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Framing of economic news and policy support during a pandemic: Evidence from a survey experiment☆

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ABSTRACT

We examine how news outlets' communication of macroeconomic information affects policy support during the COVID-19 crisis. In our survey experiment based on a representative sample from Germany, respondents are exposed to an expert forecast of GDP growth. Individuals either receive no information, the baseline forecast, or real-world media frames of the same forecast. We find that positive framing of economic growth increases policy support. This effect is stronger for respondents with more pessimistic macroeconomic expectations. Negatively framed economic news are perceived as more credible and hence less surprising in times of recession, not translating into political opinion.

1. Introduction

The COVID-19 pandemic and the corresponding global economic crisis have led to extensive and at times controversial debates about health and economic policy across countries. Due to the large scale of the crisis and its effects on many individuals worldwide, reliable information about the development of the pandemic is of high relevance (WHO, 2020b). This demand is met by a large and continuously evolving amount of information in relation to the crisis, recently coined an "infodemic" (Cinelli et al., 2020). Part of this "infodemic" are media and news outlets which offer a selection of editorially prepared information to consumers and, thereby, potentially engage in framing of its original content (Chong and Druckman, 2007).

This paper analyzes the role of news outlets in shaping public opinion about governmental policy during the COVID-19 crisis. We conduct an experiment employing a large-scale representative online sample of 3000 individuals in Germany in which we inform survey respondents about a key macroeconomic indicator: the forecasted GDP growth rate. This expert forecast of economic growth stems from a highly regarded annual report about the state of the German economy, covered by German newspapers on a regular basis.

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In the survey, we experimentally vary the provision of the baseline information, i.e. the expert forecast itself based on its press release, and its coverage in newspaper articles which engaged in framing of the baseline forecast information in relation to the pandemic. Framing in our setting is the evaluation of forecasted GDP growth as either a good or bad growth trajectory in the context of the crisis. After the provision of information, we assess individuals' support for governmental policies in response to the crisis, addressing the question whether economic information and/or its framing by news outlets affects support for pandemic policy during the ongoing pandemic.

We find that positive framing of the forecasted GDP growth rate by news outlets increases support for governmental policy during the COVID-19 crisis. This effect corresponds to an increase in policy support by up to 13 percent of a standard deviation. In addition, it is even more pronounced for respondents with more pessimistic expectations about future GDP growth, and related to the policy domains of health and education policy. In contrast, we estimate precise null effects of the baseline information about the expert forecast on support for governmental pandemic policy. This result highlights the role of the media in offering context to macroeconomic indicators.

Furthermore, we find that in times in which negative news are more frequent, i.e. during crises (Aslam et al., 2020; Krawczyk et al., 2021), there is no evidence for an adverse effect of negative framing on policy support. In line with this argument on negative news, we document that respondents perceive the negatively framed information as more credible, and observe an amplifying effect of positive framing and larger news consumption by individuals.

The analysis on beliefs in relation to GDP growth further reveals similarities to studies investigating expectations about other macroeconomic indicators: Prior beliefs about future GDP growth are largely dispersed between individuals. Interestingly, the median growth expectation lies slightly below the forecast of economic experts, potentially mirroring the perceived recession during the field phase of the survey. Furthermore, when systematically accounting for outliers, the mean expected growth rate is close to the forecast by economic experts.

Our results suggest that in a setting of an economic recession and health crisis in which news with negative sentiment are prevalent, negatively instead of positively connotated economic news are more in line with respondents' expectations about the sentiment of the information. Thus, the exposure to the expected negative news does not translate into a change in political opinion. On the contrary, we find that embedding information on expected GDP growth into a positive context related to the ongoing pandemic increases pandemic policy support in the population. The paper thus informs the understanding of the role of the media for the dissemination of economic information and its effect on public opinion formation in times of crisis. While media and news outlets produce editorially prepared information for consumers, they put economic information into a broader context, thereby translating into political assessments.

Our contribution to the literature is threefold. First, we add to the literature on how media shapes political attitudes. Previous research has found media reporting and exposure to affect political opinions and voting behavior (DellaVigna and Kaplan, 2007; Gerber et al., 2009). Other studies focus on the evaluation of individual perceptions of the information and find that consumers conversely exert a tendency to prefer like-minded news (Chopra et al., 2019; Gentzkow and Shapiro, 2010). We extend this literature by investigating the effect of framing by the media in the spirit of Tversky and Kahneman (1981) on support for governmental policy.

Our analysis thereby also informs the methodological literature on information provision experiments in terms of the relevance of framing effects related to information interventions. This is important as it is commonly advised to frame information treatments in a neutral manner (Haaland et al., 2020), but tailored research on the size of framing effects in the context of information provision experiments is sparse. In this context it is, however, crucial to point out that our framing interventions are based on real-world excerpts from newspaper articles and therefore not engineered by the researcher.

Second, we contribute to recent experiments addressing the general relevance of information provision in the context of the COVID-19 pandemic. Early analyses were conducted during the first months after the initial coronavirus outbreak. For instance, Coibion et al. (2020b) investigate how information on policy responses to the COVID-19 crisis influences households' economic expectations and spending plans. Binder (2020), in turn, studies the effect of the Fed's announcement to cut interest rates as a direct response to the virus outbreak on consumers' unemployment and inflation expectations. Similar to our analysis, Fuest et al. (2021) study support for lockdown and relaxation policies in Germany focusing on the first half of 2020. With varying effect sizes for different subgroups, they find that information about COVID-19 fatalities increases policy support, while information about the costs of lockdown measures decreases support for lockdown measures.

Relatedly, Fetzer et al. (2021) provide evidence for effects of information framing on perceptions of pandemic risk and overall economic anxiety. With respect to media effects, Bursztyn et al. (2020) find media bias to increase the spread of COVID-19 in areas in which consumed media tends to understate health risks. Simonov et al. (2022), in turn, provide evidence that media persuasion reduces the propensity to stay at home during the early stages of the pandemic. Concerning endogenous information acquisition during the crisis, Faia et al. (2021) find that individuals rate less preferred newspaper articles as significantly less credible. Our paper adds to this literature by directly investigating the effects of information consisting of economic news on pandemic policy support.

Third, our survey experiment extends the literature investigating macroeconomic expectations in the context of information provision. This literature often examines expectations about future inflation. For instance, studies on households document large differences between individuals' inflation expectations for different groups of the population. These household expectations often deviate to a great extent from the inflation rate forecasted by economic experts, and households substantially update their beliefs when confronted with experts' inflation expectations (Cavallo et al., 2017; Coibion et al., 2019). Similar studies using information provision experiments investigate expectations about interest rates, the likelihood of a recession, or house prices. They also find households' knowledge about macroeconomic variables to be limited and dispersed across individuals (Armona et al., 2019; Coibion et al., 2020a; Roth and Wohlfart, 2020).

We add to this literature via directly investigating individuals' expectations about GDP growth as another key macroeconomic indicator. We focus on GDP growth as it is often used as a central indicator for a country's prosperity and allows to capture individuals' assessment of a country's future economic prosperity within a single measure. This is of special relevance in a setting of economic recession in which individuals are exposed to a large amount of different types of (economic) information. Thereby, our experiment is the first to shed light on individuals' belief updating process in relation to their country's GDP growth rate as compared to beliefs about the likelihood of a recession (Roth and Wohlfart, 2020) or the uncertainty involved in forecasting GDP growth (Coibion et al., 2021).[1]

Based on the literature on macroeconomic beliefs, we hypothesize that there exists large variation in individual expectations about GDP growth during the crisis, and that information provision induces an exogenous shift based on the sign of biases in prior beliefs. Respondents who underestimate (overestimate) future GDP growth may support pandemic policy more (less) strongly. There is growing evidence that political attitudes are influenced by individuals' evaluation of a country's macroeconomic outlook (Jacobs et al., 2021). At the same time, recent research suggests that media and news outlets play an important role in shaping both economic perceptions and public policy assessments (Soroka et al., 2015).

Since individual expectations about a country's future prosperity further likely depend on the assessment of its policy, information provision may hence also translate into individuals' policy assessments in times of crisis. In conjunction, framing of economic news by newspapers may further influence support for governmental policy in a positive or negative manner, based on the context provided by the media. Finally, such framing effects can amplify or offset the effect of the baseline information.

The remainder of this paper is structured as follows: Section 2 introduces the pre-registered design and hypotheses of our survey experiment. Section 3 provides an overview of the data and presents descriptive statistics of key variables used in our analysis. The main results of our survey experiment are presented in Section 4. Further sensitivity analyses are presented in Section 5, while additional discussions are provided in Section 6. Section 7 concludes.

2. Experimental design

In the following, we introduce our pre-registered experimental design, consisting of four stages and four groups of respondents.[2] These groups are randomly provided with information on a GDP growth forecast, or real-world frames of this forecast obtained from related newspaper articles. The information on GDP growth which is provided to respondents stems from a highly regarded report about the state of the German economy by the German Council of Economic Experts (GCEE). The annual report is presented to the public regularly in November and includes a press release pointing out key information from the comprehensive report. For our information provision experiment, we employ both the press release – referred to as the baseline information – as well as the media coverage in German news outlets which is generated by the publication of the GCEE report on an annual basis.

2.1. Elicitation of prior beliefs

In the first stage, we elicit respondents' prior beliefs about the forecasted GDP growth rate for 2021. This elicitation of prior beliefs allows us to distinguish between respondents who underestimate and overestimate future GDP growth. While we refer to underestimation as more pessimistic beliefs, overestimation represents more optimistic beliefs of respondents.

2.2. Treatment and control groups

In the second stage, random subsets of respondents are exposed to differently framed information on the forecasted GDP growth rate. While treatment arm I receives positively framed information of the GCEE press release, Treatment arm II correspondingly receives negatively framed information. The positively and negatively framed information excerpts both stem from newspaper articles in large German online news outlets. Our experiment further involves both a passive and an active control group. The active control group (control group I) receives the original information based on the GCEE press release, whereas the passive control group (control group II) does not receive any information.[3]

On the day of the release of the GCEE report, we screened large German newspapers for media coverage on the topic.[4] While we were very careful in preserving the real-world frames used by media outlets when extracting the excerpts from the newspaper articles for our experiment, we aimed at being as close as possible to the notion of equivalent framing in the spirit of Tversky and Kahneman (1981). We therefore only made slight adjustments to harmonize differences in length and naming schemes between treatments and otherwise kept their original formulation and content.[5] Specifically, our treatments are worded as follows:

[1] In their study which investigates the effect of macroeconomic uncertainty on household spending, Coibion et al. (2021) mainly analyze second moments of future GDP growth for the euro area while abstracting from a country-specific analysis on the first moment of future GDP growth.

[2] Our pre-analysis plan is available at: www.socialscienceregistry.org/trials/6716.

[3] The passive control group is also sometimes referred to as the pure control group in the related literature on information provision experiments (Haaland et al., 2020).

[4] Specifically, we screened the ten largest online news outlets in Germany. Each news outlet had at least 84 million visits in June 2020 (Koptyug, 2020).

[5] A detailed description of the adjustments made and the news sources for the positive and negative treatments is presented in the online appendix. Both news sources are among the most trusted news sources in Germany (Weidenbach, 2020).

Treatment I: Positive framing (based on real-world newspaper coverage):
"*The German Council of Economic Experts expects an overall upturn in the coming year: It expects significant growth again in the coming year 2021 after the COVID-19 recession. The GDP will then increase by 3.7 percent.*"
Treatment II: Negative framing (based on real-world newspaper coverage):
"*The German Council of Economic Experts fears a long shadow of the COVID-19 crisis: Although it no longer expects the collapse to be as severe as in the summer, it also anticipates GDP growth of only 3.7 percent in 2021.*"
Control group I: Baseline information (based on the press release by the GCEE):
"*The German Council of Economic Experts has presented its annual report: It expects Germany's GDP to grow by 3.7 percent in 2021.*"
Control group II: No information provided.

Our experimental design enables us to differentiate between the "pure" effect of providing the original information as stated in the GCEE press release and the effects of framing of the original information by news outlets.[6]

2.3. Outcome variables

In the third stage of our experiment, respondents are asked about their evaluation and preferences with respect to the general COVID-19 policy as well as important subdomains of economic policy. These subdomains comprise of labor market policy, health policy, and education policy. In the following, we present the wording and scales of our outcome variables:
General COVID-19 policy: "*How do you assess the COVID-19 policy of the federal and state governments in general?*". Answers range from 0 for "Very bad" to 10 for "Very good".
Labor market policy: "*How do you assess the labor market policy of the federal and state governments during the COVID-19 crisis?*". Answers range from 0 for "Very bad" to 10 for "Very good".
Health policy: "*How do you assess the health policy of the federal and state governments during the COVID-19 crisis?*". Answers range from 0 for "Very bad" to 10 for "Very good".
Education policy: "*How do you assess the education policy of the federal and state governments during the COVID-19 crisis?*". Answers range from 0 for "Very bad" to 10 for "Very good".

The assessment of subdomains of pandemic policy enables us to better understand what the society refers to when evaluating COVID-19 policy in general. In addition, this distinction allows us to examine which subdomain of policy support can be shifted via (differently framed) information.

Furthermore, respondents from the active control group and treatment groups are asked to assess the credibility of the information provided (Bleemer and Zafar, 2018). This secondary outcome variable is measured as follows:
Credibility of information: "*How credible do you find the information presented to you?*". Answers range from 0 for "Not at all credible" to 10 for "Very credible".

The investigation of potential treatment effects on this secondary outcome measure allows us to investigate whether there exist differences in assessed credibility based on the specific wording of the information provided.

2.4. Elicitation of posterior beliefs

In the fourth and final stage of the experiment, we elicit posterior beliefs about the forecasted GDP growth rate for 2021 for those respondents who received information on the topic. To mitigate concerns about experimenter demand, we elicit posterior beliefs at the final stage of the survey. The elicitation of posterior beliefs allows us to investigate individuals' belief updating process in relation to expectations about GDP growth.

The structure of the experiment further enables us to not only investigate individuals' reaction to the expert forecast of GDP growth but also possible differences in belief updating in case the information is framed by the media.

2.5. Main hypotheses

In general, we expect our information treatments to induce an exogenous shift in respondents' beliefs about future GDP growth resulting in posterior beliefs closer to the GDP growth rate forecasted by experts. We expect that such a revealed bias in prior beliefs about GDP growth, i.e. an overestimation or underestimation in relation to the forecast by the GCEE, translates into an effect on policy support. As GDP growth is commonly known to the public as a measure of a country's overall prosperity which is affected by policy measures, we hypothesize that individuals learning that Germany will grow more strongly than anticipated will increase their support for governmental pandemic policy. Conversely, an individual being informed that GDP is expected to grow less than initially expected may reduce support for policies during the crisis.[7]

This argumentation is supported by recent literature suggesting that policy assessments are influenced by individuals' perceptions of a country's macroeconomic outlook (Jacobs et al., 2021), and that the media exerts influence on economic beliefs and public policy

[6] The size of our treatment arms and control groups corresponds to more than 700 individuals per experimental group, thereby fulfilling the recommendation by Haaland et al. (2020, p. 49) in the context of information provision experiments.

[7] If individuals in our sample are on average very sophisticated when forming their expectations, they may derive that if Germany is facing low economic activity today (possibly resulting from bad policies), larger growth rates in the future are very likely. This reasoning would contradict our hypotheses. However, we assume this channel to be rather limited in our representative population sample.

attitudes (Soroka et al., 2015). Hence, our hypotheses with respect to the baseline information are based on a trade-off scenario between current lockdown policy measures and future prosperity. In addition to this effect of the baseline forecast information, the framing treatments may exert effects on our outcome measures themselves by evaluating the macroeconomic information as positive or negative.

It is therefore important to distinguish between the direction of biases in prior beliefs, the effects of the baseline information, and the influence of framing. Following our pre-analysis plan, we hence investigate the following hypotheses by means of our survey experiment:

Hypothesis I: Overestimation:

Revealed overestimation of the forecasted GDP growth rate for 2021 leads to a more negative evaluation of policies and less supportive preferences.

Hypothesis II: Underestimation:

Revealed underestimation of the forecasted GDP growth rate for 2021 leads to a more positive evaluation of policies and more supportive preferences.

Hypothesis III: Positive framing:

Positive framing of the forecasted GDP growth rate for 2021 leads to a more positive evaluation of policies and more supportive preferences.

Hypothesis IV: Negative framing:

Negative framing of the forecasted GDP growth rate for 2021 leads to a more negative evaluation of policies and less supportive preferences.

There exists the possibility that effects of the information on GDP growth – conditional on prior beliefs – and framing effects amplify or offset each other when occurring simultaneously. Our experimental setup containing two control groups and two treatment arms allows us to differentiate between such effects. In our analysis, we first address the outlined hypotheses individually. We then further address potential amplifying and offsetting effects between the baseline information and effects of framing.

For the analysis of hypotheses I and II, we employ a comparison between the active and passive control group. These groups differ only in terms of the information provided to the active control group. Concerning hypotheses III and IV, we then compare our framing treatments to the active control group, thereby holding the provision of the baseline information constant. Finally, a comparison of the framing treatments with the passive control group enables the investigation of amplifying and offsetting effects between information provision and framing.

3. Data

The following section introduces the survey data collected for our analysis, discusses the time context of data collection, and presents a descriptive overview of key variables including tests for experimental balance in covariates.

3.1. Collection of survey data

We embed our survey experiment into a large-scale representative online survey of 3000 individuals in Germany. Our target population of interest are residents of voting age (i.e. 18 years and above) and the survey is representative with respect to age, gender, educational background, and place of residence in Eastern or Western Germany.[8]

The survey field phase took place in November 2020, a time when Germany was in a rather constant state of pandemic policy, a so-called "soft lockdown". The "soft lockdown" in Germany lasted in its original form from November 02 to November 25 when contact restrictions were further tightened.[9] This lockdown was characterized by contact restrictions allowing to meet only one additional household in public, closing cultural sites, restaurants, bars as well as prohibiting large parts of amateur sports. However, it was considered as "soft" as schools and shops stayed open. Importantly, during the field phase of our survey, there were no major changes to this lockdown policy in Germany.

The distribution of the survey to respondents was managed by the survey company *Respondi* via an online panel. Respondents recruited for participation in our survey received a small monetary incentive and both recruitment and incentivization were handled by the survey company.[10] Data collection was completed within 10 days of the release of the report by the GCEE, which was presented to the public on November 11. During that time, the forecast by the GCEE was the most recent information on expected GDP growth for Germany in 2021.[11] Survey respondents further had to pass a standard attention screener based on Haaland et al. (2020) to proceed answering to our survey as recommended by Chandler et al. (2019) for online panel research in the social sciences.

The survey contains measures about news and media consumption, beliefs about the forecasted GDP growth rate for 2021, support for pandemic policy, concerns about the COVID-19 crisis, and general political and social attitudes. The sum of observations for which we have full information on the variables of interest to our analysis amounts to 2923 individuals. The specific distribution of respondents across experimental groups is displayed in the first column of Table 1, i.e. 708 individuals in the active control group, 749 in the passive control group, 753 in the positive framing group, and 713 in the negative framing group.

[8] The survey is based on quota-sampling. Our data set fulfills the corresponding representativity quotas with deviations smaller than 2 percentage points. Table A.1 in the appendix presents the sample composition and representativity of our sample with respect to the quota variables.

[9] The further tightening of the contact restrictions was decided on November 23.

[10] Note that incentivization is independent of behavior during the survey and only based on survey completion. We stay away from incentivization of belief elicitation as previous research highlights potentially adverse side effects of task-based incentivization in information provision experiments, such as an increase in effort to search for official statistics online (Grewenig et al., 2020).

[11] The last forecast before the GCEE forecast on GDP growth for Germany in 2021 was published on October 30 by the German government.

Table 1
Summary statistics of prior beliefs about future GDP growth across experimental groups.

	Obs.	Mean	Robust Mean	Median	Q25	Q75	SD
Control I: baseline information	708	8.96	3.83	3	1.25	10	14.30
Control II: no information	749	8.82	3.77	3	1	10	15.00
Treatment I: positive framing	753	9.50	3.97	3	1.50	10	15.58
Treatment II: negative framing	713	7.82	3.50	3	1.20	5	13.65

Notes: The total sample size used in our analysis comprises 2923 observations for which we have full information on the variables of interest. The robust measure of the mean is based on Huber-robust estimation.

3.2. Distribution of prior beliefs

As a first step, we descriptively assess respondents' prior beliefs about the forecasted GDP growth rate. Table 1 displays summary statistics on the distribution of prior beliefs separated by experimental groups. On average, respondents' prior beliefs about future GDP growth are upward biased by around 5 percentage points. The outlier-robust mean values ranging from 3.5 to 4 percent are surprisingly close to the actual GCEE forecast. This implies that when accounting for outliers, German society's average GDP forecast is not far off the one by experts. As the forecasts in the fourth quarter of renowned German institutions only differed slightly, this holds for all expert forecasts at the time.[12]

The median values for all experimental groups align at 3 percent and are, thus, slightly lower than the expert forecast of 3.7 percent. On the one hand, this shows again that the non-robust mean value is largely driven by outliers expecting very large GDP growth in the future. On the other hand, it reveals a fraction of respondents who expect stagnant GDP growth (and some even negative growth). The values for the first and the third quartile, as well as the relatively high standard deviations, further show that there are some individuals who expect a GDP growth that is far from the expert's forecast. For these respondents, it is rather difficult to assess future GDP growth.

The large dispersion in beliefs about future economic growth is in line with related literature studying macroeconomic expectations and showing that households', on average, often exert upward biases in prior beliefs (see e.g. Binder and Rodrigue (2018) for a study on inflation expectations). However, the median value below the expert forecast seems to be more specific to GDP growth and/or the context of the investigation: The small median value in prior beliefs might mirror individuals' negative outlook in times of a crisis. This interpretation is supported by concurrent work by Coibion et al. (2021) who find that individuals' average expectations on GDP growth for 2021 in the euro area lie below the mean expected rate by experts. Coibion et al. (2021) assess households' expectations in September 2020 and, hence, similar to us during the ongoing crisis.

Furthermore, Coibion et al. (2021) point to heterogeneity in the uncertainty about future GDP growth, with Germany exerting the highest level of uncertainty when compared to other countries in the euro area. Employing a self-assessed measure of uncertainty, our findings support these results. Fig. A.1 in the appendix provides the distribution of self-assessed confidence about future GDP growth on an 11-point scale. It shows that similar to Coibion et al. (2021), there is substantial heterogeneity in confidence about future growth with individuals being very confident and individuals being not confident at all. However, the majority is clearly uncertain about future GDP growth.

In addition, Table 1 shows that the distributions of prior beliefs show similar patterns across groups of respondents.[13] This provides a first indication for successful randomization between experimental groups.

3.3. Experimental balance

To further assess randomization across experimental groups, we conduct tests for balance between control and treatment groups based on between-subject t-tests on a wide range of covariates as pre-specified in our pre-analysis plan. Specifically, these covariates comprise of measures of risk and trust attitudes, concerns about the COVID-19 crisis and economic development, media and news consumption, sociodemographics, and prior beliefs about economic growth.

The results of our balance tests are displayed in Tables A.2 and A.3 in the appendix, employing the passive and active control groups as base groups, respectively. Overall, we find only few marginal imbalances for some covariates across groups which indicates successful randomization between groups and allows for a causal interpretation of treatment effects. As specified in our pre-analysis plan, we control for the few variables exerting imbalances ($p < 0.10$) in all subsequent specifications.

4. Main results

In the following, we present our pre-registered estimation strategies and the main results of our survey experiment.

12 In the fourth quarter of 2020, the German government forecasted a GDP growth rate of 4.4 percent in 2021, the German Economic Institute of 4 percent, the German central bank of 3 percent, the Halle Institute for Economic Research of 4.4 percent, the ifo Institute of 4.2 percent, and the Kiel Institute for the World Economy of 3.1 percent.

13 Specifically, the small observed differences in non-robust mean values of prior beliefs between our experimental groups are not statistically significant when using the two control groups as base groups (see the first row of Tables A.2 and A.3 in the appendix). To ensure robustness, we nevertheless control for prior beliefs in all specifications.

Table 2
Effects of the baseline information on policy support.

	General	Labor	Health	Education
Panel A: ATE of baseline information (active vs. passive control group):				
Control group I: baseline information	−0.02 (0.05)	0.02 (0.05)	0.01 (0.05)	0.05 (0.05)
Controls	Yes	Yes	Yes	Yes
Observations	1457	1457	1457	1457
Panel B: CATE based on overestimation (hypothesis I):				
Control group I: baseline information	−0.09 (0.07)	−0.05 (0.08)	−0.05 (0.07)	−0.02 (0.08)
Controls	Yes	Yes	Yes	Yes
Observations	666	666	666	666
Panel C: CATE based on underestimation (hypothesis II):				
Control group I: baseline information	0.05 (0.07)	0.09 (0.07)	0.06 (0.07)	0.12* (0.07)
Controls	Yes	Yes	Yes	Yes
Observations	786	786	786	786

Notes: The dependent variables have been standardized in terms of their mean and standard deviation. Robust standard errors are displayed in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The controls comprise of prior beliefs, media and news consumption, trust, financial concerns due to COVID-19, age, household and city size, migration background, and (indirect) experience of a positive COVID-19 test.

4.1. Effects of the baseline information

As the first step of our analysis, we investigate the effects of the baseline information on governmental policy support during the COVID-19 crisis. This allows us to analyze whether the baseline information on the forecast by the GCEE exerts treatment effects in itself. Before directly assessing hypotheses I and II, which condition on biases in prior beliefs, we first evaluate average treatment effects (ATE) of the baseline information on support for governmental policy.

For that purpose, we estimate the following equation for the active control group using the passive control group as the base group:

$$y_i = \alpha_0 + \alpha_1 C_i^I + \theta'_{(1)} X_i + \varepsilon_{i,(1)}, \tag{1}$$

where y_i denotes our set of outcome measures of policy support of individual i, C_i^I is an indicator for the active control group, and X_i contains covariates based on the results from our balance tests.

The results from the estimation of Eq. (1) are presented in panel A of Table 2, which shows the ATE of the baseline information containing the forecast by the GCEE. We observe that the baseline information does not exhibit statistically significant effects on our policy channels of interest. In fact, the results point at precise null effects, which is reflected by coefficients which are very close to zero in conjunction with standard errors amounting to about 5 percent of a standard deviation. This implies that, for the aggregate population specification, receiving the baseline information on the expert forecast of GDP growth does not change the assessment of policies during the COVID-19 crisis in itself, neither by a statistically significant nor sizeable amount.[14]

In sum, this result shows that neutral framing of a GDP forecast does not affect pandemic policy support. There may be two potential explanations for these null effects: (i) people do not connect the neutrally framed information about the macroeconomic outlook and the current pandemic policies, or (ii) in general, there exists a link between the information about the macroeconomic outlook and the assessment of current policy measures, however, people are not able to evaluate the neutral macroeconomic information. In the latter case, a prepared evaluation of the macroeconomic information by the media might ease evaluation by individuals (see the analysis on framing effects in Section 4.2).

Furthermore, it might be the case that effects conditional on prior beliefs in opposite directions may result in an observed muted ATE. Thus, in the following, we investigate hypotheses I and II by reestimating Eq. (1) in terms of conditional average treatment effects (CATE). Specifically, we distinguish between respondents who overestimate or underestimate future GDP growth in relation to the forecast by the GCEE.

The results are displayed in panels B and C of Table 2. The direction of the estimated conditional effects of the baseline information on policy support are qualitatively in line with hypotheses I and II. Specifically, we observe negative (positive) coefficients in case of overestimation (underestimation). However, with the exception of education policy in case of underestimation, these effects are not statistically significant. In sum, our evidence suggests that the baseline information on forecasted GDP growth does little to influence our outcome measures of policy support during the pandemic.

[14] It is important to point out that with respect to our survey experiment, we do not observe systematic differences in terms of the distribution of experimental groups across survey days. This implies that treatment effects should not depend on the distance of the timing of survey participation to the release of the GCEE report.

Table 3
Effects of framing on policy support.

	General	Labor	Health	Education
Panel A: ATE of framing (treatments vs. active control group; hypotheses III and IV):				
Treatment I: positive framing	0.13** (0.05)	0.04 (0.05)	0.13*** (0.05)	0.11** (0.05)
Treatment II: negative framing	0.07 (0.05)	0.02 (0.05)	0.04 (0.05)	0.02 (0.05)
Controls	Yes	Yes	Yes	Yes
Observations	2174	2174	2174	2174
Panel B: CATE based on overestimation (treatments vs. passive control group):				
Treatment I: positive treatment	0.04 (0.07)	0.08 (0.07)	0.07 (0.07)	0.14* (0.07)
Treatment II: negative treatment	0.07 (0.07)	0.06 (0.07)	0.10 (0.07)	0.08 (0.08)
Controls	Yes	Yes	Yes	Yes
Observations	1005	1005	1005	1005
Panel C: CATE based on underestimation (treatments vs. passive control group):				
Treatment I: positive treatment	0.18*** (0.07)	0.08 (0.07)	0.19*** (0.07)	0.17** (0.07)
Treatment II: negative treatment	0.04 (0.07)	0.06 (0.07)	0.01 (0.07)	0.05 (0.07)
Controls	Yes	Yes	Yes	Yes
Observations	1208	1208	1208	1208

Notes: The dependent variables have been standardized in terms of their mean and standard deviation. Robust standard errors are displayed in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The controls comprise of prior beliefs, media and news consumption, trust, financial concerns due to COVID-19, age, household and population size, migration background, and (indirect) experience of a positive COVID-19 test.

4.2. Effects of framing

We proceed with the evaluation of hypotheses III and IV, i.e. the effects of framing on our policy channels. For that purpose, we now employ the active control group representing the baseline information as our counterfactual, holding the provision of the baseline information constant across these groups of respondents. Hence, observed treatment effects can be interpreted as effects of framing contrasted against the baseline information itself.

Specifically, we estimate the following equation to examine the ATE of framing, comparing our outcome variables across those groups which receive information, employing the active control group as base:

$$y_i = \beta_0 + \beta_1 T_i^I + \beta_2 T_i^{II} + \theta'_{(2)} X_i + \varepsilon_{i,(2)}, \tag{2}$$

where y_i represents our set of outcome measures of policy support of individual i, T_i^I and T_i^{II} are treatment indicators for the two treatment arms, and X_i contains the same set of covariates as in Eq. (1).

The estimation results of Eq. (2) are presented in panel A of Table 3. We find that positive framing of forecasted GDP growth significantly increases policy support during the COVID-19 crisis. This finding is in line with hypothesis III stating that positive framing translates positively into governmental pandemic policy support. In contrast, we do not observe statistically significant effects of negative framing. Consequently, our results do not provide evidence in favor of hypothesis IV predicting an adverse effect of negative framing on policy support. When compared with panel A on the effects of the baseline information, our results therefore suggest that information on future GDP growth translates into pandemic policy support only if it is put into positive context, i.e. framed by news outlets in an optimistic manner.

With respect to the different policy channels considered, we observe that the effect of positive framing on the subdomains of health and education policy are similar in size when compared to the general assessment of COVID-19 policy. In contrast, we do not observe a significant effect of the positive framing treatment on the labor market policy channel. Hence, these results suggest that framing effects on pandemic policy support are mostly driven by considerations concerning the subdomains of health and education policy during the crisis.[15] In Section 6.1, we discuss potential reasons for the observed differences across channels of pandemic policy.

The positive coefficients for the negative treatment might raise the concern that the positive framing effects result from the sum of two positive effects: an effect of framing in itself and an effect stemming from the positive tone of the framing instead of a negative one. To address this concern, we conduct tests on the equality of coefficients between treatment I and treatment II for each policy assessment. There is a significant difference between positive and negative framing for the assessment of health and education policy. This supports our interpretation that the results are due to the positive tone of our treatment and that an independent framing effect in itself is unlikely.

Since the coefficient for negative framing is relatively large for the general policy assessment, the difference between positive and negative framing is not statistically significant in this case. As the size for this coefficient is driven by individuals who do not

[15] In a robustness check, we reestimate our main specifications for those individuals who stated prior beliefs within a range of ±1 standard deviation. The results are very similar and are presented in Table A.4 in the appendix. Further following Coibion et al. (2021), eliminating individuals that spend less than three seconds on the treatment screens does not change our results. Note that these robustness analyses have not been pre-specified.

fully update their prior beliefs (see the coefficient size of 0.13 in Table A.5 for these individuals) and, hence, possibly individuals who did not carefully read the information, we still interpret the positive treatment effects as being due to the positive instead of the negative tone. These analyses, however, further support that for the assessment of the general COVID-19 policy (in which all policies are assembled), the positive framing effect is less pronounced and it mainly works through the subdomains of health and education policy.

In terms of effect sizes concerning the positive treatment, we observe that positive framing increases policy support by up to 13 percent of a standard deviation. This is a considerable magnitude when compared with effect sizes of around 15 percent of a standard deviation typically observed in the literature on information provision experiments (Haaland et al., 2020). In addition, it should be noted that effect sizes in our case are attributable to framing rather than a pure information effect as it is typically observed in the related literature. As such, our results also highlight the relevance of *how* pieces of statistical information are presented to respondents.

In addition to the evaluation of the average effects of framing, we again analyze potential differences in treatment responsiveness based on prior beliefs of respondents in terms of CATE. We hence reestimate Eq. (2) based on the sign of biases in prior beliefs, however, now employing the passive control group which received no information as our counterfactual. This allows us to assess whether there exist amplifying or offsetting relationships between the effects of the baseline information and our framing treatments.[16]

The estimation results are displayed in panels *B* and *C* of Table 3. In the first row of panel *B* in Table 3 we observe suggestive, albeit mostly insignificant, evidence for an offsetting effect of positive framing for respondents who overestimate future GDP growth when compared with the results for the baseline information (see the negative coefficients for overestimation in panel *B* in Table 2) and the positive framing treatment (see the significant positive coefficients in the first row of panel *A* in Table 3).

Again focusing on the influence of positive framing, effect sizes are more pronounced for those respondents who underestimate forecasted GDP growth, now amounting to an increase by about 18 percent of a standard deviation (see the first row of panel *C* in Table 3). This hints at an amplifying effect of positive framing and the baseline information for respondents with more pessimistic macroeconomic expectations. On the contrary, we do not find any evidence for similar offsetting or amplifying relationships in case of negative framing, which seems to be rather inelastic to prior beliefs in terms of effect sizes.[17]

The results on conditional effects of framing based on prior beliefs reveal that individuals who are more pessimistic about future GDP growth prior to treatment react more strongly to positive framing of the expert forecast by the GCEE. To these individuals, the forecasted economic growth rate by the GCEE seems to be rather unexpected, being further amplified by the positive context provided by news outlets. Based on these results, we will discuss, among others, the channel of news consumption in more detail in the subsequent section.

5. Sensitivity analyses

The following section discusses the results of further analyses related to the heterogeneity of framing effects and belief updating of respondents.

5.1. Further heterogeneity in framing effects

Given the observed heterogeneity in prior beliefs, we proceed to further investigate treatment effect heterogeneity as proposed in our pre-analysis plan following a systematic data-driven approach called causal tree analysis (Athey and Imbens, 2016, 2019). Specifically, we concentrate on the comparison of our positive framing treatment with the passive control group. This allows us to further investigate the amplifying effect between framing and the baseline information in a systematic way.

By means of a recursive approach, the machine learning algorithm sequentially partitions the data into a structure of subsamples. These subsamples are constructed based on the mean-squared error (MSE) of the conditional average treatment effect (CATE) (Athey and Imbens, 2016). This procedure then generates a visual representation of sequential treatment effect heterogeneity called causal tree. In our context, the algorithm is supplied with all covariates from our balance tests, employing the assessment of general COVID-19 policy as the outcome variable.[18]

The resulting causal tree is displayed in Fig. 1. The visual representation indicates that news consumption seems to be a main driver of heterogeneity in the effects of positive framing when compared to the passive control group receiving no information. This result offers further interpretation for the relevance of exposure to news during a crisis. In particular, our results suggest positive framing of economic news to exert more pronounced influence on those individuals who consume news rather often. In times of crisis, such news may be perceived as rather pessimistic in general. Hence, we interpret this observation as supporting evidence

[16] Please note that this empirical strategy to test the amplifying or offsetting hypotheses has not been pre-specified in our pre-analysis plan.

[17] Due to the slightly positive coefficients for the negative treatment one could again be concerned that the treatment effects of the positive framing are primarily driven by a general framing effect instead of the positive tone (similar to the discussion of ATE of framing). The tests on the equality of coefficients between treatment I and treatment II turn out statistically significant for the general, health, and education policy assessment and, hence, support the interpretation that the positive treatment effects are indeed mainly driven by the positive tone.

[18] Note that we increase the minimum size of subgroups considered by the algorithm to 200 compared to 50 which was indicated in our pre-analysis plan. This adjustment reduces complexity when evaluating the causal tree and increases statistical power for each coefficient.

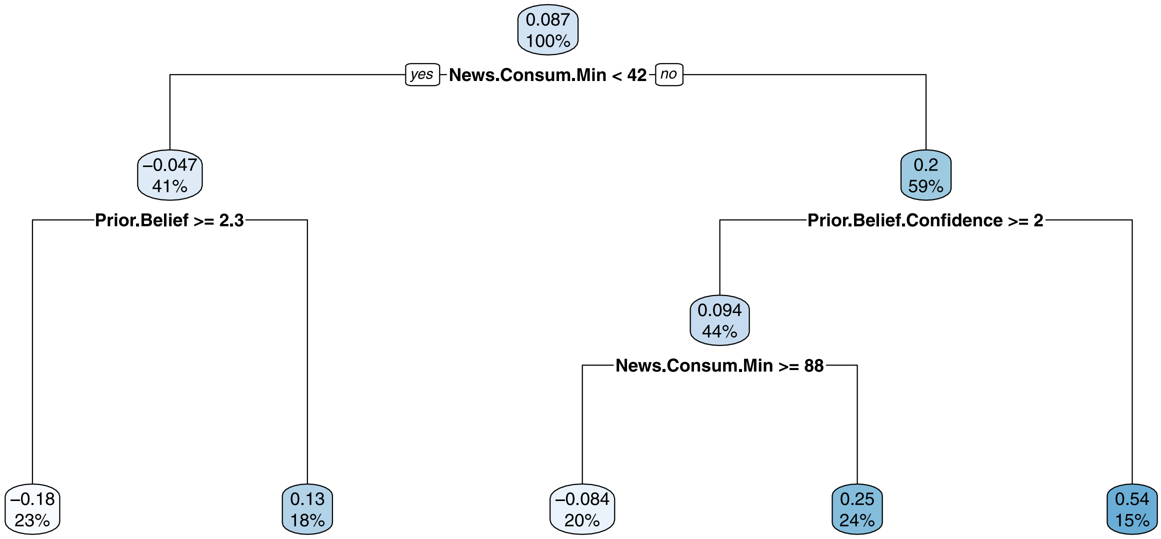

Fig. 1. Causal tree: positive framing vs. no information. *Notes:* The figure displays the structure of conditional average treatment effects (CATE) based on a causal tree (Athey and Imbens, 2016, 2019) for the positive framing treatment compared with the passive control group. The direction of the effects as well as its sizes, and the share of respondents for every leaf of the tree are displayed with blue background above the cutoff condition. (The more positive the effect is, the darker is the blue background.) Cutoff conditions stratify the sample into separate leaves based on the variable mentioned in the condition: For instance, if news consumption of respondents is larger than 42 minutes, the effect size for the positive framing treatment amounts to 0.2 standard deviations for this subgroup of individuals (i.e. 59 percent of all respondents allocated either to the positive framing treatment or the passive control group). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

that positively framed economic news are particularly relevant for support for governmental policy in times when negative news are prevalent.[19]

The results from the causal tree analysis further support our earlier investigation based on heterogeneity in prior beliefs. The cutting value found by the algorithm of 2.3 percentage points for those respondents who do not consume news very often is slightly below the original forecast of GDP growth by the GCEE. In addition, we observe that self-assessed confidence in prior beliefs is identified as a driver of treatment effect heterogeneity. Confidence in prior beliefs has also been found to be of importance for the belief updating process in case of inflation expectations, revealing that the updating process is stronger when respondents are less confident about their prior beliefs (Armantier et al., 2016; Binder and Rodrigue, 2018).[20] Specifically, we observe that among the subset of respondents consuming news more often, positive framing exerts a stronger effect on those individuals who are less confident when stating their expectations about GDP growth.

The last subdivision in the causal tree indicates that the amplifying effect of positive framing and consuming more news is not linear. For fairly confident individuals who consume a lot of news on a typical day (i.e. more than 88 min), the positive effect of positive framing vanishes. However, this result is largely driven by outliers that consume an extraordinary amount of news.[21]

5.2. Credibility of information

In line with Bleemer and Zafar (2018) and as suggested by Haaland et al. (2020), we analyze whether there exist differences in the credibility of information across groups. For that purpose, we estimate the following equation for our secondary outcome of assessed credibility as introduced in Section 2:

$$c_i = \gamma_0 + \gamma_1 T_i^I + \gamma_2 T_i^{II} + \theta'_{(3)} X_i + \varepsilon_{i,(3)}, \tag{3}$$

where c_i represents the secondary outcome variable on the credibility of the provided information as assessed by individual i, T_i^I and T_i^{II} are treatment indicators for the two treatment arms, and X_i contains the same set of covariates as in Eq. (1). The active control group serves as the base group.

[19] Note that specifically news and not media consumption is found to be a main driver by the algorithm for heterogeneous effects. This highlights the importance of news instead of general media consumption in this context, even though both types of consumption were supplied to the algorithm.

[20] We also evaluate causal trees for the baseline information and negative framing treatment against the passive control group. When compared to positive framing, the results support the relevance of prior beliefs and self-assessed confidence when stating beliefs. Furthermore, we see that for the baseline information, political attitude is rather important, while for negative framing, the household size and generalized trust seem to be relevant. We abstract from a more detailed discussion of these causal trees as only the positive framing treatment shows to be relevant in terms of statistically significant average treatment effects for policy support, and hence is worthwhile to be further partitioned into subsamples.

[21] This result is based on a reestimation of the causal tree abstracting from respondents consuming more than 180 min. of news per day (i.e. the highest 5 percent of the sample).

Table 4
Assessment of credibility of information and full updating.

	Credibility	Full Updating
Treatment I: positive framing	−0.08 (0.05)	0.00 (0.03)
Treatment II: negative framing	0.13** (0.05)	−0.04 (0.03)
Controls	Yes	Yes
Observations	2174	2174

Notes: The dependent variable measuring self-assessed credibility of information has been standardized in terms of their mean and standard deviation. Robust standard errors are displayed in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The controls comprise of prior beliefs, media and news consumption, trust, financial concerns due to COVID-19, age, household and population size, migration background, and (indirect) experience of a positive COVID-19 test.

The results are displayed in the first column of Table 4. We find that respondents exposed to the negatively framed information assess this information to be more credible when compared to the baseline information. In contrast, while we observe a negative effect size for the positively framed information, this coefficient is not statistically significant. These results provide interpretational background as to why our negative framing treatment does not exert adverse effects on policy support observed in Section 4.2. Specifically, these results suggest that in a setting of crisis, respondents expect to read news with a negative instead of a positive tone and, hence, confirming this expectation, the negative economic news are perceived as little surprising. These rather unsurprising negative news translate into (i) an evaluation of these negative news as more credible, and (ii) no change in the political opinion in an adverse manner.

In contrast, our evidence suggests positive framing of forecasted GDP growth to be more surprising in times of recession when compared to negatively framed information, revealing a translation of belief updating into policy assessments in times of crisis. This interpretation is also supported by the observation that news consumption moderates effects of positive framing, i.e. respondents consuming more news react stronger to the positive framing treatment. Because negative news are more common during times of economic and health crises, respondents who consume a lot of news have a higher expectation that the information provided will be negative. In turn, they are more surprised by the positively framed news, resulting in larger positive treatment effects for this group.[22]

Recent literature concerning the current COVID-19 crisis not only shows the large increase in information concerning the crisis (“infodemic”) but also supports that this information has primarily a negative sentiment. Aslam et al. (2020), for example, analyze COVID-19 headlines and show that 52 percent of them are written in a negative tone instead of a positive (30 percent) or neutral tone (18 percent). Similarly, Chakraborty and Bose (2020) find that negativity is a pre-dominant sentiment in over 6.34 million COVID-19 news articles. Krawczyk et al. (2021), analyzing major online news sources from 11 countries (including Germany) between January and October 2020, find that due to a substantial number of articles that can be clearly categorized as negatively polarized, the sentiment of the overall 2020 reporting can be seen as skewed toward a negative direction.[23]

5.3. Regional heterogeneity in framing effects

During the period of our survey, German regions were affected by the COVID-19 virus to varying degrees. Hence, it may be the case that framing effects on policy support as well as the credibility of the frames depend on the degree to which respondents face less or more COVID-19 infections in their area. More cases in the area possibly increase the likelihood of respondents having a negative mindset and the number of news with a negative tone in the area. This may translate into heterogeneous reactions to the positive and negative information, and the evaluation of its credibility.

For this analysis on regional heterogeneity, we match respondents to districts and district-level infection rates based on their postal code stated in the survey.[24] COVID-19 infections on the district level are measured as 7 day incidence rates per 100,000 inhabitants since this measure has been saliently reported by many German news outlets during the period of our survey. To examine heterogeneous effects with respect to the incident rate, we interact the framing treatments with incidence rates and estimate the following equation:

$$Y_i = \delta_0 + \delta_{1,a} T_i^a + \delta_2 I_i + \delta_{3,a} T_i^a \times I_i + \theta'_{(4)} X_i + \varepsilon_{i,(4)}, \tag{4}$$

where Y_i denotes the general policy support or assessed credibility as outcome measure for individual i, T_i^a with $a = \{I, II\}$ are treatment indicators for the two treatment arms, I_i is the standardized incidence rate, $T_i^a \times I_i$ denote interaction terms between treatment arms and incidence rates, and X_i contains the same set of covariates as in Eq. (1). In line with the previous section, the active control group serves as the base group.

[22] For the sake of completeness, we conduct the non-pre-specified analysis using the assessed credibility as the dependent variable and interact the positive and negative framing treatments with having over- or underestimated GDP growth. This heterogeneity analysis displays no significant difference for individuals who over- or underestimate. The results show that the over- or underestimating individuals do not react differently to the positive or negative framing treatment in terms of the credibility assessment.

[23] The large amount of negative news even lead the WHO (2020a) to give the following advice to the public: “Try to reduce how much you watch, read or listen to news that makes you feel anxious or distressed.”

[24] Note that this additional heterogeneity analysis has not been pre-specified.

Table 5
Interaction between framing effects and regional heterogeneity in COVID-19 cases.

	General	Credibility
Treatment I: positive framing	0.10* (0.05)	−0.08 (0.05)
Treatment II: negative framing	0.05 (0.05)	0.12** (0.05)
Incidence	−0.03 (0.04)	−0.05 (0.04)
Treatment I × incidence	−0.07 (0.05)	−0.06 (0.05)
Treatment II × incidence	0.06 (0.05)	0.09* (0.05)
Controls	Yes	Yes
Observations	1998	1998

Notes: The dependent variables have been standardized in terms of their mean and standard deviation. The incidence rate has been standardized in terms of its mean and standard deviation. In both regressions, we focus on incidences below the 95th percentile to ensure robustness with respect to the degree to which regions have been affected by COVID-19 cases due to large heterogeneity in the upper part of the incidence distribution. Robust standard errors are displayed in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The controls comprise of prior beliefs, media and news consumption, trust, financial concerns due to COVID-19, age, household and population size, migration background, and (indirect) experience of a positive COVID-19 test.

We estimate Eq. (4) employing both general policy support as well as the assessed credibility of our framing treatments as outcomes variables.[25] The results when general policy support is the dependent variable are displayed in the first column of Table 5. They show that the only statistically significant coefficient in this interaction specification is the one for positive framing. Hence, we see that the positive framing exerts its positive effect on the assessment of the COVID-19 policy, but this effect is not heterogeneous for different incidence rates. However, the negative albeit statistically insignificant coefficient for the incidence rate indicates that, on average, the assessment of the general COVID-19 policy is worse in districts with higher incidence rates. This observation coincides with the intuitive idea that regions hit by more COVID-19 infections are less satisfied with the handling of the pandemic by the government.

The estimation results for credibility as the dependent variable are displayed in the second column of Table 5. For this analysis, we find statistically significant effects for the negative treatment which vary by region. While the negative treatment is (as in the previous subsection) still evaluated as more credible than the baseline information or positive framing, this positive effect increases with higher incidence rates. More specifically, in comparison to the baseline information, a one standard deviation increase in the incidence rate increases the negative framing effect by 9 percent of the credibility's standard deviation. We interpret this evidence as supportive for our interpretation that individuals rate the negative framing treatment as more credible due to the salience of negative news and developments which are likely more present in areas with higher incidence rates.

5.4. Updating of prior beliefs

While the results in our previous sections show that negatively framed information on economic growth is perceived as more credible this may, however, imply that respondents exert differences in belief updating based on their assessments of the credibility of information. We hence directly assess respondents belief updating and shed light on the updating process about GDP growth.

First, we conduct within-subject t-tests between prior and posterior beliefs in the treatment groups and the active control group. Concerning belief updating of respondents, we find that posterior beliefs are significantly more in line with the true values for all three groups that receive information.[26] This indicates that respondents are processing the information provided, and form posterior beliefs more in line with the forecast by the GCEE, on average.

In addition to this quantitative assessment, Fig. 2 displays respondents' posterior beliefs against their prior beliefs, including prior beliefs in the range of ±1 standard deviation. As the graphical representation suggests, while prior beliefs vary considerably, posterior beliefs are clustered around the value of the forecasted GDP growth rate (indicated by the dashed line) which was provided during treatment. This indicates again that respondents update their beliefs after the receipt of information about the forecasted GDP growth rate.

It may still be the case that respondents update to a different extent between the active control group and those groups which receive differently framed information. We therefore also investigate whether there are differences in belief updating between these groups of respondents. For that purpose, the following equation is estimated using OLS[27]:

$$u_i = \rho_0 + \rho_1 T_i^I + \rho_2 T_i^{II} + \theta'_{(5)} X_i + \varepsilon_{i,(5)}, \tag{5}$$

[25] Since the distribution of incidence rates is highly skewed to the right, we focus on incidences below the 95th percentile to ensure robustness with respect to the degree to which regions have been affected by COVID-19 cases.

[26] Specifically, the p-values of within-subject t-tests are significant on the 1 percent level for the two treatment arms as well as the active control group.

[27] The results from a probit specification are very similar.

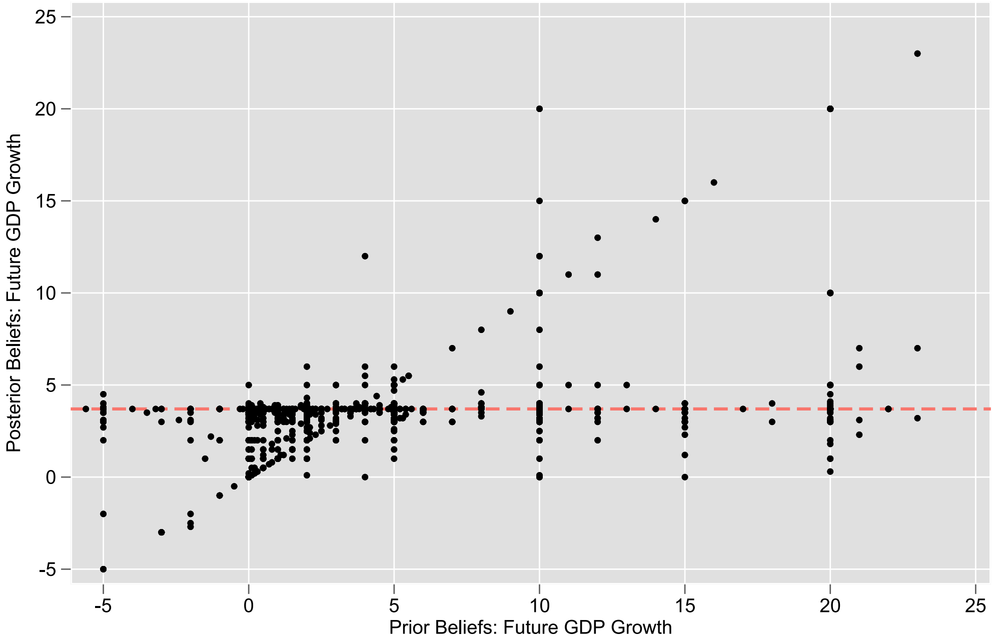

Fig. 2. Comparison of posterior and prior beliefs (±1 SD).

where u_i represents belief updating of individual i assuming a value of one if the respondent states posterior beliefs in line with the forecast and zero otherwise, T_i^I and T_i^{II} are treatment indicators for the two treatment groups, and X_i contains the same set of covariates as in Eq. (1).[28]

The estimation results are presented in the second column of Table 4. We do not find evidence for a difference in respondents who engage in full belief updating, i.e. stating posterior beliefs in line with the GCEE forecast, between groups. Hence, our results indicate that the differences in assessed credibility of the information provided between treatment arms do not translate into differences in belief updating. Instead, they may rather be interpreted in terms of negative framing not sufficiently surprising respondents in times of economic recession, while positive framing is assessed as more surprising. Still, it is credible enough to update beliefs in accordance to the information.

In line with studies on other macroeconomic expectations (see e.g. Armantier et al. (2016)), some respondents, even some with pronounced perception gaps, do not revise their expectations at all when exposed to information (see the diagonal line in Fig. 2). To account for potential differences between those individuals who engage in full belief updating and those who do not (fully) revise their expectations, we reestimate our main specifications for these groups of respondents separately. The results are presented in Table A.5 in the appendix.[29] Overall, they are very similar to our main results for those individuals who engage in full belief updating, i.e. state beliefs completely in line with the GCEE report.

On the contrary, we observe less pronounced effects of positive framing for the subgroup of respondents who do not engage in full belief updating.[30] Interestingly, we observe a marginally significant effect of negative framing on general policy support for this group. Hence, these results may be interpreted as inattentive (or updating-averse) individuals not fully processing the wording of the negative framing intervention. This is contrasted by coefficients of negative framing which are very close to zero for the group of respondents who state posterior beliefs fully in line with the GCEE forecast.

5.5. Determinants of biases in macroeconomic expectations

To further analyze prior beliefs about the macroeconomic indicator under study, we address potential reasons for biases in prior beliefs about future GDP growth by exploring their associations with a wide range of socio-economic covariates.

To analyze potential predictors of biases in macroeconomic expectations, we estimate the following equation:

$$b_i = \omega_0 + \Omega' X_i + \varepsilon_{i,(6)}, \tag{6}$$

[28] To decrease the influence of outliers in this specification, we abstract from the definition of our dependent variable indicated in the pre-analysis plan, i.e. the absolute updating. Instead, we construct a binary dependent variable which takes the value 1 if a respondent engages in full belief updating when stating posterior beliefs.

[29] Note that this robustness analysis has not been pre-specified.

[30] We also observe a marginally significant effect of positive framing on the labor market policy channel for those individuals who do not engage in full belief updating. This result is, however, not reflected by any other finding in our analysis.

Table 6
Determinants of biases in prior beliefs about future GDP growth.

	Absolute bias: Expected GDP growth
Confidence about prior belief	−0.13 (0.09)
Concerns about economic situation	0.12 (0.11)
Risk attitude	0.25** (0.11)
Trust attitude: generalized	−0.08 (0.12)
Trust attitude: statistics	−0.27* (0.14)
Trust attitude: media	0.16 (0.14)
Media consumption	−0.00 (0.00)
News consumption	0.00 (0.00)
Political attitude	0.24* (0.14)
Financial concerns about COVID-19 crisis	0.19** (0.09)
Experience of positive COVID-19 test	−0.16 (0.68)
General concerns about COVID-19 crisis	0.24** (0.10)
Age	−0.09*** (0.02)
Female	3.49*** (0.51)
Eastern Germany	1.68** (0.71)
Education	−3.21*** (0.31)
Employed	−0.11 (0.55)
Income	−0.72*** (0.24)
Household size	0.32 (0.28)
Partner	0.14 (0.57)
Migration background	1.18** (0.53)
Population size in area of residence	0.03 (0.17)
Observations	2923
Adj. R^2	0.09

Notes: Biases in prior beliefs are defined in absolute terms. Robust standard errors are displayed in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

where b_i represents the bias in the belief of individual i about the forecasted GDP growth rate in absolute terms, and X_i contains the full set of socio-demographic and attitudinal controls employed in the balance tests.

The results are displayed in Table 6. Overall, we are able to explain about 10 percent of the variation in macroeconomic expectations about GDP growth. Specifically, we observe that more risk-loving attitudes are significantly associated with larger biases in expected future GDP growth. In addition, we find that trust in statistics and science is associated with lower biases with respect to the macroeconomic outlook.

With respect to the COVID-19 crisis, both financial and general concerns about the crisis are statistically significantly associated with larger biases in expected GDP growth. Besides these attitudinal covariates, we also observe a range of sociodemographic characteristics to be good predictors of macroeconomic expectations, such as age, gender, residence in Eastern Germany, and income. In terms of the educational background of survey respondents, we observe that lower educated individuals exert stronger biases in prior beliefs. This finding is in line with literature on macroeconomic expectation formation suggesting that respondents with lower education deviate more strongly from experts' expectations, also contributing to larger standard deviations of prior beliefs in the population (Armantier et al., 2016).

6. Discussion

Our results show that framing affects three out of the four policy channels considered. In the following, we hence discuss these different policy channels and possible underlying mechanisms. Furthermore, we address concerns that may arise with respect to experimenter demand effects of our framing treatments.

6.1. Differences between policy channels

In our main analysis, we observe systematic evidence for effects of positive framing on general support for governmental policy during the crisis as well as for the subdomains of health and education policy. In contrast, we do not observe evidence for a similar effect on the assessment of pandemic labor market policy. Therefore, we further address potential reasons for these differences in terms of policy domains.

Investigating not only the general support for governmental policy, but also important subdomains has two main goals: First, the assessment of further subdomains provides an indication on what society refers to when thinking about COVID-19 policy. Second, the distinction between the different subdomains allows us to examine which subdomain of policy support can be shifted via (differently framed) information.

We begin by investigating the first goal: To evaluate what respondents think about when answering to our measure of general policy support during the crisis, we additionally included an open-ended question in our survey. This question asked respondents to state the specific type of policy they had in mind when thinking about governmental policy during the pandemic.[31] This constitutes a descriptive qualitative measure of the extent to which respondents considered our policy channels of interest in advance.

In general, we are able to assign about 45 percent of responses to one of our three measures of subdomains of governmental policy. In addition, about 20 percent of individuals specifically stated answers related to lockdown policy, which we do not consider a specific subdomain of either labor market, health or education policy. The remainder of respondents did not state a policy which could be specifically assigned to one of these four categories. In terms of the relevance of different policy channels, we observe that about 31 percent of respondents considered the subdomain of health policy. In contrast, only 10 percent of individuals' answers can be traced to labor market policy during the crisis. Finally, a relatively small magnitude of about 4 percent of respondents specifically considered the channel of education policy.

While a substantive fraction of respondents stated open-ended answers related to health policy, only small subsets of respondents thought about labor market or education policy when answering to our qualitative measure of the relevance of policy domains. This is in line with the evidence for a positive effect of framing on the assessment of health policy and a smaller and insignificant impact in terms of labor market policy as observed in our main analysis.

Interestingly, even though only a small subset of respondents had education policy in mind when answering to our open-ended question, we still observe a consistent effect on this channel of governmental policy. Hence, while respondents may not have initially thought about this subdomain, our evidence suggests that they nevertheless change their assessment due to positive framing when asked directly about education policy in times of the pandemic.

In addition to the qualitative open-text measure of policy support, we conduct further analyses to analyze how the assessments of the different policy channels relate to one another. First, we evaluate correlations between the different policy channels of interest. In the German media it has often been discussed whether there exists a tradeoff between labor market and health policy (see e.g. the discussions in Jaklin (2020) or Bardt and Hüther (2021)). However, we observe positive correlations between all four policy outcomes, which does not provide evidence in favor of a tradeoff perceived by the average respondent. Second, we analyze the average deviations in assessment of each policy channel relative to general COVID-19 policy support. We find that labor market and education policy during the crisis are evaluated as worse when compared to policy in general, while health policy is seen as more positive in relation to this benchmark, on average. These descriptive observations suggest that health policy during the crisis finds stronger support relative to other domains of pandemic policy.

We now turn to the second goal: The finding that positive framing does not exhibit a sizeable and statistically significant effect on the support for labor market policy may have several reasons. A first reason could be that individuals do not link a positively framed macroeconomic outlook to labor market policy employed during the pandemic. This reasoning, however, is rather unlikely as labor market policy during the pandemic in Germany was quite extensive, e.g. emergency aid for self-employed persons and short-time work compensation, which were frequently present in the media and can saliently be linked to a positive macroeconomic outlook. A second, more likely reason would be that the support for labor market policy is not affected by a short and positively framed piece of economic information as individuals already have a fixed and made-up mind concerning this policy. This would also go in line with the argument that labor market policies were frequently present in the media.

6.2. Contrasting framing and demand effects

A common concern related to experimental research is that treatment effects may be confounded by experimenter demand (Zizzo, 2010). However, de Quidt et al. (2018) and Mummolo and Peterson (2019) have shown that effects related to information provision are largely not affected by experimenter demand. In the following, we still discuss potential concerns about experimenter demand effects and provide arguments supporting that our results are not driven by demand instead of informational framing effects.[32]

First, if there exists experimenter demand which can be attributed to information provision itself, such experimenter demand should arguably be constant across the groups which receive some information, i.e. across treatment arms and the active control group. If this is the case, our analysis of informational framing via the comparison between treatment arms and the active control group cannot be affected by experimenter demand.

Second, it is possible that the particular framing providing a negative or positive context induces experimenter demand effects in addition to potential demand related to the baseline information. In this case, we would expect that positive (negative) framing induces positive (negative) demand. The finding that negative framing does not affect our outcome variables in a negative way, however, indicates that this is unlikely to be the case. With respect to positive framing effects, we observe heterogeneity based on prior beliefs of respondents, showing that more pessimistic individuals react more strongly to the positive framing treatment. This heterogeneity based on individual beliefs further reduces concerns about a potential demand effect which should be rather constant across different subgroups of the population.

Third, if experimenter demand is present, we would expect that a higher credibility of the treatments results in larger demand effects. We observe that respondents rate the negative framing treatment as more credible when compared to the baseline information. At the same time, we do not find that this higher credibility translates into negative framing effects, suggesting that

[31] Note that this open-ended question was asked on a separate screen from the specific policy channels and hence before respondents became aware of our questions on the subdomains of interest.

[32] As it is very unlikely that our finding on the null effect of the information provision without framing is driven by experimenter demand, we only engage in a detailed discussion on contrasting the framing effects from potential experimenter demand.

experimenter demand effects related to the framing treatments are unlikely. Hence, we are confident that our results are driven by informational framing rather than experimenter demand.

Our findings further inform the methodological literature on information provision experiments in terms of the relevance of framing effects related to information interventions. In particular, they underscore the common advise to frame information treatments in a neutral manner (Haaland et al., 2020) to avoid confounding framing and information effects if a researcher is solely interested in the effect of a baseline (statistical) information. This is of special relevance considering that one of our framing treatments shifts effects of information provision by up to 13 percent of a standard deviation when compared to effects of the baseline information.

7. Conclusion

In this paper, we evaluate the effect of how news outlets communicate economic information to consumers on support for governmental policy in the context of the COVID-19 crisis. Drawing from a large-scale survey based on a representative sample of 3000 individuals in Germany, we implement an information provision experiment. Survey respondents are randomly exposed to an expert forecast of GDP growth which differs in terms of how it is framed in real-world newspaper articles: While a subset of respondents receives the original information based on the annual report of the German Council of Economic Experts (GCEE), other groups of respondents receive the information contained in a short text stemming from real-world newspaper coverage on the topic, or no information intervention at all.

Our results show that positive framing of the expert forecast of GDP growth by news outlets increases support for pandemic policy during the crisis. In addition, we observe that this effect is more pronounced for those respondents who state more pessimistic expectations about the macroeconomic outlook, suggesting an amplifying effect related to positive framing by the media and pessimistic beliefs about the macroeconomy. On the contrary, we estimate precise null effects of the baseline information consisting of the original press release forecast information on support for governmental policy during the pandemic. These results highlight the relevance of the media for providing context to macroeconomic indicators.

In contrast to the results on positive framing, we do not find evidence for an adverse effect of negative framing on policy support during the ongoing crisis. We further document that respondents perceive the negatively framed information as more credible when compared to the baseline information and that effects of positive framing are amplified by larger news consumption of individuals. At the same time, however, the extent of belief updating does not differ between groups. Our results therefore suggest that exposure of respondents to negative economic news confirms their expectation to receive an information with a negative sentiment in times of an economic recession and health crisis. Hence, the negative connotation does not translate into a change in political opinion. Conversely, we find that providing information on forecasted GDP growth together with a positive evaluation of this forecast affects policy assessments during the crisis, likely as this is perceived as rather surprising in times of crisis.

The result that framing can shape political opinion might imply important consequences also for elections if individuals base their voting behavior on their policy assessments. This points out the power of the media when putting news about economic indicators into qualitative context. Furthermore, our analysis on the media and its influence on policy assessments is even more crucial in times of the heated debates with respect to the unforeseen COVID-19 policy measures, as it is currently the case in many Western countries. Eventually, this may also result in news outlets shaping the political spectrum over time when new parties emerge reflecting the changes in policy assessments.

Our analysis on beliefs in relation to GDP growth also shows similarities to studies investigating expectations on other macroeconomic variables, suggesting that prior beliefs about future GDP growth are largely dispersed in the population. Interestingly, when accounting for outliers, the average expected GDP growth lies fairly close to the expert forecast, while the median growth expectation lies slightly below the assessment of experts. This might mirror the perceived recession during the time context of our study. It will also be interesting to see whether future research finds negative framing to be more relevant when the economy is not in crisis.

In conclusion, our findings inform the understanding of the role of the media for the dissemination of economic statistics and its effect on public opinion formation during a global health and economic crisis: While news outlets select and provide editorially prepared information to consumers, they put economic information into context. In a setting of pronounced economic and social uncertainty, this framing by news outlets can be decisive for public opinion formation and support for governmental policy.

Declaration of competing interest

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

Data availability

Replication files and data will be made available upon request.

Appendix A

See Tables A.1–A.5 and Fig. A.1.

Table A.1
Sample composition and representativity.

	Sample: absolute	Sample: relative	Target: relative	Reference Year
Age: 18–29 years	482	16.49	16.31	2019
Age: 30–39 years	455	15.57	15.52	2019
Age: 40–49 years	422	14.44	14.65	2019
Age: 50–64 years	805	27.54	27.48	2019
Age: 65 years and above	759	25.97	26.03	2019
Gender*: female	1448	49.54	50.66	2019
Gender: male	1469	50.26	49.34	2019
Residence: Eastern Germany	441	15.09	15.07	2019
Residence: Western Germany	2482	84.91	84.93	2019
Education: low	1098	37.56	37.34	2018
Education: middle	860	29.42	29.99	2018
Education: high	965	33.01	32.67	2018

Notes: The sources for relative targets are provided by the German Federal Statistical Office. * In addition, there are 6 individuals who do neither identify as female nor male.

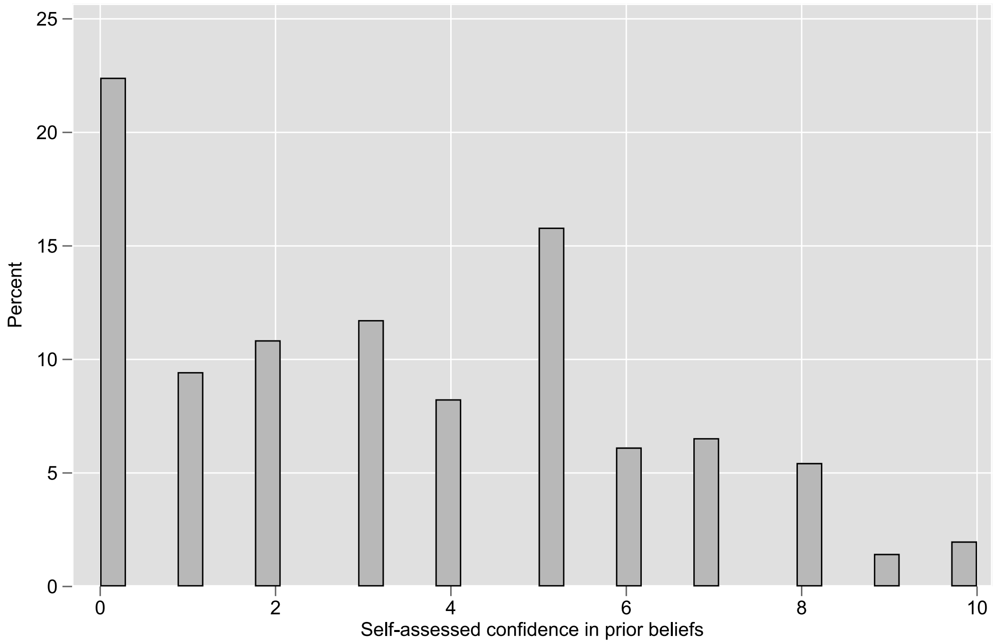

Fig. A.1. Distribution of confidence in prior beliefs.

Table A.2
Tests for experimental balance: against passive control group (no information).

	Control			Treated			
	Control *II*	Control *I*	P-value	Treatment *I*	P-value	Treatment *II*	P-value
Prior beliefs: future GDP growth	8.81	8.96	0.851	9.50	0.383	7.82	0.184
Prior beliefs: confidence	3.37	3.41	0.789	3.38	0.936	3.33	0.781
Concerns about economic development	6.45	6.64	0.129	6.56	0.385	6.46	0.962
Risk attitude	3.78	3.79	0.939	3.96	0.150	3.73	0.706
Generalized trust	4.26	4.35	0.529	4.26	0.991	4.09	0.192
Trust in statistics and science	4.91	4.90	0.993	4.92	0.900	4.96	0.664
Trust in the media	4.50	4.52	0.892	4.63	0.370	4.46	0.754
Media consumption	188.50	166.32	0.004	163.73	0.001	179.49	0.258
News consumption	74.30	67.59	0.178	61.29	0.002	66.17	0.087
Political attitude	4.66	4.74	0.371	4.61	0.608	4.64	0.829
Financial concerns about COVID-19 crisis	2.64	2.56	0.651	2.80	0.305	2.86	0.171

(*continued on next page*)

Table A.2 (*continued*).

	Control			Treated			
	Control *II*	Control *I*	P-value	Treatment *I*	P-value	Treatment *II*	P-value
Experience of COVID-19 testing	0.11	0.12	0.763	0.14	0.080	0.13	0.190
General concerns about COVID-19 crisis	6.04	5.95	0.504	5.96	0.580	5.93	0.449
Age	50.57	50.41	0.858	48.72	0.032	48.47	0.017
Female	0.50	0.50	0.775	0.50	0.796	0.48	0.586
East Germany	0.15	0.15	0.932	0.16	0.753	0.15	0.903
Education	1.93	1.93	0.849	1.98	0.229	1.98	0.201
Employed	0.47	0.50	0.209	0.52	0.039	0.50	0.285
Income	2.48	2.54	0.323	2.57	0.133	2.57	0.139
Household size	2.05	2.10	0.317	2.18	0.017	2.16	0.044
Partner	0.63	0.62	0.694	0.63	0.851	0.62	0.610
Migration background	0.28	0.33	0.073	0.31	0.264	0.31	0.214
Population size	3.29	3.15	0.073	3.24	0.551	3.20	0.215

Notes: Comparison table of active control group and treatment arms against passive control group. Information on variable measurement and the design of the questionnaire is presented in the online appendix.

Table A.3
Tests for experimental balance: against active control group (baseline information).

		Treated			
	Control *I*	Treatment *I*	P-value	Treatment *II*	P-value
Prior beliefs: future GDP growth	8.96	9.50	0.488	7.82	0.123
Prior beliefs: confidence	3.41	3.38	0.855	3.33	0.597
Concerns about economic development	6.64	6.56	0.514	6.46	0.142
Risk attitude	3.79	3.96	0.174	3.73	0.650
Generalized trust	4.35	4.26	0.523	4.09	0.059
Trust in statistics and science	4.90	4.92	0.896	4.96	0.667
Trust in the media	4.52	4.63	0.451	4.46	0.652
Media consumption	166.32	164.73	0.694	179.49	0.063
News consumption	67.59	61.29	0.104	66.17	0.756
Political attitude	4.74	4.61	0.172	4.64	0.272
Financial concerns about COVID-19 crisis	2.56	2.80	0.147	2.86	0.076
Experience of COVID-19 testing	0.12	0.14	0.155	0.13	0.320
General concerns about COVID-19 crisis	5.95	5.96	0.903	5.93	0.934
Age	50.41	48.72	0.050	48.47	0.027
Female	0.50	0.50	0.975	0.48	0.412
East Germany	0.15	0.16	0.822	0.15	0.838
Education	1.93	1.98	0.316	1.98	0.279
Employed	0.50	0.52	0.437	0.50	0.852
Income	2.54	2.57	0.622	2.57	0.638
Household size	2.10	2.18	0.174	2.16	0.322
Partner	0.62	0.63	0.835	0.62	0.908
Migration background	0.33	0.31	0.488	0.31	0.586
Population size	3.15	3.24	0.222	3.20	0.574

Notes: Comparison table of treatment arms against active control group. Information on variable measurement and the design of the questionnaire is presented in the online appendix.

Table A.4
Average treatment effects on policy support: baseline information and framing: individuals with prior beliefs within ±1 SD (robustness).

	General	Labor	Health	Education
Panel *A*: Active vs. passive control group (no information):				
Control group *I*: baseline information	−0.00 (0.05)	0.02 (0.05)	0.00 (0.05)	0.03 (0.06)
Controls	Yes	Yes	Yes	Yes
Observations	1268	1268	1268	1268
Panel *B*: Treatments vs. active control group (baseline information):				
Treatment *I*: positive treatment	0.11** (0.05)	−0.00 (0.05)	0.11** (0.05)	0.11* (0.06)
Treatment *II*: negative treatment	0.06 (0.05)	0.01 (0.05)	0.03 (0.05)	0.03 (0.06)
Controls	Yes	Yes	Yes	Yes
Observations	1911	1911	1911	1911

Notes: The dependent variables have been standardized in terms of their mean and standard deviation. Robust standard errors are displayed in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The controls comprise of prior beliefs, media and news consumption, trust, financial concerns due to COVID-19, age, household and population size, migration background, and (indirect) experience of a positive COVID-19 test.

Table A.5
Average treatment effects of framing on policy support against the active control group: full-updating vs. non-full-updating individuals (robustness).

	General		Labor		Health		Education	
Panel A: Full-updating individuals:								
Treatment I: positive treatment	0.12*	(0.07)	−0.03	(0.07)	0.15**	(0.07)	0.15**	(0.07)
Treatment II: negative treatment	0.03	(0.07)	−0.01	(0.07)	0.02	(0.07)	0.03	(0.07)
Controls	Yes		Yes		Yes		Yes	
Observations	1095		1095		1095		1095	
Panel B: Non-full-updating individuals:								
Treatment I: positive treatment	0.13*	(0.07)	0.12*	(0.07)	0.10	(0.07)	0.07	(0.07)
Treatment II: negative treatment	0.13*	(0.07)	0.08	(0.07)	0.08	(0.07)	0.01	(0.07)
Controls	Yes		Yes		Yes		Yes	
Observations	1079		1079		1079		1079	

Notes: The dependent variables have been standardized in terms of their mean and standard deviation. Robust standard errors are displayed in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The controls comprise of prior beliefs, media and news consumption, trust, financial concerns due to COVID-19, age, household and population size, migration background, and (indirect) experience of a positive COVID-19 test.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ejpoleco.2022.102249.

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