Hindsight bias and trust in government: Evidence from the United States*

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Abstract

We show experimentally that people systematically misremember their own past policy preference about how to fight Covid-19 best. At the peak of the first wave in the United States, the average participant wrongly thinks they already supported stricter restrictions at the onset of the first wave — but they did not. The larger this memory distortion, referred to as hindsight bias, the stronger a participant's reduction in trust in government. Our experimental design allows us to demonstrate that this relationship is indeed causal. Consistent with theory, we find that hindsight bias distorts ex post evaluations of others.

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1 Introduction

Hindsight bias —also known as the "I-knew-it-all-along" effect— describes peoples' tendency to believe ex-post that an outcome or event was evident from the very beginning (Fischhoff, 1975). This well-documented bias exists across various domains and populations (including experts) (see e.g. Pohl, Bayen, Arnold, Auer, & Martin, 2018; Harley, 2007). Psychologists have extensively studied the existence and robustness of the phenomenon in the laboratory (see, e.g., the meta-analysis by Guilbault, Bryant, Brockway, & Posavac, 2004), but there are also several studies documenting its presence in field settings (Fischhoff & Beyth, 1975; Leary, 1982; Bryant & Brockway, 1997; Bryant & Guilbault, 2002; Biais & Weber, 2009; Danz, Kübler, Mechtenberg, & Schmid, 2015).

Our study adds two novel insights. First, we provide evidence for the existence of hindsight bias in a new and very significant context: the Covid-19[1] pandemic. Second, and potentially more importantly, we demonstrate that the presence of this memory distortion has relevant real-life consequences, because it undermines trust in government.

Our analysis is based on an original data set that we collected in the early phase of the pandemic. On March 15, 2020, at the onset of the Covid-19 outbreak in the United States[2], we conducted the first stage of an online survey in which we elicited respondents' preferences for possible policies with different degrees of restrictiveness to fight the pandemic at this point in time. A month later, in mid-April 2020, when the pandemic was at the peak of the first wave,[3] we launched the second stage of the survey — using the same group of respondents — and used an incentivized procedure to elicit whether respondents correctly remembered their policy preferences stated one month earlier. In addition to these *recalled* past preferences, we also collected participants' *updated* preferences, that is, their retrospective view in mid-April about the right level of restrictive policies that the government should have implemented on March 15. Our data therefore not only provide us with an individual measure of hindsight bias regarding the preferred government policy, but also an individual measure of the actual change of preferences over time.

We find that participants' memory is indeed systematically biased. On March 15, when we elicited participants *original* preference, the mean of our restrictiveness index was 0.6. A month later, when we asked participants to state their *recalled* preference, they (wrongly) believed to

[1] We use the terms Covid-19 and coronavirus interchangeably, well aware that Covid-19 refers to the disease and coronavirus to the virus, see https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it.

[2] There were 3600 confirmed cases and 68 confirmed deaths as of March 15, 2020. All reported case and death numbers in this article are obtained from The New York Times Company (2020) data set.

[3] Cumulative deaths exhibited a 420-fold increase compared to the situation one months earlier. There were 637,056 confirmed cases and 28,582 confirmed deaths as of April 15, 2020.

remember that on March 15, they would have preferred to implement policies reflecting a restrictiveness index of 0.7. This difference between the original preference and the recalled preference is highly significant concerning both the mean and the distribution. We further find that participants' recalled preference is highly skewed towards their current *updated* preference.

The presence of hindsight bias suggests that our respondents systematically underestimate how difficult it was to foresee the severity of the crisis when it started. As a consequence, these respondents might evaluate the government's past measures more negatively than is justified, because they incorrectly believe that they supported stricter policies all along and think that government "should have known better". To empirically assess the potential impact of hindsight bias on evaluations of the government, we elicited participants' self-reported trust in government both on March 15 and a month later.[4] These data allows us to identify the change in trust in government across the two stages of our data collection period at the individual level.

Our data reveal a significant negative correlation between hindsight bias and the change in trust in government, that is, respondents who exhibit a strong hindsight bias also tend to experience a decrease in trust in government. However, our experimental design allows us to go beyond correlational evidence and explore whether there also is a *causal* effect. In the second stage of our survey (taking place on April 15), participants were randomly assigned to two groups. Participants in the first group were first asked to indicate their updated preference (the policies they think should have been implemented on March 15 given their knowledge on April 15) before being incentivized to recall their original preference as expressed on March 15 (we labeled this first group "UPDATED FIRST"). Participants in the second group, in contrast, answered the question in the reversed order (recalled preference *before* updated preference, we therefore label this second group "RECALLED FIRST"). The random assignment to these two groups is helpful because research in psychology shows that explicitly formed outcome knowledge (the updated preference) renders existing memory traces less accessible and serves as a reference point when reconstructing the original preference from memory (see e.g. Hell, Gigerenzer, Gauggel, Mall, & Müller, 1988; Stahlberg & Maass, 1997; Schwarz & Stahlberg, 2003). Thus, first reflecting on the updated preference is predicted to increase hindsight bias, because it is expected to shift the recalled preference closer to the updated preference. This hypothesis is confirmed by our data. We observe that that respondents in UPDATED FIRST exhibit on average a 36.8% larger hindsight bias than those in RECALLED FIRST. This exogenously induced variation allows us to use our treatments as instruments for hindsignt bias. The instrumental variable estimation confirms that hindsight bias causally and significantly reduces trust in government. In standardized terms, a one standard deviation increase in hindsight bias

[4]In both survey stages, the elicitation of trust in government followed after the preference elicitation.

leads to a sizeable decrease of trust in government by .63 standard deviations.

Aside from adding another relevant real-world example to the literature on hindsight bias, our findings also provide support for the theoretical argument that hindsight-biased principals inappropriately assess the performance of agents (Camerer, Loewenstein, & Weber, 1989; Frey & Eichenberger, 1991; Madarász, 2011; Schuett & Wagner, 2011): in ex-post evaluations, distorted memories induce hindsight-biased principals may evaluate agents too harshly and may systematically underestimate their performance. To the best of our knowledge, the only existing empirical studies on this topic so far are laboratory experiments demonstrating that hindsight bias correlates with sub-optimally low delegation rates (Danz et al., 2015) and that hindsight bias causally drives excess entry in tournaments (Danz, 2020). Our work is the first to provide direct field evidence for the link between hindsight bias and inefficient evaluations of agents.

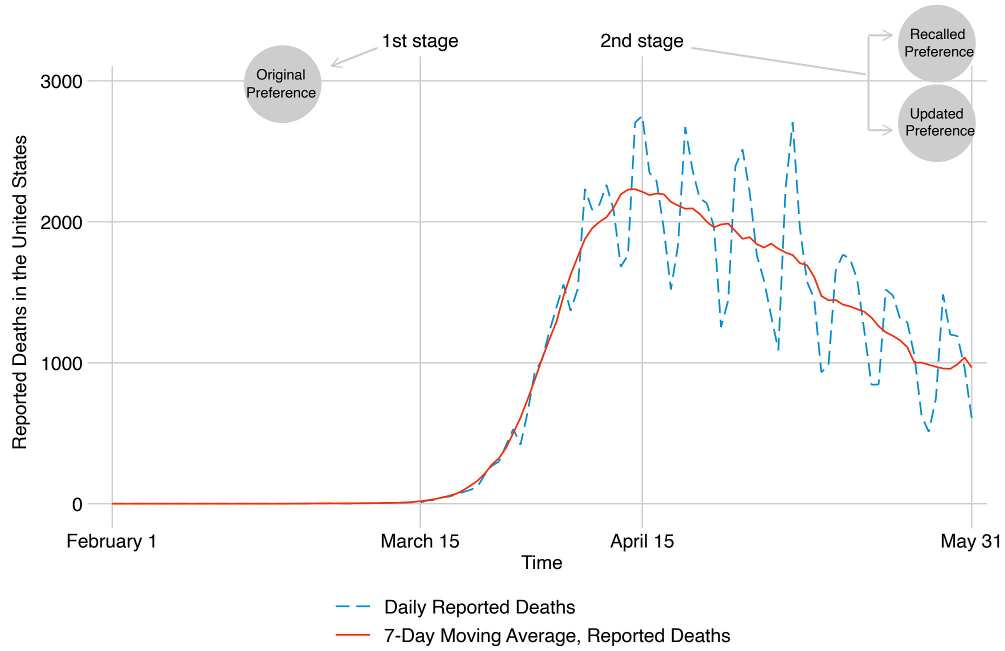
Our results also contribute new insights to the broad literature on trust in general and trust in government in particular. Trust has been shown to be a causal driver of economic growth (Algan & Cahuc, 2010; Knack & Keefer, 1997) and to promote performance in large organizations as well as the government (LaPorta, de Silanes, Shleifer, & Vishny, 1997; Knack, 2002). Strong institutions are central for economic growth, and trust in government is a crucial ingredient for a strong state (Acemoglu, 2005). A growing literature suggests that trust is one of the leading causes of economic development and responsible for the large differences in income per capita across countries (for a review see Algan & Cahuc, 2014). A lack of trust in government constitutes a major problem for a country, jeopardizing the state's legitimacy. This is why trustworthy institutions are argued to be a requirement for democracy to work (see, e.g., Acemoglu, Cheema, Khwaja, & Robinson, 2020; Fukuyama, 1995; Putnam, Leonardi, & Nanetti, 1993). Directly related to our work, the literature documents that during the Covid-19 pandemic trust in government determines citizens' compliance with public health policies (Bargain & Aminjonov, 2020) as well as vaccine acceptance (Lazarus et al., 2021). Hence, investigating the causal fundamentals of trust is of key importance, and examining potential modifications of trust by virtue of biased memories is a novel research avenue.

2 Research Design

2.1 The experiment

We conducted the online experiment during the first wave of the Covid-19 outbreak in the United States and employed a two-stage design to allow for memory imperfections, displayed in Figure 1.

Figure 1: Covid-19 deaths in the United States from February to May 2020 and the experimental timeline



Note: The graph displays the reported Covid-19 deaths in the United States on the y-axis, plotted against the timeline (February 1, 2020 to May 31, 2020). The red solid line plots the 7-day moving average while the blue dashed line plots the daily reported deaths.

The first stage was conducted on March 15, 2020. The Covid-19 outbreak in the United States was in its early days with only 3600 confirmed cases and 68 confirmed deaths. We elicited participants' preference about how to best fight the pandemic by surveying participants regarding the extent of restrictions they would want to implement on that day. We did so for four different policy dimensions: travel restrictions, social distancing restrictions in affected states, social distancing restrictions nationwide and lastly, restrictions in relation to the measures taken by the federal government and in place as of March 15. For each policy dimension, we confronted participants with a set of possible policy choices that varied in their degree of restrictiveness, see Table 1. We refer to the chosen policies on March 15 as the Original Preference.

A month later, from April 13 to April 16[5], we conducted the second stage and invited all participants to take part in a follow-up survey. As of April 15, the United States reported 637,056 confirmed cases and 28,582 deaths. The pandemic was full-on in its first wave, see Figure 1. The second survey allows us to identify whether participants correctly remember their past policy preference expressed a month ago.

To elicit this Recalled Preference, we incentivized participants to reveal their true recall of

[5]In the following, for simplicity, we will refer to April 15 when talking about the second stage. Note that the two elicited preferences in the second stage, the Updated Preference and the Recalled Preference, do not statistically significantly differ among the days of elicitation. This is true for all four policy dimensions.

Table 1: Survey questions eliciting participants belief about the appropriate extent of restrictions to implement

Policy Dimension	Question	Choices
Social distancing affected States	Please choose the policy that should, according to your opinion, now be implemented in states with 300 or more cases (currently: Washington State, California, New York State).	1 No social distancing restrictions 2 Prohibiting events with more than 250 people 3 Prohibiting events with more than 50 people 4 Closing all schools and childcare facilities 5 Close all non-indispensable businesses to the public 6 Statewide lockdown with mandatory self-confinement
Social distancing nationwide	Please choose the policy that should, according to your opinion, now be implemented in the entire United States (nationwide)	Same choice options as above (nationwide)
Travel restrictions	Please choose the policy that should, according to your opinion, now be implemented in the United States.	1 No travel restrictions 2 Requesting all travelers arriving from China or Europe to self-quarantine for 14 days 3 Requesting all arriving international travelers to self-quarantine for 14 days 4 Banning flights between the U.S. & Europe and the U.S. & China 5 Close borders to end all international travel 6 Ban all interstate travel from & to all states with more than 300 confirmed infected cases 7 Ban all interstate travel
Approval of U.S. Govt. Actions	Do you think that the actions taken by the U.S. government regarding the Coronavirus pandemic as of March 14th are...?	Likert scale (7-point), with 1=far too restrictive and 7=far too unrestrictive

Note: The table displays the four survey questions that elicit participants' belief about the appropriate extent of Covid-19 restrictions to implement. Policies were ordered from least to most restrictive, and it was made clear to the participants that the more restrictive policies always also include the proposed less restrictive policies.

what they told us a month before. Participants were confronted with the very same choice options as four weeks earlier. We paid a bonus of 25 cents for a correct recall.[6]

A unique feature of our study is that participants received real world feedback during this month. Participants likely acquired new knowledge about the Covid-19 disease and the pandemic in general. Consequently, if participants could go back in time and take the current knowledge with them, they may have chosen another option on March 15. That is why we also elicited participants' Updated Preference, that is their current view in mid-April about the extent of restrictions that should have been implemented on March 15, 2020.[7] This Updated Preference represents each individuals subjective true state of the world of what should have been done on March 15, expressed in retrospect in mid-April.

Our first hypothesis puts forward the existence of hindsight bias during the outbreak of Covid-19 in the United States. Hindsight bias is the systematic tendency to misremember

[6]Participants were instructed as follows. "On March 15th, we asked you about the policy that you thought should be implemented at that time. Please try to remember the policy that you thought should be implemented at that time. For every correct recall, you will receive a bonus payment of 25 cents."

[7]We asked participants on April 15: "As of today, please select the policy that you think should have been implemented 4 weeks ago."

past knowledge or past beliefs: People's recollection of past views of the world ought to be systematically skewed towards their current view (Fischhoff, 1975).

Hypothesis 1 (Existence of hindsight bias)**.** *Participants systematically misremember their Original Preference on how to fight Covid-19 best. Their Recalled Preference is biased towards their Updated Preference.*

For the measurement and detection of hindsight bias, the literature suggests a proximity index (Pohl, 2007). Hindsight bias is defined as when the Recalled Preference is closer to the Updated Preference than the Original Preference is. Thus, for hindsight bias to exist, the distance between Recalled Preference and Updated Preference must be smaller than the distance between the Original Preference and Updated Preference. The index is computed for each participant (separately for each policy dimension and then averaged across the four dimensions) with the normalized values[8] of the choices displayed in Table 1 as follows:

$$HB_i = |\text{Original Preference}_i - \text{Updated Preference}_i| - |\text{Recalled Preference}_i - \text{Updated Preference}_i| \tag{1}$$

The index can take on values ranging from -1 to 1. A value of 0 represents a participant with no systematic memory distortion. Values above 0 indicate hindsight bias because participants' Recalled Preference is closer to the current Updated Preference than the true Original Preference is.[9] Negative values indicate the opposite of hindsight bias, sometimes referred to as reverse hindsight bias. There is hindsight bias among our sample if the mean of the index is larger than zero. The existence of hindsight bias is a necessary condition in order to investigate the second research question.

Our second hypothesis posits that hindsight bias reduces trust in government.[10] Already three decades ago, economists suggested that hindsight bias on the principal's side may lead to distorted evaluations of agents (Camerer et al., 1989; Frey & Eichenberger, 1991). The model

[8]The scales of the four policy dimensions are min-max normalized to a range between 0 and 1, with 0 representing the least restrictive policy and 1 representing the most restrictive policy.

[9]The proximity index is a conservative measure of hindsight bias. When the Recalled Preference is larger than the Updated Preference, hindsight bias decreases again compared to when the Recalled Preference equals the Updated Preference. In Appendix B.5, we report all results when measuring hindsight bias with the less-conservative shift index that simply takes into account the distance between Original and Recalled Preference. Results are qualitatively very similar.

[10]We measured participants' trust in government on March 15 and a month later and thus can assess the change in trust in government at the individual level. Specifically, we asked participants: How much of the time do you think you can trust the federal government to do what is right? Answer options were: Always, A lot of the time, Not very often, Almost never.

of Madarász (2011) formally introduces this evaluation distortion: Hindsight-biased evaluators wrongly think that ex post, information was already available ex ante.[11] The evaluating principal projects this ex post information on the decision of the agent, which was taken with ex ante information only. The agent is evaluated too harshly since at the time of decision-making, the agent had access only to ex ante but not ex post information. As a result, hindsight-biased principals will underestimate the quality of agents on average.

Applied to our setting, we hypothesize that hindsight-biased participants will wrongly remember in April 2020 that they were supporting stricter measures already at the onset of the pandemic in March. Comparing their own (wrong) recall of what they would have done as of March 15 with what the decision-maker actually did as of March 15, biased participants are surprised by the bad decision-quality of the agent. Therefore, hindsight-biased participants will be more punitive with the government, compared to participants who do not suffer from this memory distortion.

Hypothesis 2 (Distortion in ex post evaluations)**.** *Hindsight bias causally decreases trust in government.*

Importantly, in the second survey conducted on April 15, we implemented an exogenous between-subject manipulation. The order of elicitation of the Recalled Preference and the Updated Preference was randomized by the computer. Participants in the group RECALLED FIRST were first asked about their Recalled Preference and then about their Updated Preference. For participants in the UPDATED FIRST group, the order of preference elicitation was reversed. This randomization ought to create exogenous variation in the amount of hindsight bias: Research in psychology suggests that participants in the UPDATED FIRST group should exhibit a stronger hindsight bias compared to the RECALLED FIRST group (Fischhoff, 1975). This is because the explicitly formed outcome knowledge, in our case the Updated Preference, immediately renders existing memory traces less accessible and serves as a reference point when reconstructing the Original Preference from memory (see e.g. Hell et al., 1988; Stahlberg & Maass, 1997; Schwarz & Stahlberg, 2003). The exogenous variation in the magnitude of hindsight bias allows us to detect a causal effect. We thus hypothesize that hindsight bias *causally* decreases trust in government.

2.2 Procedures and Sample

The experiment was conducted on Amazon Mechanical Turk ("AMT") with the software oTree (Chen, Schonger, & Wickens, 2016). Only individuals residing in the United States were allowed

[11] See also Schuett and Wagner (2011), who also provide a formal but less generalizable model.

to participate. To ensure data quality and prevent robots, we further required for survey participation an approval rate of at least 95% for past jobs as well as a minimum of 500 completed jobs.

Participants received USD 1 for completing the first stage. The average completion time was approx. 5 minutes, resulting in an average hourly pay of approx. USD 12. For the second experimental stage, participants were paid a fixed reward of USD 1.50. The 50% increase in the reward compared to stage 1 was implemented to achieve a high retention rate. In addition, participants received a variable bonus payment of 25 cents for each correct recall of the Original Preference regarding the four policy dimensions expressed in March. Average completion time in stage 2 was approx. 6 minutes. Together with the variable compensation, this yields an average hourly compensation of approx. USD 18.90.

1027 participants completed the survey on March 15. Of those, 813 participants completed the follow-up survey a month later, yielding a retention rate of roughly 79% — a very similar rate as for example in Kuziemko, Norton, Saez, and Stantcheva (2015). Therefore, 214 participants dropped out. The attrition seems to be random with regard to the outcome variables. We do not observe significant differences at or above the 90%-level neither for the Original Preference for all of the four policy dimensions, nor for expressed trust in government (see Table 4 in the Appendix). We further fail to reject the null that the experimental group assignment is not related to dropping out at or above the 90%-level. Refer to the Appendix for a more detailed analysis. Out of the 813 participants who completed both stages, we excluded 8 participants from the data set due to irregular, non-matching responses with regard to demographic characteristics (those were elicited in both survey stages to check consistency). Therefore, the final sample size amounts to 805 participants.

Table 3 in the Appendix displays the characteristics of our sample. The participant pool is quite diverse compared to traditional subject pools, being a great advantage of AMT. In particular, we observe our sample to be much more diverse compared to student subject pools with regard to age, education, race and political affiliation (see also, e.g. Snowberg & Yariv, 2018). Some recent work investigated the demographics of AMT workers (Berinsky, Huber, & Lenz, 2012; Kuziemko et al., 2015; Levay, Freese, & Druckman, 2016). We find very similar patterns when comparing our participant pool with the U.S. working population. In a nutshell, compared to the U.S. working population, our sample is younger and better educated. Refer to Table 3 in the Appendix for more details.

3 Results

3.1 Existence of hindsight bias during the Covid-19 outbreak

Our first result establishes the existence of hindsight bias during the Covid-19 outbreak in the United States.

Result 1. *People systematically misremember their own past Original Preference about how to fight Covid-19 best. In April 2020, at the peak of the first wave, the average participant wrongly thinks they already supported stricter restrictions at the onset of the first wave in March 2020 — but they did not.*

Figure 2 provides support for Result 1 by plotting the kernel density estimates of the extent of Covid-19 restrictions a participant was willing to implement, see Panel 2a. A value of 0 represents the least restrictive policy, a value of 1 the most restrictive policy.[12]

The solid blue line indicates the Original Preference. On March 15, the average participant was willing to implement policies reflecting a restrictiveness index of about 0.6. A month later and after the United States experienced its first wave of the Covid-19 pandemic, participants would implement much stricter measures if they could go back in time to March 15. This Updated Preference is plotted with the dash-dotted green line. In retrospect in mid-April 2020, the average participant would implement policies reflecting a restrictiveness index of 0.82.

Hindsight bias suggests that people are (systematically) unable to remember their past preference: People's memory of the past should be highly skewed towards their current view. Indeed, this is what we observe.

The dashed red line represents the Recalled Preference, elicited in mid-April with an incentivized procedure. The Recalled Preference in hindsight is different from the past Original Preference concerning the distribution (KS test: $p < .001$), the mean (paired t test: $p < .001$), and median (Wilcoxon signed rank: $p < .001$), with much more mass around more restrictive policies.[13]

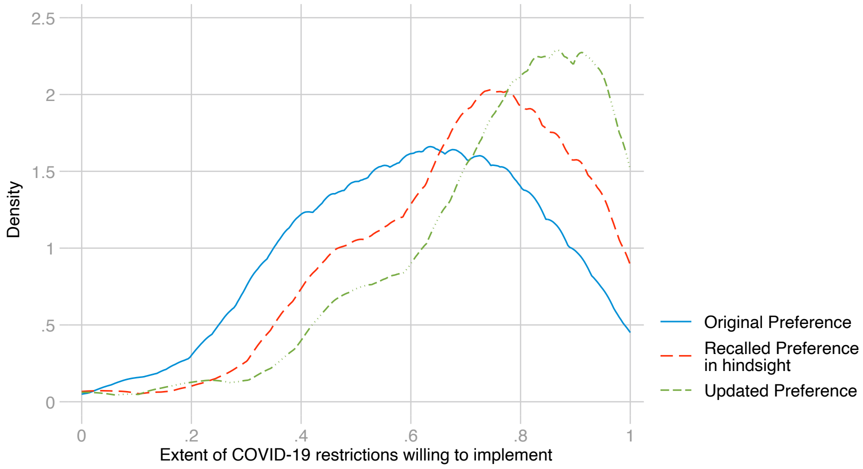
In mid-April 2020, the average participant wrongly recalls their own past policy preference and thinks they were in favor of stricter measures already at the onset of the pandemic. The

[12] For each of the three elicited preferences, there is a strong inter-item correlation across the four policy dimensions (Cronbach's $\alpha \geq .80$). In Figure 2a, the normalized values of the four policy dimensions are combined into a composite variable by taking the arithmetic mean. This procedure results in a single, quasi-continuous outcome variable representing the extent of Covid-19 restrictions a participant is willing to implement. Moreover, since three policy dimensions propose explicit policies to participants, but the fourth measures the preference relative to the policies in place as of March 14 (see Table 1), we additionally report in the Appendix the results separately, see Section B.4. The results are qualitatively and quantitatively very similar to the analysis presented in the main body of the paper.

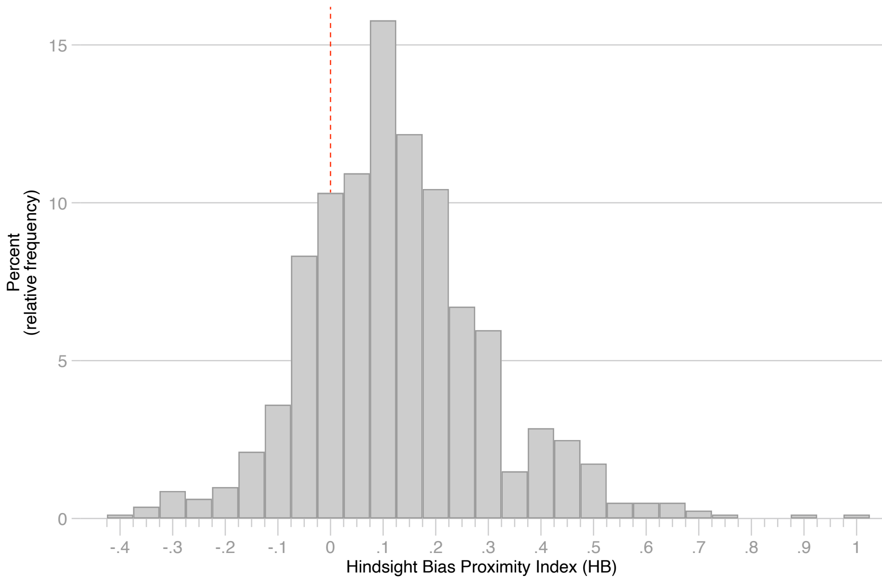
[13] Throughout this section, we report exact p values in graphs and figures unless the p value is below the 1%-level. In the text, we indicate p values in four conventional categories: $p < .10$, $p < .05$, $p < .01$ and $p < .001$.

Figure 2: Existence of hindsight bias

(a) Kernel density estimates of the three preferences



(b) Histogram of the hindsight bias proximity index



Note: Panel 2a displays the kernel density estimates of the extent of Covid-19 restrictions participants are willing to implement for the three elicited preferences, the Original Preference on March 15, the Recalled Preference on April 15 and the Updated Preference on April 15. We employ the epanechnikov kernel with the optimal bandwidth. Tests of equality for the Original Preference and the Recalled Preference reveal that the two preferences differ among their location as well as their distribution (Paired t test: $p < .001$, Wilcoxon signed-rank: $p < .001$, Kolmogorov-Smirnov: $p < .001$). The histogram in Panel 2b plots the distribution of the Hindsight Bias Proximity Index (HB) as defined in Equation 1 in Section 2.1. One-sample mean and median tests against the theoretical true value of 0 both reject the null at the 0.1%-level. Sample mean $\overline{HB} = .12$, Student's one-sample t test: $p < .001$. Sample median $m = .10$, sign test: $p < .001$.

average participant wrongly thinks that they were preferring to implement policies reflecting a restrictiveness index of 0.7 on average in mid-March, a substantial and highly significant departure from the truly expressed Original Preference of 0.6 (paired t test: $p < .001$).

Panel 2b plots a histogram of the hindsight bias index as defined in Equation 1, which provides a measure of the magnitude of hindsight bias on the individual participant level. If the null hypothesis was true and hindsight bias was absent in our sample, the HB index ought to be distributed with mean zero.[14]

We document that hindsight bias exists among our sample — the mean is significantly larger than zero (Student's one-sample t test: $p < .001$).

3.2 Hindsight bias correlates with a reduction in trust in government

The second hypothesis is concerned with the effect of hindsight bias on the change in trust in government.

We elicited trust in government on March 15 as well as on April 15. Participants' change in trust in government represents our outcome of interest since it serves as a measure of how principals change their evaluation of their elected agents during the first wave of Covid-19 — during the very same time period in which we elicited and document hindsight bias.

29% of participants change their trust in government during this month (Table 5 in the Appendix provides descriptive statistics.) Of those 29%, a smaller share of 8% expresses higher trust in government on April 15 than on March 15. The larger share of 21% decreases trust in government — there are significantly more participants who reduce trust in government (one-sample sign test: $p < .001$; test of proportions: $p < .001$). Also, we observe a decline in trust in government on average (Student's one-sample t test: $p < .001$). This decline in trust in government is in line with other public polling.[15]

Notably, the change in trust in government correlates with hindsight bias. The larger the hindsight bias of a participant, the stronger the reduction in trust in government (Pearson's $r = -.09$, $p < .01$; Spearman's $\rho = -.07$, $p < .05$; Kendall's $\tau_a = -.04$, $p < .05$).[16] This

[14] Noteworthy, we do not impose perfect memory on individual level. However, the sample population on average should not exhibit a systematic error if hindsight bias is non-existent.

[15] For example, the *Rasmussen Reports daily Presidential Tracking Poll* shows a decrease in approval of the federal government during the month under investigation, refer to https://www.rasmussenreports.com/public_content/politics/trump_administration/trump_approval_index_history, accessed on July 29, 2021.

[16] It is natural to ask whether the change in trust in government is dependent on party affiliation, or by how strongly someone was affected by the pandemic. It turns out that the negative relationship between the change in trust in government and hindsight bias is robust to controls in a regression framework. Table 6 in the Appendix shows that controlling for i) party affiliation ii) experienced adverse health effects due to Covid-19 and iii) coronavirus cases per capita in the county of residence, does neither turn hindsight bias as a predictor of change in trust in government insignificant nor does it influence its coefficient substantially.

non-causal evidence is in line with Danz et al. (2015) who show aptly in a controlled laboratory setting that hindsight bias on the principal's side correlates with less frequent delegation to agents.

3.3 Hindsight bias causally reduces trust in government

Of key interest is whether this relationship is of causal nature: Does hindsight bias *cause* the reduction in trust government? The correlational evidence may suffer from various endogeneity issues, thwarting a causal interpretation.

A neat feature of our experimental design is that we can make use of our randomly assigned order of preference elicitation to investigate the causal effect of hindsight bias on the change in trust in government. As elaborated in Section 2.1, the UPDATED FIRST group was first confronted with the Updated Preference and only then with the Recalled Preference. Those participants should exhibit a higher hindsight bias than participants in the RECALLED FIRST group, for whom the order of preference elicitation was vice-versa.

Indeed, the mean of the hindsight bias index in the UPDATED FIRST group is 0.145, while it is only 0.106 in the RECALLED FIRST group (see the left panel of Figure 3). Being confronted with the Updated Preference first increases hindsight bias by 36%, a highly significant difference (Welch's unequal variance t test: $p < .01$, MWU test: $p < .01$). The treatment effect appears to be homogeneous. The cumulative distribution function of UPDATED FIRST first-order stochastically dominates the distribution of RECALLED FIRST (Somers' D: $p < .01$).[17]

Crucially, participants who were first confronted with the Recalled Preference reduce trust in government on average by .092. Participants who were first confronted with the Updated Preference do so on average by .171, a difference of .079 (Welch's unequal variance t test: $p < .05$, MWU test: $p < .10$), see the right panel of Figure 3. This translates to an approximately 86% stronger reduction of trust in government in the UPDATED FIRST group — the group that exogenously exhibits stronger hindsight bias.

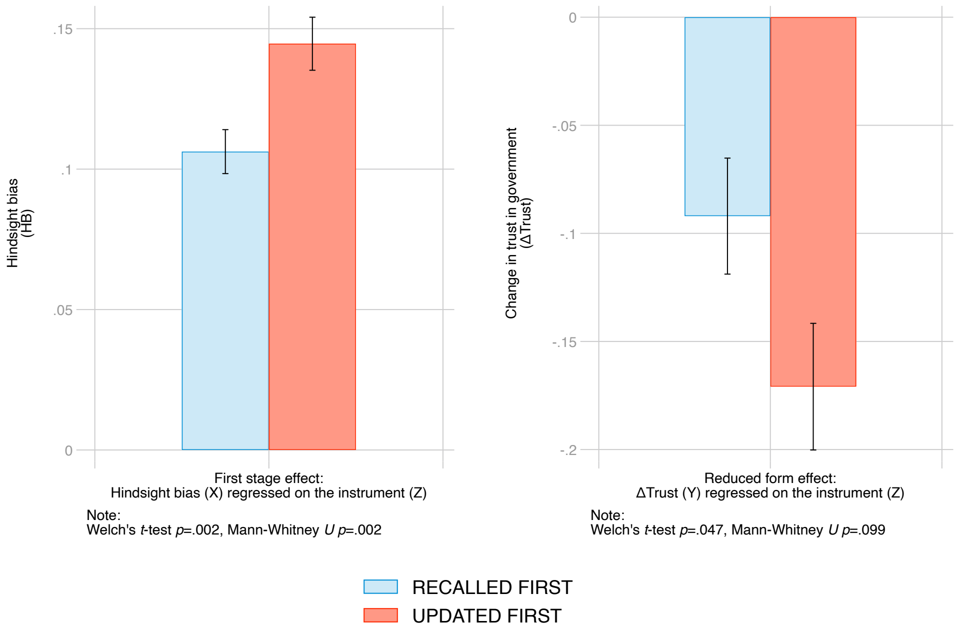
In standardized terms, being first confronted with the Updated Preference leads to a .14 standard deviations stronger decrease of trust in government.[18] The reduced form effect provides the first piece of causal evidence that hindsight bias reduces trust in government.

We now turn to an instrumental variable approach. Instrumenting hindsight bias with an exogenous variation provides a solution to the issue that the correlation of hindsight bias with

[17]See Figure 6 in the Appendix.

[18]Table 8 in the Appendix shows regressions of the change in trust in government on the two groups and employs a tobit, an ordered probit and a non-parametric kernel estimator. All three estimators confirm the observation from the t test that the UPDATED FIRST group exhibits a statistically significant larger reduction in trust in government.

Figure 3: First stage and reduced form effects



Note: The left panel depicts the first stage effect, that is the effect of regressing the hindsight bias index (being the endogenous explanatory variable X) on the experimental group dummy (being the exogenous instrument Z). The right panel displays the reduced form effect, that is the effect of regressing the change in trust in government from March 15 to April 15 (being the outcome variable Y of interest) on the experimental group dummy (being the exogenous instrument Z).

the change in trust in government may suffer from endogeneity bias. The randomly assigned experimental groups thus serve as an exogenous instrument (Z), allowing us to establish and estimate a causal relationship between hindsight bias (X) and the change in trust in government (Y). The instrumental variable approach requires some assumptions, refer to Section B.3.1 in the Appendix for a discussion.

The first stage estimation (equation 3) regresses hindsight bias on the UPDATED FIRST group dummy, while the second stage estimation (equation 2) regresses the change in trust in government on the first stage estimates of hindsight bias.

Second stage:

$$\Delta Trust_i = \beta_0 + \beta_{1i} HB_i + u_i \tag{2}$$

First stage:

$$HB_i = \gamma_0 + \gamma_{1i} UPDATED\ FIRST_i + v_i \tag{3}$$

The instrumental variable regression provides further support for Hypothesis 2. Column (1) and (2) in Table 2 report results from a two-stage least squares regression ("2SLS") in which both stages are estimated with least squares. The first stage regression (column (2)) shows that the random order of preference elicitation induces a highly significant exogenous variation in hindsight bias ($p < .01$), representing the average treatment effect we investigated previously (the left panel of Figure 3).

The second stage (column (1)) reports a negative coefficient, meaning that hindsight bias causally reduces trust in government at a statistically significant level ($p < .05$).[19] Regarding effect size, instrumented hindsight bias leads to a decrease in trust in government of .63 standard deviations.

Result 2. *Hindsight bias causally decreases trust in government.*

Importantly, ignoring endogeneity concerns by applying OLS leads to understating the relationship between hindsight bias and trust in government. In column (5), we report the endogenous OLS model. When comparing the coefficient of the OLS estimation with the 2SLS estimation in column (1), we find that the OLS coefficient to be smaller in magnitude than the 2SLS coefficient. The latter is in principle clean of all omitted variable bias. The 2SLS estimates suggest that some of the (positive) correlation between hindsight bias and the change in trust in government is due to endogeneity bias. Thus, OLS underestimates the effect of hindsight bias on trust in government.

This points out the advantage of the IV method in presence of endogeneity. Two reasons could explain the difference between the OLS and the IV estimates.[20] First, the IV coefficient is unaffected by any potential measurement error in hindsight bias, which would bias the OLS estimates downwards. Second, IV estimates are free of any omitted variable bias. For example, a changing social norm[21] or a random correlation[22] could be potential confounders.

Result 2 is robust to an ordered probit estimator. Column (3) and (4) in Table 2 display results in which the first stage is estimated with least squares and the second stage with an

[19] Anderson-Rubin weak-instrument robust 95% confidence sets are reported in brackets, as recommended by Andrews, Stock, and Sun (2019). In presence of a single instrument, identification-robust Anderson-Rubin confidence sets are always recommended for the two-stage-least-squares estimator since these are efficient regardless of the strength of the instrument and with it, the value of the F statistic in the first stage regression.

[20] Being aware that OLS estimates the average treatment effect and relies on the natural variation in hindsight bias among the entire sample, while IV estimates the local average treatment effect caused by the exogenously imposed variation in the sample. If only a sub-population for which the decrease in trust in government is larger than the average reacts to the randomly assigned instrument, the estimated local average treatment effect will not be generalizable to the entire population. In our setting, a heterogeneous reaction to the instrument is rather implausible.

[21] Suppose that in March 2020, the social norm was to be not too hysterical about Covid-19. People adapted to the social norm and misrepresented their preferences as more optimistic than they actually were. Suppose now that the norm broke down in April 2020 and people expressed their true honest preferences. If the government is a norm regulator, then the decrease in trust in government is to be expected even without hindsight bias.

[22] The existence of hindsight bias has been robustly documented in many contexts (Guilbault et al., 2004). Hindsight bias can thus be expected in any situation. If during the same time period as we capture hindsight bias also trust in government decreases — for any reason, we would estimate a random non-causal relationship that omits important variables.

Table 2: Change in trust in government regressed on instrumented hindsight bias

	Dependent variable: $\Delta Trust$				
	2SLS		*Ordered probit*		*OLS*
	(1)	(2)	(3)	(4)	(5)
	2nd stage	1st stage HB	2nd stage	1st stage HB	
Hindsight bias (HB)	-2.05		-3.49		-0.30
	[-6.29,-.05]		(1.43)		(0.12)
	{.047}		{.015}		{.013}
UPDATED FIRST (=1)		0.04		0.04	
		(0.01)		(0.01)	
		{.002}		{.002}	
Constant	0.13	0.11		0.11	-0.09
	(0.15)	(0.01)		(0.01)	(0.02)
N	805	805	805	805	805
F 1st stage (KP=Eff.)	9.81		9.81		
Weak iden. test (AR)	0.05		0.05		
Underidentificaton test	0.00		0.00		
Endogeneity test	0.08				
Corr. (e_v, e_u)			0.52		

Note: The table displays regression results of two instrumental variable regressions that investigate the effect of hindsight bias on the change in trust in government ($\Delta Trust$) with the accompanying OLS estimation. Model (1) and (2) report the results from a two-stage least squares estimation, regressing $\Delta Trust$ on the instrumented hindsight bias index. The first stage instruments hindsight bias with the UPDATED FIRST group dummy (column (2)). Model (3) employs an ordered probit estimator and regresses $\Delta Trust$ on the instrumented hindsight bias index. Cut-off points are not reported. Model (4) is the corresponding first stage and employs a ordinary least squares estimator to instrument hindsight bias with the UPDATED FIRST group dummy. Model (5) employs an ordinary least squares estimator and suffers potentially from endogeneity bias. For model (1), we report weak-instrument robust Anderson-Rubin 95% confidence sets for the instrumented variable in brackets. Robust standard errors are reported in column (2), (3), (4) and (5) in parentheses. p-values are reported in braces. The reported F-statistic is the Kleibergen-Paap effective F. The weak identification test reports the traditional Anderson-Rubin test based on the F-stat. The underidentification test is a Lagrange-Multiplier test based on the Kleibergen-Paap rk statistic of whether the equation is identified. The endogeneity test reports a Durbin-Wu-Hausman statistic and tests the null hypothesis whether the endogenous instrumented variable can be treated as exogenous. Corr. (e_v, e_u) indicates the correlation between the error terms of the first and second stage in the ordered probit model.

ordered probit estimator. Again, the coefficient is significantly negative ($p < .05$). A one standard deviation increase in hindsight bias decreases trust in government by .71 standard deviations.[23]

We further run the same instrumental variable estimations but include controls for party affiliation and self-reported experienced adverse effects of Covid-19 on own health (see Table 10 in the Appendix), as well as cases per capita in the county of residence (see Table 11 in the Appendix). In all models, the included control variable does not predict at a statistically significant level the change in trust in government. More importantly, the causal effect remains valid. Instrumented hindsight bias reduces trust in government significantly at conventional levels in all models.

4 Concluding Remarks

Certainly, we do not want to attribute the entire decline in trust in government in the United States during the first wave of Covid-19 to hindsight bias.

Nevertheless, we believe this article provides essential insight for the literature. Our finding that the memory distortion can causally reduce trust in government aligns with the hypothesis that hindsight-biased voters excessively punish the government (Camerer et al., 1989; Madarász, 2011). For example, Frey and Eichenberger (1991) conjecture that "[...] hindsight bias may again be relevant for citizens' evaluation of the government's actions. If politics leads to unfavourable results, people wrongly believe that this was foreseeable. Therefore they blame government for having committed a grave mistake."

Madarász (2011) posits that anticipating agents may engage in defensive, risk-averse actions to protect themselves from distorted evaluations, resulting in an inefficient allocation of risk and a reduction of welfare. It is left for future research to provide evidence for these sound theoretical arguments.

[23]Table 9 in the Appendix estimates the same instrumental variable models but employing trust in government on April 15 as outcome, conditional on trust in government on March 15. Results are qualitatively very similar.

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For online publication: Appendix

A Appendix: The data

A.1 Demographics characteristics of the sample

We briefly compare the workers who participated in our experiment with the U.S. working population in this section. In general, our sample is remarkably diverse and relatively similar to the representative U.S. working population.

Table 3 provides an overview. Our sample consists of slightly more men (56%) compared to the representative U.S. working population (53%). Our participants are on average younger and better educated than the U.S. working population, two well-known features of AMT samples (Levay et al., 2016; Berinsky et al., 2012). Blacks/African-Americans are underrepresented while Asians are over-represented in our sample. Minorities are more common in our sample with 7% of our participants not identifying themselves with any race ("Other"), compared to the representative share of 4% among U.S. workers. These patterns well align with previous literature, see for example Kuziemko et al. (2015). The Top-5 states where our participants reside are exactly the same five states where most of the U.S. working population lives. Our participants are almost as likely as the U.S. working population to identify themselves as Democrat, Lean Democrat and Lean Republican. In contrast, we observe that our sample is less affiliated with the Republican party (15%) than the U.S. working population (26%). Our participants identify themselves as "Independent" or "Other" more often (18% vs. 11%).

Table 3: Demographics of our data set compared with the U.S. working population

		in %	
Variable	Categories	Our Sample	U.S. working population (2019)
Gender	Women	43	47
	Men	56	53
	Other / Non-binary	1	-
Age	29 or younger	22	24
	30-39	35	22
	40-49	21	20
	50-59	13	20
	60 or older	9	14
Race	White or Caucasian	74	78
	Black or African American	8	12
	Asian or Pacific Islander	10	7
	Other	8	4
Education	High school or less	10	32
	Some college no degree	20	15
	Associate degree	12	11
	Bachelor's degree	42	26
	Graduate or above	17	16
State (Top 5)	California	11	11
	New York	8	5
	Pennsylvania	7	4
	Florida	7	6
	Texas	6	8
Party	Democrat	35	32
	Lean Democrat	19	18
	Lean Republican	13	13
	Republican	15	26
	Independent / Other	18	11
	N=	805	

Note: The table displays the demographic characteristics of our sample versus a representative sample for the U.S. labor market, namely characteristics of the U.S. working population. The source for all characteristics except party affiliation are the "Labor Force Statistics of the Current Population Survey" (2019) published by the U.S. Bureau of Labor Statistics, see https://www.bls.gov/cps/tables.htm. Party affiliation refers to the year 2020, the source is a Gallup survey https://news.gallup.com/poll/315734/party-preferences-swung-sharply-toward-democrats.aspx.

A.2 Attrition

Table 4: Attrition between stage 1 and stage 2

Variable (predicting not dropping out after survey stage 1)	Coeff.	p
Key variables		
Original Preference: Travel restrictions	0.035	0.472
Original Preference: Restrictions relative to gvt.	0.017	0.765
Original Preference: Social distancing restrictions in affected states	0.048	0.287
Original Preference: Social distancing restrictions nationwide	0.019	0.659
Trust in government on March 15	0.031	0.571
Demographics		
Female (=1)	-0.033	0.195
Other gender or non-binary (=1)	-0.042	0.785
Age	0.050	0.000
Bachelor degree (=1)	0.028	0.275
Some college but no degree (=1)	-0.034	0.296
Graduate degree (e.g. Master degree) or above (=1)	0.021	0.521
Associate degree (=1)	-0.041	0.314
High school or equivalent (=1)	0.004	0.919
Less than high school (=1)	-0.042	0.847
White or Caucasian (=1)	0.017	0.569
Asian, or Pacific Islander (=1)	0.090	0.014
African American or Black (=1)	-0.055	0.248
Hispanic or Spanish or Latino (=1)	-0.125	0.060
Native American (=1)	0.066	0.620
Alaskan Native or American Indian (=1)	0.209	0.000
Other race or none of the listed (=1)	-0.066	0.493
Party affiliation		
Democrat (=1)	0.019	0.477
Lean Democrat (=1)	0.033	0.286
Independent or Other party affiliation (=1)	-0.051	0.130
Lean Republican (=1)	-0.009	0.808
Republican (=1)	-0.003	0.944

Note: The table displays the key outcome variables, demographic characteristics and party affiliation in the leftmost column with the goal to test the ability of these variables to predict whether respondents drop out after the first survey on March 15 (stage 1). For each row, the coefficient and p-value are obtained from a regression model of the form $FinishedBothStages_i = \alpha + \beta \times Variable_i + \varepsilon_i$, where the respective $Variable$ is listed in the leftmost column.

As elaborated in Section 2.2, we do not observe significant differences between the 214 participants who dropped out and the 813 participants who completed both stages regarding neither the Original Preference of all four policy dimension nor expressed trust in government.

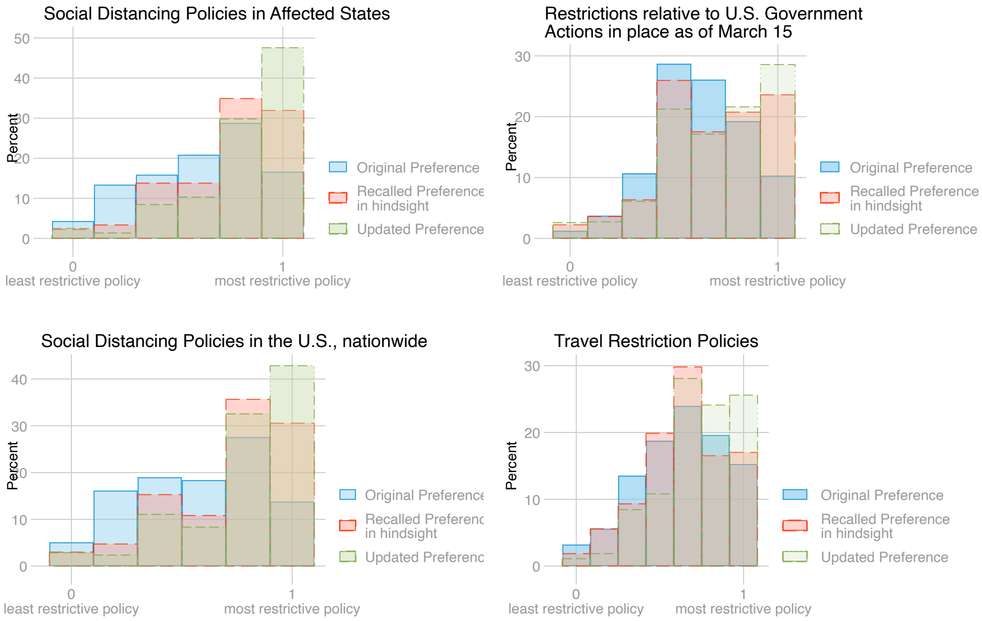
Continuing this analysis with demographic variables, we further fail to reject the null that attrition is not random at or above the 90%-level for gender and education. We find that age predicts dropping out: Younger people are significantly more likely to drop out ($p < .001$), the retention rate significantly increases with the age. Moreover, it seems that "Asian, or Pacific Islanders" ($p < .05$) and "Alaskan Native or American Indian" ($p < .001$) have a higher probability while "Hispanic or Spanish or Latino" have a lower probability ($p < .10$) to finish both survey stages. Note however that there does not seem a systematic pattern that minorities are either more or less likely to drop out. It is also possible that we face some false positives given the number of tests conducted.

Importantly, of those 214 who dropped out, 197 participants dropped out before the exogenous variation in hindsight bias was induced. These 197 participants did not even start the second survey. 17 participants or about 1.7% of all participants dropped out while participating in the second stage, that is after they were assigned to either RECALLED FIRST or UPDATED FIRST. We fail to reject the null that the experimental group assignment is not related to dropping out at the 90%-level.

B Appendix: Results

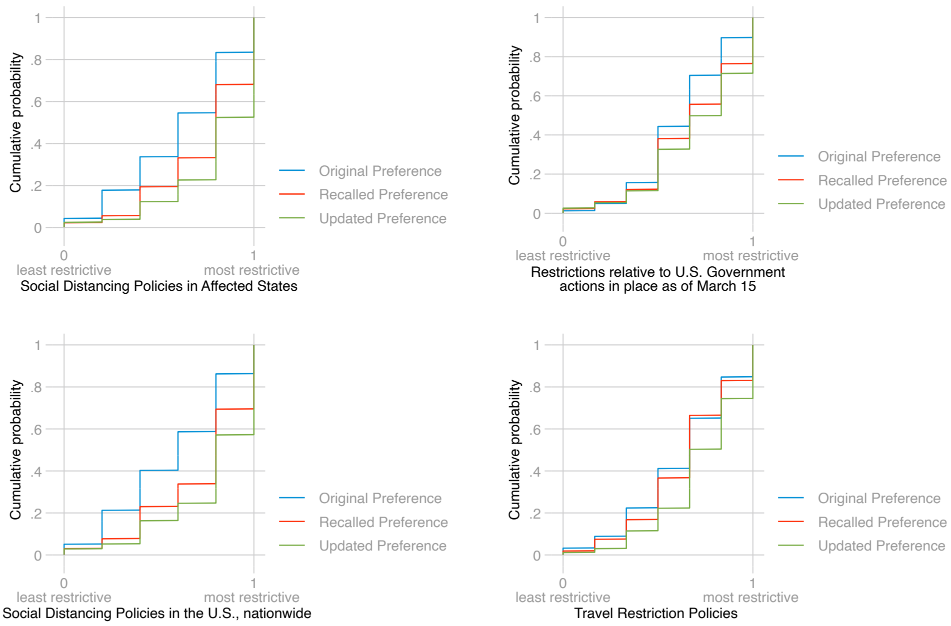
B.1 Existence of hindsight bias during the outbreak of Covid-19

Figure 4: Distribution of the Original Preference, Recalled Preference in hindsight and Updated Preference: Histograms for the four policy dimensions



Note: The graph displays a histogram of the estimates of the extent of Covid-19 restrictions participants are willing to implement for the three elicited preferences, the Original Preference on March 15, the Recalled Preference in hindsight on April 15 and the Updated Preference on April 15, separately for each policy dimension. For all four variables, tests of equality for the Original Preference and the Recalled Preference reveal that the two preferences differ among their location as well as their distribution (Paired t test: $p < .001$, Wilcoxon signed-rank: $p < .001$, Kolmogorov-Smirnov: $p < .001$).

Figure 5: Distribution of the Original Preference, Recalled Preference in hindsight and Updated Preference: Cumulative distribution functions for the four policy dimensions



Note: The graph displays a cumulative distribution function of the estimates of the extent of Covid-19 restrictions participants are willing to implement for the three elicited preferences, the Original Preference on March 15, the Recalled Preference in hindsight on April 15 and the Updated Preference on April 15, separately for each policy dimension. For all four variables, tests of equality for the Original Preference and the Recalled Preference reveal that the two preferences differ among their location as well as their distribution (Paired t test: $p < .001$, Wilcoxon signed-rank: $p < .001$, Kolmogorov-Smirnov: $p < .001$).

B.2 Hindsight bias correlates with a reduction in trust in government

Table 5 provides descriptive statistics for trust in government on March 15, on April 15 and its difference — the change in trust in government $\Delta Trust$ — between the two dates. Negative (positive) values of $\Delta Trust$ represent a decrease (increase) in trust in government.

Table 5: Trust in government

	Expressed trust in government			
	on March 15		on April 15	
How often do you trust the federal government in Washington D.C. to do what is right?	n	%	n	%
Almost never (1)	101	12.55	146	18.14
Not very often (2)	418	51.93	436	54.16
A lot of the time (3)	268	33.29	202	25.09
Always (4)	18	2.24	21	2.61
Total	805	100	805	100

	Change in trust in government	
Δ Trust: Trust on April 15 − Trust on March 15	n	%
-3 (decrease)	1	0.12
-2	4	0.50
-1	163	20.25
0 (no change)	573	71.18
1	60	7.45
2	3	0.37
3 (increase)	1	0.12
Total	805	100.00

Note: The table displays summary statistics for the survey question "How often do you trust the federal government in Washington D.C. to do what is right?". Participants were surveyed twice about their trust in government, on March 15 and a month later. We calculate the change in trust government as the difference between expressed trust on April 15 and expressed trust on March 15 and denote the variable as $\Delta Trust$.

Table 6: Δ Trust in government regressed on hindsight bias and controls

	(1)	(2)	(3)	(4)	(5)
	Δ Trust in government				
Hindsight Bias	-0.30	-0.29	-0.30	-0.30	-0.30
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Lean Democrat		-0.07			
		(0.06)			
Other party or Independent		0.08			
		(0.05)			
Lean Republican		-0.03			
		(0.06)			
Republican		0.09			
		(0.07)			
Cases per capita (in county), March 15			172.80		
			(543.70)		
Cases per capita (in county), April 15				0.89	
				(1.29)	
Adversely affected: Own health					0.00
					(0.01)
Constant	-0.09	-0.11	-0.10	-0.09	-0.09
	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)
r2	0.008	0.019	0.009	0.009	0.008
N	805	805	805	805	805

Note: The table reports OLS regressions that investigate the effect of hindsight bias on the change in trust in government ($\Delta Trust$). Model (1) is the raw model and regresses $\Delta Trust$ on the hindsight bias index. Model (2) to (5) add control variables: Model (2) controls for party affiliation, Model (3) for cases per capita in the county of residence as of March 15, Model (4) for cases per capita in the county of residence as of April 15 and Model (5) for how strongly a participants' health was negatively affected due to Covid-19 as of April 15. Robust standard errors reported in parentheses.

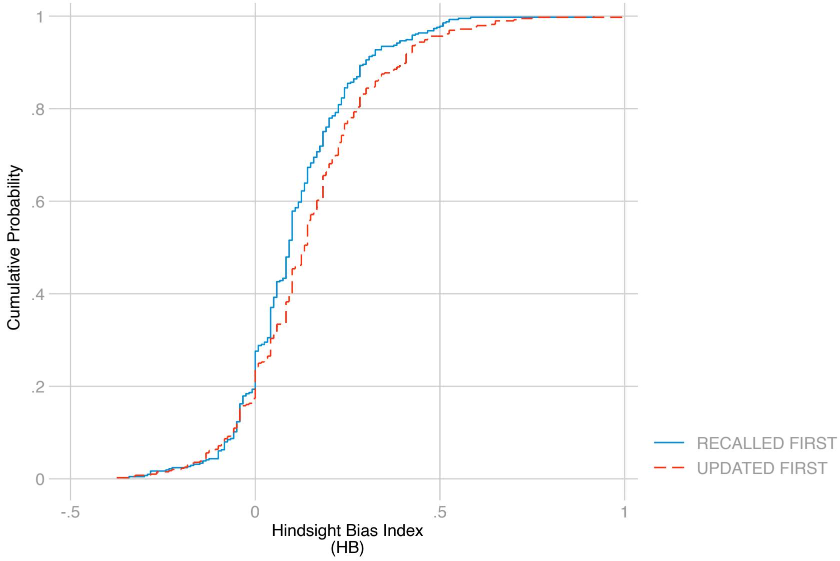
Table 7: Trust in government on April 15 regressed on Trust in government on March 15, hindsight bias and controls

	(1)	(2)	(3)	(4)	(5)
	Trust in government (April 15)				
Trust in government (March 15)	1.58	1.55	1.58	1.58	1.57
	(0.11)	(0.12)	(0.11)	(0.11)	(0.11)
Hindsight Bias	-0.63	-0.57	-0.63	-0.63	-0.61
	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)
Lean Democrat		-0.08			
		(0.12)			
Other party or Independent		0.15			
		(0.12)			
Lean Republican		0.18			
		(0.13)			
Republican		0.48			
		(0.14)			
Cases per capita (in county), March 15			86.39		
			(1276.31)		
Cases per capita (in county), April 15				0.30	
				(3.18)	
Adversely affected: Own health					0.01
					(0.03)
Pseudo r2	0.292	0.302	0.292	0.292	0.292
N	805	805	805	805	805

Note: The table reports ordered probit regressions that investigate the effect of hindsight bias on trust in government on April 15, controlling for the trust in government on March 15. Model (1) is the raw model and regresses Trust in government on April 15 on the hindsight bias index. Model (2) to (5) add control variables: Model (2) controls for party affiliation, Model (3) for cases per capita in the county of residence as of March 15, Model (4) for cases per capita in the county of residence as of April 15 and Model (5) for how strongly a participant's health was negatively affected due to Covid-19 as of April 15. Cut-off points are not reported. Robust standard errors reported in parentheses.

B.3 Hindsight bias causally reduces trust in government

Figure 6: Cumulative Distribution Function, by experimental group assignment



Note: The graph plots the empirical cumulative distribution function separately by experimental group. The CDF of the RECALLED FIRST group is plotted in solid blue, the CDF of the UPDATED FIRST group in dashed red.

Table 8: The reduced form effect: ΔTrust in government regressed on the experimental groups

	(1) Tobit	(2) Ordered Probit	(3) Kernel
UPDATED FIRST (=1)	-0.08	-0.16	-0.03
	(0.04)	(0.08)	(0.02)
Constant	-0.09		
	(0.03)		
Pseudo r2	0.003	0.003	
r2			0.005
N	805	805	805

Note: All models regress Δ Trust in government on the UPDATED FIRST group dummy. Model (1) is a tobit model, with censored lower limit set to -3 and censored upper limit set to 3, robust standard errors are reported in parentheses. Model (2) is an ordered probit model, robust standard errors are reported in parentheses. Cut-off points are omitted. Model (3) reports the results of a non-parametric kernel regression, employing a Li-Racine kernel density function. Bootstrap standard errors reported in parentheses are obtained from 500 replications.

Table 9: Trust in government on April 15 regressed on instrumented hindsight bias, conditional on trust in government on March 15

	Dependent variable: Trust (April 15)				
	2SLS		*Ordered probit*		*OLS*
	(1)	(2)	(3)	(4)	(5)
	2nd stage	1st stage HB	2nd stage	1st stage HB	
Hindsight bias (HB)	-1.64		-3.34		-0.29
	[-5.36, .24]		(1.50)		(0.11)
	{.088}		{.026}		{.009}
Trust (March 15)	0.72		1.38		0.71
	(0.03)		(0.27)		(0.03)
	{.000}		{.000}		{.000}
UPDATED FIRST (=1)		0.04		0.04	
		(0.01)		(0.01)	
		{.002}		{.002}	
Constant	0.72	0.11		0.11	0.55
	(0.15)	(0.01)		(0.01)	(0.07)
N	805	805	805	805	805
F 1st stage (KP=Eff.)	9.66		9.66		
Weak iden. test (AR)	0.09		0.09		
Underidentificaton test	0.00		0.00		
Endogeneity test	0.15				
Corr. (e_v, e_u)			0.49		

Note: The table shows the results of two instrumental variable regressions that investigate the effect of hindsight bias on trust in government on April 15, conditional on trust in government on March 15, and the accompanying OLS model in (Model (5)). Model (1) and (2) report the results from a two-stage least squares estimation, regressing $Trust$ (*April* 15) on the instrumented hindsight bias index. The first stage instruments hindsight bias with the UPDATED FIRST group (column (2)). Model (3) employs an ordered probit estimator and regresses $Trust$ (*April* 15) on the instrumented hindsight bias index. Cut-off points are not reported. The first stage employs a ordinary least squares estimator and instruments hindsight bias with the UPDATED FIRST group (column (4)). The Durbin-Wu-Hausman endogeneity test is not rejected in model (1), favoring the OLS instead the 2SLS model. Therefore, model (5) reports the standard OLS model that does not instrument hindsight bias. For model (1), we report weak-instrument robust Anderson-Rubin confidence sets for the instrumented variable. Robust standard errors are reported in column (2), (3), (4) and (5). The reported F-statistic is the Kleibergen-Paap effective F. The weak identification test reports the traditional Anderson-Rubin test based on the F-stat. The underidentification test is a Lagrange-Multiplier test based on the Kleibergen-Paap rk statistic of whether the equation is identified. The endogeneity test reports a Durbin-Wu-Hausman statistic and tests the null hypothesis whether the endogenous instrumented variable can be treated as exogenous. Corr. (e_v, e_u) indicates the correlation between the error terms of the first and second stage in the ordered probit model.

Table 10: Change in trust in government regressed on instrumented hindsight bias and control variables

	Dependent variable: $\Delta Trust$				
	2SLS		*2SLS*		*OLS*
	(1)	(2)	(3)	(4)	(5)
	2nd stage	1st stage HB	2nd stage	1st stage HB	
Hindsight bias (HB)	-1.96		-1.94		-0.29
	[-6.56, .12]		[-5.48, -.10]		(0.12)
	{.072}		{.045}		{.016}
UPDATED FIRST (=1)		0.04		0.04	
		(0.01)		(0.01)	
		{.003}		{.003}	
Lean Democrat	-0.09	-0.02			-0.07
	(0.07)	(0.02)			(0.06)
Other party or Independent	0.06	-0.01			0.08
	(0.07)	(0.02)			(0.05)
Lean Republican	-0.09	-0.03			-0.03
	(0.08)	(0.02)			(0.06)
Republican	0.03	-0.04			0.09
	(0.09)	(0.02)			(0.07)
Adversely affected: Own health			-0.02	-0.02	
			(0.02)	(0.00)	
Constant	0.13	0.12	0.16	0.13	-0.11
	(0.18)	(0.01)	(0.17)	(0.01)	(0.04)
N	805	805	805	805	805
F 1st stage (KP=Eff.)	8.95		11.39		
Weak identification test (AR)	0.07		0.05		
Underidentificaton test	0.00		0.00		
Endogeneity test	0.12		0.08		

Note: The table shows the results of two instrumental variable regressions that investigate the effect of hindsight bias on the change in trust in government ($\Delta Trust$), and a accompanying OLS model. Model (1) and (2) report the results from a two-stage least squares estimation, regressing $\Delta Trust$ on the instrumented hindsight bias index and controlling for party affiliation. Model (3) and (4) report the results from a two-stage least squares estimation, regressing $\Delta Trust$ on the instrumented hindsight bias index and controlling for how strongly a participants' health was negatively affected due to Covid-19 as of April 15. The first stage instruments hindsight bias with the UPDATED FIRST group dummy and the respective control variable (column (2) and (4)). The Durbin-Wu-Hausman endogeneity test is not rejected in model (1), favoring the OLS instead the 2SLS model. Therefore, model (5) reports the standard OLS model that does not instrument hindsight bias. For the second stage regressions, we report weak-instrument robust Anderson-Rubin confidence sets for the instrumented variable. Robust standard errors are reported in column (2), (4) and (5). The reported F-statistic is the Kleibergen-Paap effective F. The weak identification test reports the traditional Anderson-Rubin test based on the F-stat. The underidentification test is a Lagrange-Multiplier test based on the Kleibergen-Paap rk statistic of whether the equation is identified. The endogeneity test reports a Durbin-Wu-Hausman statistic and tests the null hypothesis whether the endogenous instrumented variable can be treated as exogenous.

Table 11: Change in trust in government regressed on instrumented hindsight bias and control variables

	Dependent variable: $\Delta Trust$			
	2SLS		*2SLS*	
	(1)	(2)	(3)	(4)
	2nd stage	1st stage HB	2nd stage	1st stage HB
Hindsight bias (HB)	-2.07		-2.11	
	[-6.41,-.06]		[-6.65,-.05]	
	{.046}		{.046}	
UPDATED FIRST (=1)		0.04		0.04
		(0.01)		(0.01)
		{.002}		{.002}
Cases per capita (in county), March 15	220.41	8.31		
	(768.38)	(243.86)		
Cases per capita (in county), April 15			3.31	1.20
			(2.85)	(0.90)
Constant	0.13	0.11	0.13	0.10
	(0.15)	(0.01)	(0.15)	(0.01)
N	805	805	805	805
F 1st stage (KP=Eff.)	9.81		9.42	
Weak identification test (AR)	0.05		0.05	
Underidentificaton test	0.00		0.00	
Endogeneity test	0.08		0.08	

Note: The table shows the results of two instrumental variable regressions that investigate the effect of hindsight bias on the change in trust in government ($\Delta Trust$). Model (1) and (2) report the results from a two-stage least squares estimation, regressing $\Delta Trust$ on the instrumented hindsight bias index and controlling for for cases per capita in the county of residence as of March 15. Model (3) and (4) report the results from a two-stage least squares estimation, regressing $\Delta Trust$ on the instrumented hindsight bias index and controlling for for cases per capita in the county of residence as of April 15. The first stage instruments hindsight bias with the UPDATED FIRST group dummy and the respective control variable (column (2) and (4)). For the second stage regressions, we report weak-instrument robust Anderson-Rubin confidence sets for the instrumented variable. Robust standard errors are reported in column (2) and (4). The reported F-statistic is the Kleibergen-Paap effective F. The weak identification test reports the traditional Anderson-Rubin test based on the F-stat. The underidentification test is a Lagrange-Multiplier test based on the Kleibergen-Paap rk statistic of whether the equation is identified. The endogeneity test reports a Durbin-Wu-Hausman statistic and tests the null hypothesis whether the endogenous instrumented variable can be treated as exogenous.

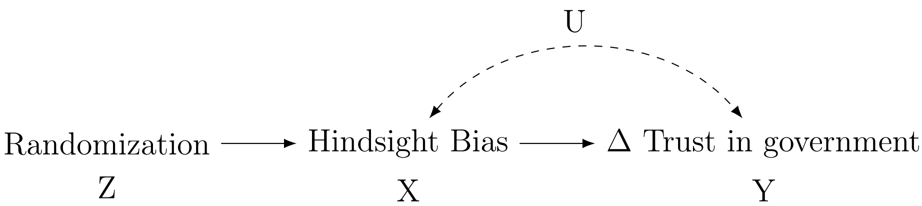
B.3.1 Instrumental Variable Assumptions

An empirical challenge is to establish a causal relationship between hindsight bias and the change in trust in government. The degree of hindsight bias is a subject-specific individual characteristic. A correlation between hindsight bias and trust in government may therefore suffer from endogeneity bias since the error term U may be correlated.

The random order of preference elicitation that we introduced in the second stage of our survey induces an exogenous variation in the extent of hindsight bias: In the UPDATED FIRST group, participants were first confronted with their Updated Preference. After that, we asked them about their Recalled Preference. This order was reversed for the RECALLED FIRST group.

With the randomization of the order of elicitation, we exogenously vary the degree of hindsight bias. This exogenous variation in hindsight bias allows us to apply a instrumental variable approach with the aim to causally assess the effect of hindsight bias on the change in trust in government. As an instrument, we employ the randomly induced instrument Z which varies the order of elicitation between the two experimental groups, see the causal graph in Figure 7.

Figure 7: Identification strategy



The IV approach requires some assumptions (Angrist, Imbens, & Rubin, 1996; Huber & Wüthrich, 2019).

Assumption 1: Relevance.

First, the instrument must be relevant. The instrument Z must have a causal effect on hindsight bias X.[24] Assumption 1 is empirically testable by inspecting the first stage F-value and the underidentification test which is a Lagrange-Multiplier test based on the Kleibergen-Paap rk statistic of whether the equation is identified. The tests are reported in Table 2. The underidentification test rejects the null that the instrument is not relevant: The test shows that the first stage model is identified ($p < .01$). Regarding the instrument to be weak, we observe the F-statistic to be 9.81, a value below the rule-of-thumb of 12. However, the weak instrument robust inference test (Anderson-Rubin) rejects the null that the coefficient of hindsight bias is equal to zero, and, in addition, that the over-identifying restrictions are valid. Nevertheless, we report weak-instrument robust Anderson-Rubin confidence sets for the linear 2SLS model

[24] In formal terms, $E[X|Z = 1] - E[X|Z = 0] \neq 0$.

as recommended by Isaiah, James, and Liyang (2018). These confidence sets are efficient regardless of the strength of the first stage.

Assumption 2: Monotonicity.

A technical assumption is that the effect of the instrument on the endogenous variable is homogeneous.[25] Our binary instrument Z should have a monotonous effect on X. To test monotonicity in a setting with a binary instrument Z and a continuous endogenous variable X, the cumulative distribution function of hindsight bias conditional on the instrument status should exhibit no crossings (Angrist & Imbens, 1995). Refer to the Figure 6 in the Appendix that plots the CDF of hindsight bias by experimental group. We observe that the two lines exhibit some crossings at negatives values of hindsight bias. In this range of hindsight bias, however, there are relatively few observations. Indeed, a statistical test reveals that the RECALLED FIRST group actually first order stochastically dominates the UPDATED FIRST group (Somers' D, $p = .002$). The instrument thus impacts hindsight bias monotonically and the monotonicity assumption is sufficiently satisfied.

Assumption 3: Exogeneity.

Exogeneity requires that the instrument Z is exogenous to X and Y.[26] In simple terms, the assumption states that the instrument is as good as randomly assigned. The assumption cannot be empirically tested in a just-identified model. However, in our case, the instrument is indeed randomly assigned and thus exogenous. Therefore, in a successfully conducted experiment, the randomness of Z holds by construction and the exogeneity assumption is satisfied by design.

Assumption 4: Exclusion restriction.

The exclusion restriction is a non-testable assumption in just-identified models. It requires that the instrument Z is independent of the change in trust in government Y.[27] The exclusion restriction holds if the instrument, that is the randomization of the order of elicitation of the Recalled Original Preference and the Updated Preference, does not have a direct effect on the change in trust in government. The instrument must have only an indirect effect on the change in trust in government through affecting the amount of hindsight bias one exhibits. While empirically not testable, in our case, we deem it plausible that the exclusion restriction holds. It seems hard to find many plausible cases of how the mere randomization of the elicitation order shall affect the change in trust in government directly other than through hindsight bias.

One example we deem plausible and like to address is misrepresentation of preferences.[28] Participants might like to appear consistent towards the experimenters. Participants might

[25] Formally, $Pr[(X|Z=1) \geq (X|Z=0)] = 1$.
[26] Formally, for parametric models the assumption is that $E[v_i|Z_i] = 0$ and $E[u_i|Z_i] = 0$.
[27] Formally, $Y(X, Z(1)) = Y(X, Z(0)) = Y(X)$.
[28] Thanks to Lydia Mechtenberg for pointing this out.

thus anchor their evaluation of trust in government on the policy preferences that we elicited before trust in government.

Participants in the UPDATED FIRST group needed first to report their current view, that is the Updated Preference, which on average is more restrictive than the Recalled Preference. Participants in RECALLED FIRST need to report first the incentivized Recalled Preference, which tends towards less restrictive policies compared to the Updated Preference, see Figure 2.

For consistency reasons, participants in the RECALLED FIRST group may feel compelled to report also a less restrictive (non-incentivized) Updated Preference compared to the UPDATED FIRST group, and in turn, again for consistency reasons, a higher trust in government compared to the UPDATED FIRST group. As a consequence, even without the existence of hindsight bias, we would find lower trust in government in the UPDATED FIRST group.

However, if this explanation has some merit, the Updated Preference should differ among the two groups. Importantly, we find that the Updated Preference does not significantly differ among the two groups (Welch's unequal variance t test: $p = .33$).[29] It is only the incentivized Recalled Preference that differs among the two groups, which is much in line with hindsight bias.

B.4 Results separately for explicit policy choices and the policy choice relative to actions taken by the U.S. government

We asked participants about four policy dimensions, refer to Table 1 for an overview. For three policy dimensions — social distancing measures in affected States, social distancing measures nationwide and travel restrictions — participants' had the choice between a selection of explicit policy choices, as summarized in Table 1. For the fourth policy dimension, participants' were requested to indicate whether they would implement less or more restrictive policies than the policies in place as of March 14, facing a relative judgment without explicit policy choices to choose from. In this section, we report all Tables and Figures from the main body separately, first for the preferences regarding the three dimensions with explicit policy choices[30] and then for the preference regarding the approval of the U.S. government measures in place as of March 14.

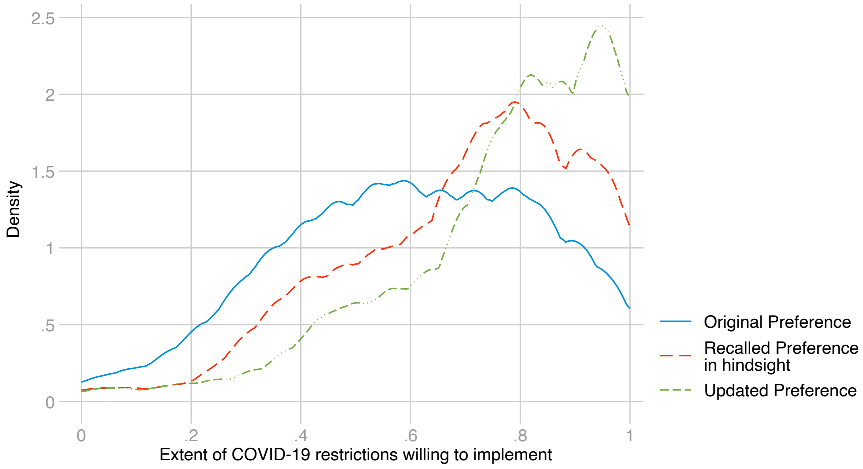
We find that the two results, the existence of hindsight bias as well as the decrease in trust in government due to hindsight bias, both hold.

[29]Moreover, note that between the elicitation of the policy preferences and trust in government, we elicited a set of demographic variables. It is thus unlikely that participants anchor trust in government on the policy preferences.

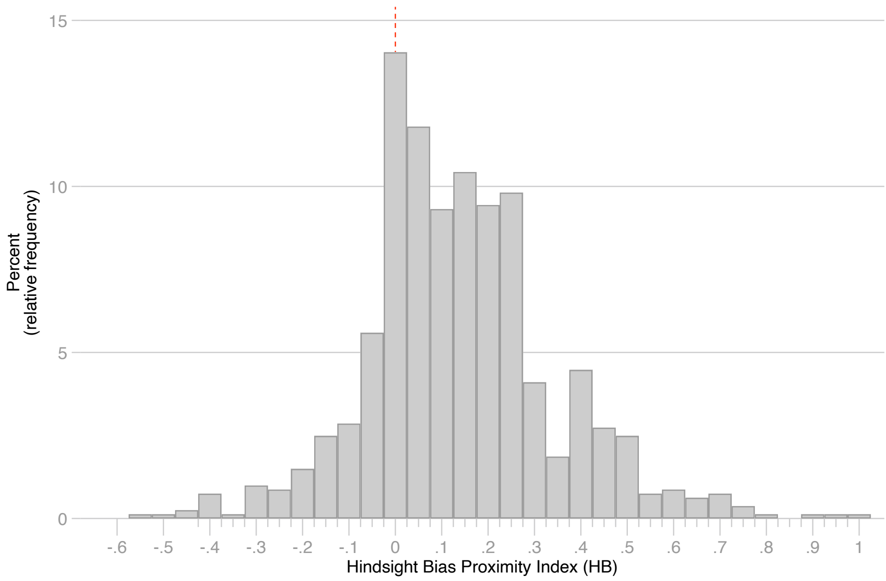
[30]Social distancing measures in affected States, social distancing measures nationwide and travel restrictions.

Figure 8: Existence of hindsight bias

(a) Kernel density estimates of the three preferences



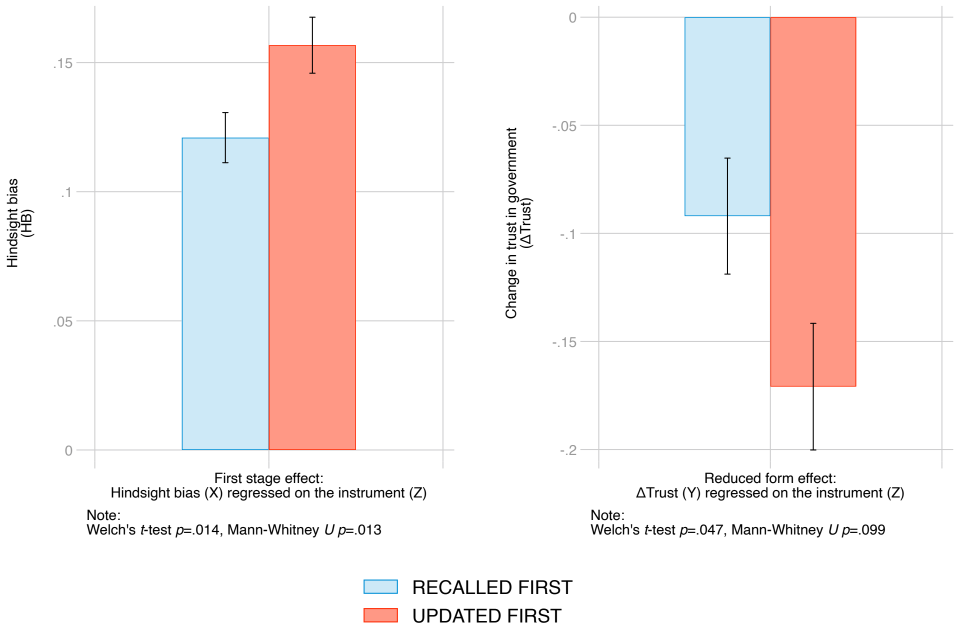
(b) Histogram of the hindsight bias proximity index



Note: Panel 8a displays the kernel density estimates of the extent of Covid-19 restrictions participants are willing to implement for the three elicited preferences, the Original Preference on March 15, the Recalled Preference on April 15 and the Updated Preference on April 15. We employ the epanechnikov kernel with the optimal bandwidth. Tests of equality for the Original Preference and the Recalled Preference reveal that the two preferences differ among their location as well as their distribution (Paired t test: $p < .001$, Wilcoxon signed-rank: $p < .001$, Kolmogorov-Smirnov: $p < .001$). The histogram in Panel 8b plots the distribution of the Hindsight Bias Proximity Index (HB) as defined in Equation 1 in Section 2.1. One-sample mean and median tests against the theoretical true value of 0 both reject the null at the 0.1%-level. Sample mean $\overline{HB} = .14$, Student's one-sample t test: $p < .001$. Sample median $m = .12$, sign test: $p < .001$.

Results for the three policy dimensions with explicit choices

Figure 9: First stage and reduced form effects



Note: The left panel depicts the first stage effect, that is the effect of regressing the hindsight bias index (being the endogenous explanatory variable X) on the experimental group dummy (being the exogenous instrument Z). The right panel displays the reduced form effect, that is the effect of regressing the change in trust in government from March 15 to April 15 (being the outcome variable Y of interest) on the experimental group dummy (being the exogenous instrument Z).

Table 12: Change in trust in government regressed on instrumented hindsight bias

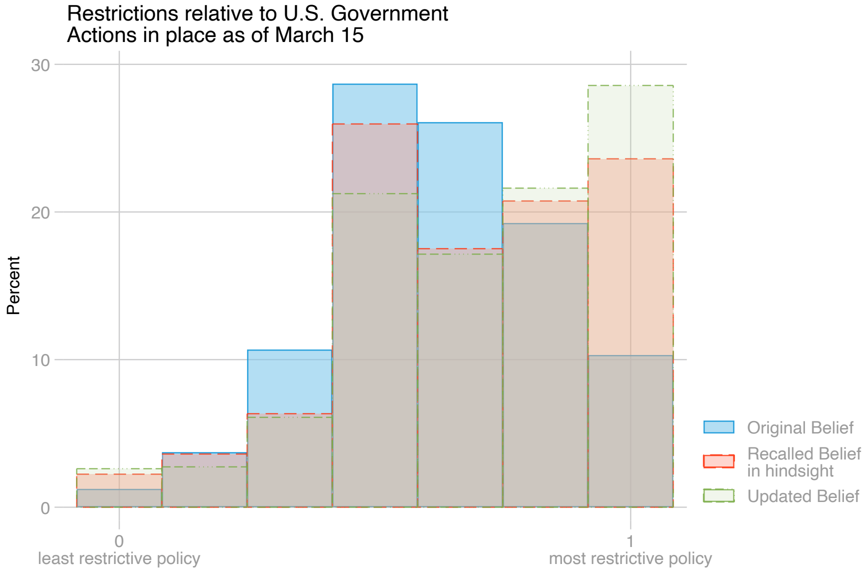
	Dependent variable: $\Delta Trust$			
	2SLS		*Ordered probit*	
	(1)	(2)	(3)	(4)
	2nd stage	1st stage	2nd stage	1st stage
		HB		HB
Hindsight bias (HB)	-2.20		-3.43	
	[...,-.10]		(1.23)	
	{.047}		{.005}	
UPDATED FIRST (=1)		0.04		0.04
		(0.01)		(0.01)
		{.014}		{.014}
Constant	0.17	0.12		0.12
	(0.19)	(0.01)		(0.01)
N	805	805	805	805
F 1st stage (KP=Eff.)	6.05		6.05	
Weak identification test (AR)	0.05		0.05	
Underidentificaton test	0.01		0.01	
Endogeneity test	0.07			
Corr. (e_v, e_u)			0.63	

Note: The table shows the results of two instrumental variable regressions that investigate the effect of hindsight bias on the change in trust in government ($\Delta Trust$). Model (1) and (2) report the results from a two-stage least squares estimation, regressing $\Delta Trust$ on the instrumented hindsight bias index. The first stage instruments hindsight bias with the UPDATED FIRST group dummy (column (2)). Model (3) employs an ordered probit estimator and regresses $\Delta Trust$ on the instrumented hindsight bias index. Cut-off points are not reported. Model (4) is the corresponding first stage and employs a ordinary least squares estimator to instrument hindsight bias with the UPDATED FIRST group dummy. For model (1), we report weak-instrument robust Anderson-Rubin 95% confidence sets for the instrumented variable. Robust standard errors are reported in column (2), (3) and (4). The reported F-statistic is the Kleibergen-Paap effective F. The weak identification test reports the traditional Anderson-Rubin test based on the F-stat. The underidentification test is a Lagrange-Multiplier test based on the Kleibergen-Paap rk statistic of whether the equation is identified. The endogeneity test reports a Durbin-Wu-Hausman statistic and tests the null hypothesis whether the endogenous instrumented variable can be treated as exogenous. Corr. (e_v, e_u) indicates the correlation between the error terms of the first and second stage in the ordered probit model.

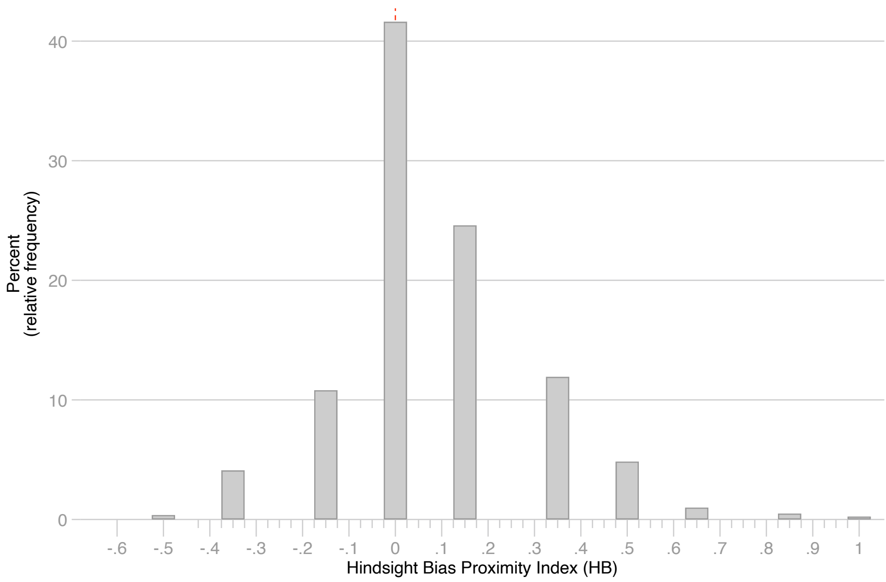
Results for the policy dimension with relative judgment

Figure 10: Existence of hindsight bias

(a) Histogram

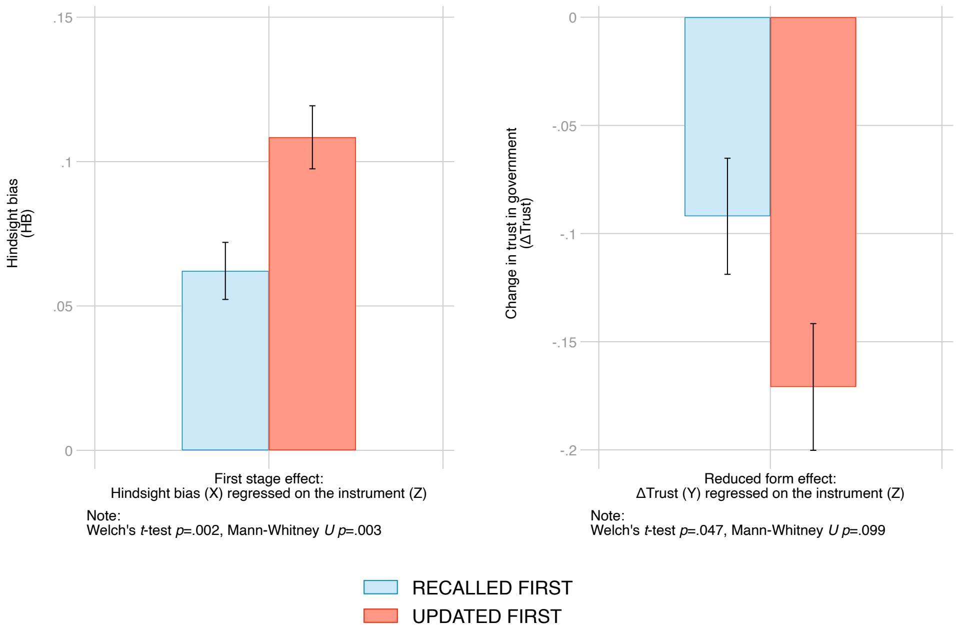


(b) Histogram of the hindsight bias proximity index



Note: Panel 10a displays the histogram of the extent of Covid-19 restrictions participants are willing to implement for the three elicited preferences, the Original Preference on March 15, the Recalled Preference on April 15 and the Updated Preference on April 15. Tests of equality for the Original Preference and the Recalled Preference reveal that the two preferences differ among their location as well as their distribution (Paired t test: $p < .001$, Wilcoxon signed-rank: $p < .001$, Kolmogorov-Smirnov: $p < .001$). The histogram in Panel 10b plots the distribution of the Hindsight Bias Proximity Index (HB) as defined in Equation 1 in Section 2.1. One-sample mean and median tests against the theoretical true value of 0 both reject the null at the 0.1%-level. Sample mean $\overline{HB} = .08$, Student's one-sample t test: $p < .001$. Sample median $m = .00$, sign test: $p < .001$.

Figure 11: First stage and reduced form effects



Note: The left panel depicts the first stage effect, that is the effect of regressing the hindsight bias index (being the endogenous explanatory variable X) on the experimental group dummy (being the exogenous instrument Z). The right panel displays the reduced form effect, that is the effect of regressing the change in trust in government from March 15 to April 15 (being the outcome variable Y of interest) on the experimental group dummy (being the exogenous instrument Z).

Table 13: Change in trust in government regressed on instrumented hindsight bias

	Dependent variable: $\Delta Trust$			
	2SLS		*Ordered probit*	
	(1)	(2)	(3)	(4)
	2nd stage	1st stage HB	2nd stage	1st stage HB
Hindsight bias (HB)	-1.71		-2.80	
	[-5.48,-.08]		(1.15)	
	{.047}		{.015}	
UPDATED FIRST (=1)		0.05		0.05
		(0.01)		(0.01)
		{.002}		{.002}
Constant	0.01	0.06		0.06
	(0.09)	(0.01)		(0.01)
N	805	805	805	805
F 1st stage (KP=Eff.)	9.88		9.88	
Weak identification test (AR)	0.05		0.05	
Underidentificaton test	0.00		0.00	
Endogeneity test	0.06			
Corr. (e_v, e_u)			0.56	

Note: The table shows the results of two instrumental variable regressions that investigate the effect of hindsight bias on the change in trust in government ($\Delta Trust$). Model (1) and (2) report the results from a two-stage least squares estimation, regressing $\Delta Trust$ on the instrumented hindsight bias index. The first stage instruments hindsight bias with the UPDATED FIRST group dummy (column (2)). Model (3) employs an ordered probit estimator and regresses $\Delta Trust$ on the instrumented hindsight bias index. Cut-off points are not reported. Model (4) is the corresponding first stage and employs a ordinary least squares estimator to instrument hindsight bias with the UPDATED FIRST group dummy. For model (1), we report weak-instrument robust Anderson-Rubin 95% confidence sets for the instrumented variable. Robust standard errors are reported in column (2), (3) and (4). The reported F-statistic is the Kleibergen-Paap effective F. The weak identification test reports the traditional Anderson-Rubin test based on the F-stat. The underidentification test is a Lagrange-Multiplier test based on the Kleibergen-Paap rk statistic of whether the equation is identified. The endogeneity test reports a Durbin-Wu-Hausman statistic and tests the null hypothesis whether the endogenous instrumented variable can be treated as exogenous. Corr. (e_v, e_u) indicates the correlation between the error terms of the first and second stage in the ordered probit model.

B.5 Results for hindsight bias measured with the shift index

In the following, we report all results of the main body of the paper with hindsight bias measured by the shift index. This shift index is computed as follows (Pohl, 2007):

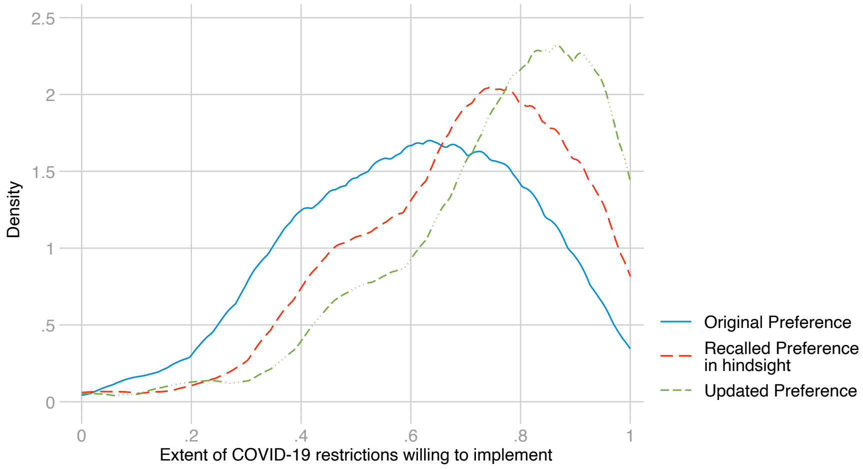
$$HB_{shift} = \begin{cases} \text{Original Preference} - \text{Recalled Preference}, & \text{if Updated Pref.} < \text{Original Pref.} \\ \text{Recalled Preference} - \text{Original Preference}, & \text{if Updated Pref.} > \text{Original Pref.} \end{cases} \tag{4}$$

HB_{shift} measures whether the Recalled Preference shifts towards the Updated Preference. The index is not defined if the Updated Preference exactly equals the Original Preference.[31] In our sample, the index is not defined for 27 participants. Therefore, the sample size for the analysis with the shift index amounts to 778 participants. Hindsight bias exists if the mean of the index is larger than zero.

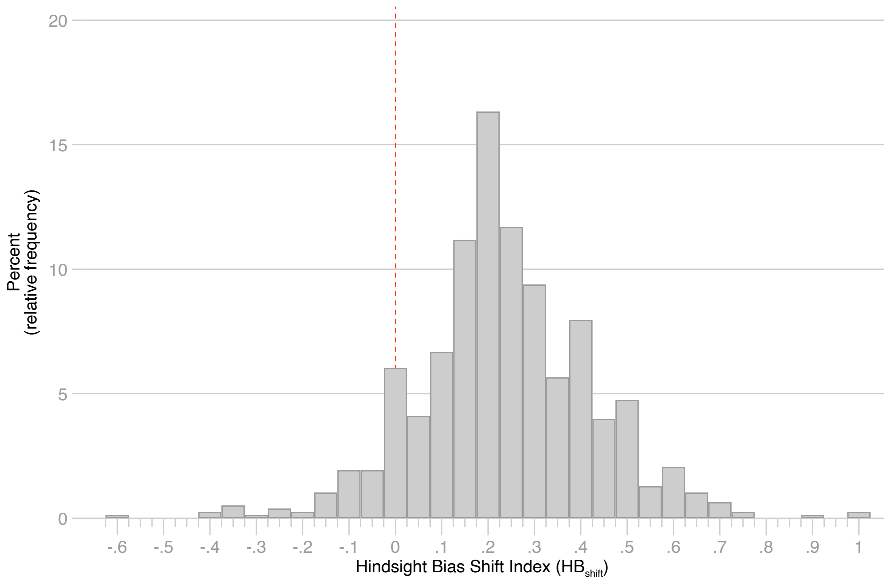
[31] Refer to Pohl (2007) for a discussion why this is reasonable.

Figure 12: Existence of hindsight bias

(a) Kernel density estimates of the three preferences



(b) Histogram of the hindsight bias shift index



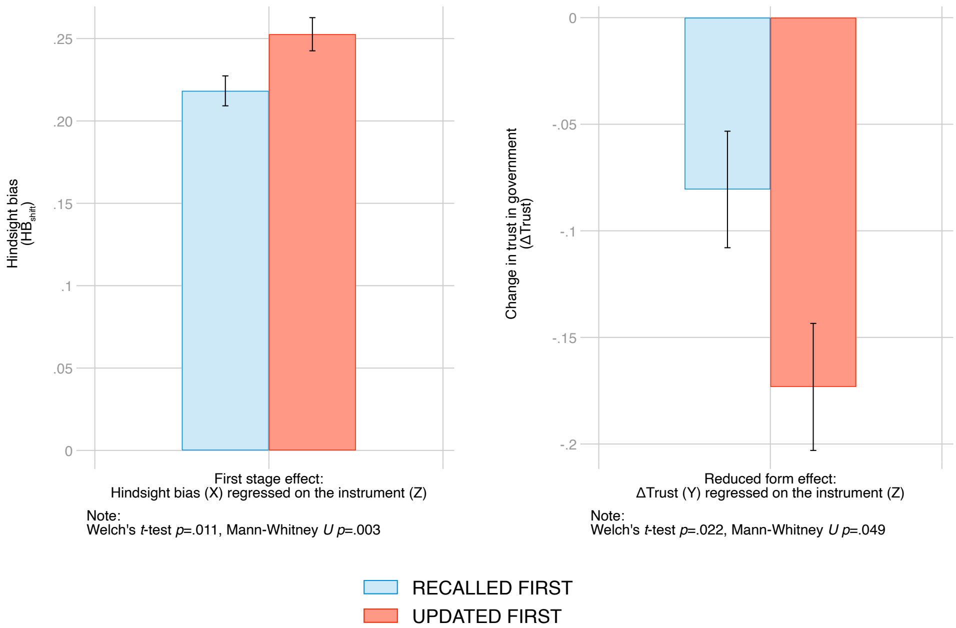
Note: Panel 12a displays the kernel density estimates of the extent of Covid-19 restrictions participants are willing to implement for the three elicited preferences, the Original Preference on March 15, the Recalled Preference on April 15 and the Updated Preference on April 15. We employ the epanechnikov kernel with the optimal bandwidth. Tests of equality for the Original Preference and the Recalled Preference reveal that the two preferences differ among their location as well as their distribution (Paired t test: $p < .001$, Wilcoxon signed-rank: $p < .001$, Kolmogorov-Smirnov: $p < .001$). The histogram in Panel 12b plots the distribution of the Hindsight Bias Shift Index (HB_{shift}) as defined in Equation 4. One-sample mean and median tests against the theoretical true value of 0 both reject the null at the 0.1%-level. Sample mean $\overline{HB}_{shift} = .24$, Student's one-sample t test: $p < .001$. Sample median $m = .23$, sign test: $p < .001$.

Table 14: Change in trust in government regressed on instrumented hindsight bias

	Dependent variable: $\Delta Trust$				
	2SLS		*Ordered probit*		*OLS*
	(1)	(2)	(3)	(4)	(5)
	2nd stage	1st stage HB	2nd stage	1st stage HB	
Hindsight bias (HB_{shift})	-2.70		-3.89		-0.16
	[...,-.43]		(1.12)		(0.11)
	{.022}		{.001}		{.145}
UPDATED FIRST (=1)		0.03		0.03	
		(0.01)		(0.01)	
		{.011}		{.011}	
Constant	0.51	0.22		0.22	-0.09
	(0.36)	(0.01)		(0.01)	(0.03)
N	778	778	778	778	778
F 1st stage (KP=Eff.)	6.43		6.43		
Weak iden. test (AR)	0.02		0.02		
Underidentificaton test	0.01		0.01		
Endogeneity test	0.03				
Corr. (e_v, e_u)			0.69		

Note: The table displays regression results of two instrumental variable regressions that investigate the effect of hindsight bias on the change in trust in government ($\Delta Trust$) with the accompanying OLS estimation. Model (1) and (2) report the results from a two-stage least squares estimation, regressing $\Delta Trust$ on the instrumented hindsight bias shift index. The first stage instruments hindsight bias with the UPDATED FIRST group dummy (column (2)). Model (3) employs an ordered probit estimator and regresses $\Delta Trust$ on the instrumented hindsight bias index. Cut-off points are not reported. Model (4) is the corresponding first stage and employs a ordinary least squares estimator to instrument hindsight bias with the UPDATED FIRST group dummy. Model (5) employs an ordinary least squares estimator and suffers potentially from endogeneity bias. For model (1), we report weak-instrument robust Anderson-Rubin 95% confidence sets for the instrumented variable. Robust standard errors are reported in column (2), (3), (4) and (5). The reported F-statistic is the Kleibergen-Paap effective F. The weak identification test reports the traditional Anderson-Rubin test based on the F-stat. The underidentification test is a Lagrange-Multiplier test based on the Kleibergen-Paap rk statistic of whether the equation is identified. The endogeneity test reports a Durbin-Wu-Hausman statistic and tests the null hypothesis whether the endogenous instrumented variable can be treated as exogenous. Corr. (e_v, e_u) indicates the correlation between the error terms of the first and second stage in the ordered probit model.

Figure 13: First stage and reduced form effects



Note: The left panel depicts the first stage effect, that is the effect of regressing the hindsight bias index (being the endogenous explanatory variable X) on the experimental group dummy (being the exogenous instrument Z). The right panel displays the reduced form effect, that is the effect of regressing the change in trust in government from March 15 to April 15 (being the outcome variable Y of interest) on the experimental group dummy (being the exogenous instrument Z).