An Outbreak of Selective Attribution: Partisanship and Blame in the COVID-19 Pandemic

Matthew H. Graham*

Shikhar Singh[†]

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Abstract

Crises and disasters give voters an opportunity to observe the incumbent's response and reward or punish them for successes and failures. Yet even when voters perceive events similarly, they tend to attribute responsibility selectively, disproportionately crediting their party for positive developments and blaming opponents for negative developments. We examine selective attribution during the COVID-19 pandemic in the United States, reporting three key findings. First, selective attribution rapidly emerged during the first weeks of the pandemic, a time in which Democrats and Republicans were otherwise updating their perceptions and behavior in parallel. Second, selective attribution is caused by individual-level changes in perceptions of the pandemic. Third, existing research has been too quick to explain selective attribution in terms of partisan-motivated reasoning. We find stronger evidence for an explanation rooted in beliefs about presidential competence. This recasts selective attribution's implications for democratic accountability.

* Assistant Professor, Department of Political Science, Temple University. mattgraham@temple.edu.

[†] Postdoctoral Research Fellow, Center for the Advanced Study of India, University of Pennsylvania. shikhars@sas.upenn.edu. For helpful comments on earlier versions of this work, we thank Alex Coppock, Alan Gerber, Daniel Goldstein, Jacob Hacker, Greg Huber, Josh Kalla, Lilla Orr, Kyle Peyton, Jen Wu, seminar participants at Yale University, poster session participants at the New York University CESS conference, and panel participants at the annual meetings of the American Political Science Association and the Midwest Political Science Association. We thank Zac Jones and Rebecca Graham for coding the open-ended question in Study 1.

Crises and disasters give voters an opportunity to observe the incumbent’s response and punish or reward them for successes and failures (Ashworth and Bueno De Mesquita 2014). Yet even when voters agree on the facts, they tend to attribute responsibility in a selective manner. Compared to opposition voters, supporters of the incumbent party are more likely to credit the government for positive outcomes and less likely to blame it for negative outcomes. In contrast, opposition supporters more readily blame the government for negative outcomes and give it less credit for positive outcomes. This sort of selective punishing and rewarding performance is widely considered a threat to democratic accountability (Healy and Malhotra 2013).

In this paper, we study partisan selectivity in attributions of responsibility (hereafter “selective attribution”) through the lens of the COVID-19 pandemic in the United States. We report three main findings, which are summarized in Table 1. First, we show that selective attribution emerged quickly alongside the outbreak of COVID-19 in March and April 2020. Using an original time series spanning the six weeks between the country’s 500th confirmed COVID-19 case and its 500,000th, we show that as the reality of a pandemic set in, Democrats and Republicans changed their perceptions of the crisis and behaviors in a near-parallel fashion. However, even as Democrats increasingly blamed then-President Donald Trump for the pandemic, Republicans held firm in assigning him little responsibility for it.

Second, we show that selective attribution occurs as a result of individual-level changes in perceptions of the pandemic.¹ We demonstrate this using three experiments, two conducted during Trump’s presidency and one conducted under Trump’s successor, Joe Biden. In each experiment, subjects were randomly assigned to read vignettes that highlighted relatively positive or negative facts about the pandemic in the United States. Democrats and Republicans alike revised their perceptions of the pandemic in the direction of the evidence, and by about the same amount. However, when asked about presidential responsibility for the pandemic, Democrats and Republicans used the same information to make opposite

¹By contrast, elite cues could cause the selective attribution that emerges in observational studies.

inferences. After seeing positively (negatively) valenced information about the pandemic, the president’s co-partisans attributed more (less) responsibility to the president. Opposing partisans responded in the opposite way, holding the president more responsible when they saw negatively valenced information and less responsible when they saw positively valenced information.

Third, we conduct the first tests of alternative explanations for selective attribution. Conventional wisdom holds that selective attribution occurs due to partisan-motivated reasoning (PMR). The PMR account holds that selective attribution occurs because voters’ partisan identities create a psychological motivation to avoid blaming their party. This explanation has never been tested against any alternative (Table 2). We develop an explanation rooted in *competence beliefs*, which we define as voters’ perceptions of whether the incumbent is likely to deliver good performance. This explanation is floated briefly in one existing account of selective attribution (Sirin and Villalobos 2011) and connects with classic work on democratic accountability (Key 1966a; Fearon 1999). A voter who believes that the incumbent is competent (i.e. likely to deliver good performance) responds to positive news by attributing more responsibility to the incumbent, and negative news by attributing less responsibility to the incumbent. A voter who believes the incumbent is incompetent assigns responsibility and evaluates performance in the opposite way. These explanations are related to a broader debate over whether group-based differences in information processing are traceable to directional motivation or prior beliefs (Druckman and Levendusky 2019; Little 2021).

We compare the PMR and competence beliefs explanations using two empirical tests. First, we conduct two regression-based “horse races” using data from two survey experiments, one fielded during Trump’s presidency and the other during Biden’s presidency. The horse races compare the ability of partisan identity and competence beliefs to predict variation in how voters attribute responsibility. Under both Trump and Biden, we find support for the competence beliefs account. Independent of partisan identity, variation in competence

Table 1: Key Findings and Implications

Data	Finding	Implication
Time Series	1. Partisan differences in attributions of responsibility emerge early in the pandemic, despite parallel trends in perceptions and behavior.	Selective attribution quickly emerges in times of crisis. Could be due to individual-level factors or correlated factors like elite cues.
Experiments 1-3	2. Voters from the president’s party are more (less) likely to hold the president responsible when they see positively (negatively) valenced information. Voters from the opposition party do the opposite.	Consistent with two individual-level explanations, partisan-motivated reasoning and beliefs about the incumbent’s competence.
Experiments 2-3	3a. Compared with partisan identity, competence beliefs are a better predictor of selective attribution.	Descriptive evidence in favor of the competence beliefs account.
Experiment 3	3b. Accuracy motivation does not reduce selective attribution.	Causal evidence in favor of the competence beliefs account.

beliefs still moderates the effect of performance information on attributions of responsibility; independent of competence beliefs, variation in partisan identity does not moderate the same effect. Moreover, whereas competence beliefs retain their explanatory power when only within-party variation is used, within-party variation in identity strength fails to predict variation in the degree of selective attribution. Second, we experimentally alter the motivational context using an accuracy prime that has been shown in other contexts to neutralize the effects of PMR (Bolsen, Druckman and Cook 2014; Bolsen and Druckman 2015). Whereas the PMR account predicts that accuracy motivation will counteract selective attribution, we find that selective attribution persists with equal strength when accuracy motivation is heightened. This suggests that selective attribution occurs as a function of voters’ competence beliefs, not because their identities motivate them to reach convenient conclusions.

Our findings make several contributions. Most immediately, the novel evidence that selective attribution predated the widening of other partisan differences over the pandemic demonstrates its importance in a once-in-a-century public health crisis. More broadly, by

conducting the first tests of the individual-level mechanisms behind selective attribution, we add a new dimension to the study of impediments to democratic accountability. The tests of mechanisms have wide-ranging implications for partisanship, polarization, and democratic accountability. As we elaborate in the concluding section, our findings bridge two competing accounts of partisanship: one in which partisanship is a “running tally” of competence evaluations (Fiorina 1978, 1981) and another in which it is a “perceptual screen” rooted in social identity (Campbell et al. 1960). Our findings suggest that through the channel of selective attribution, a running tally of competence beliefs can harden into a perceptual screen over time. In turn, this suggests that party reputation-building—elsewhere viewed as an important component of parties’ incentives to govern responsibly (Rosenbluth and Shapiro 2018)—can also dampen democratic accountability. These insights open new doors for examining the importance of selective attribution for a broader range of political contexts, as well as understanding how ethnic, ideological, or issue-based divisions shape voters’ evaluation of performance information (Adida et al. 2017; Singh 2022).

Perceptions, Attributions, and Accountability

A potential advantage of democratic political systems is that elections may select competent politicians and provide incentives for politicians to deliver better performance (Fearon 1999; Ferejohn 1986; Manin 1997). A base-level question for such accounts is whether voters perceive government performance at all, given their limited exposure to political information and limited incentives to gather it (Downs 1957). Voters are thought to form impressions of performance not through a detailed analysis of public policies and their effects, but by paying attention to their own pocketbook (Fiorina 1981), their local context (Snowberg et al. 2011), or the news (Kayser and Leininger 2015).

To the extent that voters perceive the political world at all, another concern is that partisan voters perceive it differently. Ideally, one would hope Democrats and Republicans share a common set of factual basis for their debates, disagreeing only over matters of policy

(Delli Carpini and Keeter 1996). In practice, partisans appear to know more about facts that are politically convenient (Bartels 2002; Jerit and Barabas 2012; Roush and Sood 2020). Yet, they also respond to changing economic conditions by similarly updating their beliefs in the direction of the evidence (Bisgaard 2015; Gerber and Green 1999; Parker-Stephen 2013). Existing analyses of large question banks put the typical partisan belief difference at 5 to 15 percentage points (Jerit and Barabas 2012; Roush and Sood 2020).

Even when voters perceive the world accurately, democratic accountability requires that voters also hold the incumbent responsible for what they observe. Whereas early research on performance-based accountability largely looked past the steps between performance perceptions and vote choice (Downs 1957; Key 1966a), subsequent scholarship argued that attributions of responsibility are crucial to how voters convert perceptions of the world into political attitudes and preferences. Perception of social and economic conditions, and of one’s personal circumstances, only predict vote choice among those who hold the government responsible for bringing those conditions about (Feldman 1982; Peffley and Williams 1985; Abramowitz et al. 1988; Rudolph and Grant 2002). For example, Republican success in the 1982 midterm elections is credited to the American electorate’s refusal to blame President Reagan for the preceding recession (Petrocik and Steeper 1986).

A growing body of scholarship finds that voters are selective in their attributions of responsibility. We define *selective attribution* as the tendency of partisan voters to disproportionately credit their party for positive outcomes and blame their political opponents for negative outcomes. A vivid example emerges from Bisgaard’s (2015) account of economic perceptions in the United Kingdom during the Great Recession of 2007-09. Even as Britons near-universally recognized worsening economic conditions, supporters and opponents of the governing Labour party differed in their attributions of political responsibility for the economy. Labour supporters assigned less responsibility to the government, effectively making excuses for their party. Labour opponents assigned more responsibility to the government, blaming it for the tough times.

Selective attribution has been documented in several other policy domains in the United States and Europe (Table 2). In cross-sectional analyses, opposite-signed relationships between evaluations and attributions of responsibility have been detected among supporters and opponents of the governing party when it comes to national economic conditions (Marsh and Tilley 2009; Nawara 2015; Bisgaard 2015; c.f. Rudolph 2003b), state-level fiscal conditions (Brown 2010; Rudolph 2003a), and personal experiences with the health care system (McCabe 2016).² Though these accounts describe selective attribution as an individual-level process (particularly PMR; Table 2), selective attribution could occur through other means. For example, partisan voters may take cues from elected officials’ tendency to seek credit for good outcomes (Mayhew 1974; Grimmer et al. 2012) and deflect blame for bad outcomes (McGraw 1990).

The best evidence that selective attribution is an individual-level phenomenon emerges from a set of experiments that randomly assign positively or negatively valenced information about economic conditions in the United States and Denmark (Bisgaard 2019). In-partisans were more likely to hold the incumbent responsible when they read positively framed information, and less responsible when they read negatively framed information. Out-partisans did the opposite. Bisgaard’s experiments suggest that selective attribution occurs at least in part through some individual-level process that is triggered by exposure to performance information. A related set of experiments find that randomly assigning partisan labels to government officials causes Democrats and Republicans to diverge in their attributions of responsibility for Hurricane Katrina (Malhotra and Kuo 2008), the September 11 attacks (Healy et al. 2014), and hypothetical state-level fiscal conditions (Rudolph 2006).

²Similar results also obtain when voters attribute responsibility between their national governments and the European Union (Hobolt et al. 2013; Hobolt and Tilley 2014), and when they reward or punish co-ethnic and non-coethnic politicians for their performance in developing democracies (Adida et al. 2017).

Table 2: Existing research on partisan selectivity in attributions of responsibility.

Citation	Countries	Topics	Dates	Data	Source of variation	Explanation(s) considered
Rudolph (2003a)	United States	Fiscal conditions (state level)	Summer 1991	ABC/Washington Post poll	Cross-sectional variation in sociotropic perceptions	None*
Rudolph (2003b)	United States	Economy	Fall 1998	American National Election Studies	Cross-sectional variation in sociotropic perceptions	Partisan-motivated reasoning
Rudolph (2006)	United States	Fiscal conditions (state level, hypothetical)	Unknown	Original laboratory experiment	Randomly assigned partisan labels	Partisan-motivated reasoning
Malhotra and Kuo (2008)	United States	Natural disasters (Hurricane Katrina)	May 2006	Original survey	Randomly assigned partisan labels	None
Marsh and Tilley (2009)	Ireland, United Kingdom	UK: living standards, health care, taxes, education. Ireland: economy, health care.	1998-2001 and 2002-2007	British and Irish Election Studies	Cross-sectional variation in sociotropic perceptions	None [†]
Brown (2010)	United States	Economy (1982 recession)	Nov. 1982	CBS/New York Times exit poll	Cross-sectional variation in state political context	None
Sirin and Villalobos (2011)	United States	Domestic and foreign policy	Unknown	Original laboratory experiment	Randomly assigned partisan labels	Competence beliefs
Healy et al. (2014)	United States	Terrorism (September 11, 2001)	February 2007	Original survey	Randomly assigned partisan labels	Partisan-motivated reasoning
Bisgaard (2015)	United Kingdom	Economy (Great Recession)	April 2004 - May 2010	British Continuous Monitoring Survey	Temporal variation in economic conditions	Partisan-motivated reasoning
Nawara (2015)	United States	Economy, war (Iraq)	August 2010	Original survey	Cross-sectional variation in sociotropic perceptions	Partisan-motivated reasoning
McCabe (2016)	United States	Health care (Affordable Care Act of 2010)	January 2014	Kaiser Family Foundation poll	Cross-sectional variation in personal experiences	Partisan-motivated reasoning
Bisgaard (2019)	Denmark, United States	Economy	Dec. 2015 - April 2016	Original surveys	Randomly assigned performance information	Partisan-motivated reasoning
This paper	United States	International crisis (COVID-19 pandemic)	2020-22	Original surveys	Temporal variation, randomly assigned performance information	Competence beliefs, partisan-motivated reasoning

*Cites “group-serving attributional bias” but does not specify a mechanism for it (196). [†]Concludes that selective attribution is evidence of “partisan filters” (134). Partisan filters are described as opposed to performance-based accounts (119), but mechanisms for partisan filtering are not discussed.

Explaining Selective Attribution

Why does exposure to identical information cause partisans to make opposite attributions of responsibility? One possibility is that individuals attribute responsibility in a manner that is consistent with their prior beliefs about who delivers good performance. Consider a voter who believes that the incumbent delivers good performance (i.e., is competent). When this voter observes positive information they infer that the incumbent may have been responsible for the outcome. By contrast, a voter who believes the incumbent is incompetent reacts to positive news by inferring that the incumbent may *not* have been responsible. We call this the *competence beliefs* explanation. In the appendix, we show that once selective attribution is expressed mathematically, this explanation directly follows from the laws of probability (Appendix F.1). By default, one should expect individuals to maintain proportionality between their perceptions of performance and their beliefs about the president’s effect on performance (i.e., the president’s competence).

The existing research on selective attribution favors a different explanation: partisan-motivated reasoning (PMR). Motivated reasoning holds that group identities create a psychological need to maintain a positive evaluation of one’s group. These directional motivations cause individuals to find support for conclusions that are consistent with their identities (Kunda 1990; Leeper and Slothuus 2014). As a result, people place disproportionate weight on favorable information and down-weight or ignore inconvenient information. Crucially, not all group-based differences in reasoning are directionally motivated. In particular, the desire to positively evaluate one’s group must influence how people use information when they reason, over and above the influence of prior beliefs. For example, the first paragraph of Kunda’s (1990) oft-cited case for motivated reasoning notes that instances in which people “draw self-serving conclusions not because they wanted to but because these conclusions seemed more plausible, given their prior beliefs and expectancies” would not qualify as motivated reasoning (also see Tappin, Pennycook and Rand 2020; Little 2021; Coppock 2022). In Druckman and McGrath’s (2019) terminology, the competence beliefs explanation is an

instance of priors bias and the PMR explanation is an instance of directional bias.

No previous research tests competing explanations for partisan selectivity in attributions of responsibility. Instead, almost every published study treats selective attribution as face-value evidence of PMR (Table 2). This ignores an observational equivalence problem: in theory, any instance in which groups use identical information to reach different conclusions can be explained either in terms of differences in prior beliefs or in terms of directional motivations (Little 2021; Coppock 2022). Recognition of this problem once spurred psychologists to carefully evaluate both motivational and non-motivational explanations for selective attribution in non-political contexts (Miller and Ross 1975; Kunda 1990). As the concept of motivated reasoning gained wider attention, research increasingly jumped straight to psychological motivations without considering alternative mechanisms that can produce the same patterns (Druckman and McGrath 2019; Tappin, Pennycook and Rand 2020).³

Some preliminary evidence for the competence beliefs explanation emerges in two studies with cross-pressured individuals: those whose partisan identity conflicts with their beliefs about the incumbent’s competence. Using cross-sectional data from the 1998 ANES, Rudolph (2003b) finds that Democrats selectively credited President Clinton, a fellow Democrat, for economic performance. Democrats who viewed the economy more positively were also more likely to say the president is responsible for economic conditions. However, there was “no evidence of partisan rationalizations among Republicans” (704). Instead, the estimates for Republicans took the same sign as the estimates for Democrats in all three models and were statistically significant in one case (Rudolph 2003b, Table 2). This cannot be due to PMR, but can be explained by beliefs about Clinton’s competence. In the same data, 67 percent of Republicans approved of Clinton’s handling of the economy, with 29 percent disapproving. Republicans, who thought on average that Clinton was good at managing the economy, reacted to positive economic news by assigning more responsibility to Clinton.

³It is instructive that the only previous study of partisan selective attribution to cite a competence beliefs explanation (Sirin and Villalobos 2011) develops its explanation through engagement with the psychology literature rather than the political science literature.

More evidence that PMR cannot fully explain selective attribution emerges from Denmark, a multiparty system in which some parties that are ideologically aligned with the governing party are not part of the ruling coalition. For such voters, partisan identity is likely to come into conflict with their beliefs about whether the government will deliver good performance. [Bisgaard \(2019, study 2\)](#) finds that supporters of the center-left coalition government attributed more responsibility to the government when they saw positively framed information about the economy, and less responsibility when they saw negatively framed information. Supporters of right-wing opposition parties did the opposite. A third group of cross-pressured voters—supporters of further-left parties excluded from the ruling coalition—attributed responsibility similar to supporters of the ruling coalition. Eighteen months later a center-right party (the Liberals) took control of the government. A subsequent experiment found the same pattern for right-wing voters not part of the ruling coalition ([Bisgaard 2019, study 3](#)). The cross-pressured voters’ pattern of attribution cannot be explained by PMR, but is quite plausibly explained by competence beliefs. If voters believe that governments that share their ideology are likely to govern competently, they may react to good (bad) news by reasoning that the government is more (less) responsible.

In sum, even though existing studies treat selective attribution as evidence of PMR, our reanalysis slightly favors the competence beliefs explanation. In both previously studied cases in which we could identify a plausible conflict between partisan motivations and competence beliefs, the latter appear to win out.

Research Design

Our analysis of selective attribution in the COVID-19 pandemic follows the same order as the foregoing discussion. In our first section of results, we use time series data to show that selective attribution emerged in real time in the early days of the pandemic. This evidence establishes the external validity of our findings but is limited in its ability to describe why selective attribution occurred.

Figure 1: Timeline

Note: This figure plots daily COVID-19 case rates in the United States (grey bars) against the dates of our time series survey (red shaded box) and experiments (red vertical lines). *Data:* New York Times, “[Coronavirus \(COVID-19\) Data in the United States](#),” accessed January 15, 2022.

Next, we search for a mechanism. Our first step is to show that selective attribution is an individual-level phenomenon that occurs as a function of voters’ perceptions of performance. This justifies our focus on two individual-level explanations, competence beliefs and PMR. We selected competence beliefs as a plausible alternative to PMR based on some further analysis, which appears in the appendix.⁴

Based on our theory, we developed and pre-registered two tests of which mechanism is more plausible. Our approach embodies [Little’s \(2021\)](#) recommendation that researchers “manipulate (or find natural variance in) accuracy and directional motives while holding informational content as equal as possible” (abstract). The strategies have complementary strengths and weaknesses. To make use of natural variation, we run a regression-based horse race that examines whether measures of competence beliefs or partisan identity are the stronger predictor of selective attribution. This is highly specific in terms of what mech-

⁴First, strength of partisanship, as measured by the traditional seven-point scale, is a poor predictor of selective attribution (Appendix F.3). This signals a potential need for an alternative explanation. Second, Bayes’ rule implies that agents should maintain proportionality between their perceptions of performance and beliefs about the incumbent’s effect on performance (Appendix F.1). This suggests competence beliefs as a plausible alternative. Third, we show that information about Trump’s responsibility for the CDC causes Democrats and Republicans to make opposite inferences about its performance (Appendix C). This suggests that voters have competence beliefs.

anisms are being tested. However, because the variation in partisan identity and competence beliefs is descriptive, the comparison between the two explanations is not causally identified. To manipulate motives, we examine the degree to which selective attribution persists in the presence of a randomly assigned accuracy motivation treatment. This provides causal evidence that beliefs are a better explanation than directional motivation, but is agnostic as to exactly what beliefs or directional motivations are at play.

Empirical tests between belief-based and motivation-based explanations generally only consider the “last mile,” the moment at which subjects evaluate information and/or update their beliefs. Our approaches share this limitation. Even if subjects’ competence beliefs are the more proximate explanation for selective attribution, it is possible that motivated reasoning plays a role in the formation of those beliefs. Though the analysis below makes clear that competence beliefs are not entirely a function of partisan identity (Figure 6), we would not go so far as to say that we can rule it out at all stages of the process. Within this limitation, we endeavor to provide a complete account of selective attribution in the COVID-19 pandemic, beginning by establishing external validity and culminating in a more thorough analysis of mechanisms than has been conducted for other cases (Table 2).

An Outbreak of Selective Attribution

Our first finding is that selective attribution emerged early in the pandemic, at a time when Democrats’ and Republicans’ perceptions of the threat from COVID-19 otherwise moved in tandem. To measure public reactions to the emerging crisis, we partnered with Lucid to field a time series cross-sectional survey, recruiting about 600 respondents each Sunday from March 8 to April 12, 2020 (six weeks; total $n = 3,748$). The data span a critical period in the pandemic. On March 8, the United States recorded its 500th confirmed COVID-19 case. Only one state, Washington, had confirmed a COVID-19 death. The World Health Organization had yet declare a pandemic. By April 12, the pandemic was well underway, with more than 500,000 cases and 23,000 deaths confirmed in the United States

alone.

The pandemic’s dramatic escalation during this period produced close-to-parallel changes in perceptions among Democrats and Republicans.⁵ We document this using three groups of measures. First, factual beliefs: the respondent’s best guess of the cumulative number of confirmed cases and deaths recorded nationwide and in the respondent’s own state. Figure 2a displays a box and whisker plot of the distribution of Democrats’ and Republicans’ best guesses. Each week, Democrats and Republicans made similar guesses about the number of cases and deaths.⁶ Second, subjective threat perceptions. Respondents assessed the threat from COVID-19 on a five-point Likert scale from “no threat” to “imminent” (Figure 2b). On this measure, a partisan gap of about 0.5 scale points consistently appears each week, equal to about 13 percent of the 1 to 5 scale. Despite this persistent gap, Democrats and Republicans also updated their perceptions by a similar amount—close to a full scale point in each party. Third, a battery of self-reported behavioral changes (Figure 2c). On each of several indicators including avoiding physical contact with others, isolating oneself for at least 24 hours, and purchasing masks or other protective gear, Democrats and Republicans changed their behavior by about the same amount at approximately the same time.

In contrast to Democrats’ and Republicans’ parallel updating in threat perceptions, the time series documents substantial partisan divergence in blame attributions. Each respondent rated several actors’ blameworthiness for the pandemic on a four-point Likert scale ranging from “not at all” to “a lot.” First consider blame attributed to Trump. From March 8 to April 12, the average rating among Democrats increased by about 0.79 scale points,

⁵Although the pandemic’s subsequent politicization is a more common object of study, data collected in March and early to mid-April consistently reflects Democrats’ and Republicans’ shared recognition of the growing threat, dwarfing any partisan divides. Gollust, Nagler and Fowler (2020) note that “[i]n mid-April, there was a strong bipartisan consensus on the threat and support for shelter-in-place recommendations” that soon broke down (973). Similarly, Sides, Tausanovitch and Vavreck (2020) describe an early “consensus” that “broke down ... largely along partisan lines” (4-5). To provide more specific verification that the patterns we document are consistent with existing research, Appendix A.3 analyzes replication data from previously published articles on partisanship and the pandemic (Allcott et al. 2020; Clinton et al. 2021).

⁶Consistent with best practices (Ansolabehere et al. 2013), respondents were told the total population of the country and state before they made their guess (y-axis, Figure 2a). Using the paradata detection method described by Graham (2022), we flagged respondents as suspected of looking up the answers and dropped them from our analysis of these items only.

Figure 2: Time trends in perceptions, behavior, and blame attributions, March-April 2020.

Note: Figure (a) displays box and whisker plots of the distribution of respondents' best guesses. In each pair, Democrats are represented by the blue box and whiskers on the left; Republicans, by the red box and whiskers on the right. Middle line is median, box borders are 25th and 75th percentiles, whiskers are 2.5th and 97.5th percentiles, and dots are outliers. Figures (b), (c), and (d) display means. Democrats are blue diamonds connected by dots; Republicans, by red squares connected by dashes. Vertical bars represent 95 percent confidence intervals. * indicates questions that were only asked if applicable to the respondent.

which is 23.5 percent of the scale (s.e. = 3.2), compared with 0.26 scale points or 8.9 percent of the scale for Republicans (s.e. = 2.8; partisan difference = 16.1, s.e. = 4.4). A muted version of the same pattern appears in attributions of blame to Trump’s party, the Republicans (partisan difference = 15.3, s.e. = 4.2). By contrast, little such divergence is seen in the extent to which Americans blame Democrats, U.S. government agencies, immigrants, bad luck, or nature. A slight partisan divergence emerges in attributions of blame to China, Trump’s preferred scapegoat.⁷

The combination of parallel changes in perception but divergence in attributions of responsibility provide the basis for our claim that selective attribution emerged early in the pandemic. As the threat escalated, Democrats and Republicans reacted to new developments by similarly revising their factual beliefs, threat perceptions, and behavior. Yet despite their parallel reactions, Democrats and Republicans increasingly diverged on the question of blaming Trump for the pandemic.

The Causal Effect of Performance Information

Even as the time series establishes that selective attribution emerged as the pandemic unfolded, observational data have limitations when it comes to testing explanations for this pattern. Even though previous observational research overwhelmingly frames selective attribution as an individual-level process (Table 2), it is also possible that selective attribution emerges because of partisan leaders’ tendency to take credit for positive developments and deflect blame for negative ones (Mayhew 1974; McGraw 1990).⁸ To better-isolate the relationship between individual perception and selective attribution, we turn to experiments. By randomly assigning information that positively or negatively affects perceptions of the pandemic at the individual level, we can be sure that consequent changes in attributions

⁷In the appendix, we use regression to summarize these patterns more precisely.

⁸We think this factor is unlikely to seriously confound our time series analysis. A quintet of *New York Times* reporters date the Trump administration’s pivot from taking credit for the pandemic response to disowning it to “a critical period in mid-April” that began “soon after” April 11, 2020 (Shear et al. 2020). However, the need to make arguments like this crystallizes the value of experiments.

of responsibility are a function of voters’ cognitive processes, not exposure to elite rhetoric. This lays the foundation for our subsequent analysis of which individual-level explanation is more plausible.

Experiment 1

In May 2020, we recruited 1,059 respondents using Amazon Mechanical Turk (MTurk), which provides diverse national samples that skew young. Our sample included 564 Democrats or independents who lean toward the Democrats (“Democrat leaners”), 360 Republicans and Republican leaners, and 134 independents who do not lean toward either party.

The experiment examined the causal effect of information about the severity of the pandemic on two outcomes: (a) perceptions of how well the U.S. is doing in the fight against COVID-19, and (b) attributions of responsibility to President Trump. Each participant read four short vignettes providing information on the number of COVID-19 cases, number of deaths, testing capacity, and progress in developing treatments. Within these fixed topic areas, half of the respondents were randomly assigned to read positively valenced information, while the other half saw negatively valenced information. The information made no reference to the government or to any political figure. Following this, respondents answered three questions: an open-ended question about who is responsible for handling of the pandemic, a closed-ended question about how responsible Trump is for the pandemic, and a closed-ended question about how well the U.S. is handling the pandemic.

The experiment successfully manipulated perceptions of the pandemic among both Democrats and Republicans (Figure 3, left). On average, Republicans who read negatively valenced information rated the country’s performance as “neither good nor bad,” while Republicans who read positively valenced information rated it as “fairly good.” The difference, about 16 percent of the scale, was statistically significant ($\widehat{CATE}_R = 0.163$, s.e. = 0.029). Similarly, the average Democrat moved from “fairly bad” to “neither good nor bad” ($\widehat{CATE}_D = 0.173$, s.e. = 0.024). The difference in treatment effects for Republicans and Democrats is statistically insignificant ($\widehat{CATE}_R - \widehat{CATE}_D = -0.010$, s.e. = 0.038). Appendix B shows

Figure 3: Experiment 1

Note: The figure reports the group means for Democrats (blue diamonds) and Republicans (red squares) by experimental treatment (negatively or positively valenced information). In the left panel, the outcome is an assessment of the U.S.’ performance during the pandemic. In the right panel, the outcome is how much President Trump is responsible for the U.S.’ pandemic performance. Vertical bars represent 95 percent confidence intervals. For numerical tables and difference-in-means estimates, see the appendix.

that the treatment moved perceptions of performance on each of the four dimensions, for both Democrats and Republicans (see Figure B.1).

Despite these parallel changes in perceptions, Democrats and Republicans made opposite inferences about presidential responsibility (Figure 3, right). Compared with Republicans who read negatively valenced performance information, those that read positively valenced information said Trump was more responsible for the country’s performance ($\widehat{CATE}_R = 0.060$, s.e. = 0.026). For Democrats, we observe the opposite. Compared with Democrats who read negatively valenced information, those that read positively valenced information said Trump was less responsible ($\widehat{CATE}_D = -0.070$, s.e. = 0.023). The difference in treatment effects is approximately 13 percent of the scale ($\widehat{CATE}_R - \widehat{CATE}_D = 0.130$, s.e. = 0.035).

Immediately before this close-ended question, we asked respondents an open-ended question about who is responsible for the pandemic. The question did not mention Trump or any other political figure. We coded responses as “1” if the respondent said Trump was

responsible, else “0.” We coded all responses using an automated dictionary-based approach and a research assistant who was blind to the hypotheses and the computer’s coding. This procedure yielded a 97.9 percent inter-coder agreement. A second research assistant, also blind to the hypotheses and the other codings, independently broke all ties.

The open-ended outcome yields a similar pattern. The difference-in-means is positive for Republicans ($\widehat{CATE}_R = 0.008$, s.e. = 0.043) and negative for Democrats ($\widehat{CATE}_D = -0.095$, s.e. = 0.041), resulting in a borderline-statistically significant difference ($\widehat{CATE}_R - \widehat{CATE}_D = 0.103$, s.e. = 0.059, $p = 0.08$). In effect, partisan differences appear to exist even when questions of accountability are not explicitly stated in political terms.

Experiment 2

The second experiment is a pre-registered replication of the first experiment in a more politicized context: eight months into the pandemic, three weeks after the president tested positive for COVID-19, and one week before the presidential election. Between October 23 and 25, 2020, we used MTurk to recruit a diverse national sample ($n = 3,592$) for a baseline survey that collected the respondent’s demographics, partisan identity, beliefs about presidential competence, and pre-treatment measures of the outcomes. On October 26-28, six to eight days before the election, we invited the 3,234 partisans and independent leaners to complete a follow-up survey containing only the experiment and the outcomes.⁹ Of these, 2,504 respondents completed the second experiment.

The design was very similar to Experiment 1. Each respondent was randomly assigned to read a set of positively or negatively framed vignettes, which were updated to include the most recent information within the same four topic areas. Following this, respondents answered two close-ended questions: one on how responsible Trump is for handling of the pandemic, another on how well the U.S. is handling the pandemic. At no point prior to measuring outcomes did the follow-up survey mention any political party or figure.

⁹Methodological research suggests that the proximity of our pre- and post-treatment measures of the outcome is unlikely to have biased our estimates (Clifford et al. 2020).

Figure 4: Experiment 2

Note: See note to Figure 3.

Once again, the experiment successfully manipulated perceptions of the pandemic among both Democrats and Republicans (Figure 4, left). In fact, the point estimates are almost identical to those in Experiment 1. On average, Republicans who viewed negatively valenced information rated the country’s performance as “neither good nor bad”, while those that read positively valenced information rated it as “fairly good” ($\widehat{CATE}_R = 0.175$, s.e. = 0.013). The difference between the two conditions was about the same for Democrats ($\widehat{CATE}_D = 0.165$, s.e. = 0.011). The difference in treatment effects for Republicans and Democrats is not statistically significant ($\widehat{CATE}_R - \widehat{CATE}_D = 0.010$, s.e. = 0.017). Appendix E shows that the treatment moved perceptions of U.S. performance on all four dimensions, for both Democrats and Republicans (see Figure E.1).

As before, Democrats and Republicans used the same information to make opposite inferences about presidential responsibility for the pandemic. Republicans who saw positively valenced information attributed more responsibility to President Trump, compared with Republicans who saw negatively valenced information ($\widehat{CATE}_R = 0.099$, s.e. = 0.014). By contrast, Democrats who saw positively valenced information attributed less responsibility to Trump, compared with those that read negatively valenced information ($\widehat{CATE}_D = -0.059$,

s.e. = 0.013). The difference in treatment effects is about 16 percent of the scale and is statistically significant ($\widehat{CATE_R - CATE_D} = 0.156$, s.e. = 0.019).

One key difference between the results of Experiments 1 and 2 is that regardless of treatment condition, Democrats and Republicans differ more in their evaluations of the country’s performance and attributions of responsibility. We attribute this to the fact that Experiment 2 was conducted later in the pandemic and closer to a presidential election.

Experiment 3

The third experiment is another pre-registered replication conducted more than one year after Experiment 2. On December 29-30, 2021, we used MTurk to recruit another diverse national sample ($n = 4,484$). By this time, the political and public health context differed in two crucial respects. First, a Democrat, Joe Biden, had been elected U.S. President and led the country’s pandemic response for slightly longer than President Trump. Second, the country was experiencing its largest COVID-19 surge to date. The day before the experiment was launched, the country broke its previous record for the number of COVID-19 cases recorded in a single day. On the first day of the experiment, the country set the world record for the most cases recorded by any country in a single day.

Again, the design closely followed Experiments 1 and 2. Each respondent was randomly assigned to read positively or negatively framed vignettes in four topic areas: the number of COVID-19 cases, number of deaths, testing and treatment capacity, and the Omicron variant. The first three topic areas are the same as those in Experiments 1 and 2, while the fourth topic reflects the growing prominence of new variants in the fight against COVID-19. Following the vignettes, all respondents answered two closed-ended questions: one on how well the U.S. is handling the pandemic, and another on President Biden’s responsibility for the country’s performance. The questions were identical to Experiments 1 and 2 with the exception that “Biden” was substituted for “Trump”. The experiment also included a second treatment that randomly assigned respondents to read (or not read) a prime that enhanced accuracy motivations. We examine this manipulation arm in a separate section

Figure 5: Experiment 3

Note: See note to Figure 3.

(see “Altering the Motivational Context”).

We observe parallel updating in perceptions of how well the country is weathering the pandemic. Republicans who read negatively valenced information rated the country’s performance as “neither good nor bad,” while Republicans who read positively valenced information moved half the distance to “fairly good.” This difference was equal to about 13 percent of the scale ($\widehat{CATE}_R = 0.128$, s.e. = 0.010). A similar pattern was observed for Democrats ($\widehat{CATE}_D = 0.138$, s.e. = 0.008).

Just as they did under Trump, Democrats and Republicans used identical information to make opposite inferences about Biden’s responsibility for the pandemic. Democrats who read positively valenced information assigned more responsibility to Biden, relative to Democrats who read negatively valenced information ($\widehat{CATE}_D = 0.027$, s.e. = 0.006). By contrast, Republicans who read positively valenced information assigned less responsibility to Biden, compared to those that read negatively valenced information ($\widehat{CATE}_R = 0.040$, s.e. = 0.009). The difference in treatment effects is about 7 percent of the scale and is statistically significant ($\widehat{CATE}_R - \widehat{CATE}_D = 0.067$, s.e. = 0.011).

The results differ from Experiments 1 and 2 in three respects. None contradict our

theoretical account, but all deserve explanation. First, regardless of treatment condition, Democrats and Republicans, on average, had more similar perceptions of the pandemic. We attribute this divided issue ownership: at the time of the survey, a Democratic and Republican president had lead the country’s pandemic effort for roughly similar amounts of time. Second, the treatment effects on performance perceptions are smaller. We attribute this to the fact that this experiment was conducted much later in the pandemic. By this time, Americans had been exposed to much more information about the pandemic, a form of “pre-treatment” that has been shown to reduce persuadeability (Druckman and Leeper 2012). Third, the treatment effects on attributions of responsibility are smaller. We attribute this to the fact that attributions of responsibility are changing as a function of perceptions of performance. A smaller upstream effect on performance evaluations should result in a smaller downstream effect on attributions of responsibility.

Competence Beliefs as a Moderator

Having established the need for an individual-level explanation, we now turn to the question of what explains selective attribution. Experiments 2 and 3 each included a regression-based horse race that pits the prevailing explanation, PMR, against the alternative, competence beliefs. Because “the goal of directionally motivated reasoning is *identity protection*” (Kahan 2016, 4, emphasis original), researchers expect the tendency to engage in motivated reasoning to be strongest among those with the strongest identities (e.g., Nyhan and Reifler 2010; Leeper and Slothuus 2014). By comparison, the competence beliefs account predicts that beliefs about the incumbent’s effect on performance will be the stronger moderator.

Our strategy is to measure our respondents’ competence beliefs and partisan identities, then use regression to examine how these measures predict responses to an exogenous shock to perceptions of the pandemic (in the form of randomly assigned information). In other words, we enter both factors into a regression as moderators of the treatment effect and see

which moderator retains its explanatory power. This strategy has two key strengths. First, when both measures are entered as moderators, regression uses only the variation in each measure that is independent of the other measure. This addresses concerns that competence beliefs may be partly determined by identity or vice versa. Second, the experimental design addresses concerns about reverse causality. In an observational version of the following analysis, one might worry that attributions of responsibility influence competence beliefs. This is not a concern in our setup because competence beliefs are measured before the treatment induces an exogenous shock to attributions of responsibility.

Measurement

Our measure of partisan identity is adapted from [Greene \(1999\)](#) and [Huddy, Mason and Aaroe \(2015\)](#). All respondents who indicated a partisan preference were asked to rate three statements, each using five-point Likert scales ranging from “strongly disagree” to “strongly agree.” We take a simple average of the three measures, then rescale so that 0 indicates strong identification as a Democrat, 1 strong identification as a Republican, and 0.5 no identification with either party (i.e., strong disagreement with all three statements). We refer to this as the partisan identity scale. The index relies on agreement or disagreement with the following statements:

- When I talk about [Democrats/Republicans], I say “we” rather than “they.”
- I think of myself as a [Democrat/Republican].
- Being a [Democrat/Republican] is important to me.

To measure competence beliefs, we developed a three-item scale based on the measures analyzed in [Key \(1966a\)](#) and our formal statement of the competence beliefs account (see Appendix F.1) . The scale was minimally modified between Experiments 2 and 3 to account for differences in political context. These changes are indicated in brackets:

- When President [*Experiment 2: Trump / Experiment 3: Biden*] is running the government, do you expect government performance to get better or worse? (Definitely worse, probably worse, makes no difference, probably better, definitely better)

- What effect would you say President [Trump / Biden] has on the government’s ability to solve problems? (Completely negative, mostly negative, neither negative nor positive, mostly positive, completely positive)
- Who would you say is more competent: [Democratic presidential candidate Joe / President] Biden or [Republican presidential candidate Donald / former President] Trump? (Definitely Trump, probably Trump, equally competent, probably Biden, definitely Biden)

The scale meets conventional standards for internal consistency (Cronbach’s $\alpha = 0.92$ and 0.89).

The two indices are related but distinct. In Experiment 2, the correlation between the partisan identity and Trump competence scales was 0.75 . In Experiment 3, the correlation between the partisan identity and Biden competence scales was 0.47 . To identify sources of common and residual variation, Figure 6 presents a scatter plot of the two indices, with a loess-smoothed line depicting the average competence belief conditional on partisan identity. Under both Biden and Trump, partisan identity and competence beliefs were strongly correlated among the president’s co-partisans: stronger identity predicted a more favorable perception of the president’s competence. In the opposing party, there was no relationship under Trump and a reverse relationship under Biden: stronger identification as a Republican was associated with *more* favorable assessment of Biden’s competence.¹⁰

To test which of these measures is a better predictor of selective attribution, we pre-registered a linear model,

$$Y_i = \alpha + \beta_1 \text{Partisan identity}_i + \beta_2 \text{Competence belief}_i + \beta_3 Z_i + \beta_4 (Z_i \times \text{Partisan identity}_i) + \beta_5 (Z_i \times \text{Competence belief}_i) + \beta_6 X_i + \epsilon_i, \quad (1)$$

where Y_i is the amount of responsibility attributed to Trump or Biden, Z_i is an indicator of the respondent’s treatment status in the experiment (0 = negatively valenced information, 1 = positively valenced information), $\text{Partisan identity}_i$ and $\text{Competence belief}_i$ are the indices

¹⁰Though we knew from Experiment 2 that the relationship between identity and competence beliefs was imperfect, the reverse relationship surprised us. We conducted a series of checks to verify that it was not an indication of poor data quality (Appendix F.5).

Figure 6: Partisan identity versus beliefs about presidential competence.

just described, and X_i is the baseline measure of Y_i . In this model, α is the mean for a strong Democrat who is certain that the President delivers bad performance and is exposed to negatively valenced information. For such a respondent, β_3 is the predicted treatment effect of a switch to positive information. The key parameters are β_4 and β_5 , which respectively capture how this effect varies as a function of partisan identity and competence beliefs. Since our specification includes both indices, the OLS parameters estimate the residual predictive power of each variable after controlling for the other, or “partialling out” the variation predicted by the other variable (Wooldridge 2012). Consequently, we interpret β_5 (β_4) as answering the following question: after removing the variation in the treatment effect predicted by partisan identity (competence beliefs), what is the remaining explanatory power of competence beliefs (partisan identity)?

Results

We find that competence beliefs are a better moderator of treatment effects (i.e., a better predictor of selective attribution). Table 3 presents OLS estimates of the parameters. We begin by considering the first four columns, which contain the horse race under Trump.

In Experiment 2, the estimate of β_5 tells us that compared with someone who thinks Trump never delivers good performance, a person who thinks Trump always delivers good performance responds to positively valenced information by attributing 0.22 more responsibility to Trump on the $[0, 1]$ scale (Table 3, column 4). By comparison, the estimate of β_4 suggests that partisan identity does not predict much heterogeneity in treatment effects after accounting for competence beliefs. β_4 is about one-fifth the size and statistically insignificant.

The same pattern of attribution appears under Biden. In Experiment 3, the estimate of β_5 indicates that compared to someone who thinks that Biden never delivers good performance, a person who thinks he always delivers good performance responds to positively valenced information by attributing 0.15 scale units more responsibility to him for the pandemic (Table 3, column 8). Again, the estimate of β_4 is about one-fifth the size and statistically insignificant. Whereas both estimates of β_5 indicate that competence beliefs are a moderator independently of partisan identity, both estimates of β_4 indicate that partisan identity has little if any moderating effect independent of competence beliefs.

Table 3: Treatment effect heterogeneity, experiments 2 and 3.

		Experiment 2 (Trump)				Experiment 3 (Biden)			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	Constant	0.295** (0.017)	0.402** (0.022)	0.434** (0.021)	0.429** (0.022)	0.166** (0.009)	0.148** (0.009)	0.200** (0.014)	0.173** (0.016)
β_1	Partisan identity		-0.204** (0.022)		0.027 (0.031)		0.046** (0.012)		0.037** (0.013)
β_2	Competence beliefs			-0.274** (0.020)	-0.294** (0.029)			-0.047** (0.014)	-0.026 (0.016)
β_3	Treatment (1 = positive)	0.007 (0.010)	-0.095** (0.017)	-0.089** (0.014)	-0.097** (0.017)	0.003 (0.005)	0.041** (0.008)	-0.103** (0.015)	-0.080** (0.020)
β_4	Treatment $\times$ partisan ID		0.220** (0.029)		0.042 (0.041)		-0.093** (0.017)		-0.030 (0.018)
β_5	Treatment $\times$ comp. beliefs			0.244** (0.027)	0.216** (0.038)			0.168** (0.020)	0.152** (0.022)
β_6	Presidential responsibility, wave 1	0.551** (0.021)	0.533** (0.021)	0.503** (0.022)	0.502** (0.022)	0.743** (0.012)	0.743** (0.012)	0.737** (0.012)	0.734** (0.012)
Adj. R ²		0.317	0.344	0.369	0.370	0.563	0.567	0.574	0.574
Num. obs.		2503	2503	2503	2503	4065	4065	4065	4065

Note: Table displays parameter estimates from equation (1). HC2 robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

To contextualize the main result, Table 3 also examines treatment effect heterogeneity in specifications that consider each index separately. Partisan identity is examined in the second and sixth columns, and competence beliefs in the third and seventh columns. In Experiment 2, both scales predict heterogeneity in treatment effects ($\beta_4 = 0.220$, s.e. = 0.029 in column 2; $\beta_5 = 0.244$, s.e. = 0.027 in column 3). This indicates that partisan identity and competence beliefs are capable of predicting selective attribution. In Experiment 3, both scales are again predictive of treatment effect heterogeneity. However, competence beliefs are a stronger moderator: $|\hat{\beta}_5|$ is about twice as large as $|\hat{\beta}_4|$. In column 6, $\beta_4 = -0.093$, s.e. = 0.017, and in column 7, $\beta_5 = 0.168$, s.e. = 0.020. This indicates that on average, respondents at the extremes of the competence beliefs scale attribute responsibility about twice as selectively as respondents at the extremes of the partisan identity scale.

Partisan identity scales can be thought of as encoding two types of information: party affiliation and strength of identification. Because regression imposes the assumption of a linear relationship, tests like those presented above can find statistically significant interactions even the partisan difference, rather than the strength of identification, is the main driver of the results. The appendix includes two pre-registered tests of this possibility. First, we estimate the same models presented in Table 3 separately for Democrats and Republicans (Tables F.1 and F.2). When considering the two factors separately, competence beliefs have a statistically significant relationship with selective attribution (columns 3 and 7), but partisan identity does not (columns 2 and 6).¹¹ Second, we examine how selective attribution varies according to the strength of partisanship, as measured by the traditional seven-point scale of partisan identity. This measure of identity strength also fails to predict heterogeneity in selective attribution. This means that the relationship between partisan identity and selective attribution reported in Table 3 is driven mainly by across-the-board differences between the two parties as a whole, not by within-party variation in identity strength.

In sum, the horse race yields two key findings: (1) competence beliefs are a stronger

¹¹Given this, it is no surprise that the within-party version of the horse race (columns 4 and 8) also favors the competence beliefs explanation.

predictor of selective attribution than is partisan identity and (2) measures of partisan identity draw their explanatory power from the difference between Democrats and Republicans, not from variation in identity strength within each party.

Altering the Motivational Context

Theories of motivated reasoning holds that directional motivation must influence conclusions over and above what conclusion would be reached by an accuracy-motivated reasoner with the same beliefs (Kunda 1990; see discussion above). Consequently, researchers often demonstrate motivated reasoning’s influence by countering it with an accuracy prime. If some phenomenon is the product of directional motivation, enhanced accuracy motivation should lead to more objective conclusions. For example, Bolsen, Druckman and Cook (2014) and Bolsen and Druckman (2015) find that an accuracy prime eliminates the influence of partisan cues on policy evaluations. In our context, the PMR account predicts that enhancing accuracy motivation should reduce selective attribution. By contrast, the competence beliefs account predicts that enhancing accuracy primes should have no effect on selective attribution. We tested these predictions in Experiment 3.

To enhance accuracy motivation, we borrow a canonical strategy from the motivated reasoning literature: creating the expectation that one will have to justify their beliefs to others (Tetlock 1983, 1985; Kunda 1990; Redlawsk 2002). We closely modelled it after Bolsen et al. (2014) and Bolsen and Druckman (2015). Prior to the reading the information about the pandemic, treated subjects were told that “[w]hen thinking about your opinion, please try to view the questions in an evenhanded way and from various perspectives. We will later ask that you justify the reasons for your responses.” On each of the two pages containing the outcome questions, treated subjects were reminded, “[r]emember that you will have to justify the reasons for your response.”

To quantify the accuracy treatment’s influence on selective attribution, we pre-specified

a linear model:

$$\begin{aligned}
Y_i = & \alpha + \beta_1 Z_i + \beta_2 \text{Republican}_i + \beta_3 (\text{Republican}_i \times Z_i) + \\
& \beta_4 \text{Accuracy}_i + \beta_5 (\text{Accuracy} \times Z_i) + \beta_6 (\text{Accuracy}_i \times \text{Republican}_i) + \\
& \beta_7 (\text{Accuracy}_i \times \text{Republican}_i \times Z_i) + \beta_8 X_i + \epsilon_i
\end{aligned} \tag{2}$$

where Accuracy_i is an indicator for the accuracy motivation treatment and all other variables are as defined above. Here, β_1 and β_3 quantify selective attribution in the absence of the accuracy treatment. β_1 is the effect of the information treatment on Democrats' attributions of responsibility when no accuracy prime is present. β_3 is the difference in treatment effects between Republicans and Democrats. The primary coefficient of interest is β_7 , which quantifies how the partisan difference in selective attribution (i.e., β_3) changes when the accuracy prime is introduced. If selective attribution were entirely due to PMR, we would expect that $\beta_7 = -\beta_3$. If selective attribution were entirely due to competence beliefs, we would expect that $\beta_7 \approx 0$.

We find no evidence that heightened accuracy motivation diminishes selective attribution. The second column of Table 4 presents the estimates for parameters in Equation 2. We estimate $\beta_1 = 0.034$ (s.e. = 0.009) and $\beta_3 = -0.068$ (s.e. = 0.016). This indicates that when no accuracy prime is present, Democrats reading positive information assign 0.034 more responsibility to Biden on the 0-1 scale. Republicans respond in the opposite way, attributing 0.068 less responsibility to Biden than Democrats. No evidence emerges that the accuracy treatment reduces selective attribution. We estimate $\beta_7 = 0.000$ (s.e. = 0.022), which indicates that selective attribution persists at its full strength in the presence of an accuracy motivation.

Our first set of results for this experiment pooled across the two accuracy motivation treatment conditions (Figure 5 and surrounding text). To facilitate comparisons between those results and what we present here, Table 4 also includes a model that omits β_4 through

Table 4: Effect of accuracy prime on selective attribution, Experiment 3.

	(1)	(2)
α Constant	0.153** (0.009)	0.153** (0.010)
β_1 Information treatment (1 = positive)	0.027** (0.006)	0.034** (0.009)
β_2 Republican	0.037** (0.008)	0.037** (0.011)
β_3 Information $\times$ Republican	-0.067** (0.011)	-0.068** (0.016)
β_4 Accuracy treatment		0.001 (0.009)
β_5 Accuracy $\times$ Information		-0.015 (0.013)
β_6 Accuracy $\times$ Republican		0.001 (0.016)
β_7 Accuracy $\times$ Information $\times$ Republican		-0.000 (0.022)
β_8 Biden responsibility, pre-treatment	0.742** (0.012)	0.742** (0.012)
Adj. R ²	0.567	0.567
Num. obs.	4065	4065

Note: Table displays parameter estimates from equation (2). HC2 robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

β_7 . The CATE among Democrats ($\beta_1 = 0.027$, s.e. = 0.006) and the difference in CATEs between Democrats and Republicans ($\beta_3 = 0.067$, s.e. = 0.011) are each equal to what we reported above. Comparing the two columns in Table 4 reiterates the accuracy treatment’s minimal effect on selective attribution.

In sum, the accuracy motivation treatment yields no support for the PMR explanation. When accuracy motivation is enhanced, our respondents attributed responsibility just as selectively as they did at baseline. This suggests that selective attribution emerges largely as a function of our subjects’ beliefs, not due to directional motivations like partisanship.

Implications

The findings in this paper contribute to collective understanding of politics in several respects. With respect to the scope of the selective attribution phenomenon, our findings show that selective attribution emerged early in the COVID-19 pandemic, a period in which Democrats and Republicans were otherwise reacting similarly to the crisis. Our study is only the second to document the emergence of selective attribution over the course of a time of crisis, following [Bisgaard’s \(2015\)](#) analysis of the Great Recession in the United Kingdom. As national crises unfold, partisans appear to diverge in their attributions of responsibility immediately, and as a function of individuals’ perceptions of the severity of the crisis.

Our evidence suggests that selective attribution should be understood as an individual-level inference that emerges as a function of two factors: perceptions of the country’s performance and beliefs about the incumbent’s competence. When voters learn new information about the state of the world, they also make inferences about whether the incumbent is likely to have brought those conditions about. A voter who believes that the incumbent is competent (incompetent) finds it more plausible that the incumbent was responsible for positive (negative) developments and updates their beliefs accordingly. In showing that beliefs can provide a better explanation for findings that first appear to be textbook examples of directionally motivated reasoning, we join recent scholarship on information processing ([Tappin, Pennycook and Rand 2020](#); [Zhang and Rand 2021](#)), persuasion ([Coppock 2022](#)), and attitudes toward climate change ([Druckman and McGrath 2019](#); [Bago, Rand and Pennycook 2020](#)) and racialized police violence ([Jefferson et al. 2020](#)), as well as a longer tradition among psychologists who study selective attribution in non-political settings ([Miller and Ross 1975](#); [Kunda 1990](#)).

Though our evidence gives more support to the competence beliefs explanation, we think it would be premature to rule out PMR (or other alternative explanations) in all cases. Instead, we hope that our approach will spur more tests in other contexts. Specific to partisanship, our review of existing evidence points toward several underutilized points of

leverage, including cross-pressure between ideology and partisanship in multiparty systems (see discussion of [Bisgaard 2019](#), page 9), parties and politicians with strong issue reputations among out-partisans (see discussion of [Rudolph 2003b](#), page 9), and variation in party control between subnational governments. The same approach can be applied to the study of ethnic politics in developing countries, which is increasingly interested in how identity-protective behavior shapes attributions of credit and blame ([Adida et al. 2017](#); [Singh 2022](#)).

The competence beliefs account changes the implications of selective attribution for voters’ capacity to reason objectively. The partisan-motivated reasoning explanation is rooted in the notion that group identities inherently skew reasoning. This suggests that so long as politically-relevant social groups exist, people will be incapable of reasoning objectively. The competence-based explanation holds that people use the same information differently not due to identity-based biases in reasoning but because they have different prior beliefs and expectations about performance. Competence beliefs may sometimes be shaped by partisan identity, just as partisan identity may sometimes be shaped by competence beliefs. Crucially, however, the competence beliefs explanation leaves hope that people who think of themselves as members of a group are still capable of objective reasoning.

The competence beliefs account also suggests a bridge between conflicting accounts of partisanship. Traditionally, the ideas that partisanship is a “perceptual screen” ([Campbell et al. 1960](#)) and “running tally” of performance evaluations ([Fiorina 1981](#)) have been treated as opposing possibilities. Our framework suggests a bridge between them: a perceptual screen may be raised by the running tally itself.¹² Voters who maintain such a tally develop stronger beliefs about which party delivers better performance—particularly when their tally begins during an event like the Great Depression, which had long-lasting effects on Americans’ perceptions of the parties ([Campbell et al. 1960](#)). As a general matter, initial impressions have an outsized effect on later evaluations ([Druckman et al. 2012](#)), including the formation of impressions of party performance ([Peffley 1989](#)). An initial, favorable im-

¹²This aligns with [Lupu \(2016\)](#) who contends that psychological attachments to a party emerge from party brands, specifically the voters’ observations of the party’s behavior over time.

pression of the parties may be all it takes for voters to begin interpreting subsequent events in a light that is favorable to one party.

In turn, the implications for partisanship have implications for the role of party reputation-building in the democratic process. A wide range of accounts of politics maintain that if voters hold parties responsible for their actions in government, parties have an incentive to build a reputation for governing effectively ([Ranney 1954](#); [Key 1966b](#); [Sundquist 1988](#); [Jones and McDermott 2004](#)). Necessarily, a party's success in developing such a reputation implies the existence of competence beliefs among the voting public. Our account suggests that such reputations may be a double-edged sword. Even as parties' incentives to develop good reputations encourages responsible governance ([Manin 1997](#); [Rosenbluth and Shapiro 2018](#)), these same reputations may have a self-reinforcing quality, locking in voters' judgments in a way that stifles the electorate's ability to punish and reward parties for their subsequent performance. This casts selective attribution as a counterweight to the positive effects of party reputations on democratic functioning.

In conclusion, even as our findings add to the evidence that selective attribution is a highly general pattern, our larger account demonstrates that understanding of this phenomenon is far from complete. In particular, our findings and reading of prior work each suggest that beliefs about the incumbent's competence deserve strong consideration as an explanation. This opens the door to new perspectives on the nature and consequences of selective attribution.

Declarations

Human subjects: The authors declare the human subjects research in this article were reviewed and approved by the Yale University Institutional Review Board (Protocol Numbers 2000028095 and 2000026693) with a concurrence from the George Washington University Institutional Review Board. The authors affirm that this article adheres to the APSA's Principles and Guidance on Human Subject Research.

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Data transparency: Research documentation and/or data that support the findings of this study are openly available in the APSR Dataverse at <https://doi.org/10.7910/DVN/3FF05Y>.

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Appendix to
An Outbreak of Selective Attribution:
Partisanship and Blame in the COVID-19 Pandemic

Matthew H. Graham Shikhar Singh

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A Time Series

A.1 Survey information

Platform: Lucid.

Dates: March 8-April 12, 2020.

Screeners: Captcha verification.

Consent: Subjects read an IRB-approved consent form, then voluntarily consented to participate in a research study.

Refusal rate: 1.6 percent.

Compensation: \$1 (waves 1-4 and 6) or \$0.75 (wave 5), excluding a service fee of \$0.25 per respondent. These amounts were chosen to meet or exceed prevailing rates set by the vendor, which typically charges \$1 inclusive of all fees.

Sample size: 3,794 (total), 662 (wave 1), 633 (wave 2), 638 (wave 3), 625 (wave 4), 639 (wave 5), 597 (wave 6).

A.2 Regression analysis

The main text presents a graphical analysis of time series data (Figure 2). To statistically test our claims, we specify a linear model of the time trends in all of these areas. We subset our data to Democrats and Republicans only, then use ordinary least squares (OLS) to estimate the parameters in

$$Y_i = \alpha + \beta_1(\text{Wave-1})_i + \beta_2\text{Republican}_i + \beta_3(\text{Wave-1})_i \times \text{Republican}_i + \epsilon_i, \quad (3)$$

where Y_i is one of the variables appearing on the y-axis in the graphical analysis, α is the average on March 8 among Democrats, β_1 is the average weekly change among Democrats, β_2 is the difference between Democrats and Republicans on March 8, and β_3 is the average weekly change in the difference between Democrats and Republicans. The key parameters are β_2 and β_3 . If partisans update in parallel, β_3 should be close to 0. If partisans diverge, β_2 and β_3 should take the same sign. If partisans converge, β_2 and β_3 should take opposite signs. We also estimate a version of this model that splits the estimate of β_1 into five intercept shifts, which relaxes the assumption of a linear time trend.

In the tables below, the parameter estimates are consistent with the hypothesis of parallel updating. Of the thirteen estimates of β_3 in these categories, we can only detect a statistical difference from zero in three cases (see Tables A.1, A.3, and A.5). In all three of these—contact with others, hand-washing, and changing travel plan—the estimate takes the opposite sign of β_2 , indicating partisan convergence over time. This supports our claim that over this period Democrats and Republicans updated their perceptions in the same direction, usually by about the same magnitude, and occasionally in a way that narrowed partisan perceptual differences.

In contrast to this, we find growing partisan divergence in attributions of political responsibility. Consistent with the graphical analysis (Figure 2), this divergence was most evident in attributions of responsibility to President Trump. Each week, Democrats assigned 0.044 units more blame to Trump on a 0 to 1 scale, compared with 0.016 for Republicans. As a result, the partisan difference increased by 0.028 scale units each week ($\beta_3 = 0.028$, s.e. = 0.007; see Table A.7). A comparable divergence emerges while attributing blame to Republicans ($\beta_3 = 0.026$, s.e. = 0.007). The regression-based estimates also suggest partisan divergence in blaming China, and of no divergence with respect to other entities or factors.

Table A.1: Regression estimate of time trends in objective perceptions.

		State cases	State deaths	National cases	National deaths
α	Baseline	0.134** (0.004)	0.016** (0.002)	0.261** (0.005)	0.092** (0.003)
β_1	Wave (0-5)	0.063** (0.002)	0.029** (0.001)	0.051** (0.002)	0.041** (0.001)
β_2	Republican	-0.000 (0.007)	0.002 (0.003)	-0.011 (0.007)	-0.005 (0.004)
β_3	Republican $\times$ wave	-0.001 (0.002)	-0.002 (0.001)	0.002 (0.002)	0.001 (0.001)
Adj. R ²		0.467	0.410	0.404	0.524
Num. obs.		3161	3159	3114	3151

Table A.2: Robustness check on Table A.1: non-linear time trend.

		State cases	State deaths	National cases	National deaths
α	Baseline	0.111** (0.005)	0.022** (0.002)	0.239** (0.006)	0.090** (0.003)
	Wave 2	0.077** (0.007)	0.015** (0.003)	0.066** (0.006)	0.035** (0.004)
	Wave 3	0.178** (0.007)	0.048** (0.003)	0.148** (0.007)	0.088** (0.004)
	Wave 4	0.245** (0.007)	0.088** (0.004)	0.206** (0.007)	0.139** (0.004)
	Wave 5	0.277** (0.008)	0.119** (0.004)	0.233** (0.009)	0.173** (0.005)
	Wave 6	0.308** (0.008)	0.135** (0.004)	0.240** (0.009)	0.192** (0.005)
β_2	Republican	0.001 (0.009)	0.003 (0.004)	-0.012 (0.008)	-0.005 (0.005)
β_3	Republican $\times$ wave	-0.002 (0.002)	-0.002 (0.001)	0.002 (0.002)	0.001 (0.001)
Adj. R ²		0.489	0.417	0.433	0.533
Num. obs.		3161	3159	3114	3151

Table A.3: Regression estimate of time trends in threat perceptions.

	National	State
α Baseline	0.736** (0.011)	0.699** (0.012)
β_1 Wave (0-5)	0.034** (0.003)	0.036** (0.004)
β_2 Republican	-0.102** (0.017)	-0.087** (0.018)
β_3 Republican $\times$ wave	0.006 (0.005)	0.005 (0.006)
Adj. R^2	0.085	0.072
Num. obs.	3264	3264

Table A.4: Robustness check on Table A.3: non-linear time trend

	National	State
α Baseline	0.701** (0.014)	0.647** (0.015)
Wave 2	0.062** (0.017)	0.102** (0.018)
Wave 3	0.155** (0.016)	0.173** (0.018)
Wave 4	0.146** (0.017)	0.178** (0.018)
Wave 5	0.183** (0.018)	0.208** (0.019)
Wave 6	0.163** (0.019)	0.185** (0.021)
β_2 Republican	-0.107** (0.021)	-0.088** (0.023)
β_3 Republican $\times$ wave	0.005 (0.005)	0.005 (0.006)
Adj. R^2	0.098	0.089
Num. obs.	3264	3264

Table A.5: Regression table of time trends in behavioral changes.

		Avoid contact	Isolate ≥ 24 h	Mask/PPE	School	Travel	Wash hands	Work at home
α	Baseline	0.714** (0.018)	0.663** (0.026)	0.195** (0.019)	0.471** (0.034)	0.472** (0.020)	0.871** (0.014)	0.408** (0.026)
β_1	Wave (0-5)	0.062** (0.005)	0.060** (0.007)	0.077** (0.007)	0.122** (0.010)	0.077** (0.007)	0.020** (0.004)	0.067** (0.009)
β_2	Republican	-0.089** (0.027)	-0.117** (0.041)	-0.043 (0.027)	-0.067 (0.048)	-0.110** (0.029)	-0.084** (0.022)	-0.106** (0.037)
β_3	Republican $\times$ wave	0.020** (0.008)	0.015 (0.011)	-0.003 (0.009)	0.009 (0.014)	0.022* (0.009)	0.017** (0.007)	0.015 (0.012)
Adj. R ²		0.121	0.064	0.074	0.259	0.101	0.032	0.066
Num. obs.		3269	2699	3268	1114	3265	3269	2038

Table A.6: Robustness check on Table A.5: non-linear time trend

		Avoid contact	Isolate ≥ 24 h	Mask/PPE	School	Travel	Wash hands	Work at home
α	Baseline	0.580** (0.025)	0.633** (0.024)	0.240** (0.022)	0.236** (0.038)	0.357** (0.024)	0.822** (0.019)	0.310** (0.030)
	Wave 2	0.271** (0.027)		0.046 (0.026)	0.425** (0.048)	0.218** (0.030)	0.104** (0.022)	0.185** (0.037)
	Wave 3	0.348** (0.025)	0.238** (0.027)	0.067* (0.028)	0.688** (0.040)	0.392** (0.029)	0.118** (0.021)	0.323** (0.038)
	Wave 4	0.369** (0.026)	0.266** (0.027)	0.114** (0.030)	0.718** (0.039)	0.405** (0.031)	0.124** (0.022)	0.337** (0.040)
	Wave 5	0.368** (0.027)	0.281** (0.029)	0.244** (0.033)	0.719** (0.044)	0.421** (0.032)	0.117** (0.023)	0.372** (0.042)
	Wave 6	0.371** (0.029)	0.270** (0.030)	0.413** (0.035)	0.682** (0.049)	0.413** (0.035)	0.131** (0.022)	0.358** (0.046)
β_2	Republican	-0.097** (0.034)	-0.148** (0.051)	-0.042 (0.034)	-0.034 (0.056)	-0.125** (0.037)	-0.097** (0.028)	-0.111* (0.047)
β_3	Republican $\times$ wave	0.018* (0.007)	0.018 (0.011)	-0.002 (0.009)	0.001 (0.013)	0.021* (0.009)	0.017* (0.007)	0.013 (0.012)
Adj. R ²		0.172	0.092	0.083	0.386	0.129	0.041	0.082
Num. obs.		3269	2699	3268	1114	3265	3269	2038

Table A.7: Regression table of time trends in blame attributions.

		Bad luck	China	Democrats	Immigrants	Nature	Republicans	Trump	U.S. gov't agencies
α	Baseline	0.389** (0.016)	0.623** (0.016)	0.175** (0.013)	0.233** (0.014)	0.545** (0.015)	0.336** (0.016)	0.505** (0.017)	0.443** (0.015)
β_1	Wave (0-5)	0.002 (0.005)	-0.011* (0.005)	0.026** (0.004)	-0.001 (0.005)	-0.009 (0.005)	0.045** (0.005)	0.044** (0.006)	0.022** (0.005)
β_2	Republican	0.014 (0.022)	0.111** (0.022)	0.066** (0.021)	0.156** (0.021)	0.023 (0.022)	-0.187** (0.021)	-0.333** (0.022)	-0.175** (0.021)
β_3	Republican $\times$ wave	-0.003 (0.008)	0.018* (0.007)	0.010 (0.007)	-0.001 (0.007)	0.005 (0.007)	-0.026** (0.007)	-0.028** (0.007)	-0.005 (0.007)
Adj. R ²		-0.001	0.049	0.041	0.046	0.003	0.133	0.250	0.079
Num. obs.		3211	3213	3212	3213	3212	3213	3213	3213

Table A.8: Robustness check on Table A.7: non-linear time trend

		Bad luck	China	Democrats	Immigrants	Nature	Republicans	Trump	U.S. gov't agencies
α	Baseline	0.391** (0.019)	0.634** (0.019)	0.181** (0.017)	0.246** (0.017)	0.529** (0.018)	0.331** (0.019)	0.487** (0.021)	0.450** (0.018)
	Wave 2	0.001 (0.023)	-0.044* (0.022)	0.007 (0.020)	-0.039 (0.021)	0.002 (0.021)	0.056** (0.022)	0.080** (0.023)	0.011 (0.021)
	Wave 3	-0.011 (0.023)	-0.026 (0.022)	0.052* (0.021)	-0.016 (0.022)	0.030 (0.022)	0.103** (0.023)	0.111** (0.024)	0.046* (0.022)
	Wave 4	0.015 (0.025)	-0.025 (0.024)	0.062** (0.022)	0.001 (0.023)	-0.001 (0.024)	0.124** (0.025)	0.151** (0.026)	0.031 (0.023)
	Wave 5	0.001 (0.027)	-0.074** (0.026)	0.118** (0.024)	-0.005 (0.024)	-0.028 (0.025)	0.189** (0.027)	0.206** (0.028)	0.107** (0.025)
	Wave 6	0.009 (0.029)	-0.059* (0.029)	0.110** (0.025)	-0.030 (0.026)	-0.037 (0.027)	0.231** (0.030)	0.226** (0.030)	0.103** (0.027)
β_2	Republican	0.016 (0.029)	0.091** (0.028)	0.054* (0.027)	0.155** (0.028)	0.018 (0.028)	-0.160** (0.027)	-0.302** (0.029)	-0.170** (0.028)
β_3	Republican $\times$ wave	-0.002 (0.008)	0.019** (0.007)	0.010 (0.007)	-0.001 (0.007)	0.005 (0.007)	-0.026** (0.007)	-0.029** (0.007)	-0.005 (0.007)
Adj. R ²		-0.002	0.050	0.041	0.046	0.004	0.132	0.250	0.080
Num. obs.		3211	3213	3212	3213	3212	3213	3213	3213

A.3 Benchmarking

Relative to existing research on partisanship’s relationship to responses to the pandemic, our emphasis on parallel changes in perception between Democrats and Republicans is unusual. This section shows that similar patterns are observed in two previously published studies using data from this time period ([Allcott et al. 2020](#); [Clinton et al. 2021](#)).

Figure A.1: Replicating [Allcott et al. \(2020\)](#)’s Figure 3A (mobility changes).

Note: This is a replication of Figure 3, Panel A in [Allcott et al. \(2020\)](#) for the time period March 8 to April 15, 2020. The x-axis plots the date, the y-axis plots the number of visits each week (normalized to one) to SafeGraph’s places of interest (POIs). The data are separately plotted for Democratic counties (in blue) and Republican counties (in red). Exactly following [Allcott et al. \(2020\)](#), Republican counties are “defined to be those whose 2016 Republican vote share is greater than the median vote share (66.4 percent) across the counties in [their] sample” (25).

Figure A.2: Replicating Clinton et al. (2021)’s Figure 1A (subjective threat perceptions).

Note: This is a replication of Figure 1A in Clinton et al. (2021) for the time period March 8 to April 13, 2020. The x-axis plots the date, the y-axis plots “the weighted (to the adult U.S. population) daily [proportion] of respondents who are “very” or “somewhat” worried about catching COVID-19”. The data are separately plotted for Democrats (in blue) and Republicans (in red). The figure includes a LOESS fit (solid line) along with a 95% confidence interval (gray shaded area).

A.4 Tables of estimates plotted in Figure 2

Table A.9: Estimates plotted in Figure 2a (cases and deaths).

Variable	Party	Date	Wave	Percentile					Actual
				2.5	25	50	75	97.5	
State cases	D	3/8	1	0	1	4	13	120	26
		3/15	2	1	11	30	100	4000	191
		3/22	3	5	100	250	866	10775	2027
		3/29	4	36	500	1200	4150	57750	8033
		4/5	5	44	900	2000	10200	113787	17805
		4/12	6	55	1200	5000	15000	150000	23033
	I	3/8	1	0	1	3	12	83	18
		3/15	2	1	12	30	100	3186	184
		3/22	3	3	56	200	782	103125	1114
		3/29	4	12	364	1200	4000	347500	5311
		4/5	5	100	1000	2100	6500	108400	14560
		4/12	6	94	1222	4750	19648	33750	22861
	R	3/8	1	0	1	4	10	112	25
		3/15	2	1	10	30	100	1140	129
		3/22	3	10	100	248	707	12975	1356
		3/29	4	12	300	1000	4200	84250	6876
		4/5	5	52	650	2000	7885	82750	15448
		4/12	6	91	1425	4000	14500	188500	30208
State deaths	D	3/8	1	0	0	0	1	100	0
		3/15	2	0	0	1	5	134	3
		3/22	3	0	2	8	30	375	24
		3/29	4	1	13	50	150	2388	153
		4/5	5	4	50	200	800	11500	611
		4/12	6	2	100	400	1500	20000	1033
	I	3/8	1	0	0	0	1	7	0
		3/15	2	0	0	1	3	36	4
		3/22	3	0	2	4	14	2624	13
		3/29	4	0	8	29	130	2525	100
		4/5	5	4	35	100	400	2480	490
		4/12	6	11	94	475	1275	8125	1075
	R	3/8	1	0	0	0	1	13	1
		3/15	2	0	0	1	4	85	1
		3/22	3	0	2	6	25	400	17
		3/29	4	1	7	32	100	1065	130
		4/5	5	3	41	130	400	3992	533
		4/12	6	2	81	295	1000	18413	1514
National cases	D	3/8	1	10	100	300	600	7725000	547
		3/15	2	53	1000	2732	5000	192525	3600
		3/22	3	162	3800	18000	31000	925000	33073
		3/29	4	1831	42500	100000	134000	932500	142486
		4/5	5	1729	60000	200000	300000	9500000	338141
		4/12	6	1860	90000	200000	500000	14000000	558249
	I	3/8	1	13	89	250	500	23325	547
		3/15	2	36	300	1500	3500	775000	3600
		3/22	3	281	3000	15500	31500	36250000	33073
		3/29	4	2000	32500	100000	146000	1000000	142486
		4/5	5	5649	40000	200000	300000	1252000	338141
		4/12	6	10547	100000	397500	542500	67000000	558249
	R	3/8	1	11	100	300	1000	85000	547

Variable	Party	Date	Wave	Percentile					Actual
				2.5	25	50	75	97.5	
National deaths	D	3/15	2	50	600	1700	3000	85000	3600
		3/22	3	386	4750	17500	40000	425500	33073
		3/29	4	573	29500	100000	140000	899550	142486
		4/5	5	1575	100000	200000	300000	2745000	338141
		4/12	6	5017	92500	200000	500000	1977246	558249
		3/8	1	1	9	16	26	4077	22
		3/15	2	4	21	50	100	10000	68
		3/22	3	10	150	328	600	14750	458
		3/29	4	75	1000	2000	3000	100000	2707
		4/5	5	184	4000	8000	10000	377775	10856
		4/12	6	100	9000	19000	22000	220000	24849
	I	3/8	1	2	10	16	20	295	22
		3/15	2	1	15	54	100	5000	68
		3/22	3	11	148	300	430	56250	458
		3/29	4	66	800	2000	5000	64750	2707
		4/5	5	245	2000	4000	9500	100000	10856
		4/12	6	250	5000	15000	20250	193750	24849
	R	3/8	1	1	5	12	20	625	22
		3/15	2	1	20	50	97	6960	68
		3/22	3	10	150	300	500	15975	458
		3/29	4	29	700	2000	2424	43000	2707
		4/5	5	222	2250	6300	10000	556500	10856
		4/12	6	512	6000	20000	25000	131125	24849

Table A.10: Estimates plotted in Figure 2b (threat).

Variable	Party	Date	Wave	Estimate	SE	CI	N
State	D	3/8	1	0.659	0.017	(0.625, 0.693)	289
		3/15	2	0.754	0.015	(0.724, 0.784)	305
		3/22	3	0.799	0.015	(0.769, 0.829)	287
		3/29	4	0.820	0.014	(0.792, 0.847)	280
		4/5	5	0.855	0.014	(0.829, 0.882)	278
		4/12	6	0.845	0.014	(0.817, 0.872)	272
	I	3/8	1	0.588	0.034	(0.521, 0.655)	91
		3/15	2	0.699	0.030	(0.640, 0.759)	94
		3/22	3	0.747	0.028	(0.691, 0.803)	85
		3/29	4	0.801	0.027	(0.748, 0.853)	89
		4/5	5	0.763	0.028	(0.706, 0.819)	78
		4/12	6	0.760	0.032	(0.696, 0.824)	77
	R	3/8	1	0.552	0.018	(0.516, 0.587)	281
		3/15	2	0.665	0.019	(0.628, 0.702)	232
		3/22	3	0.770	0.017	(0.737, 0.803)	262
		3/29	4	0.762	0.017	(0.729, 0.795)	253
		4/5	5	0.791	0.016	(0.761, 0.822)	278
		4/12	6	0.758	0.017	(0.724, 0.792)	247
National	D	3/8	1	0.712	0.016	(0.681, 0.743)	289
		3/15	2	0.766	0.015	(0.737, 0.795)	305
		3/22	3	0.835	0.013	(0.810, 0.861)	287
		3/29	4	0.848	0.012	(0.823, 0.872)	281
		4/5	5	0.885	0.012	(0.862, 0.908)	278
		4/12	6	0.871	0.012	(0.847, 0.896)	272
	I	3/8	1	0.624	0.031	(0.561, 0.686)	91
		3/15	2	0.707	0.029	(0.650, 0.765)	94
		3/22	3	0.744	0.028	(0.688, 0.801)	86
		3/29	4	0.820	0.026	(0.769, 0.871)	89
		4/5	5	0.794	0.026	(0.742, 0.846)	79
		4/12	6	0.756	0.029	(0.698, 0.815)	77
	R	3/8	1	0.589	0.018	(0.554, 0.624)	281
		3/15	2	0.665	0.018	(0.629, 0.701)	232
		3/22	3	0.788	0.015	(0.758, 0.818)	262
		3/29	4	0.761	0.017	(0.728, 0.794)	252
		4/5	5	0.802	0.015	(0.773, 0.832)	278
		4/12	6	0.780	0.016	(0.749, 0.811)	247

Table A.11: Estimates plotted in Figure 2c (behavior).

Variable	Party	Date	Wave	Estimate	SE	CI	N
Avoid contact	D	3/8	1	0.578	0.029	(0.521, 0.635)	289
		3/15	2	0.873	0.019	(0.835, 0.910)	306
		3/22	3	0.916	0.016	(0.884, 0.949)	287
		3/29	4	0.929	0.015	(0.899, 0.959)	283
		4/5	5	0.950	0.013	(0.924, 0.976)	278
		4/12	6	0.963	0.011	(0.941, 0.986)	272
	I	3/8	1	0.527	0.053	(0.423, 0.632)	91
		3/15	2	0.702	0.047	(0.608, 0.796)	94
		3/22	3	0.802	0.043	(0.716, 0.888)	86
		3/29	4	0.966	0.019	(0.928, 1.005)	89
		4/5	5	0.938	0.027	(0.885, 0.992)	81
		4/12	6	0.909	0.033	(0.843, 0.975)	77
	R	3/8	1	0.504	0.030	(0.445, 0.562)	280
		3/15	2	0.763	0.028	(0.708, 0.818)	232
		3/22	3	0.898	0.019	(0.861, 0.935)	264
		3/29	4	0.945	0.014	(0.916, 0.973)	253
		4/5	5	0.939	0.014	(0.911, 0.967)	279
		4/12	6	0.947	0.014	(0.919, 0.975)	246
Wash hands	D	3/8	1	0.834	0.022	(0.791, 0.877)	289
		3/15	2	0.928	0.015	(0.899, 0.957)	306
		3/22	3	0.934	0.015	(0.905, 0.963)	287
		3/29	4	0.922	0.016	(0.891, 0.954)	283
		4/5	5	0.928	0.016	(0.897, 0.959)	278
		4/12	6	0.978	0.009	(0.960, 0.996)	272
	I	3/8	1	0.747	0.046	(0.656, 0.838)	91
		3/15	2	0.753	0.045	(0.663, 0.842)	93
		3/22	3	0.837	0.040	(0.758, 0.917)	86
		3/29	4	0.955	0.022	(0.911, 0.999)	89
		4/5	5	0.901	0.033	(0.835, 0.968)	81
		4/12	6	0.857	0.040	(0.777, 0.937)	77
	R	3/8	1	0.729	0.027	(0.676, 0.781)	280
		3/15	2	0.858	0.023	(0.812, 0.903)	232
		3/22	3	0.898	0.019	(0.861, 0.935)	264
		3/29	4	0.941	0.015	(0.911, 0.970)	253
		4/5	5	0.935	0.015	(0.906, 0.964)	279
		4/12	6	0.927	0.017	(0.894, 0.960)	246
Isolate >24h	D	3/15	2	0.649	0.027	(0.595, 0.703)	305
		3/22	3	0.861	0.020	(0.820, 0.901)	287
		3/29	4	0.887	0.019	(0.850, 0.924)	283
		4/5	5	0.899	0.018	(0.864, 0.935)	278
		4/12	6	0.923	0.016	(0.891, 0.955)	272
	I	3/15	2	0.500	0.052	(0.397, 0.603)	94
		3/22	3	0.756	0.047	(0.663, 0.848)	86
		3/29	4	0.820	0.041	(0.739, 0.902)	89
		4/5	5	0.827	0.042	(0.743, 0.911)	81
		4/12	6	0.818	0.044	(0.730, 0.906)	77
	R	3/15	2	0.500	0.033	(0.435, 0.565)	232
		3/22	3	0.788	0.025	(0.738, 0.838)	264
		3/29	4	0.838	0.023	(0.792, 0.884)	253
		4/5	5	0.871	0.020	(0.831, 0.911)	279
		4/12	6	0.841	0.023	(0.796, 0.887)	246
Mask/PPE	D	3/8	1	0.232	0.025	(0.183, 0.281)	289
		3/15	2	0.304	0.026	(0.252, 0.356)	306

Table A.11: Estimates plotted in Figure 2c (behavior, continued).

Variable	Party	Date	Wave	Estimate	SE	CI	N
Kid's school*	I	3/22	3	0.307	0.027	(0.253, 0.360)	287
		3/29	4	0.343	0.028	(0.287, 0.398)	283
		4/5	5	0.468	0.030	(0.409, 0.527)	278
		4/12	6	0.669	0.029	(0.613, 0.725)	272
		3/8	1	0.121	0.034	(0.053, 0.189)	91
		3/15	2	0.149	0.037	(0.076, 0.222)	94
		3/22	3	0.267	0.048	(0.172, 0.363)	86
		3/29	4	0.326	0.050	(0.227, 0.425)	89
		4/5	5	0.432	0.055	(0.322, 0.542)	81
		4/12	6	0.532	0.057	(0.418, 0.646)	77
	R	3/8	1	0.204	0.024	(0.156, 0.251)	280
		3/15	2	0.216	0.027	(0.162, 0.269)	232
		3/22	3	0.258	0.027	(0.204, 0.311)	264
		3/29	4	0.316	0.029	(0.259, 0.374)	253
		4/5	5	0.448	0.030	(0.389, 0.507)	279
		4/12	6	0.580	0.032	(0.517, 0.642)	245
	D	3/8	1	0.211	0.043	(0.125, 0.297)	90
		3/15	2	0.695	0.045	(0.606, 0.785)	105
		3/22	3	0.907	0.032	(0.844, 0.970)	86
		3/29	4	0.961	0.019	(0.923, 0.999)	103
		4/5	5	0.949	0.025	(0.900, 0.999)	79
		4/12	6	0.915	0.029	(0.857, 0.972)	94
Travel	I	3/8	1	0.083	0.058	(-0.036, 0.203)	24
		3/15	2	0.609	0.104	(0.393, 0.824)	23
		3/22	3	0.875	0.069	(0.732, 1.018)	24
		3/29	4	1.000	0.000	(1.000, 1.000)	22
		4/5	5	0.870	0.072	(0.721, 1.018)	23
		4/12	6	0.840	0.075	(0.686, 0.994)	25
	R	3/8	1	0.224	0.041	(0.144, 0.305)	107
		3/15	2	0.581	0.058	(0.466, 0.696)	74
		3/22	3	0.912	0.032	(0.849, 0.976)	80
		3/29	4	0.918	0.028	(0.862, 0.973)	97
		4/5	5	0.933	0.025	(0.884, 0.982)	104
		4/12	6	0.895	0.032	(0.832, 0.958)	95
	D	3/8	1	0.339	0.028	(0.284, 0.394)	289
		3/15	2	0.585	0.028	(0.529, 0.640)	306
		3/22	3	0.770	0.025	(0.721, 0.819)	287
		3/29	4	0.755	0.026	(0.705, 0.806)	282
		4/5	5	0.776	0.025	(0.727, 0.826)	277
		4/12	6	0.765	0.026	(0.714, 0.815)	272
Work at home*	I	3/8	1	0.209	0.043	(0.124, 0.294)	91
		3/15	2	0.340	0.049	(0.243, 0.438)	94
		3/22	3	0.558	0.054	(0.451, 0.665)	86
		3/29	4	0.629	0.051	(0.527, 0.732)	89
		4/5	5	0.741	0.049	(0.643, 0.838)	81
		4/12	6	0.688	0.053	(0.582, 0.794)	77
	R	3/8	1	0.271	0.027	(0.219, 0.324)	280
		3/15	2	0.478	0.033	(0.414, 0.543)	232
		3/22	3	0.663	0.029	(0.605, 0.720)	264
		3/29	4	0.727	0.028	(0.672, 0.783)	253
		4/5	5	0.759	0.026	(0.708, 0.810)	278
		4/12	6	0.776	0.027	(0.723, 0.828)	245
	D	3/8	1	0.274	0.034	(0.208, 0.341)	175

Table A.11: Estimates plotted in Figure 2c (behavior, continued).

Variable	Party	Date	Wave	Estimate	SE	CI	N
	I	3/15	2	0.535	0.036	(0.465, 0.605)	198
		3/22	3	0.600	0.035	(0.531, 0.669)	195
		3/29	4	0.684	0.034	(0.617, 0.752)	187
		4/5	5	0.713	0.034	(0.646, 0.779)	181
		4/12	6	0.626	0.036	(0.554, 0.697)	179
		3/8	1	0.233	0.065	(0.101, 0.364)	43
		3/15	2	0.340	0.066	(0.208, 0.471)	53
		3/22	3	0.552	0.066	(0.420, 0.684)	58
		3/29	4	0.533	0.065	(0.403, 0.663)	60
		4/5	5	0.452	0.078	(0.295, 0.609)	42
		4/12	6	0.529	0.071	(0.388, 0.671)	51
	R	3/8	1	0.252	0.035	(0.183, 0.320)	159
		3/15	2	0.355	0.040	(0.275, 0.435)	141
		3/22	3	0.605	0.040	(0.525, 0.685)	147
		3/29	4	0.544	0.040	(0.466, 0.623)	158
		4/5	5	0.602	0.038	(0.527, 0.678)	166
		4/12	6	0.684	0.038	(0.609, 0.759)	152

Note: * indicates that the school and work at home questions were only asked of respondents who reported having a school-aged child or being employed.

Table A.12: Estimates plotted in Figure 2d (blame).

Variable	Party	Date	Wave	Estimate	SE	CI	N
China	D	3/8	1	0.636	0.022	(0.593, 0.680)	287
		3/15	2	0.613	0.022	(0.570, 0.655)	297
		3/22	3	0.578	0.022	(0.534, 0.621)	281
		3/29	4	0.601	0.022	(0.558, 0.643)	274
		4/5	5	0.555	0.022	(0.511, 0.599)	272
		4/12	6	0.591	0.022	(0.547, 0.634)	272
	I	3/8	1	0.629	0.043	(0.544, 0.715)	89
		3/15	2	0.562	0.042	(0.478, 0.645)	92
		3/22	3	0.632	0.041	(0.552, 0.713)	78
		3/29	4	0.647	0.040	(0.569, 0.726)	86
		4/5	5	0.611	0.040	(0.531, 0.691)	78
		4/12	6	0.636	0.042	(0.552, 0.721)	77
	R	3/8	1	0.741	0.019	(0.703, 0.779)	279
		3/15	2	0.687	0.023	(0.642, 0.732)	226
		3/22	3	0.788	0.019	(0.751, 0.825)	256
		3/29	4	0.784	0.019	(0.746, 0.821)	248
		4/5	5	0.749	0.020	(0.711, 0.788)	274
		4/12	6	0.760	0.021	(0.719, 0.801)	247
Democrats	D	3/8	1	0.185	0.018	(0.149, 0.221)	287
		3/15	2	0.184	0.016	(0.152, 0.216)	297
		3/22	3	0.236	0.018	(0.201, 0.271)	281
		3/29	4	0.247	0.019	(0.210, 0.284)	274
		4/5	5	0.282	0.020	(0.243, 0.321)	272
		4/12	6	0.303	0.020	(0.264, 0.341)	272
	I	3/8	1	0.169	0.031	(0.108, 0.229)	89
		3/15	2	0.236	0.032	(0.173, 0.298)	92
		3/22	3	0.291	0.036	(0.219, 0.363)	78
		3/29	4	0.353	0.040	(0.274, 0.431)	86
		4/5	5	0.372	0.041	(0.291, 0.453)	78
		4/12	6	0.342	0.041	(0.261, 0.423)	77
	R	3/8	1	0.243	0.022	(0.200, 0.285)	279
		3/15	2	0.268	0.024	(0.222, 0.315)	226
		3/22	3	0.315	0.023	(0.271, 0.360)	256
		3/29	4	0.335	0.023	(0.289, 0.380)	247
		4/5	5	0.423	0.023	(0.377, 0.470)	274
		4/12	6	0.395	0.024	(0.347, 0.444)	247
Immigrants	D	3/8	1	0.238	0.019	(0.201, 0.275)	287
		3/15	2	0.222	0.019	(0.186, 0.259)	297
		3/22	3	0.238	0.019	(0.201, 0.276)	281
		3/29	4	0.235	0.020	(0.195, 0.274)	274
		4/5	5	0.219	0.020	(0.181, 0.258)	272
		4/12	6	0.235	0.020	(0.195, 0.276)	272
	I	3/8	1	0.273	0.038	(0.197, 0.349)	89
		3/15	2	0.286	0.035	(0.216, 0.356)	92
		3/22	3	0.286	0.035	(0.216, 0.357)	78
		3/29	4	0.295	0.036	(0.223, 0.366)	86
		4/5	5	0.329	0.038	(0.254, 0.404)	78
		4/12	6	0.229	0.036	(0.158, 0.301)	77
	R	3/8	1	0.409	0.023	(0.363, 0.454)	279
		3/15	2	0.341	0.022	(0.298, 0.383)	226
		3/22	3	0.375	0.023	(0.329, 0.421)	256
		3/29	4	0.414	0.024	(0.366, 0.462)	248
		4/5	5	0.415	0.023	(0.369, 0.460)	274

Table A.12: Estimates plotted in Figure 2d (blame, continued).

Variable	Party	Date	Wave	Estimate	SE	CI	N
Bad luck	D	4/12	6	0.347	0.022	(0.303, 0.391)	247
		3/8	1	0.401	0.022	(0.357, 0.444)	287
		3/15	2	0.386	0.021	(0.345, 0.427)	297
		3/22	3	0.367	0.021	(0.326, 0.408)	281
		3/29	4	0.427	0.021	(0.385, 0.469)	274
		4/5	5	0.370	0.022	(0.327, 0.413)	272
		4/12	6	0.413	0.022	(0.370, 0.456)	272
	I	3/8	1	0.352	0.035	(0.283, 0.421)	89
		3/15	2	0.380	0.036	(0.308, 0.452)	92
		3/22	3	0.376	0.036	(0.304, 0.448)	78
		3/29	4	0.357	0.036	(0.285, 0.428)	86
		4/5	5	0.359	0.038	(0.284, 0.434)	78
		4/12	6	0.329	0.039	(0.251, 0.407)	77
	R	3/8	1	0.395	0.021	(0.354, 0.437)	279
		3/15	2	0.412	0.024	(0.364, 0.460)	225
		3/22	3	0.404	0.023	(0.359, 0.448)	256
		3/29	4	0.390	0.024	(0.344, 0.436)	247
		4/5	5	0.418	0.024	(0.372, 0.465)	274
		4/12	6	0.389	0.023	(0.343, 0.434)	247
Nature	D	3/8	1	0.542	0.021	(0.502, 0.583)	287
		3/15	2	0.523	0.020	(0.483, 0.563)	297
		3/22	3	0.552	0.020	(0.512, 0.591)	281
		3/29	4	0.523	0.021	(0.482, 0.564)	274
		4/5	5	0.499	0.020	(0.459, 0.539)	272
		4/12	6	0.501	0.021	(0.460, 0.542)	272
	I	3/8	1	0.479	0.037	(0.407, 0.552)	89
		3/15	2	0.493	0.039	(0.416, 0.570)	92
		3/22	3	0.513	0.041	(0.432, 0.594)	78
		3/29	4	0.465	0.035	(0.395, 0.536)	86
		4/5	5	0.455	0.037	(0.381, 0.528)	77
		4/12	6	0.450	0.037	(0.376, 0.525)	77
	R	3/8	1	0.539	0.021	(0.497, 0.581)	279
		3/15	2	0.569	0.022	(0.526, 0.613)	226
		3/22	3	0.602	0.020	(0.561, 0.642)	256
		3/29	4	0.571	0.021	(0.529, 0.613)	248
		4/5	5	0.546	0.022	(0.504, 0.589)	274
		4/12	6	0.530	0.022	(0.486, 0.573)	246
Republicans	D	3/8	1	0.331	0.022	(0.287, 0.375)	287
		3/15	2	0.389	0.022	(0.346, 0.433)	297
		3/22	3	0.438	0.023	(0.393, 0.483)	281
		3/29	4	0.454	0.024	(0.406, 0.501)	274
		4/5	5	0.505	0.023	(0.459, 0.551)	272
		4/12	6	0.574	0.023	(0.528, 0.619)	272
	I	3/8	1	0.195	0.034	(0.128, 0.262)	89
		3/15	2	0.293	0.036	(0.221, 0.366)	92
		3/22	3	0.282	0.040	(0.203, 0.362)	78
		3/29	4	0.376	0.040	(0.296, 0.456)	86
		4/5	5	0.368	0.040	(0.288, 0.447)	78
		4/12	6	0.359	0.041	(0.277, 0.441)	77
	R	3/8	1	0.146	0.018	(0.110, 0.181)	279
		3/15	2	0.173	0.020	(0.133, 0.212)	226
		3/22	3	0.193	0.020	(0.154, 0.231)	256
		3/29	4	0.194	0.019	(0.157, 0.230)	248

Table A.12: Estimates plotted in Figure 2d (blame, continued).

Variable	Party	Date	Wave	Estimate	SE	CI	N
Trump	D	4/5	5	0.246	0.020	(0.207, 0.285)	274
		4/12	6	0.235	0.021	(0.194, 0.276)	247
		3/8	1	0.477	0.024	(0.430, 0.525)	287
		3/15	2	0.575	0.023	(0.530, 0.620)	297
		3/22	3	0.604	0.023	(0.559, 0.648)	281
		3/29	4	0.640	0.023	(0.594, 0.685)	274
		4/5	5	0.687	0.023	(0.642, 0.733)	272
		4/12	6	0.712	0.022	(0.668, 0.756)	272
	I	3/8	1	0.281	0.041	(0.200, 0.361)	89
		3/15	2	0.341	0.041	(0.259, 0.422)	92
		3/22	3	0.350	0.041	(0.269, 0.432)	78
		3/29	4	0.465	0.044	(0.378, 0.552)	86
		4/5	5	0.474	0.046	(0.382, 0.566)	78
		4/12	6	0.429	0.042	(0.345, 0.513)	77
	R	3/8	1	0.166	0.019	(0.128, 0.204)	279
		3/15	2	0.198	0.022	(0.154, 0.241)	226
		3/22	3	0.203	0.020	(0.164, 0.243)	256
		3/29	4	0.219	0.021	(0.177, 0.261)	248
		4/5	5	0.252	0.021	(0.211, 0.292)	274
		4/12	6	0.240	0.022	(0.198, 0.283)	247
Gov. agencies	D	3/8	1	0.448	0.021	(0.406, 0.490)	287
		3/15	2	0.460	0.020	(0.421, 0.500)	297
		3/22	3	0.497	0.021	(0.456, 0.538)	281
		3/29	4	0.489	0.020	(0.450, 0.528)	274
		4/5	5	0.543	0.021	(0.501, 0.585)	272
		4/12	6	0.558	0.021	(0.517, 0.598)	272
	I	3/8	1	0.315	0.038	(0.239, 0.390)	89
		3/15	2	0.315	0.034	(0.249, 0.382)	92
		3/22	3	0.363	0.039	(0.286, 0.441)	78
		3/29	4	0.407	0.037	(0.333, 0.481)	86
		4/5	5	0.440	0.040	(0.361, 0.519)	78
		4/12	6	0.446	0.038	(0.371, 0.521)	77
	R	3/8	1	0.276	0.021	(0.234, 0.318)	279
		3/15	2	0.280	0.021	(0.239, 0.321)	226
		3/22	3	0.309	0.020	(0.269, 0.348)	256
		3/29	4	0.281	0.020	(0.241, 0.321)	248
		4/5	5	0.375	0.020	(0.336, 0.414)	274
		4/12	6	0.347	0.020	(0.307, 0.387)	247

B Experiment 1

B.1 Survey information

Platform: MTurk.

Dates: May 15-16, 2020.

Sample size: 1,059.

Screeners: Captcha verification.

Consent: Subjects read an IRB-approved consent form, then voluntarily consented to participate in a research study.

Refusal rate: 0 percent.

Compensation: \$0.50. As the vendor does not set any standard rate, this amount was chosen to exceed the hourly minimum wage in the United States.

Treatments and outcomes: See Appendix [G](#).

No deception: As indicated in the approved IRB application, the experimental treatments did not involve deception.

B.2 Manipulation check

Figure B.1: Experiment 1, Manipulation Checks

Note: This figure plots the average response among Democrats (in blue) and Republicans (in red) when they read positively and negatively framed performance information. The point estimate is accompanied by a 95% confidence interval constructed using heteroskedasticity-robust HC2 standard errors. We measure perceptions of U.S. performance, separately for each dimension, using the question: Would you say the U.S. is doing a good job or a bad job of [controlling the spread of COVID-19/ limiting the number of deaths from COVID-19/ testing for COVID-19/ improving the health care system's ability to care for COVID-19 patients]? (Very bad, fairly bad, neither good nor bad, fairly good, very good).

Table B.1: Experiment 1: Data for Supplemental Figure B.1

Variable	Party	Z	Mean	SE
Performance Assessments				
Limiting deaths	Democrat	Negative	0.220	0.017
Limiting deaths	Democrat	Positive	0.518	0.017
Limiting deaths	Republican	Negative	0.452	0.022
Limiting deaths	Republican	Positive	0.711	0.020
U.S. performance	Democrat	Negative	0.275	0.018
U.S. performance	Democrat	Positive	0.449	0.017
U.S. performance	Republican	Negative	0.539	0.021
U.S. performance	Republican	Positive	0.702	0.020
Containing spread	Democrat	Negative	0.236	0.016
Containing spread	Democrat	Positive	0.491	0.016
Containing spread	Republican	Negative	0.471	0.021
Containing spread	Republican	Positive	0.644	0.022
Testing capacity	Democrat	Negative	0.270	0.018
Testing capacity	Democrat	Positive	0.499	0.018
Testing capacity	Republican	Negative	0.514	0.023
Testing capacity	Republican	Positive	0.707	0.021
Treatment capacity	Democrat	Negative	0.295	0.018
Treatment capacity	Democrat	Positive	0.572	0.015
Treatment capacity	Republican	Negative	0.525	0.021
Treatment capacity	Republican	Positive	0.734	0.018

Note: All variables measured on a [0-1] scale. Higher values indicate better performance or greater responsibility

B.3 Randomization check

Table B.2: Randomization Check, Experiment 1

Variable	Group Means		Diff	SD	Std. Diff	z	p
	Z=0	Z=1					
age	38.705	36.608	-2.098	0.796	-0.162	-2.634	0.008
white	0.798	0.721	-0.077	0.026	-0.181	-2.928	0.003
black	0.085	0.130	0.045	0.019	0.146	2.368	0.018
asian	0.106	0.138	0.032	0.020	0.097	1.585	0.113
hispanic	0.106	0.142	0.036	0.020	0.108	1.761	0.078
female	0.495	0.500	0.005	0.031	0.009	0.154	0.878
partyID	3.720	3.392	-0.328	0.134	-0.150	-2.438	0.015
age(missing)	0.000	0.008	0.008	0.004	0.123	2.001	0.045
hispanic(missing)	0.000	0.004	0.004	0.003	0.087	1.414	0.157
female(missing)	0.000	0.004	0.004	0.003	0.087	1.414	0.157
partyID(missing)	0.000	0.002	0.002	0.002	0.061	0.999	0.318

Overall: Chi-squared statistic= 25.3(df=10,p=0.005)

Note: Diff refers to the difference in means for a covariate. SD denotes the standard deviation of the difference in means. Std. Diff refers to the standardized difference in means.

B.4 Table of estimates plotted in Figure 3

Table B.3: Experiment 1: Data for Figure 3

Variable	Party	Z	Mean	SE
Perceptions of				
U.S. performance	Democrat	Negative	0.275	0.018
U.S. performance	Democrat	Positive	0.449	0.017
U.S. performance	Republican	Negative	0.539	0.021
U.S. performance	Republican	Positive	0.702	0.020
Responsibility				
Trump responsibility	Democrat	Negative	0.710	0.016
Trump responsibility	Democrat	Positive	0.639	0.017
Trump responsibility	Republican	Negative	0.573	0.018
Trump responsibility	Republican	Positive	0.632	0.018
Trump responsible (text)	Democrat	Negative	0.409	0.030
Trump responsible (text)	Democrat	Positive	0.314	0.027
Trump responsible (text)	Republican	Negative	0.198	0.029
Trump responsible (text)	Republican	Positive	0.206	0.032

Note: All variables measured on a [0-1] scale. Higher values indicate better performance or greater responsibility

C Experiment 1B

C.1 Description and results

A version of the following text appeared in previous versions of the manuscript under the header, “Testing a Novel Prediction.” It supports our account but did not prove essential to it. We include our full results here for transparency and completeness.

In the formal statement of our competence beliefs account (Appendix F.1), voters respond to the same information by attributing responsibility differently because they have different beliefs about who can deliver good performance. We looked for evidence of such beliefs by conducting a second experiment that estimates the quantity on the right-hand side of (8), $\mu_{G|R=1} - \mu_{G|R=0}$. If randomly-assigned information about responsibility ($R = 1$ versus $R = 0$) does not induce Democrats and Republicans to make opposite inferences about performance, our account is unlikely to hold the key to understanding selective attribution.

For this study, we recruited another diverse sample on MTurk ($n = 1099$) in May 2020. Each participant read three short vignettes about how much control the president has over the CDC’s budget, personnel, and the degree to which the CDC collaborated with the White House on pandemic-related guidance. Within these topic areas, the experiment introduced exogenous variation in presidential control, and through it perceptions of responsibility for the CDC. Half of the respondents were randomly assigned to see information that emphasized presidential control, while the other half saw information that minimized it. Following the treatment, respondents answered two closed-ended questions, one on how much Trump was responsible for the CDC’s performance and another on the CDC’s performance fighting the COVID-19 pandemic.

Figure C.1: Experiment 1B

Note: See note to Figure 3.

The experiment successfully manipulated perceptions of presidential responsibility for the CDC’s performance, among both Republicans and Democrats (Figure C.1, left). Compared with Republicans who read information that understated presidential control, Republicans who read information that emphasized presidential control thought Trump was more responsible for the CDC’s performance ($\widehat{CATE}_R = 0.201$, s.e. = 0.028). Democrats responded similarly to the treatment ($\widehat{CATE}_D = 0.231$, s.e. = 0.024). In both cases, the treatment effect was equal to about 20 percent of the scale. The difference in conditional average treatment effects is statistically insignificant ($\widehat{CATE}_R - \widehat{CATE}_D = -0.0299$, s.e. = 0.0364). In section C.3, we show that the treatment moved perceptions of presidential responsibility on each of the three dimensions, for both Democrats and Republicans (see Figure C.2).

Even as Democrats and Republicans made the same inference about presidential control over the CDC, they made opposite inferences about the agency’s performance. Compared with Republicans who read facts that minimized presidential control over the CDC, those who read facts emphasizing it inferred better CDC performance ($\widehat{CATE}_R = 0.0525$, s.e. = 0.0259). Democrats responded in the opposite way, rating the CDC’s performance as better when presidential control was low and worse when presidential control was high ($\widehat{CATE}_D = -0.0999$, s.e. = 0.0212). The difference between these treatment effects is statistically significant ($\widehat{CATE}_R - \widehat{CATE}_D = 0.1524$, s.e. = 0.0334).

Combined with our first experiment, these results provide further evidence of the performance-based account’s plausibility. Democrats and Republicans use performance information to make inferences about responsibility (Experiment 1, left-hand side of (7)) and responsibility information to make opposite inferences about performance (Experiment 1b, right-hand side of (7)). Though existing accounts do not predict the latter result, we suspect that a rationale for identity-protective inferences about the performance of federal agencies could be developed *ex post*. Accordingly, we interpret this result mainly as an encouraging sign for our account’s ability to generate testable, accurate predictions.

C.2 Survey information

Platform: MTurk.

Dates: May 24-25, 2020.

Sample size: 1,099.

Consent: Subjects read an IRB-approved consent form, then voluntarily consented to participate in a research study.

Refusal rate: 0 percent.

Compensation: \$0.30. As the vendor does not set any standard rate, this amount was chosen to exceed the hourly minimum wage in the United States.

Treatments and outcomes: See Appendix G.

No deception: As indicated in the approved IRB application, the experimental treatments did not involve deception.

C.3 Manipulation check

Figure C.2: Experiment 2, Manipulation Checks

Note: This figure plots the average response among Democrats (in blue) and Republicans (in red) when they were told presidential control over the CDC was high (“responsible”) and low (“not responsible”). The point estimate is accompanied by a 95% confidence interval constructed using heteroskedasticity-robust HC2 standard errors. We measure presidential responsibility separately for each dimension using the question: How responsible would you say the President is for [how CDC spends its money/ the quality of leadership at the CDC/ the CDC’s strategies for fighting the COVID-19 outbreak]? (Not at all responsible, a little responsible, somewhat responsible, mostly responsible, fully responsible).

Table C.1: Experiment 1B: Data for Supplemental Figure C.2

Variable	Party	Z	Mean	SE
Trump responsible for				
CDC's overall performance	Democrat	Not Responsible	0.402	0.018
CDC's overall performance	Democrat	Responsible	0.634	0.015
CDC's overall performance	Republican	Not Responsible	0.389	0.022
CDC's overall performance	Republican	Responsible	0.590	0.017
Budget	Democrat	Not Responsible	0.363	0.017
Budget	Democrat	Responsible	0.649	0.015
Budget	Republican	Not Responsible	0.404	0.021
Budget	Republican	Responsible	0.603	0.018
Collaboration with White House	Democrat	Not Responsible	0.367	0.019
Collaboration with White House	Democrat	Responsible	0.596	0.016
Collaboration with White House	Republican	Not Responsible	0.429	0.023
Collaboration with White House	Republican	Responsible	0.634	0.015
Staffing	Democrat	Not Responsible	0.321	0.017
Staffing	Democrat	Responsible	0.709	0.016
Staffing	Republican	Not Responsible	0.374	0.023
Staffing	Republican	Responsible	0.686	0.015

Note: All variables measured on a [0-1] scale. Higher values indicate better performance or greater responsibility

C.4 Randomization check

Table C.2: Randomization Check, Experiment 1B

Variable	Group Means		Diff	SD	Std. Diff	z	p
	Z=0	Z=1					
age	38.375	38.982	0.607	0.801	0.046	0.757	0.449
white	0.756	0.765	0.010	0.026	0.022	0.370	0.711
black	0.107	0.104	-0.004	0.019	-0.012	-0.207	0.836
asian	0.120	0.127	0.007	0.020	0.021	0.355	0.723
hispanic	0.000	0.000	0.000	0.000	NaN	0.000	1.000
female	0.534	0.538	0.004	0.030	0.009	0.149	0.882
partyID	3.370	3.607	0.238	0.132	0.109	1.805	0.071
age(missing)	0.007	0.002	-0.005	0.004	-0.081	-1.346	0.178
hispanic(missing)	0.000	0.002	0.002	0.002	0.060	0.999	0.318
female(missing)	0.000	0.002	0.002	0.002	0.060	0.999	0.318
partyID(missing)	0.000	0.002	0.002	0.002	0.060	0.999	0.318

Overall: Chi-squared statistic= 10.217(df=8,p=0.25)

Note: Diff refers to the difference in means for a covariate. SD denotes the standard deviation of the difference in means. Std. Diff refers to the standardized difference in means.

C.5 Table of estimates plotted in Figure C.1

Table C.3: Experiment 1B: Data for Figure C.1

Variable	Party	Z	Mean	SE
Perceptions of				
CDC performance	Democrat	Not Responsible	0.617	0.015
CDC performance	Democrat	Responsible	0.517	0.015
CDC performance	Republican	Not Responsible	0.618	0.019
CDC performance	Republican	Responsible	0.671	0.017
Trump responsible for				
CDC's overall performance	Democrat	Not Responsible	0.402	0.018
CDC's overall performance	Democrat	Responsible	0.634	0.015
CDC's overall performance	Republican	Not Responsible	0.389	0.022
CDC's overall performance	Republican	Responsible	0.590	0.017

Note: All variables measured on a [0-1] scale. Higher values indicate better performance or greater responsibility

D Experiment 2

D.1 Survey information

Platform: MTurk.

Dates: October 23-26, 2020 (wave 1); October 25-28, 2020 (wave 2)

Sample size: 3,572 (wave 1), 2,524 (wave 2).

Consent: Subjects read an IRB-approved consent form, then voluntarily consented to participate in a research study.

Refusal rate: 0 percent.

Compensation: \$0.60. As the vendor does not set any standard rate, this amount was chosen to exceed the hourly minimum wage in the United States.

Treatments and outcomes: See Appendix G.

No deception: As indicated in the approved IRB application, the experimental treatments did not involve deception.

Real-world impact: As the experiment was conducted shortly before a presidential election, the design (1) examined the intervention’s effect on preference between the major party candidates and (2) excluded political independents, among whom our theory predicted the strongest effect on candidate preference. We find no evidence that the treatment affected candidate preferences (see Appendix D.5).

Recontact: In wave 1, 3,234 respondents identified themselves as a partisan or independent leaner. We invited all of these respondents to complete the wave 2 survey. Of these, 2,524 completed the wave 2 survey (78 percent). This table displays the dated on which respondents completed the surveys. In total, 101 respondents took the wave 2 survey on the same day as wave 1; 800, one day later; 956, two days later; 443, three days later; 183, four days later; and 40, five days later.

Wave 1 start date	Wave 2 start date			
	2020-10-25	2020-10-26	2020-10-27	2020-10-28
2020-10-23	627	326	173	40
2020-10-24	174	82	68	10
2020-10-25	30	296	204	49
2020-10-26	0	71	330	43

Preregistration: <https://osf.io/eyg4p>

D.2 Manipulation check

Figure D.1: Experiment 2, Manipulation Checks

Note: This figure plots the average response among Democrats (in blue) and Republicans (in red) when they read positively and negatively framed performance information. The point estimate is accompanied by a 95% confidence interval constructed using heteroskedasticity-robust HC2 standard errors. We measure perceptions of U.S. performance, separately for each dimension, using the question: Would you say the U.S. is doing a good job or a bad job of [controlling the spread of COVID-19/ limiting the number of deaths from COVID-19/ testing for COVID-19/ developing treatments and vaccines for COVID-19]? (Very bad, fairly bad, neither good nor bad, fairly good, very good).

Table D.1: Experiment 2: Data for Supplemental Figure D.1

Variable	Party	Z	Mean	SE
Performance Assessments				
Limiting deaths	Democrat	Negative	0.137	0.009
Limiting deaths	Democrat	Positive	0.418	0.011
Limiting deaths	Republican	Negative	0.467	0.014
Limiting deaths	Republican	Positive	0.717	0.011
U.S. performance	Democrat	Negative	0.161	0.010
U.S. performance	Democrat	Positive	0.338	0.012
U.S. performance	Republican	Negative	0.550	0.014
U.S. performance	Republican	Positive	0.714	0.011
Containing spread	Democrat	Negative	0.128	0.009
Containing spread	Democrat	Positive	0.413	0.011
Containing spread	Republican	Negative	0.466	0.014
Containing spread	Republican	Positive	0.703	0.011
Testing capacity	Democrat	Negative	0.191	0.010
Testing capacity	Democrat	Positive	0.596	0.011
Testing capacity	Republican	Negative	0.519	0.013
Testing capacity	Republican	Positive	0.792	0.010
Treatment capacity	Democrat	Negative	0.285	0.010
Treatment capacity	Democrat	Positive	0.623	0.010
Treatment capacity	Republican	Negative	0.581	0.013
Treatment capacity	Republican	Positive	0.787	0.010

Note: All variables measured on a [0-1] scale. Higher values indicate better performance or greater responsibility

D.3 Randomization check

Table D.2: Randomization Check, Experiment 2

Variable	Group Means		Diff	SD	Std. Diff	z	p
	Z=0	Z=1					
age	39.095	39.965	0.870	0.502	0.069	1.732	0.083
white	0.806	0.784	-0.022	0.016	-0.054	-1.362	0.173
black	0.095	0.108	0.013	0.012	0.043	1.075	0.282
asian	0.088	0.095	0.007	0.011	0.023	0.572	0.567
hispanic	0.128	0.131	0.003	0.013	0.008	0.201	0.841
female	0.514	0.522	0.008	0.020	0.017	0.421	0.674
partyID	3.642	3.687	0.044	0.096	0.018	0.464	0.643
education	4.437	4.502	0.065	0.048	0.054	1.352	0.176
trump responsible	0.653	0.646	-0.007	0.012	-0.024	-0.607	0.544
voted for trump	0.411	0.423	0.012	0.019	0.025	0.636	0.525
performance beliefs index	0.391	0.396	0.005	0.014	0.014	0.348	0.728
social partisanship index	0.463	0.469	0.006	0.013	0.019	0.484	0.628
age(missing)	0.001	0.001	0.000	0.001	0.000	0.002	0.999
hispanic(missing)	0.000	0.002	0.002	0.001	0.069	1.735	0.083
female(missing)	0.001	0.001	0.000	0.001	0.000	0.002	0.999
partyID(missing)	0.000	0.001	0.001	0.001	0.040	1.001	0.317
education(missing)	0.000	0.001	0.001	0.001	0.040	1.001	0.317
trump responsible(missing)	0.000	0.002	0.002	0.001	0.056	1.416	0.157
voted for trump(missing)	0.000	0.001	0.001	0.001	0.040	1.001	0.317
performance beliefs index(missing)	0.000	0.001	0.001	0.001	0.040	1.001	0.317
social partisanship index(missing)	0.000	0.001	0.001	0.001	0.040	1.001	0.317

Overall: Chi-squared statistic= 14.915(df=17,p=0.602)

Note: Diff refers to the difference in means for a covariate. SD denotes the standard deviation of the difference in means. Std. Diff refers to the standardized difference in means.

D.4 Table of estimates plotted in Figure 4

Table D.3: Experiment 2: Data for Figure 4

Variable	Party	Z	Mean	SE
Perceptions of				
U.S. performance	Democrat	Negative	0.161	0.010
U.S. performance	Democrat	Positive	0.338	0.012
U.S. performance	Republican	Negative	0.550	0.014
U.S. performance	Republican	Positive	0.714	0.011
Responsibility				
Trump responsibility	Democrat	Negative	0.747	0.010
Trump responsibility	Democrat	Positive	0.693	0.011
Trump responsibility	Republican	Negative	0.528	0.013
Trump responsibility	Republican	Positive	0.612	0.011
Voted Trump	Democrat	Negative	0.089	0.010
Voted Trump	Democrat	Positive	0.099	0.011
Voted Trump	Republican	Negative	0.843	0.014
Voted Trump	Republican	Positive	0.847	0.014

Note: All variables measured on a [0-1] scale. Higher values indicate better performance or greater responsibility

D.5 Presidential vote choice

Table D.4: Treatment effect on presidential vote choice.

	All	Democrat	Republican
Constant	0.032** (0.006)	0.029** (0.007)	0.112** (0.027)
Treatment (1 = positive)	0.010 (0.008)	0.003 (0.010)	0.018 (0.012)
Pre-treatment DV	0.911** (0.008)	0.796** (0.038)	0.839** (0.028)
Adj. R ²	0.833	0.539	0.630
Num. obs.	2504	1426	1078

** $p < 0.01$; * $p < 0.05$

Table D.5: Treatment effect on presidential vote choice, independent leaners.

	All	Democrat	Republican
Constant	0.019 (0.011)	0.013 (0.012)	0.056* (0.028)
Treatment (1 = positive)	0.030 (0.018)	0.035 (0.023)	0.019 (0.028)
Pre-treatment DV	0.907** (0.021)	0.827** (0.081)	0.884** (0.032)
Adj. R ²	0.826	0.586	0.708
Num. obs.	472	258	214

** $p < 0.01$; * $p < 0.05$

Table D.6: Treatment effect on presidential vote choice, weak partisans.

	All	Democrat	Republican
Constant	0.028** (0.010)	0.035** (0.012)	0.040 (0.025)
Treatment (1 = positive)	0.006 (0.011)	-0.014 (0.015)	0.033* (0.016)
Pre-treatment DV	0.942** (0.011)	0.887** (0.043)	0.921** (0.028)
Adj. R ²	0.887	0.626	0.848
Num. obs.	802	459	343

** $p < 0.01$; * $p < 0.05$

Table D.7: Treatment effect on presidential vote choice, strong partisans.

	All	Democrat	Republican
Constant	0.040** (0.010)	0.030** (0.010)	0.403** (0.105)
Treatment (1 = positive)	0.005 (0.012)	0.003 (0.015)	0.005 (0.019)
Pre-treatment DV	0.895** (0.013)	0.737** (0.061)	0.549** (0.105)
Adj. R ²	0.804	0.479	0.197
Num. obs.	1230	709	521

** $p < 0.01$; * $p < 0.05$

Table D.8: Treatment effect on presidential vote choice, partisan differences.

	Model 1	Model 2	Model 3
α Constant	0.027** (0.007)	0.017 (0.012)	0.014 (0.014)
β_1 Z	0.003 (0.010)	0.030 (0.017)	0.036 (0.022)
β_2 Republican	0.102** (0.024)		0.097** (0.031)
β_3 Weak		0.022 (0.015)	0.026 (0.019)
β_9 Strong		0.016 (0.015)	0.010 (0.018)
β_6 Weak $\times$ Republican			-0.014 (0.031)
β_{10} Strong $\times$ Republican			0.027 (0.032)
β_4 Z $\times$ Republican	0.014 (0.016)		-0.020 (0.036)
β_5 Z $\times$ Weak		-0.023 (0.021)	-0.049 (0.027)
β_{11} Z $\times$ Strong		-0.025 (0.021)	-0.034 (0.027)
β_7 Z $\times$ Weak $\times$ Republican			0.067 (0.042)
β_{12} Z $\times$ Strong $\times$ Republican			0.026 (0.043)
β_8 Pre-treatment DV	0.819** (0.023)	0.911** (0.008)	0.814** (0.024)
Adj. R ²	0.838	0.833	0.838
Num. obs.	2504	2504	2504

D.6 Crosswalk to pre-analysis plan

This section is designed to aid readers who wish to assess the consistency between the analysis and the pre-analysis plan, which is available at <https://osf.io/eyg4p>.

The pre-analysis plan specified seven hypotheses that would replicate results from the time series data and the first two experiments:

- *Hypothesis 1: parallel updating in response to information.* Tested in the main text subsection on Experiment 2. See Figure 4 and surrounding text.
- *Hypothesis 2: selective attribution by Democrats.* Tested in the main text subsection on Experiment 2. See Figure 4 and surrounding text.
- *Hypothesis 3: selective attribution by Republicans.* Tested in the main text subsection on Experiment 2. See Figure 4 and surrounding text.
- *Hypothesis 4: weak partisans identify more strongly with a party than do independents leaning toward a party.* Tested in the appendix on group identity and selective attribution. See the left set of columns in Table F.4.
- *Hypothesis 5: partisan differences in competence beliefs are more pronounced among leaners than among weak partisans.* Tested in the appendix on group identity and selective attribution. See the right set of columns in Table F.4.

Note that due to a typographical or proofing error, the preregistration document reads “partisan differences in selective attributions of responsibility” rather than “partisan differences in competence beliefs.” The pre-specified statistical test of this hypothesis makes the document’s intent clear, as does the redundancy that that the error creates between hypotheses 5 and 6.

- *Hypothesis 6: selective attributions of responsibility are more pronounced among leaners.* Tested in the appendix item on group identity and selective attribution. See Figure F.1 and Table F.3.
- *Hypothesis 7: same treatment effect on presidential vote choice.* See section D.5.

We supplemented this with four hypotheses that were generated entirely by our theory, and were not designed to replicate any previous result.

- *Hypothesis S1: competence beliefs moderate the treatment effect.* See column 3 of Tables 3, F.1, and F.2.
- *Hypothesis S2: partisan identity moderates the treatment effect.* See column 2 of Tables 3, F.1, and F.2.
- *Hypothesis S3: independent of partisan identity, competence beliefs moderate the treatment effect.* See column 4 of Tables 3, F.1, and F.2.
- *Hypothesis S4: randomization check.* See Appendix D.3.

E Experiment 3

E.1 Survey information

Platform: MTurk.

Dates: December 29-30, 2021.

Sample size: 4,484.

Consent: Subjects read an IRB-approved consent form, then voluntarily consented to participate in a research study.

Refusal rate: 0.1 percent.

Additional screening: All respondents who left the survey at least twice during the pre-treatment questions were dropped. This was pre-registered.

Compensation: \$0.60. As the vendor does not set any standard rate, this amount was chosen to exceed the hourly minimum wage in the United States.

Treatments and outcomes: See Appendix G.

No deception: As indicated in the approved IRB application, the experimental treatments did not involve deception.

Preregistration: <https://osf.io/s3u5m>

E.2 Manipulation check

Figure E.1: Experiment 3, Manipulation Checks

Note: This figure plots the average response among Democrats (in blue) and Republicans (in red) when they read positively and negatively framed performance information. The point estimate is accompanied by a 95% confidence interval constructed using heteroskedasticity-robust HC2 standard errors. We measure perceptions of U.S. performance, separately for each dimension, using the questions: Would you say the U.S. is doing a good job or a bad job of [controlling the spread of COVID-19/ limiting the number of deaths from COVID-19/ handling new COVID-19 cases once they emerge]? Would you say that the emergence of the Omicron variant is good news or bad news? (Very bad, fairly bad, neither good nor bad, fairly good, very good).

Table E.1: Experiment 3: Data for Supplemental Figure E.1

Variable	Party	Z	Mean	SE
Performance Assessments				
Limiting deaths	Democrat	Negative	0.436	0.009
Limiting deaths	Democrat	Positive	0.562	0.007
Limiting deaths	Republican	Negative	0.449	0.012
Limiting deaths	Republican	Positive	0.597	0.010
Omicron variant	Democrat	Negative	0.363	0.009
Omicron variant	Democrat	Positive	0.560	0.008
Omicron variant	Republican	Negative	0.438	0.013
Omicron variant	Republican	Positive	0.644	0.011
U.S. performance	Democrat	Negative	0.496	0.009
U.S. performance	Democrat	Positive	0.627	0.007
U.S. performance	Republican	Negative	0.498	0.012
U.S. performance	Republican	Positive	0.595	0.011
Containing spread	Democrat	Negative	0.451	0.009
Containing spread	Democrat	Positive	0.652	0.007
Containing spread	Republican	Negative	0.473	0.012
Containing spread	Republican	Positive	0.642	0.009
Testing & treatment	Democrat	Negative	0.455	0.009
Testing & treatment	Democrat	Positive	0.680	0.007
Testing & treatment	Republican	Negative	0.466	0.012
Testing & treatment	Republican	Positive	0.649	0.010

Note: All variables measured on a [0-1] scale. Higher values indicate better performance.

E.3 Randomization check

Table E.2: Randomization Check (Performance Information), Experiment 3

Variable	Group Means		Diff	SD	Std. Diff	z	p
	Z=0	Z=1					
age	38.762	38.226	-0.536	0.373	-0.043	-1.437	0.151
white	0.835	0.823	-0.011	0.011	-0.030	-1.015	0.310
black	0.090	0.097	0.007	0.009	0.025	0.833	0.405
asian	0.063	0.066	0.004	0.007	0.016	0.524	0.600
hispanic	0.162	0.191	0.029	0.011	0.077	2.582	0.010
female	0.462	0.453	-0.009	0.015	-0.017	-0.581	0.561
partyID	3.328	3.325	-0.003	0.069	-0.001	-0.037	0.970
education	4.517	4.547	0.030	0.036	0.025	0.832	0.405
performance beliefs index	0.620	0.612	-0.009	0.008	-0.031	-1.033	0.302
social partisanship index	0.397	0.395	-0.002	0.010	-0.005	-0.175	0.861
biden responsible	0.626	0.615	-0.012	0.008	-0.045	-1.503	0.133
age(missing)	0.001	0.001	0.000	0.001	0.001	0.025	0.980
hispanic(missing)	0.001	0.001	0.000	0.001	0.014	0.475	0.634
female(missing)	0.001	0.000	0.000	0.001	-0.017	-0.556	0.578
partyID(missing)	0.001	0.000	0.000	0.001	-0.017	-0.556	0.578
education(missing)	0.000	0.000	0.000	0.001	0.001	0.018	0.986
performance beliefs index(missing)	0.000	0.001	0.000	0.001	0.018	0.599	0.549
social partisanship index(missing)	0.091	0.092	0.001	0.009	0.003	0.110	0.913
biden responsible(missing)	0.002	0.002	0.000	0.001	0.011	0.371	0.710

Overall: Chi-squared statistic= 24.728(df=19,p=0.17)

Note: Diff refers to the difference in means for a covariate. SD denotes the standard deviation of the difference in means. Std. Diff refers to the standardized difference in means.

Table E.3: Randomization Check (Accuracy Prime), Experiment 3

Variable	Group Means		Diff	SD	Std. Diff	z	p
	Z=0	Z=1					
age	38.374	38.624	0.250	0.373	0.020	0.672	0.502
white	0.830	0.828	-0.003	0.011	-0.007	-0.231	0.818
black	0.093	0.094	0.002	0.009	0.006	0.214	0.830
asian	0.065	0.064	0.000	0.007	-0.001	-0.049	0.961
hispanic	0.169	0.184	0.015	0.011	0.040	1.333	0.183
female	0.455	0.460	0.005	0.015	0.009	0.317	0.751
partyID	3.316	3.337	0.021	0.069	0.009	0.307	0.759
education	4.529	4.535	0.006	0.036	0.005	0.163	0.870
performance beliefs index	0.617	0.615	-0.002	0.008	-0.007	-0.241	0.809
social partisanship index	0.396	0.395	-0.001	0.010	-0.002	-0.076	0.940
biden responsible	0.623	0.618	-0.004	0.008	-0.017	-0.558	0.577
age(missing)	0.001	0.000	-0.001	0.001	-0.029	-0.985	0.325
hispanic(missing)	0.001	0.001	0.000	0.001	0.014	0.464	0.642
female(missing)	0.001	0.000	0.000	0.001	-0.017	-0.564	0.573
partyID(missing)	0.001	0.000	0.000	0.001	-0.017	-0.564	0.573
education(missing)	0.000	0.000	0.000	0.001	0.000	0.011	0.991
performance beliefs index(missing)	0.000	0.001	0.000	0.001	0.018	0.591	0.555
social partisanship index(missing)	0.083	0.099	0.016	0.009	0.056	1.873	0.061
biden responsible(missing)	0.002	0.002	0.000	0.001	-0.009	-0.311	0.756

Overall: Chi-squared statistic= 13.272(df=19,p=0.824)

Note: Diff refers to the difference in means for a covariate. SD denotes the standard deviation of the difference in means. Std. Diff refers to the standardized difference in means.

E.4 Table of estimates plotted in Figure 5

Table E.4: Experiment 3: Data for Figure 5

Variable	Party	Z	Mean	SE
Perceptions of				
U.S. performance	Democrat	Negative	0.496	0.009
U.S. performance	Democrat	Positive	0.627	0.007
U.S. performance	Republican	Negative	0.498	0.012
U.S. performance	Republican	Positive	0.595	0.011
Responsibility				
Biden responsibility	Democrat	Negative	0.614	0.007
Biden responsibility	Democrat	Positive	0.632	0.007
Biden responsibility	Republican	Negative	0.682	0.009
Biden responsibility	Republican	Positive	0.633	0.011

Note: All variables measured on a [0-1] scale. Higher values indicate better performance or greater responsibility

E.5 Accuracy prime manipulation check

To verify that the accuracy prime was administered properly, we examined whether our subjects could recall its presence. After the dependent variables were measured, all subjects were asked, “Before you reached this page, did the survey warn you that you would have to justify your answers?” with the response options “Yes” and “No.”

To estimate the treatment’s effect on this question, we used OLS to estimate

$$\mathbb{1}(\text{Yes})_i \sim \alpha + \beta \text{Accuracy treatment}_i + \epsilon, \quad (4)$$

where $\mathbb{1}(\text{Yes})$ is an indicator for saying “Yes” and $\text{Accuracy treatment}_i$ is an indicator for the accuracy motivation treatment. Table E.5 displays the results. We estimate $\beta = 0.40$, a large positive effect.

Table E.5: Manipulation check, accuracy motivation treatment.

	Model 1
Constant	0.424** (0.011)
Accuracy treatment	0.398** (0.013)
Adj. R ²	0.168
Num. obs.	4365

** $p < 0.01$; * $p < 0.05$

Our estimate of α , 0.42, indicates that many untreated respondents reported that they remembered the treatment. We do not find this discouraging, as respondents who did not see the treatment could not possibly have been affected by it. Our best guess is that such respondents were worried that failing to notice an instruction would result in non-payment, which is a common practice among some requestors on the survey platform.

E.6 Crosswalk to pre-analysis plan

This section is designed to aid readers who wish to assess the consistency between the analysis and the pre-analysis plan, available at <https://osf.io/s3u5m>.

The pre-analysis plan specified seven hypotheses that would replicate results from the time series data and the first two experiments:

- *Hypothesis 1: parallel updating in response to information.* Tested in the main text subsection on Experiment 3. See Figure 5 and surrounding text.
- *Hypothesis 2a: selective attribution by Democrats.* Tested in the main text subsection on Experiment 3. See Figure 5 and surrounding text.
- *Hypothesis 2b: selective attribution by Republicans.* Tested in the main text subsection on Experiment 3. See Figure 5 and surrounding text.
- *Hypothesis 3: accuracy motivation.* Tested in the main text section “Altering the Motivational Context.” See Table 4 and surrounding text.
- *Hypothesis 4: competence beliefs moderate the treatment effect.* See column 6 of Tables 3, F.1, and F.2.
- *Hypothesis 5: partisan identity moderates the treatment effect.* See column 7 of Tables 3, F.1, and F.2.
- *Hypothesis 6: independent of partisan identity, competence beliefs moderate the treatment effect.* See column 8 of Tables 3, F.1, and F.2.
- *Hypothesis 7: randomization check.* See Appendix D.3.
- *Hypothesis 8: accuracy prime manipulation check.* See Appendix E.5.

F Supplemental Results

F.1 Formal statement of the competence beliefs explanation

Detailed Explanation

Classic accounts of democratic accountability note that voters overwhelmingly view their preferred candidate as more able to deliver good performance (Key 1966a; Sigelman and Knight 1985). In this section, we examine how Bayes' rule predicts that a voter with *competence beliefs* of this kind would use them to make inferences about responsibility for events and social conditions. Though we do not have any expectation that voters actually follow Bayes' rule, its roots in the laws of probability make it a convenient model of how one might reason absent any directional motivation (e.g., Gerber and Green 1999; Little 2019). In this section, we present a brief exposition of our analytic results. The next section provides more detailed proofs.

We begin by mathematically expressing the phenomenon of interest: that the state of the world appears to affect voters' perceptions of the government's responsibility for creating those conditions. To do so, we consider the probabilistic beliefs of a representative voter in each of two possible two states of the world, good (G) and bad ($\neg G$). Let $R = 1$ indicate that the incumbent is responsible and $R = 0$ indicate the opposite. According to Bayes' rule, the voter's belief that the incumbent is responsible, $P(R = 1|\cdot)$, should equal

$$P(R = 1|G) = \frac{P(G|R = 1) \cdot P(R = 1)}{P(G|R = 1) \cdot P(R = 1) + P(G|R = 0) \cdot P(R = 0)} \quad (5)$$

in the good state of the world, and

$$P(R = 1|\neg G) = \frac{P(\neg G|R = 1) \cdot P(R = 1)}{P(\neg G|R = 1) \cdot P(R = 1) + P(\neg G|R = 0) \cdot P(R = 0)} \quad (6)$$

in the bad state of the world. Subtracting (6) from (5) expresses a key result from the selective attribution literature: voters' attributions of responsibility depend on how well they think things are going.¹³ Substituting and rearranging terms yields our key analytic result,

$$P(R = 1|G) - P(R = 1|\neg G) \propto P(G|R = 1) - P(G|R = 0). \quad (7)$$

The left-hand side is simply the difference between (6) and (5), implying that voters' attributions of responsibility depend on how well things are going. The right-hand side indicates that any such tendency should emerge in proportion to the voter's beliefs about the incumbent's ability to deliver good performance. To see this, consider that the first term,

¹³More specifically, subtracting (6) from (5) expresses the relationship between attributions of responsibility and the state of the world using potential outcomes notation, where G is the treatment variable and R is the outcome variable (Rubin 1974).

$P(G|R = 1)$, is the probability of good performance when the incumbent is responsible; the second term, $P(G|R = 0)$, is this probability when the incumbent is not responsible. The difference between these two terms is the voter’s belief about the incumbent’s effect on performance. The proportionality symbol, $\propto$, indicates that the two sides are equal up to a constant factor. This means that a Bayesian agent’s competence beliefs and attributions of responsibility always take the same sign and covary steadily as functions of one another.

To grasp the key implication of equation (7), consider a Bayesian voter who believes good outcomes are likely under the incumbent (i.e., $P(G|R = 1) - P(G|R = 0) > 0$). When such a voter observes good outcomes, that voter will think it is more likely that the incumbent is responsible for performance in that area (i.e., $P(R = 1|G) - P(R = 1|\neg G) > 0$). In contrast, for a Bayesian voter who believes that good outcomes are unlikely under the incumbent, the right-hand side takes the opposite sign (i.e., $P(G|R = 1) - P(G|R = 0) < 0$). When such a voter observes good outcomes, they should be less likely to attribute responsibility to the incumbent (i.e., $P(R = 1|G) - P(R = 1|\neg G) < 0$).

We show below in the proof statement that this same principle holds for population averages, implying that

$$\mu_{R|G} - \mu_{R|\neg G} \propto \mu_{G|R=1} - \mu_{G|R=0}. \quad (8)$$

This means that when two groups of people have oppositely-signed beliefs about the incumbent’s effect on performance (right side), they should respond to the same changes in the state of the world by making opposite inferences about whether the incumbent is responsible for performance (left side).

Existing research establishes that in many cases, the left-hand side of expression (8) takes opposite signs for Democrats and Republicans.¹⁴ We have shown that Bayes’ rule implies that the right-hand side, which is aptly described as a competence belief, should take the same sign as the left-hand side, which expresses selective attribution. This implies that selective attribution can emerge as a function of differences in competence beliefs, which are documented in classic work on democratic accountability (Key 1966a; Sigelman and Knight 1985).

¹⁴That is, most of the studies in Table 2 suggest in one way or another that when the state of the world becomes better or worse, partisans make opposite inferences about whether the incumbent is responsible.

Proof Statement

Start with the estimand: $P(R = 1|G) - P(R = 1|\neg G)$.

Apply Bayes' rule, and re-write it as:

$$\left(\frac{P(G|R = 1) \cdot P(R = 1)}{P(G|R = 1) \cdot P(R = 1) + P(G|R = 0) \cdot P(R = 0)} \right) - \left(\frac{P(\neg G|R = 1) \cdot P(R = 1)}{P(\neg G|R = 1) \cdot P(R = 1) + P(\neg G|R = 0) \cdot P(R = 0)} \right)$$

Multiply through by the product of the denominators, which is equal to $P(G)P(\neg G)$

$$\begin{aligned} & \left(P(R = 1|G) - P(R = 1|\neg G) \right) P(G)P(\neg G) = \\ & P(G|R = 1)P(R = 1) \left(P(\neg G|R = 1)P(R = 1) + P(\neg G|R = 0)P(R = 0) \right) \\ & - P(\neg G|R = 1)P(R = 1) \left(P(G|R = 1)P(R = 1) + P(G|R = 0)P(R = 0) \right) \end{aligned}$$

Note that the right hand side can be rewritten as $A(B + C) - B(A + D)$, which reduces to $AC - BD$

$$\begin{aligned} & \left(P(R = 1|G) - P(R = 1|\neg G) \right) P(G)P(\neg G) = \\ & P(G|R = 1)P(R = 1)P(\neg G|R = 0)P(R = 0) - P(\neg G|R = 1)P(R = 1)P(G|R = 0)P(R = 0) \end{aligned}$$

Divide through by $P(R = 1)P(R = 0)$

$$\begin{aligned} & \left(P(R = 1|G) - P(R = 1|\neg G) \right) \frac{P(G)P(\neg G)}{P(R = 1)P(R = 0)} = \\ & P(G|R = 1)P(\neg G|R = 0) - P(\neg G|R = 1)P(G|R = 0) \end{aligned}$$

Note that $\frac{P(G)P(\neg G)}{P(R=1)P(R=0)}$ is always positive. Drop this term from the left side and be satisfied that for any individual, the two sides are proportional

$$\left(P(R = 1|G) - P(R = 1|\neg G) \right) \propto P(G|R = 1)P(\neg G|R = 0) - P(\neg G|R = 1)P(G|R = 0)$$

Now on the right side, substitute $P(\neg G|R = \cdot) = 1 - P(G|R = \cdot)$

$$\left(P(R = 1|G) - P(R = 1|\neg G) \right) \propto P(G|R = 1)[1 - P(G|R = 0)] - [1 - P(G|R = 1)]P(G|R = 0)$$

Solve on the right-hand side to get:

$$\begin{aligned} & \left(P(R = 1|G) - P(R = 1|\neg G) \right) \\ & \propto P(G|R = 1) - [P(G|R = 1)P(G|R = 0)] - P(G|R = 0) + [P(G|R = 1)P(G|R = 0)] \end{aligned}$$

$$\left(P(R = 1|G) - P(R = 1|\neg G) \right) \propto P(G|R = 1) - P(G|R = 0)$$

If we average over all individuals in a population, this relationship can be expressed as a population quantity or estimand. Let there be k voters in the population, then the above relationship can be expressed as:

$$E_k[E(R = 1|G)] - E_k[E(R = 1|\neg G)] \propto E_k[E(G|R = 1)] - E_k[E(G|R = 0)] \quad (9)$$

Where the expectation operator $E_k[\cdot]$ averages over k individuals, and $E(\cdot)$ is one individual's conditional expectation about presidential responsibility or performance. An equivalent way to describe these population means is:

$$\mu_{R|G} - \mu_{R|\neg G} \propto \mu_{G|R=1} - \mu_{G|R=0} \quad (10)$$

F.2 Within-party horse race

This section presents the equivalent of main text Table 3 using only variation within each party.

Table F.1: Treatment effect heterogeneity, Democrats only, experiments 2 and 3.

	Experiment 2 (Trump)				Experiment 3 (Biden)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α Constant	0.407** (0.025)	0.409** (0.032)	0.471** (0.029)	0.479** (0.036)	0.154** (0.010)	0.217** (0.016)	0.152** (0.024)	0.262** (0.035)
β_1 Partisan identity		-0.005 (0.071)		-0.026 (0.070)		-0.213** (0.042)		-0.247** (0.049)
β_2 Competence beliefs			-0.251** (0.042)	-0.253** (0.042)			0.009 (0.031)	-0.054 (0.035)
β_3 Treatment (1 = positive)	-0.059** (0.013)	-0.040 (0.026)	-0.080** (0.016)	-0.060* (0.029)	0.027** (0.006)	0.033** (0.011)	-0.056 (0.032)	-0.069 (0.042)
β_4 Treatment $\times$ partisan ID		-0.095 (0.105)		-0.098 (0.105)		-0.029 (0.050)		0.044 (0.058)
β_5 Treatment $\times$ comp. beliefs			0.136* (0.056)	0.130* (0.056)			0.111** (0.042)	0.121** (0.047)
β_6 Presidential responsibility, wave 1	0.481** (0.031)	0.480** (0.031)	0.447** (0.032)	0.444** (0.033)	0.740** (0.014)	0.699** (0.016)	0.734** (0.014)	0.700** (0.016)
Adj. R ²	0.262	0.262	0.282	0.282	0.570	0.580	0.573	0.581
Num. obs.	1426	1426	1426	1426	2595	2595	2595	2595

Table F.2: Treatment effect heterogeneity, Republicans only, experiments 2 and 3.

	Experiment 2 (Trump)				Experiment 3 (Biden)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α Constant	0.187** (0.019)	0.144 (0.075)	0.396** (0.037)	0.131 (0.068)	0.188** (0.018)	0.018 (0.045)	0.216** (0.021)	-0.010 (0.047)
β_1 Partisan identity		0.064 (0.093)		0.443** (0.093)		0.238** (0.060)		0.316** (0.068)
β_2 Competence beliefs			-0.291** (0.043)	-0.394** (0.047)			-0.029 (0.018)	-0.065** (0.021)
β_3 Treatment (1 = positive)	0.098** (0.014)	-0.039 (0.099)	-0.084* (0.042)	-0.009 (0.093)	-0.040** (0.009)	-0.063 (0.061)	-0.114** (0.017)	0.016 (0.065)
β_4 Treatment $\times$ partisan ID		0.168 (0.120)		-0.130 (0.122)		0.026 (0.074)		-0.172* (0.087)
β_5 Treatment $\times$ comp. beliefs			0.258** (0.059)	0.304** (0.064)			0.170** (0.028)	0.194** (0.032)
β_6 Presidential responsibility, wave 1	0.590** (0.028)	0.572** (0.029)	0.584** (0.027)	0.538** (0.030)	0.745** (0.022)	0.707** (0.025)	0.723** (0.022)	0.696** (0.024)
Adj. R ²	0.366	0.370	0.394	0.412	0.558	0.568	0.573	0.581
Num. obs.	1077	1077	1077	1077	1470	1470	1470	1470

F.3 Selective attribution and the traditional partisan identity scale

Our initial doubts about partisan-motivated reasoning’s ability to explain selective attribution were raised in large part by the traditional 7-point partisan identity scale’s inconsistent relationship to variation in the phenomenon. Experiment 2 included pre-registered tests for this pattern as well as the regression-based horse race. The results of the latter rendered the former redundant; as we explain in the main text, within-party variation in identity strength also fails to predict selective attribution in the horse race. Consequently, we focused on the horse race in the main text and our design for Experiment 3. This section presents our analysis using the traditional scale.

Figure F.1 displays selective attribution separately for three groups: respondents who think of themselves as strong partisans, respondents who think of themselves as partisans but not strongly so (henceforth, weak partisans), and respondents who do not think of themselves as partisans but lean toward one party or the other (henceforth, independent leaners or leaners). This is equivalent to the difference in CATEs described in the main text’s “The Causal Effect of Performance Information” section. For greater comparability, between studies, we estimate the difference between presidential copartisans and the opposing party. In Experiments 1, 1b, and 2, this is $CATE_R - CATE_D$; in Experiment 3, $CATE_D - CATE_R$.

In Experiments 1 and 1b, selective attribution appears to be non-monotonic in strength of partisanship: weak partisans appear to attribute responsibility less selectively than independents leaning toward a party (Figure F.1, left and center-left panels). We pre-registered a test for this pattern in Experiment 2, which focused in particular on the difference between weak partisan identifiers and leaners. We instead find a flat relationship, with no meaningful differences between strong partisans, weak partisans, and independents who lean toward a party. We replicated this pattern again in Experiment 3.

To statistically test for subgroup differences in selective attribution, we use regression. Table F.3 presents results for hypothesis 6 from the Experiment 2 PAP, regarding subgroup differences between leaners and weak partisan identifiers. The reference group is respondents who do not identify with a political party, but lean toward Democrats (“Democrat leaners”). The coefficient of interest, β_7 , suggests that relative to leaners, weak partisan identifiers have an equal or slightly lesser tendency to selectively attribute responsibility. The equivalent coefficient for comparing leaners and strong partisans, β_{12} , provides almost no evidence that strong partisans attribute responsibility more selectively than do leaners.

In sum, our analysis of the traditional party identity scale suggests that strength of partisan identity is a weak and inconsistent predictor of selective attribution. This is consistent with our conclusion in the main text that partisan identity predicts selective attribution primarily due to group differences between Democrats and Republicans, not due to differences in identity strength within the parties.

Figure F.1: Selective attribution by strength of partisan identity.

Note: Each point estimate is the difference in attributions of responsibility. Vertical bars represent 95 percent confidence intervals. For numerical tables and difference-in-means estimates, see the appendix.

Table F.3: Regression test for identity-based differences in selective attribution.

Term	Exp. 1	Exp. 1b	Exp. 2	Exp. 3	Pooled
α Constant	0.684** (0.034)	0.618** (0.032)	0.394** (0.023)	0.180** (0.017)	0.692** (0.028)
β_1 Z	-0.040 (0.057)	-0.115* (0.045)	-0.071** (0.027)	-0.027 (0.021)	-0.057** (0.019)
β_2 Copartisan	-0.184** (0.049)	-0.030 (0.055)	-0.184** (0.028)	-0.043* (0.019)	-0.183** (0.039)
β_3 Weak	-0.036 (0.043)	-0.033 (0.040)	-0.025 (0.023)	-0.002 (0.018)	-0.018 (0.035)
β_9 Strong	0.085* (0.040)	0.020 (0.039)	-0.003 (0.020)	0.046** (0.017)	0.045 (0.034)
β_6 Weak $\times$ Copartisan	0.111 (0.063)	0.025 (0.066)	0.038 (0.037)	0.016 (0.023)	0.055 (0.049)
β_{10} Strong $\times$ Copartisan	0.013 (0.060)	0.062 (0.067)	0.036 (0.034)	-0.007 (0.022)	0.084 (0.047)
β_4 Z $\times$ Copartisan	0.110 (0.075)	0.151* (0.074)	0.149** (0.041)	0.069** (0.027)	0.110** (0.026)
β_5 Z $\times$ Weak	0.025 (0.069)	0.087 (0.057)	-0.032 (0.035)	-0.031 (0.026)	-0.004 (0.024)
β_{11} Z $\times$ Strong	-0.087 (0.066)	-0.027 (0.056)	0.045 (0.033)	-0.015 (0.024)	-0.010 (0.022)
β_7 Z $\times$ Weak $\times$ Copartisan	-0.133 (0.094)	-0.081 (0.092)	0.033 (0.052)	0.004 (0.033)	-0.028 (0.033)
β_{12} Z $\times$ Strong $\times$ Copartisan	0.166 (0.091)	0.048 (0.090)	-0.005 (0.049)	0.003 (0.031)	0.009 (0.031)
β_8 Pre-treatment DV			0.513** (0.022)	0.724** (0.013)	
Survey-specific intercepts	N/A	N/A	N/A	N/A	Yes
Adj. R ²	0.060	0.056	0.357	0.572	0.081
Num. obs.	924	972	2503	4065	8470

F.4 Comparison to traditional partisan identity scale

In this section, we compare the partisan identity and competence beliefs scales examined in the main text to the traditional, 7-point partisan identity scale used in the American National Election Studies and elsewhere. For clarity, we refer to the scale from the main text as the Greene-Huddy scale.

To begin, we report the correlations between the scales. The traditional and Greene-Huddy measures of partisan identity are highly correlated: 0.96 in Experiment 2 and 0.95 in Experiment 3. The traditional scale’s correlation with competence beliefs is weaker: 0.75 in Experiment 2 and 0.48 in Experiment 3. These latter figures are similar to the correlations between the Greene-Huddy scale and the competence belief scales, which we report in the main text.

To take a closer look at the sources of each scale’s similarities and differences to the traditional partisan identity scale, Tables F.4 and F.5 display each scale’s conditional average for each category of partisanship. Both tables show a monotonic relationship between the Greene-Huddy and traditional measures of partisan identity.

By contrast, there is a non-monotonic relationship between competence beliefs and the traditional partisan identity scale; just as in the main text, the non-monotonicity appears in the opposition party. Under Trump, weak Democrats have a more positive view of Trump’s competence than do strong Democrats or Democrat leaners (Table F.4). Under Biden, strong Republicans have a more positive view of Biden’s competence than do weak Republicans or Republican leaners (Table F.5).

Table F.4: Partisan identity and competence scales by traditional party identity scale, Experiment 2.

Party	Identity	N	Partisan social ID		Competence beliefs	
			Mean	Diff.	Mean	Diff.
Democrat	Strong partisan	715	0.130 (0.003)	-0.097 (0.006)	0.149 (0.009)	-0.035 (0.013)
	Weak partisan	462	0.227 (0.005)		0.184 (0.009)	
	Indep. leaner	259	0.334 (0.007)	0.108 (0.008)	0.149 (0.012)	-0.035 (0.015)
Republican	Indep. leaner	216	0.703 (0.008)	-0.071 (0.010)	0.626 (0.018)	-0.011 (0.023)
	Weak partisan	345	0.774 (0.005)		0.637 (0.014)	
	Strong partisan	526	0.898 (0.003)	0.125 (0.006)	0.777 (0.008)	0.140 (0.016)

Note: Table displays respondents' average partisan social identity (middle columns) and competence beliefs (right columns), conditional on the traditional partisan identity scale (left columns). The "mean" column is the group mean. The "diff." column displays the difference from weak partisans. HC2 robust standard errors in parentheses.

Table F.5: Partisan identity and competence scales by traditional party identity scale, Experiment 3.

Party	Identity	N	Partisan social ID		Competence beliefs	
			Mean	Diff.	Mean	Diff.
Democrat	Strong partisan	1536	0.120 (0.002)	-0.109 (0.004)	0.779 (0.004)	0.090 (0.008)
	Weak partisan	698	0.230 (0.004)		0.689 (0.007)	
	Indep. leaner	365	0.305 (0.007)	0.075 (0.008)	0.663 (0.010)	-0.026 (0.012)
Republican	Indep. leaner	338	0.743 (0.008)	-0.031 (0.009)	0.437 (0.018)	0.107 (0.022)
	Weak partisan	386	0.774 (0.005)		0.330 (0.013)	
	Strong partisan	748	0.887 (0.003)	0.114 (0.006)	0.508 (0.013)	0.178 (0.019)

Note: Table duplicates Table F.4, but for Experiment 3.

F.5 Data quality audit of partisan identity and competence scales

In the main text, we report an inverse relationship between Republicans’ partisan identity and perceptions of Biden’s competence: weak identifiers view Biden as incompetent on average, while stronger partisans take a neutral view on average (Figure 6 and surrounding text). This relationship emerges because relative to Republicans with weak partisan identities, those with strong partisan identities are more likely to have neutral or modestly positive views of Biden’s competence (e.g., Biden has no effect or a slightly positive effect on government performance).

Given that this relationship is not anticipated by prevailing accounts of partisan identity, we conducted three of checks to ensure that this relationship was not an artifact of poor data quality. We focus in particular on the possibility that stronger partisans’ neutral perception is actually due to inattention. We begin by briefly considering the relationship between the two scales and other key variables in our survey. These relationships would have been unlikely to realize in the face of substantial inattention. Next, we conduct checks for speeding or straightlining, two response patterns that are commonly associated with inattentive respondents. We find no evidence that the observed relationships are contaminated by these factors.

First, we reexamined the relationship between the two scales and other measures in the survey in light of the concern that poor data quality is afoot. We note in the previous section that the Greene-Huddy partisan identity scale is highly correlated with the traditional seven-point partisan identity scale (0.96 and 0.95). Such high correlations would be unlikely to obtain in the face of substantial inattention. Further, note that the Biden competence scale is strongly predictive of selective attribution. By contrast, inattention tends to weaken treatment effects (because inattentive respondents do not pay attention to treatments). The relationships we report in Table 3 would be unlikely to obtain in the face of substantial inattention.

Second, we examined how response time moderates the relationship between partisan identity and competence beliefs among Republicans. If the relationship were an artifact of poor data quality, we might expect it to be concentrated among respondents who speed through the survey, filling out the scales too quickly to fully comprehend them.

To summarize the relationship between competence beliefs and partisan identity, we subset the Experiment 3 data to Republicans only, then used OLS to estimate

$$\text{Competence belief}_i \sim \alpha + \beta \text{Partisan identity}_i + \epsilon. \quad (11)$$

Here, β is a linear approximation of the relationship between competence beliefs and partisan identity; the puzzle at hand is that whereas conventional wisdom holds that β should be negative, Figure 6 shows that it is positive.

To examine whether this relationship is an artifact of poor data quality, we calculated a series of estimates of β , each based on a different definition of speeding through the questions. To do so, we collected every unique value of response times on the two scales. For each unique

Figure F.2: Relationship between partisan identity and Biden competence scales among Republicans by speeding cutoff.

Note: Figure plots a coefficient estimate of β from Equation 11 (y-axis) against a possible definition of speeding (x-axis). All respondents who completed at least one of the two scales more quickly than the time specified on the x-axis were dropped. Shaded area represents 95 percent confidence intervals based on HC2 robust standard errors. Above the plot, a histogram displays the distribution of response time cutoffs (i.e., the distribution of the x variable).

value x , we dropped all respondents who took less than x seconds to fill out at least one of the two scales. This yielded 2,731 estimates of β . Because 95 percent of respondents responded in 37 seconds or less, we report estimates for all response time cutoffs below 37 seconds.

We find no evidence that the relationship between competence beliefs and partisan identity is an artifact of speeding (Figure F.2). Regardless of the speeding cutoff, the estimate of β is positive and retains approximately the same magnitude. It retains statistical significance until a threshold of 32.4 seconds is imposed, which is the 93rd percentile value (i.e., only 7 percent of the data are retained at this point).

Third, we look for evidence of straightlining, i.e. the practice of selecting the same response option for every item in a scale. This can happen either because this is the best reflection of the respondent's beliefs or because the respondent is going quickly and not really paying attention.

To check for straightlining, Figures F.3 and F.4 display the distributions of the Biden competence and partisan identity scales separately for Democrats and Republicans. Respondents who may have straightlined (i.e., who chose the same response for every scale item) are high-

lighted in grey. highlighted in grey. Two features of the distributions suggest an absence of straightlining. First, there are no noticeable spikes at the scale scores that can be afflicted by straightlining. If anything, removing possible instances of straightlining would create more discontinuous distributions. Second, the possibly straightlined responses does not contribute disproportionately to conflicts between competence beliefs and partisan identity. For example, Republicans who give Biden the worst possible rating make up the largest group of possible straightliners. Meanwhile, almost no Republicans give Biden the best possible rating, which one would expect if positive Republican perceptions of Biden’s competence were in fact artifacts of straightlining.

Figure F.3: Distribution of Biden competence scale, Experiment 3.

Figure F.4: Distribution of partisan identity scale, Experiment 3.

Note: Figures display the distributions of the Biden competence (F.3) and partisan identity (F.4) scales. Grey shading represents respondents who chose the same scale point for each scale item (i.e., possible straightliners).

G Survey Text

The following pages contain the survey treatments, outcome measures, and relevant covariates used in the paper.

Measures and Treatments

Experiment 1

Treatments

Introduction

On each of the next four pages, you will read a short informational message about the coronavirus / COVID-19 pandemic in the United States, then answer a question about each one.

Please read the messages carefully. On each page, the "next" button will appear after 10 seconds.

Cases

If $z = \text{Negative}$

Outside of New York City, the number of new cases of COVID-19 reported each day has continued to rise despite the continuing shortage of tests. Experts expect the virus to spread even faster now that many states have begun to reopen.

This chart shows the number of new cases per day in the whole United States, excluding the New York City metro area.

If z = Positive

Over the past several weeks, the number of new cases of COVID-19 reported each day in the United States has steadily declined despite increases in testing capacity. According to the CDC, the number new cases reported on May 11 was the lowest number since March.

This chart shows the number of new cases per day in the whole United States.

(Both) Given this, would you say the U.S. is doing a good job or a bad job of controlling the spread of COVID-19?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

Testing Capacity

If z = Positive

Since the start of the pandemic, the U.S. has dramatically increased its capacity to test for COVID-19. So far, the U.S. has tested about 9 million people for COVID-19, more than any other country in the world.

If z = Negative

Since the start of the pandemic, the U.S. has struggled to increase its capacity to test for COVID-19. So far, the U.S. has tested about 9 million people for COVID-19, which is less than 3 percent of the country's population.

(Both): Given this, would you say the U.S. is doing a good job or a bad job of testing for COVID-19?

- Very bad (1)

- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

Deaths

If z = Positive

So far during the coronavirus outbreak, the United States has had 179 deaths for every million people living in the country. This is much lower than many other countries, including France, Spain, and the United Kingdom.

If z = Negative

More than 85,000 people have died of COVID-19 in the United States, the most of any country in the world. Though the U.S. has a large population, it also has a large number of deaths per person. According to some estimates, the U.S. death rate is five times the global average.

(Both) Given this, would you say the U.S. is doing a good job or a bad job of limiting the number of deaths from COVID-19?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

COVID-19 Treatments

If z = Positive

The United States has taken important steps to improve its capacity to treat patients with COVID-19. In a recent clinical trial, the anti-viral drug remdesivir helped shorten the recovery time for people who were seriously ill. The outbreak has slowed enough that the U.S. has been able to send medical equipment and other assistance to other countries to help with their outbreaks.

If z = Negative

The United States has struggled to increase its capacity to treat patients with COVID-19. In a recent clinical trial, the anti-viral drug remdesivir did not improve patient survival rates. The outbreak has overwhelmed the medical system, forcing the U.S. to accept assistance from other countries to meet its needs for protective equipment for health care workers.

(Both) Given this, would you say the U.S. is doing a good job or a bad job of improving the health care system's ability to care for COVID-19 patients?

- Very bad (1)
- Fairly bad (2)

- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

Outcomes

1. All things considered, would you say the U.S. is doing a good job or a bad job of handling the outbreak of COVID-19?
 - Very bad (1)
 - Fairly bad (2)
 - Neither good nor bad (3)
 - Fairly good (4)
 - Very good (5)
2. Many people have a role to play in the fight against the pandemic, from ordinary people to leaders in communities, business, and government.
Who would you say is most responsible for the United States' performance in the fight against COVID-19? Please write a sentence or two. (Open-ended)
3. How responsible is President Trump for the United States' performance in the fight against COVID-19?
 - Not at all responsible (1)
 - A little responsible (2)
 - Somewhat responsible (3)
 - Mostly responsible (4)
 - Fully responsible (5)

Experiment 1B

Treatments

Introduction

On each of the next three pages, you will read a short informational message about the Centers for Disease Control and Prevention (CDC), then answer a question about each message.

Please read the messages carefully. On each page, the "next" button will appear after 10 seconds.

CDC Budget

If z = responsible

The President influences the activities and priorities of the CDC through his annual budget proposal. The President's budget specifies how much money should go to each of CDC's programs and directorates. Each year during his term, President Trump's budget has included over a dozen major changes to the CDC's budget.

If z = not_responsible

The President has little influence over the activities and priorities of the CDC. Though the President submits an annual budget proposal, this is regarded as a political document that has little influence over Congress' final decision. Each year during his term, President Trump has proposed substantial cuts to the CDC's budget, but Congress mostly rejected these proposals.

(Both) Given this, how responsible would you say the President is for how the CDC spends its money?

- Not at all responsible (1)
- A little responsible (2)
- Somewhat responsible (3)
- Mostly responsible (4)
- Fully responsible (5)

Staffing

If z = responsible

The President's appointment power gives him a lot of influence over the CDC. The President has the power to appoint political allies to the CDC's 25 leadership positions. This includes Director of the CDC, Robert Redfield, as well as top leaders in the Office of Public Health Preparedness and Response, the Office of Infectious Diseases, and the Center for Global Health.

If z = not_responsible

The President does not exercise much control over the CDC's staffing. The vast majority of CDC employees, who make crucial decisions, are career civil servants not

selected by the President. Even the current director of the CDC, Robert Redfield, was not directly appointed by the President. He was chosen by the Secretary of Health and Human Services, Alex Azar.

(Both) Given this, how responsible would you say the President is for the quality of leadership at the CDC?

- Not at all responsible (1)
- A little responsible (2)
- Somewhat responsible (3)
- Mostly responsible (4)
- Fully responsible (5)

Coordination with White House

If z = responsible

During the outbreak of COVID-19, the White House and the CDC have worked together to combat the virus. President Trump made the CDC director, Robert Redfield, one of the highest-ranking leaders serving on the White House Coronavirus Task Force. As the U.S. moved to reopen its economy, the CDC and the White House jointly developed guidelines for schools, businesses, and state governments.

If z = not_responsible

During the COVID-19 outbreak, the White House and the CDC have largely worked separately to combat the virus. The CDC director, Robert Redfield, plays a minor role on the White House Coronavirus Task Force. As the U.S. moved to reopen its economy, the CDC and the White House separately developed their own guidelines for schools, businesses, and state governments.

(Both) Given this, how responsible would you say the President is for the CDC's strategies for fighting the COVID-19 outbreak?

- Not at all responsible (1)
- A little responsible (2)
- Somewhat responsible (3)
- Mostly responsible (4)
- Fully responsible (5)

Outcomes

1. All things considered, how responsible is President Trump for the CDC's performance in the fight against COVID-19?

- Not at all responsible (1)
- A little responsible (2)
- Somewhat responsible (3)
- Mostly responsible (4)

- Fully responsible (5)
2. How good or bad of a job has the CDC done in the fight against COVID-19?
- Very bad (1)
 - Fairly bad (2)
 - Neither good nor bad (3)
 - Fairly good (4)
 - Very good (5)

Experiment 2

Covariates

1. Social Partisanship: Do you agree or disagree with the following statements?

a) When I talk about [Republicans / Democrats], I say "we" rather than "they."

b) I think of myself as a [Republican / Democrat].

c) Being a [Republican / Democrat] is important to me.

- Strongly disagree (1)
- Disagree (2)
- Neither agree nor disagree (3)
- Agree (4)
- Strongly agree (5)

2. Performance beliefs

a) What effect would you say President Trump has on the government's ability to solve problems?

- Completely negative (1)
- Mostly negative (2)
- Neither negative nor positive (3)
- Mostly positive (4)
- Completely positive (5)

b) When President Trump is running the government, do you expect government performance to get better or worse?

- Definitely worse (1)
- Probably worse (2)
- Makes no difference (3)
- Probably better (4)
- Definitely better (5)

c) Who would you say is more competent: Democratic presidential candidate Joe Biden or Republican presidential candidate Donald Trump?

- Definitely Trump (1)
- Probably Trump (2)
- Equally competent (3)
- Probably Biden (4)
- Definitely Biden (5)

Treatments

On each of the next four pages, you will read a short informational message about the coronavirus / COVID-19 pandemic in the United States, then answer a question about each one.

Please read the messages carefully. On each page, the "next" button will appear after 10 seconds.

Cases

If z = Positive

Few countries have managed to control the spread of COVID-19. In fact, many countries that seemed to be doing better than the U.S. at first have seen rapid increases in case counts in recent weeks.

The graphic below shows that COVID-19 is now spreading faster in France, Spain, and the United Kingdom than it is in the U.S. On average over the past seven days, the U.S. reported 169 new cases per million people, compared with 355 new cases per million in France, 231 per million in Spain, and 250 per million in the United Kingdom.

If z = Negative

Because the United States did not manage to control the spread of COVID-19 in the spring and summer, it is seeing a larger surge in the fall than in many other countries.

On Friday and Saturday, the U.S. recorded more than 83,000 new cases, the highest single-day totals so far during the pandemic.

The graphic below shows that in Australia and Germany, the number of new cases per person has consistently been lower than in the U.S. On average over the past seven days, the U.S. reported more than twice as many cases per person as Germany, more than 100 times as many cases per person as Australia, and more than four times as many cases per person as the average country worldwide.

(Both) Given this, would you say the U.S. is doing a good job or a bad job of controlling the spread of COVID-19?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

Testing Capacity

If z = Positive

Since the start of the pandemic, the United States has dramatically increased its capacity to test for COVID-19. So far, the U.S. has conducted about 132 million tests,

more than any other country in the world. In the past week, the U.S. conducted over 1 million tests per day.

If z = Negative

Since the start of the pandemic, the United States has failed to increase testing capacity as quickly as the virus has spread. According to researchers at the Harvard Global Health Institute, the U.S. only conducts a bit more than half of the 1.9 million daily tests it would need to help reduce the spread of the virus. Only eight U.S. states have met their testing targets.

(Both) Given this, would you say the U.S. is doing a good job or a bad job of testing for COVID-19?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

Death Count

If z = Positive

So far during the pandemic, the United States has had 67 confirmed deaths from COVID-19 for every 100,000 people living in the country. This is lower than many other countries that are doing less testing than the U.S., including Belgium, Brazil, Mexico, and Spain.

If z = Negative

More than 220,000 people have died of COVID-19 in the United States, the most of any country in the world. Though the U.S. has a large population, it also has a large number of deaths per person. According to some estimates, the U.S. death rate is four times the global average.

(Both) Given this, would you say the U.S. is doing a good job or a bad job of limiting the number of deaths from COVID-19?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

COVID-19 Treatments

If z = Positive

Since the beginning of the pandemic, the United States has made significant progress on treating COVID-19. Over the summer, remdesvir and dexamethasone became

available as treatments for COVID-19 patients. These treatments reduce death rates substantially.

Meanwhile, the U.S. and other countries are developing vaccines at an unprecedented pace. Just seven months into the pandemic, four American vaccines have advanced to phase three trials, which is the final stage of testing before approval.

If z = Negative

The U.S. is not playing a leading role in the global effort to develop treatments and vaccines for COVID-19. The U.S. has not joined COVAX, a global partnership between 164 countries that is working to develop and distribute a vaccine to all of its members.

The U.S. effort to develop a vaccine is lagging behind the global effort. Of the eleven vaccines that have reached phase three trials, the final step before regulators approve their use, only three are American. There are four Chinese vaccines and one Russian vaccine that are in phase 3 trials and approved for early use.

(Both) Given this, would you say the U.S. is doing a good job or a bad job of developing treatments and vaccines for COVID-19?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

Outcomes

1. All things considered, would you say the U.S. is doing a good job or a bad job of handling the COVID-19 pandemic?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

2. How responsible is President Trump for the United States' performance in the fight against COVID-19?

- Not at all responsible (1)
- A little responsible (2)
- Somewhat responsible (3)
- Mostly responsible (4)
- Fully responsible (5)

3. In the November 3 election for President of the United States, which candidate do you prefer?

- Donald Trump (Republican) (1)
- Joe Biden (Democrat) (2)
- Other (3)
- Not sure (4)

Experiment 3

Covariates

1. Social Partisanship: Do you agree or disagree with the following statements?

a) When I talk about [Republicans / Democrats], I say "we" rather than "they."

b) I think of myself as a [Republican / Democrat].

c) Being a [Republican / Democrat] is important to me.

- Strongly disagree (1)
- Disagree (2)
- Neither agree nor disagree (3)
- Agree (4)
- Strongly agree (5)

2. Performance beliefs

a) What effect would you say President Biden has on the government's ability to solve problems?

- Completely negative (1)
- Mostly negative (2)
- Neither negative nor positive (3)
- Mostly positive (4)
- Completely positive (5)

b) When President Biden is running the government, do you expect government performance to get better or worse?

- Definitely worse (1)
- Probably worse (2)
- Makes no difference (3)
- Probably better (4)
- Definitely better (5)

c) Who would you say is more competent: President Biden or former President Trump?

- Definitely Trump (1)
- Probably Trump (2)
- Equally competent (3)
- Probably Biden (4)
- Definitely Biden (5)

Performance Treatments

COVID-19 Cases

If Z = Positive

So far in 2021 the United States has done a better job of controlling the spread of COVID-19 than many countries. For example, the United Kingdom recently surpassed its all-time record number of COVID-19 cases in a single day.

The plot below shows that the United States is currently experiencing fewer COVID-19 cases per million people than European countries like France, Spain and the United Kingdom. On average over the past seven days, the U.S. reported 549 new cases per million people, compared with 907 new cases per million in France, 904 per million in Spain, and 1411 per million in the United Kingdom.

Source: Our World in Data.

If Z= Negative

The United States is currently seeing one of the largest surges of new COVID-19 cases in the world. On December 28, the U.S. recorded 267,000 new cases, which is its highest single-day total so far during the pandemic.

The plot below shows that the United States is has consistently seen far more COVID-19 cases per million people than most other countries around the world. On average

over the past seven days, the U.S. reported 549 new cases per million people, compared with 94 per million in the world as a whole.

Source: Our World in Data.

(Both): Given this, would you say the U.S. is doing a good job or a bad job of controlling the spread of COVID-19?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

COVID-19 Treatments and Testing Capacity

If Z = Positive

COVID-19 has become less of a threat in the United States due to the widespread availability of protective equipment, testing, and effective treatments. Initially, even doctors and nurses had trouble finding masks. Now, front-line workers and ordinary people have easy access to protective equipment. Meanwhile, new treatments have been developed that are highly effective at preventing severe illness and death among people who already have COVID-19.

If Z= Negative

The United States still suffers from critical shortfalls in COVID-19 testing, protective equipment, and treatment. In Europe, rapid tests are abundant and are either free or

cheap. In the United States, rapid tests are more expensive and harder to obtain. Meanwhile, hospitals all over the country are suffering from shortages of nurses and critical supplies like oxygen, making it harder to prevent severe illness and death among people who already have COVID-19.

(Both): Given this, would you say the U.S. is doing a good job or a bad job of handling new COVID-19 cases once they emerge?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

COVID-19 Deaths and Severe Illness

If Z = Positive

Although the United States has experienced about 800,000 deaths from COVID-19, the death rate does not seem as high after accounting for the country's large population. For example, current daily death rate in Europe is 4.35 deaths per million people, compared with 4.27 deaths per million people in the United States.

If Z= Negative

Little progress has been made in slowing the COVID-19 death toll. In fact, more Americans died of COVID-19 in 2021 than in 2020. In total, about 800,000 Americans have died of COVID-19, equal to 1 out of every 300 people in the country. Currently, more than 1,000 additional Americans are dying of COVID-19 every day.

(Both): Given this, would you say the U.S. is doing a good job or a bad job of limiting the number of deaths from COVID-19?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

COVID-19 Variants

If Z= Positive

Many experts believe that viruses tend to become less deadly over time. Early data on the new Omicron variant suggests that this is happening to COVID-19. Although Omicron has rapidly become the dominant COVID-19 variant in many places around the

world, early data suggest that people who are infected with the new variant are much less likely to become seriously ill.

If Z= Negative

Efforts to fight COVID-19 have been undermined by new variants. The new Omicron variant has an alarming number of mutations relative to the original version of COVID-19. Omicron spreads faster and vaccines are less effective against it. Experts worry that the virus may continue to mutate too quickly for us to successfully reduce its spread.

(Both): Given this, would you say that the emergence of the Omicron variant is good news or bad news?

- Very bad (1)
- Fairly bad (2)
- Neither good nor bad (3)
- Fairly good (4)
- Very good (5)

Accuracy Treatments

If Z = Receive Accuracy Prime

In the last part of the survey, you will answer two more questions about the outbreak of coronavirus / COVID-19.

When thinking about your opinion, please try to view the questions in an evenhanded way and from various perspectives. We will later ask that you justify the reasons for your responses.

If Z = Not Receive Accuracy Prime

control In the last part of the survey, you will answer two more questions about the outbreak of coronavirus / COVID-19.

(Both):

You said that the United States is doing a (respondent's response) job of handling the COVID-19 pandemic. Why?

You said that President Biden is (respondent's response) for the country's performance. Why?

Outcomes

1. All things considered, would you say the U.S. is doing a good job or a bad job of handling the COVID-19 pandemic?
 - Very bad (1)
 - Fairly bad (2)
 - Neither good nor bad (3)
 - Fairly good (4)
 - Very good (5)

2. How responsible is President Biden for the United States' performance in the fight against COVID-19?
 - Not at all responsible (1)
 - A little responsible (2)
 - Somewhat responsible (3)
 - Mostly responsible (4)
 - Fully responsible (5)