translate into actionable policies. Therefore, it is reasonable to expect that partisanship (i.e., the identification with political parties) plays a major role in how people react to a worldwide healthcare crisis. In fact, extensive research has reported partisan differences in people's beliefs about the COVID-19 pandemic (11-13). For example, in the United States, Democrats are more concerned than Republicans about the economic consequences of the crisis and the contagiousness and mortality of the virus (20). At the behavioral level, partisanship explains objective metrics of social distancing in the United States better than the actual local incidence of COVID-19 (14, 16). Similarly, in Brazil, social distancing considerably decreased after the president publicly dismissed the risks associated with contracting the virus, and this effect was stronger in pro-government localities (33).

But while there is compelling evidence that partisanship modulates public responses to the pandemic, what has been far less investigated are the cognitive roots of this phenomenon. One possible explanation is that the observed variability in behavior emerges as a consequence of partisan differences in beliefs about the intensity of the crisis (18, 19, 22). In line with this idea, previous theoretical research has proposed that partisan reactions could be attributed to the optimization of utility functions with dissimilar risk perceptions (22). One key prediction of this rational model is that partisan differences in support for COVID-19 policies should be strongly mediated by differences in the perceived severity of the pandemic. Our results clearly reject this idea by showing that policy preferences are independent from beliefs about the intensity of the crisis. In other words, we provide evidence for a remarkable lack of association between perceptions about the gravity of pandemic and support for COVID-19 policies. This finding is consistent with the idea that partisan differences in policy support result from the abandonment of individual beliefs in favor of party loyalty, as predicted by tribal theories of partisan behavior (25-27).

With very few exceptions (33, 34), the overwhelming majority of studies reporting partisan reactions to the COVID-19 pandemic are focused on the United States, leaving open the question of whether this phenomenon is similarly strong in other countries. Here, we show that the tribal partisanship model explains policy preferences across four countries with very different political contexts and where the impact of the crisis has been highly dissimilar. We found, across all experiments, that greater support to the ruling party is strongly associated with more optimistic beliefs about the severity of the pandemic (**Figure 4B**) and with different policy preferences (**Figure 4C**). In the United States and Brazil, two countries where the presidents publicly minimized the severity of the crisis (21, 33), greater support to the ruling party was associated with less agreement with COVID-19 policies. In Argentina and Uruguay, two countries that applied swift and strong non-pharmaceutical interventions, greater support to the ruling party correlated with more agreement with COVID-19 policies (35, 36). These results also suggests that ideology plays a minor role in explaining partisan reactions (34) given that the ruling parties in Argentina and Uruguay have markedly different political platforms (i.e., left-leaning in Argentina and right-leaning in Uruguay).

Our results reveal that a reasonable assumption of a recently proposed rational model of partisan behavior might be ill-founded, at least in the context of the COVID-19 pandemic (22). However, these findings cannot rule out other rational explanations of partisan effects on policy preferences. For example, individuals might be optimizing more complex utility functions with individual differences in moral values, which tend to be clustered across different political parties (37). While further research should explore this possibility, our study contributes to the understanding of polarized reactions to the pandemic by uncovering the irrational interplay between partisanship, individual beliefs about the severity of the crisis, and public support for COVID-19 policies. The irrational association between these three variables is particularly salient in the data obtained in Argentina and Uruguay, where people opposing the government forecasted more deaths but showed less agreement with public policies aimed at preventing those deaths.

Finally, these findings not only shed light on the psychological roots of public beliefs and attitudes during the pandemic but also have strong implications for policy makers. Given that policy preferences are dissociated from individual beliefs about the severity of the crisis, our results suggest that even the most effective communication strategy focused on alerting the public about the severity of the pandemic would not translate into greater agreement with COVID-19 policies (38-40). In turn, these results highlight the importance of building consensus at the elite level and suggests that a coordinated response to the pandemic may be impossible to achieve without a unified message from leaders across the political spectrum.

Materials and Methods

Participants

In Experiment 1 (Argentina), we obtained data from a convenient sample of six hundred and forty subjects (N=640, 60.3% female, aged 27.0 ± 10.8 y.o., 41.3% with complete university education). Participants were graduate and undergraduate students recruited from subject pools from four Argentinian universities (Universidad Torcuato Di Tella, Universidad de San Andrés, Universidad Favaloro, and Universidad de Buenos Aires).

In Experiment 2 (Uruguay) and Experiment 3 (Brazil), we obtained two convenient samples through Offerwise (<https://offerwise.com/>), a panel company specialized in Latin American countries. Three hundred and seventy two subjects from Uruguay participated in Experiment 2 (N=372, 49.7% female, aged 35.7 ± 13.6 y.o., 52.9% with at least complete middle education) and three hundred and fifty three subjects from Brazil participated in Experiment 3 (N=353, 52.1% female, aged 33.2 ± 11.1 y.o., 65.4% with at least complete middle education).

In Experiment 4 (United States), we collected data through Prolific, an online platform to recruit human participants for scientific research (<https://www.prolific.co/>). The collected sample is representative of the United States in terms of age, gender, and ethnicity. Six hundred and fifteen subjects participated in the experiment (N=615, 51.2% female, aged 45.8 ± 15.9 y.o., 58.1% with at least complete college education). For more information about the representativeness of the sample, see <https://researcher-help.prolific.co/hc/en-gb/articles/360019236753-Representative-Samples-on-Prolific>. All protocols described in this study were approved by the ethics committee of CEMIC (Centro de Educación Médica e Investigaciones Clínicas Norberto Quirno, Buenos Aires, Argentina).

Experiment 1 (Argentina)

Participants first provided information about their age, gender, and educational level. We then collected a series of pre-treatment variables associated to the political orientation of participants: we asked them to report the extent to which they support the ruling party (from “I am strongly against” to

“I strongly support”). They also indicated the party that they voted in the 2019 National Election, and completed a two-item affective polarization scale by which they indicated their feelings of happiness/sadness in the hypothetical scenario that they had a child who supported the ruling party or the opposition.

Participants were then asked to report whether they believe that the number of COVID-19 deaths by 31 December 2020 will be greater or lower than a target value. We randomized that number between two alternatives: 600 deaths (“low anchor” condition) and 60,000 deaths (“high anchor” condition). In the screen immediately after that question, we asked them to forecast the total number of COVID-19 deaths in Argentina by 31 December 2020.

Finally, we asked participants to report their degree of agreement with nine public policies. 1) *Schools should reopen before the end of the academic year*, 2) *Non-essential public meetings should be banned until the development of a vaccine*, 3) *People should be allowed to leave their homes and exercise at least once a day*, 4) *People over 70 years old should not be allowed to leave their homes until a vaccine is found*, 5) *People who are found in a public space without a valid reason should have a criminal record*, 6) *People should be allowed to freely travel within the country without requesting permission to the government*, 7) *The government should track the movements of all patients who tested positive for COVID-19 using their cell-phone data*, 8) *The government should fine those individuals who upload false information to the official virus-tracking app*, 9) *The government should force the citizenship to share their geolocation through an official virus-tracking app*. The 9 statements were presented in random order and participants rated their level of agreement with each phrase using a Likert scale from 0 (strongly disagree) to 7 (strongly agree). For data analysis purposes, we reverse coded the ratings of statements 1, 3, and 6.

Experiment 2 (Uruguay) and Experiment 3 (Brazil)

Experiment 2 and Experiment 3 were designed with exactly the same experimental procedure used in Experiment 1. The two only differences were the numbers used in the anchoring procedure and the statements about COVID-19 policies.

In Experiment 2, the low and high anchors were 40 and 4,000 deaths, respectively. The nine statements were: 1) *Universities should reopen and resume face-to-face teaching by the end of the year*, 2) *Gatherings of more than 10 people should not be allowed until a vaccine is developed*, 3) *The government should fine people who do not respect social distancing in the street*, 4) *People over 70 years old should not be allowed to leave their homes until a vaccine is found*, 5) *People diagnosed with COVID-19 should have a criminal record if they are found in a public space during the period when transmission risk is high*, 6) *People should be allowed to freely travel within the country without requesting permission to the government*, 7) *The government should track the movements of all patients who tested positive for COVID-19 using their cell-phone data*, 8) *The government should fine those individuals who upload false information to the official virus-tracking app*, 9) *The government should force the citizenship to share their geolocation through an official virus-tracking app*. Note that in this case statement 1 was about universities rather than schools given that in-person classes for school-aged children had already gone back partially in Uruguay at the moment of the survey. For data analysis purposes, we reverse coded the ratings of statements 1 and 6.

In Experiment 3, the low and high anchors were 80,000 and 8,000,000 deaths, respectively. The nine statements were: 1) *Schools should reopen and resume face-to-face teaching by the end of the year*, 2) *Non-essential public meetings should be banned until the development of a vaccine*, 3) *Gatherings of more than 10 people should not be allowed until a vaccine is developed*, 4) *People over 70 years old should not be allowed to leave their homes until a vaccine is found*, 5) *People who are found in a public space without a valid reason should have a criminal record*, 6) *All businesses and stores should reopen without requiring them to obtain an official authorization*, 7) *The government should track the movements of all patients who tested positive for COVID-19 using their cell-phone data*, 8) *The government should fine those individuals who upload false information to the official virus-tracking app*, 9) *The government should force the citizenship to share their geolocation through an official virus-tracking app*. For data analysis purposes, we reverse coded the ratings of statements 1 and 6.

Experiment 4 (United States)

Finally, we performed a fourth experiment where we recruited participants from the United States. The hypotheses and analysis plan were pre-registered at <https://aspredicted.org/wj8de.pdf>.

The experiment had three parts. In the first part, we measured partisanship using a single pre-treatment item where people indicated their preference between the Democratic or Republican Party on an 11-point Likert scale with one extreme indicating “I strongly prefer the Democratic Party” and the other extreme reading “I strongly prefer the Republican Party”. We also asked participants to report their voting intentions for the 2020 National Election.

The second part of the experiment consisted in a forecasting competition. We asked participants to estimate, to their best knowledge, the number of COVID-19 cases and deaths in the United States in the upcoming week. They were incentivized for accuracy: participants were instructed that the 10% best forecasters would obtain a bonus payment of USD 2 (which was added to the standard participation fee of USD 1). The most accurate forecasters were defined as the ones with least absolute error. In practice, accuracy was separately computed for each treatment and we provided with the bonus payment to the 10% best forecasters of each experimental condition.

There were six conditions in this experiment. In Condition 1, we used a “low anchor” on COVID-19 deaths: we asked participants whether they thought there would be more or less than 40 new deaths in the upcoming week (from 27 July 2020 to 2 August 2020) and then asked them to estimate that number. In the following screen, participants forecasted the number of new COVID-19 cases in the same week. Condition 2 was identical to Condition 1 except for the fact that we used a “high anchor” of 400,000 new deaths. In Condition 3, we did not anchor people’s expectations (“control condition”). We first asked people to forecast the number of new deaths in the upcoming week and, in the following screen, participants estimated the number of new COVID-19 cases in the same week.

In Condition 4, we used a “low anchor” on COVID-19 cases: we asked participants whether they thought there would be more or less than 8,000 new cases in the upcoming week, and then asked them to estimate the number of new cases. In the following screen, participants forecasted the

number of new COVID-19 deaths in the same week. Condition 5 was identical to Condition 4 except for the fact that we used a “high anchor” of 8,000,000 new cases. In Condition 6, we did not anchor people’s expectations (“control condition”). We first asked people to forecast the number of new cases in the upcoming week and, in the following screen, participants estimated the number of new COVID-19 deaths in the same week.

The nine statements used to measure participants’ agreement with COVID-19 policies were:

1) *All schools in the United States should reopen before the end of 2020*, 2) *All non-essential public events should be banned until a vaccine is found*, 3) *The Federal Government should track the location of people infected with COVID-19 using a mobile phone app*, 4) *Wearing a mask in public spaces should be optional*, 5) *People over 70 years old should not be allowed to leave their homes until a vaccine is found*, 6) *People should request permission to the Federal Government to travel from one state to another*, 7) *Until a vaccine is found, the Federal Government should not allow mass protests in the United States*. For data analysis purposes, we reverse coded policies 1 and 4.

Monte Carlo power analyses

We performed two types of Monte Carlo power analyses (29) to study the relationship between expectations and policy preferences in Experiment 1, 2, and 3. The first one tested the post-hoc power of the two-sample t-tests performed on agreement ratings across the two anchoring conditions (**Figures 2B, 2E, and 2H**). We simulated data by sampling from normal distributions with the same mean and variance observed in the real data, but where the difference between means was chosen so that there was a small effect size (Cohen’s $d = .2$). We then set the same upper and lower bounds and resolution present in the real data (i.e., the average of 9 Likert ratings between 0 and 7). With this procedure, we created a synthetic dataset with 100,000 observations. We subsampled this dataset without replacement using sample sizes that ranged from 100 to 700 in steps of 10 observations. For each sample size, we performed 1,000 artificial experiments and estimated power as the fraction of times that a two-sample t-test would yield a significant result using a 5% significance level (left panel **Figure S1**).

The second post-hoc power analysis was performed on the correlation test between the forecasted number of deaths and the mean ratings of agreement with COVID-19 policies (**Figures 2C, 2F, and 2I**). We created a synthetic dataset by obtaining 100,000 samples from two normal distributions with a weak association between them ($r = .15$). We then repeated the procedure explained in the previous paragraph, and estimated power as the fraction of times that a correlation test would yield a significant result using a 5% significance level (right panel in **Figure S1**).

Equivalence tests

We performed two one-sided tests (TOST) for equivalence (30) to evaluate if the observed differences in agreement across experimental conditions was within a small interval. In these tests, the null hypothesis is that the two samples have different means (i.e., the difference between the means of the two samples falls outside a small equivalence interval) and the alternative hypothesis is that the two samples are equivalent (i.e., the difference between the means of the two samples falls within a small equivalence interval). To perform this test, one needs to define the size of the equivalence interval so that differences that fall within that interval are deemed irrelevant from a practical point of view. In this study, we assumed that differences smaller than half a Likert point are negligible. We also performed a sensitivity analysis of this assumption by studying whether and how results change as a function of the equivalence interval limit (**Figure S2**).

Bayes factor hypothesis testing

To quantify the relative amount of evidence for each hypothesis, we performed Bayes factor analyses (31) using Matlab (<https://github.com/klabhub/bayesFactor>). This analysis was performed to estimate the evidence in favor of the null hypothesis that there is no difference in agreement ratings the two anchoring conditions (**Figures 2B, 2E, and 2H**), and to evaluate the amount of evidence in favor of an absent association between forecasted deaths and agreement ratings (**Figures 2C, 2F, and 2I**). To measure the aggregate amount of evidence for each hypothesis, we multiplied the Bayes factors across different experiments.

Structural equation models

To formally compare the rational and tribal partisanship models, we estimated a path analysis model by fitting three simultaneous equations (41). First, we modelled the support for the ruling party as a function of three demographic variables: age, gender, and years of education,

$$\text{Support for Ruling Party}_i = \beta_0 + \beta_1 \text{Age}_i + \beta_2 \text{Gender}_i + \beta_3 \text{Education}_i + \epsilon_{1i}, \quad [1]$$

where Gender_i is a dummy variable referenced to female participants. Second, we explained the forecasted number of deaths as a function of the participants' support for the ruling party and a dummy variable High_i coding the experimental treatment (referenced to the “low anchor” condition),

$$\text{Forecasted number of deaths}_i = \beta_3 + \beta_4 \text{High}_i + \beta_5 \text{Support for Ruling Party}_i + \epsilon_{2i} \quad [2]$$

Third, we modelled participants' agreement with COVID-19 policies as a function of the forecasted number of deaths and participants' support for the ruling party,

$$\text{Agreement}_i = \beta_6 + \beta_7 \text{Forecasted number of deaths}_i + \beta_8 \text{Support for Ruling Party}_i + \epsilon_{3i}. \quad [3]$$

To compare between alternative theories of partisan behavior, we fitted three alternative models. The first one is the “full model” (**Figure 4A**) which consists in Equations 1-3 (for the best-fitting parameters, see **Tables S1-S4**). We compared this model with two simpler alternatives: the “rational partisanship model” (**Figure 1A**) where $\beta_8 = 0$ in Equation 3 and the “tribal partisanship model” (**Figure 1B**) where $\beta_7 = 0$ in Equation 3. All models were fitted using maximum likelihood estimation in Stata (<https://www.stata.com/>) and we compared the three models using the Bayesian Information Criterion (BIC).

Data and code availability

All data and codes to reproduce our findings are available at <https://osf.io/ef8pk/>.

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Supplementary Material

Figure S1. Monte Carlo power analyses. **A)** We simulated a treatment effect with a small effect size given by the anchoring manipulations (Cohen's $d=.2$) and 100,000 observations (see **Materials and Methods** for details). **B)** We simulated a weak association between forecasts and policy ratings (correlation coefficient $r=.15$). In both cases, we estimated power by randomly subsampling these synthetic datasets and computing the fraction of times that the effect showed up significant in a two-sample independent t-test (5% significance level). Blue dots: Probability to observe a significant effect (power) as a function of simulated sample size. Red dot: estimated power of the sample sized used in Experiment 1. Red square: same for Experiment 2. Red triangle: same for Experiment 3.

Figure S2. Sensitivity analysis of the two one-sided tests (TOST) for equivalence. Equivalence testing requires defining an equivalence interval for which differences that are within such interval are deemed insignificant from a practical point of view. In the main text, we assumed that differences smaller than half a Likert point are deemed irrelevant. Here, we show a sensitivity analysis for that assumption. **A)** For each interval limit (x-axis) we show the t-value of the TOST for equivalence (y-axis). **B)** For each interval limit (x-axis) we show the p-value in log-10 units of the TOST for equivalence (y-axis). In both panels, circles represent data from Experiment 1, squares from Experiment 2, and triangles from Experiment 3. Red markers show non-significant results (i.e., the null hypothesis of a relevant difference cannot be rejected) and green markers show significant results (i.e., the null hypothesis of a relevant difference is rejected) with a 5% significance level.

Argentina

Dependent variable		Independent variables		Results		
			Estimate	SE	z-value	p-value
Equation 1	Support for Ruling Party	Age	-0.003	0.006	-0.54	0.59
		Gender	-0.075	0.115	-0.65	0.51
		Education	0.007	0.035	0.20	0.84
Equation 2	Forecasted number of deaths	Support for Ruling Party	-0.079	0.022	-3.61	3×10 ⁻⁴
		High Anchor	1.229	0.062	19.91	0
Equation 3	Agreement with COVID-19 policies	Support for Ruling Party	0.373	0.038	9.82	0
		Forecasted number of deaths	-0.019	0.054	-0.36	0.722
BIC: 15156.162		Observations: 640				
AIC: 15098.163						

Table S1. Results of the path analysis performed in Experiment 1 (Argentina). We fitted three simultaneous equations to explain the relationship between partisanship, expectations, and policy support. For details about the linear regressions fitted on each variable, see Materials and Methods.

Uruguay

Dependent variable		Independent variables		Results		
			Estimate	SE	z-value	p-value
Equation 1	Support for Ruling Party	Age	0.013	0.007	1.88	0.06
		Gender	0.014	0.183	0.08	0.94
		Education	-0.012	0.029	-0.39	0.69
Equation 2	Forecasted number of deaths	Support for Ruling Party	-0.083	0.026	-3.17	2×10 ⁻³
		High Anchor	0.851	0.092	9.20	0
Equation 3	Agreement with COVID-19 policies	Support for Ruling Party	0.120	0.040	2.99	3×10 ⁻³
		Forecasted number of deaths	0.137	0.071	1.93	0.05
BIC: 9769.564 AIC: 9718.619		Observations: 372				

Table S2. Results of the path analysis performed in Experiment 2 (Uruguay). We fitted three simultaneous equations to explain the relationship between partisanship, expectations, and policy support. For details about the linear regressions fitted on each variable, see Materials and Methods.

Brazil

Dependent variable		Independent variables	Results			
			Estimate	SE	z-value	p-value
Equation 1	Support for Ruling Party	Age	0.019	0.008	2.38	0.02
		Gender	0.312	0.178	1.75	0.08
		Education	0.012	0.027	0.46	0.64
Equation 2	Forecasted number of deaths	Support for Ruling Party	-0.128	0.030	-4.24	2×10 ⁻⁵
		High Anchor	0.465	0.102	4.56	5×10 ⁻⁶
Equation 3	Agreement with COVID-19 policies	Support for Ruling Party	-0.206	0.046	-4.48	7×10 ⁻⁶
		Forecasted number of deaths	0.082	0.078	1.06	0.29
BIC: 9231.863		Observations: 353				
AIC: 9181.599						

Table S3. Results of the path analysis performed in Experiment 3 (Brazil). We fitted three simultaneous equations to explain the relationship between partisanship, expectations, and policy support. For details about the linear regressions fitted on each variable, see Materials and Methods.

United States

Dependent variable		Independent variables		Results		
			Estimate	SE	z-value	p-value
Equation 1	Support for Ruling Party	Age	0.011	0.014	0.81	0.42
		Gender	1.053	0.438	2.41	0.02
		Education	-0.072	0.069	-1.05	0.29
Equation 2	Forecasted number of deaths	Support for Ruling Party	-0.055	0.020	-2.73	6×10 ⁻³
		High Anchor	1.333	0.133	10.03	0.
Equation 3	Agreement with COVID-19 policies	Support for Ruling Party	-0.100	0.028	-3.53	4×10 ⁻⁴
		Forecasted number of deaths	-0.112	0.077	-1.45	0.15
BIC: 6346.861		Observations: 225				
AIC: 6302.452						

Table S4. Results of the path analysis performed in Experiment 4 (United States). We fitted three simultaneous equations to explain the relationship between partisanship, expectations, and policy support. For details about the linear regressions fitted on each variable, see Materials and Methods.