



FRIEDRICH-SCHILLER-
UNIVERSITÄT
JENA

Framing of Economic News and Policy Support During a Pandemic: Evidence from an Information Experiment

Patrick Bareinz | Fabian Koenings

JENA ECONOMIC RESEARCH PAPERS · # 2021-004

Framing of Economic News and Policy Support During a Pandemic: Evidence from an Information Experiment.*

Patrick Bareinz[†]
University of Jena

Fabian Koenings[‡]
University of Jena

March 29, 2021

Abstract

We investigate the effect of how news outlets communicate macroeconomic information to consumers on support for governmental policy in the context of the COVID-19 crisis. In our survey experiment based on a representative sample of 3000 individuals in Germany, respondents are exposed to an expert forecast of GDP growth. Individuals are randomly assigned to either receive no information, the baseline forecast information, or real-world frames of the same information used in newspaper articles on the topic. We find that in contrast to the baseline information, positive framing of forecasted economic growth by news outlets increases support for pandemic policy. This effect is especially pronounced for respondents with more pessimistic macroeconomic expectations. Further evidence suggests that negative economic news are perceived as more credible and hence less surprising in times of recession, not translating into a change in political opinion.

JEL classification: C90, D83, D84, D91.

Keywords: expectation formation, information experiment, media framing, macroeconomic information, policy support, COVID-19 crisis.

*We would like to thank Silke Uebelmesser, Jana Schuetz and participants of the staff member seminar of the German Council of Economic Experts (Sachverständigenrat Wirtschaft) for valuable comments and discussions. Janina Voigt provided excellent research assistance. This study has been pre-registered in the RCT registry of the American Economic Association under ID: AEARCTR-0006716. The pre-registration and our corresponding pre-analysis plan are available at: www.socialscicenterregistry.org/trials/6716. IRB approval was obtained at the University of Jena.

[†]University of Jena, Carl-Zeiss-Str. 3, 07743 Jena, Germany, email: patrick.bareinz@uni-jena.de.

[‡]University of Jena, Carl-Zeiss-Str. 3, 07743 Jena, Germany, email: fabian.koenings@uni-jena.de.

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 2020). 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.

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 on the topic which engaged in framing of the baseline forecast information in relation to the pandemic. We then 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.

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 experimentally investigating the effect of economic news framed by the media in the spirit of Tversky and Kahneman (1981) on support for governmental policy.

Second, we contribute to recent experiments addressing the 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.

Relatedly, Fetzner et al. (2020) 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. Faia et al. (2021), in turn, investigate endogenous information acquisition during the crisis and 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 on economic news on pandemic policy support during the ongoing crisis.

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 measure 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 GDP growth rates as compared to beliefs about the likelihood of a recession (Roth and Wohlfart 2020).

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 experimental information provision induces an exogenous shift based on the sign of biases in prior beliefs. In addition, framing of the economic information by newspapers may amplify or offset the effect of this baseline information. Since individual expectations about a country's future prosperity also depend on the assessment of its policy, it is likely that information provision further translates into individuals' policy assessments.

We find that positive framing of the forecasted GDP growth rate by news outlets increases support for governmental policy during the COVID-19 crisis. In addition, this effect is more pronounced for respondents with more pessimistic prior beliefs 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.

In contrast to the results on positive framing, we do not find evidence for an adverse effect of negative framing on policy support. We further document that respondents perceive the negatively framed information as more credible when compared to the baseline information. In addition, we observe an amplifying effect of positive framing and larger news consumption by individuals. Our 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.

Our results suggest that, in a setting of an economic recession and health crisis in which negative news are prevalent, exposure of respondents to negative economic news is more in line with their expectations and thus less surprising while not necessarily translating 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 influences policy assessments in the population positively.

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 analyses are discussed in Section 5. Section 6 concludes.

2 Experimental Design

In the following, we introduce our pre-registered experimental design, consisting of four stages and four experimental groups, following the description in our pre-analysis plan.¹ Survey respondents are randomly assigned to one of two treatment arms which differ with respect to the framing of the information provided, to the active control group receiving the original information (i.e. the baseline information), or to the passive control group which does not receive any information.²

The information 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 original press release 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.

¹Our pre-analysis plan is available at: www.socialscienceregistry.org/trials/6716.

²The 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).

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 *I* receives the original information based on the GCEE press release, whereas the passive control group *II* does not receive any information.

On the day of the release of the GCEE report, we screened large German newspapers for media coverage on the topic. 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.³ Specifically, our treatments are worded as follows:

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.”

³For a detailed description of the adjustments made and the news sources for the positive and negative treatments, see appendix C.

Control group II: No information provided.

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. 39) in the context of information provision experiments. 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.

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”.

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 terms of the updating of beliefs 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 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. In addition to this effect of the baseline forecast information, the framing treatments may exert effects on our outcome measures themselves by making a positive or negative context of the macroeconomic information more or less salient to respondents.

It is therefore important to distinguish between the effects of the baseline information, the influence of framing, and the direction of biases in prior beliefs. Based on 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 related to this information 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 groups which differ only in terms of the information provided to the active control group. Concerning hypotheses *III* and *IV*, we then proceed to 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 over 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

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

	Obs.	Mean	Median	SD	Min	Max
Control group I: baseline information	712	8.93	3	14.26	-10	85
Control group II: no information	754	8.79	3	14.96	-30	90
Treatment I: positive framing	758	9.46	3	15.54	-17	80
Treatment II: negative framing	717	7.89	3	13.78	-10	80

Notes: The total sample size used in our analysis comprises 2941 observations for which we have full information on the variables of interest.

above) and the survey is representative with respect to age, gender, educational background, and place of residence in Eastern or Western Germany.⁴

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 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.⁵

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. With respect to our survey experiment, we do not observe systematic differences in terms of the distribution of experimental groups across survey days. 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 the assessment of the current economic situation, 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 2941 individuals. The specific distribution of respondents across experimental groups is displayed in the first column of table 1.

⁴Specifically, our data set fulfills the corresponding representativity quotas with deviations smaller than 2 percentage points. The reference statistics are provided by the German Federal Statistical Office.

⁵Note 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).

3.2 Distribution of prior beliefs

As a first step, we descriptively compare respondents' prior beliefs about the forecasted GDP growth rate across experimental groups. Table 1 displays summary statistics on the distribution of prior beliefs. We observe that for some respondents, it seems to be rather difficult to assess future GDP growth as indicated by the wide range between the extreme values of the distributions of prior beliefs.

On average, respondents' prior beliefs about future GDP growth are positively biased by around 5 percentage points. 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 that the mean value is largely driven by outliers expecting very large GDP growth in the future. On the other hand, it reveals a substantive fraction of respondents who expect stagnant or negative 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, exert positive 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.

In order to assess prior beliefs graphically, we focus on the center of the distributions. Figure 1 displays the distribution of prior beliefs as well as its kernel density across experimental groups for those respondents whose beliefs are within a range of ± 1 standard deviation.⁶ The forecast by the GCEE is indicated by the dashed lines. The distributions of prior beliefs show similar patterns mirroring median values below the experts' forecast across experimental groups.⁷

⁶For the purpose of graphical presentation, 10% of respondents' prior beliefs are thus not displayed. We include these observations in our subsequent analyses.

⁷Specifically, the small observed differences in prior beliefs between our experimental groups are not statistically significant when using the two control groups as base groups (see first row of tables B1 and B2 in appendix B). While there is a slight imbalance in prior beliefs between treatment arms, it does not affect our estimation results against the control groups. To ensure robustness, we nevertheless control for prior beliefs in all specifications.

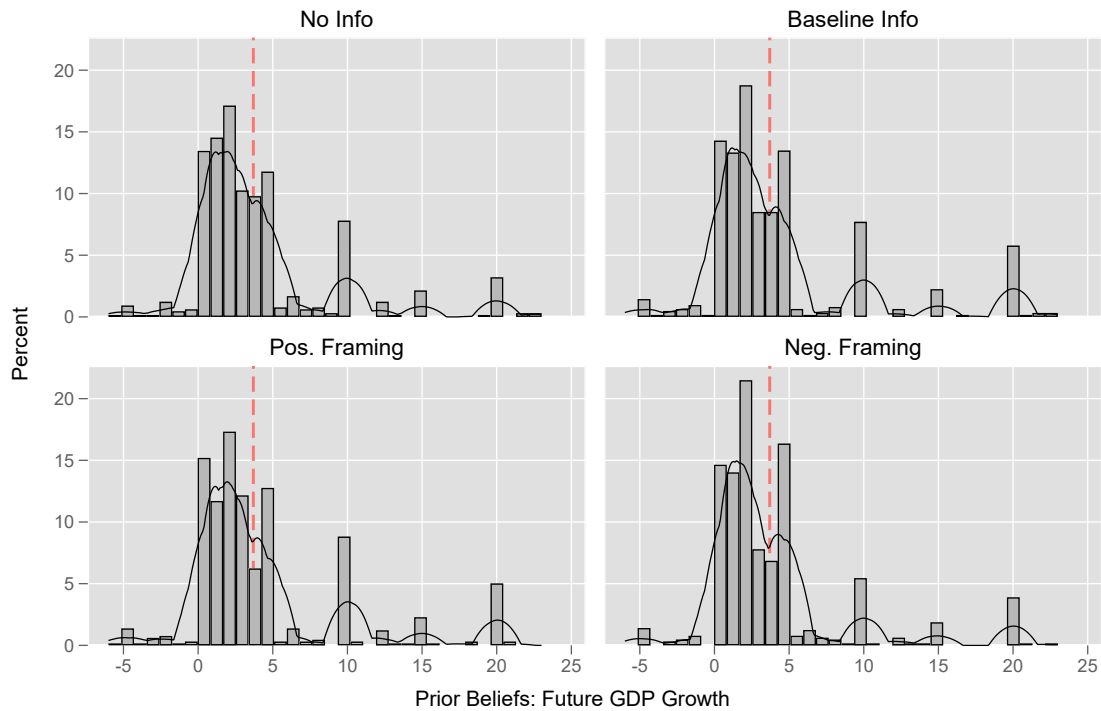


Figure 1: Distribution of prior beliefs across experimental groups (± 1 SD).

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 socio-economic 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 B1 and B2 in appendix B, 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.

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* based on biases in prior beliefs, we hence 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:

$$y_i = \alpha_0 + \alpha_1 C_i^I + \theta' X_i + \varepsilon_i, \quad (1)$$

where y_i denotes our set of outcome measures of policy support, C_i^I is an indicator for the active control group, and X_i contains covariates based on the results from our balance tests.⁸

The results from the estimation of equation (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. Conversely, 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 nor economically significant amount.

It may nevertheless be the case that exist treatment effects of the baseline information conditional on prior beliefs as reflected by our hypotheses *I* and *II*, and that an evaluation of

⁸Note that in our pre-analysis plan, we further indicated an estimation equation combining all experimental groups into a single specification. Given that our experimental groups are mutually exclusive, these results are reflected by the separated estimation equations presented here.

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	-0.01 (0.05)	0.03 (0.05)	0.01 (0.05)	0.05 (0.05)
Controls	Yes	Yes	Yes	Yes
Observations	1466	1466	1466	1466
Panel B: CATE based on overestimation (hypothesis I):				
Control group I: baseline information	-0.09 (0.07)	-0.05 (0.07)	-0.04 (0.07)	-0.02 (0.08)
Controls	Yes	Yes	Yes	Yes
Observations	668	668	668	668
Panel C: CATE based on underestimation (hypothesis II):				
Control group I: baseline information	0.06 (0.07)	0.09 (0.07)	0.06 (0.07)	0.13* (0.07)
Controls	Yes	Yes	Yes	Yes
Observations	790	790	790	790

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.

average treatment effects may mute such results. We therefore directly address these hypotheses by reestimating equation (1) in terms of conditional average treatment effects (CATE), by distinguishing 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 health 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.

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

Table 3: Effects of framing on policy support.

	General		Labor		Health		Education	
Panel A: ATE of framing (treatments vs. active control group; hypotheses <i>III</i> and <i>IV</i>):								
Treatment <i>I</i> : positive framing	0.12**	(0.05)	0.04	(0.05)	0.12**	(0.05)	0.11**	(0.05)
Treatment <i>II</i> : negative framing	0.07	(0.05)	0.02	(0.05)	0.04	(0.05)	0.02	(0.05)
Controls	Yes		Yes		Yes		Yes	
Observations	2187		2187		2187		2187	
Panel B: CATE based on overestimation (treatments vs. passive control group):								
Treatment <i>I</i> : positive treatment	0.04	(0.07)	0.08	(0.07)	0.08	(0.07)	0.14*	(0.07)
Treatment <i>II</i> : negative treatment	0.07	(0.07)	0.05	(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>I</i> : positive treatment	0.18***	(0.07)	0.09	(0.07)	0.19***	(0.07)	0.17**	(0.07)
Treatment <i>II</i> : negative treatment	0.04	(0.07)	0.06	(0.07)	0.01	(0.07)	0.05	(0.07)
Controls	Yes		Yes		Yes		Yes	
Observations	1215		1215		1215		1215	

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.

information as our counterfactual. Hence, observed treatment effects between the active control group and our framing treatments can be interpreted as effects of framing rather than of 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:

$$y_i = \beta_0 + \beta_1 T_i^I + \beta_2 T_i^{II} + \theta' X_i + \varepsilon_i, \quad (2)$$

where y_i represents our set of outcome measures of policy support, T_i^I and T_i^{II} are treatment indicators for the two treatment arms, and X_i contains covariates based on the results from our balance tests.

The estimation results of equation (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.⁹

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. In section 5.5, we discuss potential reasons for the observed differences across channels of pandemic policy.

In terms of effect sizes, we observe that positive framing increases policy support by about 12 percent of a standard deviation, on average. 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 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 equation 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.

The estimation results are displayed in panels *B* and *C* of table 3. Concerning the effects 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 second 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

⁹In addition, 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 A1 in appendix A. Note that this robustness analysis has not been pre-specified.

expectations. We further observe suggestive, albeit mostly insignificant, evidence for an offsetting effect of positive framing for respondents who overestimate future GDP growth (see the positive coefficients in the first row of panel *B* in table 2) when compared with the results for the baseline information (see the negative coefficients in panel *B* of table 2). We do not find any evidence for a similar relationship in case of negative framing, which seems to be rather inelastic to prior beliefs in terms of effect sizes.

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 the channel of news consumption in more detail in the subsequent section.

5 Discussion and Further Analyses

The following section discusses the results of further analyses related to the investigation 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 developed by Athey and Imbens (2016, 2019) called causal tree analysis. Specifically, we concentrate on the comparison of our positive framing treatment with the passive control group. This allows us to further investigate potential amplifying effects 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

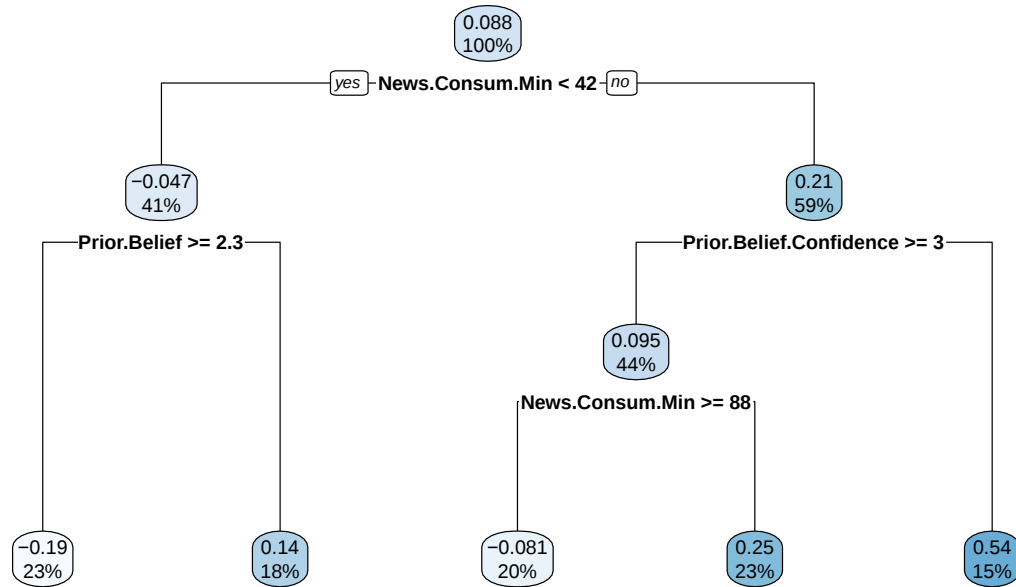


Figure 2: Causal tree: positive framing vs. no information.

from our balance tests, employing the assessment of general COVID-19 policy as the outcome variable.¹⁰

The resulting causal tree is displayed in figure 2. 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 that positively framed economic news are particularly relevant for support for governmental policy in times when negative news are prevalent.¹¹

¹⁰Note 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 avoids the over-evaluation of very small subpopulations.

¹¹Note that specifically news and not media consumption is found to be a main driver by the algorithm for heterogeneous framing effects. This highlights the importance of news instead of general media consumption in this context.

The results from the causal tree analysis further support our earlier investigation based on heterogeneity in prior beliefs. Interestingly, the cutting value found by the algorithm of 2.3 percentage points for those respondents who do not consume news very often is very close to the original forecast of GDP growth by the GCEE. In addition, we observe that self-assessed confidence in prior beliefs is found to be 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 greater when respondents are less confident about their prior beliefs (Armantier et al. 2016; Binder and Rodrigue 2018).¹² 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.

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:

$$c_i = \beta_0 + \beta_1 T_i^I + \beta_2 T_i^{II} + \theta' X_i + \varepsilon_i, \quad (3)$$

where c_i represents the secondary outcome variable on the credibility of the provided information as assessed by respondents, T_i^I and T_i^{II} are treatment indicators for the two treatment arms, and X_i contains covariates based on the results from our balance tests.

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 difference is not statistically significant. These results provide interpretational background as to why our negative framing treatment does not exert adverse effects on policy support. It seems to be the case that in a setting of economic recession, exposure of respondents to negatively framed economic news is more in line with their expectations and

¹²We 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.

Table 4: Assessment of credibility of information and full updating.

	Assessed 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	2187		2187	

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.

may hence not necessarily translate into 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 as negative news about the macroeconomic situation are more prevalent in times of recession and consumers are therefore exposed to such negative news on a regular basis.

5.3 Updating of prior beliefs

While the results in our previous section indicate that negatively framed information on economic growth is perceived as less surprising in times of recession, 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 experimental groups that receive information, on average.¹³ This indicates that respondents are processing the information provided, and form posterior beliefs more in line with the forecast by the GCEE, on average. Hence, these results also reduce concerns about potential experimenter demand

¹³Specifically, 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 groups.

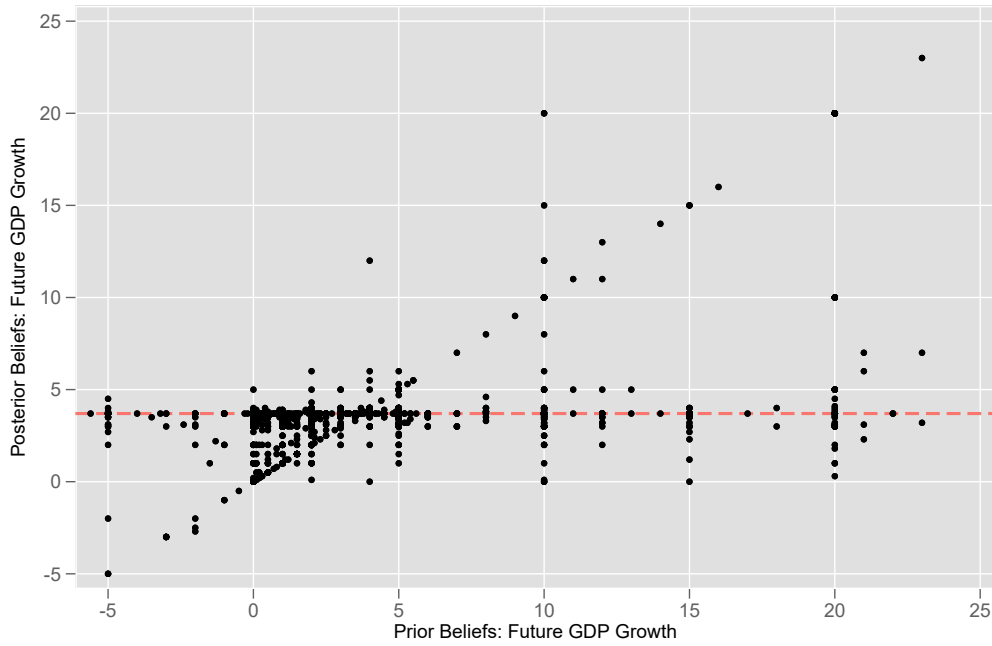


Figure 3: Comparison of posterior and prior beliefs (± 1 SD).

related to information provision as they indicate consistent belief updating across treatment arms and the active control group.

In addition to this quantitative assessment, figure 3 displays respondents' posterior beliefs against their prior beliefs using the same axes ranges as in figure 1 (i.e. ± 1 SD of prior beliefs). 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 experimental groups. For that purpose, the following equation is estimated:

$$u_i = \delta_0 + \delta_1 T_i^I + \delta_2 T_i^{II} + \theta' X_i + \varepsilon_i, \quad (4)$$

representing a linear probability model¹⁴, where u_i represents belief updating of respondents assuming a value of one if a respondent states posterior beliefs in line with the forecast and zero

¹⁴The results from a probit specification are very similar.

otherwise, T_i^I and T_i^{II} are treatment indicators for the two treatment groups, and X_i contains covariates based on the results from our balance tests.¹⁵ Since there are no posterior beliefs for the passive control group which does not receive any information, this specification is only estimated for the two treatment arms employing the active control group as the base group.

The estimation results are presented in the second column of table 4. We do not find evidence for a difference in shares of respondents who engage in full belief updating, i.e. stating posterior beliefs in line with the GCEE forecast, between experimental groups. Hence, our results indicate that the differences in assessed credibility of the information provided between treatment arms do not depend on 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 appears to be a less expected context provided by the media.

In line with studies on other macroeconomic expectations, some respondents, even some with pronounced perception gaps, do not revise their expectations at all when exposed to information (Armantier et al. 2016). 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 A2 in appendix A.¹⁶ 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.¹⁷ 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.

¹⁵To decrease the influence of outliers in this specification, we abstract from the definition of our dependent variable indicated in the pre-analysis plan. Instead, we construct a binary dependent variable which takes the value 1 if a respondent engages in full belief updating when stating posterior beliefs.

¹⁶Note that this robustness analysis has not been pre-specified.

¹⁷We 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 5: 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	0.11	(0.11)
Risk attitude	0.25**	(0.11)
Trust attitude: generalized	−0.07	(0.12)
Trust attitude: statistics	−0.28*	(0.14)
Trust attitude: media	0.17	(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	0.20**	(0.09)
Experience of positive COVID-19 test	0.15	(0.68)
General concerns about COVID-19 crisis	0.25**	(0.10)
Age	−0.09***	(0.02)
Female	3.49***	(0.51)
Eastern Germany	1.62**	(0.70)
Education	−3.20***	(0.31)
Employed	−0.04	(0.55)
Income	−0.73***	(0.24)
Household size	0.35	(0.28)
Partner	−0.15	(0.57)
Migration background	−1.21**	(0.53)
Population size in area of residence	0.05	(0.17)
Observations	2941	
Adj. R^2	0.09	

Notes: Biases in prior beliefs are defined in absolute terms. Robust standard errors are displayed in parentheses;

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4 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:

$$b_i = \theta_0 + \theta'X_i + \varepsilon_i, \quad (5)$$

where b_i represents biases in beliefs about the forecasted GDP growth rate in absolute terms, and X_i contains the socio-demographic and attitudinal controls employed in the balance tests.

The results are displayed in table 5. 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).

5.5 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.

To evaluate what respondents think about when answering to our measure of general policy support during the crisis, we 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.¹⁸ 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

¹⁸Note 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.

the relevance of different policy channels, we observe that about 30 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.

5.6 Contrasting framing and demand effects

A common concern related to experimental research is that treatment effects may be confounded by experimenter demand (de Quidt et al. 2018; Zizzo 2010). In the following, we therefore discuss potential concerns about experimenter demand effects and provide arguments supporting that our results are not driven by demand instead of than informational framing effects.¹⁹

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

¹⁹As 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.

(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 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 advice to frame information treatments in a neutral manner (Haaland et al. 2020) to avoid confoundment of 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 about 10 percent of a standard deviation when compared to effects of the baseline information. Thereby, our findings also highlight the relevance of news outlets for public opinion formation as these usually provide context and statistical information to consumers in a joint manner.

6 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 framing of the expert forecast of GDP growth in a positive context by news outlets increases support for pandemic policy during the ongoing 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 prior 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 experimental groups. Our results therefore suggest that exposure of respondents to negative economic news is more in line with their expectations in times of an economic recession and health crisis and hence do not necessarily translate into a change in political opinion. Conversely, we find that providing information on forecasted GDP growth together with a positive context by news outlets affects policy assessments during the crisis.

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, the median growth expectation lies slightly below the expectation of economic experts, which offers interesting avenues for future research. 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.

References

- Armantier, Olivier, Scott Nelson, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar (2016). "The Price Is Right: Updating Inflation Expectations in a Randomized Price Information Experiment". *The Review of Economics and Statistics* 98 (3), 503–523.
- Armona, Luis, Andreas Fuster, and Basit Zafar (2019). "Home Price Expectations and Behaviour: Evidence from a Randomized Information Experiment". *The Review of Economic Studies* 86 (4), 1371–1410.
- Athey, Susan and Guido W. Imbens (2016). "Recursive Partitioning for Heterogeneous Causal Effects". *Proceedings of the National Academy of Sciences* 113 (27), 7353–7360.
- (2019). "Machine Learning Methods That Economists Should Know About". *Annual Review of Economics* 11 (1), 685–725.
- Binder, Carola (2020). "Coronavirus Fears and Macroeconomic Expectations". *The Review of Economics and Statistics* 102 (4), 721–730.
- Binder, Carola and Alex Rodrigue (2018). "Household Informedness and Long-Run Inflation Expectations: Experimental Evidence". *Southern Economic Journal* 85 (2), 580–598.
- Bleemer, Zachary and Basit Zafar (2018). "Intended College Attendance: Evidence from an Experiment on College Returns and Costs". *Journal of Public Economics* 157, 184–211.
- Bursztyn, Leonardo, Aakaash Rao, Christopher Roth, and David Yanagizawa-Drott (2020). *Misinformation During a Pandemic*. Becker Friedman Institute for Economics Working Paper No. 2020-44.
- Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia (2017). "Inflation Expectations, Learning, and Supermarket Prices: Evidence from Survey Experiments". *American Economic Journal: Macroeconomics* 9 (3), 1–35.
- Chandler, Jesse, Cheskie Rosenzweig, Aaron J. Moss, Jonathan Robinson, and Leib Litman (2019). "Online Panels in Social Science Research: Expanding Sampling Methods beyond Mechanical Turk". *Behavior Research Methods* 51 (5), 2022–2038.
- Chong, Dennis and James N. Druckman (2007). "Framing Theory". *Annual Review of Political Science* 10 (1), 103–126.
- Chopra, Felix, Ingar Haaland, and Christopher Roth (2019). "Do People Value More Informative News?" mimeo.

- Cinelli, Matteo et al. (2020). "The COVID-19 Social Media Infodemic". *Nature Scientific Reports* 10 (1), 16598.
- Coibion, Olivier, Dimitris Georgarakos, Yuriy Gorodnichenko, and Michael Weber (2020a). *Forward Guidance and Household Expectations*. NBER Working Paper No. 26778.
- Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber (2019). *Monetary Policy Communications and Their Effects on Household Inflation Expectations*. NBER Working Paper No. 25482.
- (2020b). *Does Policy Communication During Covid Work?* NBER Working Paper No. 27384.
- De Quidt, Jonathan, Johannes Haushofer, and Christopher Roth (2018). "Measuring and Bounding Experimenter Demand". *American Economic Review* 108 (11), 3266–3302.
- DellaVigna, Stefano and Ethan Kaplan (2007). "The Fox News Effect: Media Bias and Voting". *The Quarterly Journal of Economics* 122 (3), 1187–1234.
- Faia, Ester, Andreas Fuster, Vincenzo Pezone, and Basit Zafar (2021). *Biases in Information Selection and Processing: Survey Evidence from the Pandemic*. NBER Working Paper No. 28484.
- Fetzer, Thiemo, Lukas Hensel, Johannes Hermle, and Christopher Roth (2020). "Coronavirus Perceptions and Economic Anxiety". *The Review of Economics and Statistics*, forthcoming.
- Gentzkow, Matthew and Jesse M. Shapiro (2010). "What Drives Media Slant? Evidence From U.S. Daily Newspapers". *Econometrica* 78 (1), 35–71.
- Gerber, Alan S., Dean Karlan, and Daniel Bergan (2009). "Does the Media Matter? A Field Experiment Measuring the Effect of Newspapers on Voting Behavior and Political Opinions". *American Economic Journal: Applied Economics* 1 (2), 35–52.
- Grewenig, Elisabeth, Philipp Lergetporer, Katharina Werner, and Ludger Woessmann (2020). "Incentives, Search Engines, and the Elicitation of Subjective Beliefs: Evidence from Representative Online Survey Experiments". *Journal of Econometrics*.
- Haaland, Ingar, Christopher Roth, and Johannes Wohlfart (2020). *Designing Information Provision Experiments*. CESifo Working Paper No. 8406.
- Roth, Christopher and Johannes Wohlfart (2020). "How Do Expectations about the Macroeconomy Affect Personal Expectations and Behavior?" *The Review of Economics and Statistics* 102 (4), 731–748.
- Tversky, A. and D. Kahneman (1981). "The Framing of Decisions and the Psychology of Choice". *Science* 211 (4481), 453–458.

WHO (2020). *WHO Situation Report 13*. Available online: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200202-sitrep-13-ncov-v3.pdf?sfvrsn=195f4010_6.

Zizzo, Daniel John (2010). "Experimenter Demand Effects in Economic Experiments". *Experimental Economics* 13 (1), 75–98.

Appendix A: Robustness Analyses

Table A1: 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)	0.04	(0.06)
Controls	Yes		Yes		Yes		Yes	
Observations	1277		1277		1277		1277	
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)	0.10*	(0.06)
Treatment II: negative treatment	0.05	(0.05)	0.00	(0.05)	0.03	(0.05)	0.02	(0.06)
Controls	Yes		Yes		Yes		Yes	
Observations	1923		1923		1923		1923	

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 A2: Average treatment effects of framing on policy support: full-updating vs. non-full-updating individuals (robustness).

	General		Labor		Health		Education	
Panel A: Full-updating individuals:								
Treatment I: positive treatment	0.11*	(0.07)	−0.03	(0.07)	0.16**	(0.07)	0.15**	(0.07)
Treatment II: negative treatment	0.02	(0.07)	−0.02	(0.07)	0.01	(0.07)	0.02	(0.07)
Controls	Yes		Yes		Yes		Yes	
Observations	1103		1103		1103		1103	
Panel B: Non-full-updating individuals:								
Treatment I: positive treatment	0.13*	(0.07)	0.13*	(0.07)	0.10	(0.07)	0.07	(0.07)
Treatment II: negative treatment	0.12*	(0.07)	0.07	(0.07)	0.08	(0.07)	0.01	(0.07)
Controls	Yes		Yes		Yes		Yes	
Observations	1084		1084		1084		1084	

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: Experimental Balance

Table B1: Tests for experimental balance: against passive control group (no information).

	Control II	Control Control I	P-value	Treatment I	P-value	Treated Treatment II	P-value
Prior beliefs: future GDP growth	8.79	8.93	0.855	9.46	0.395	7.89	0.231
Prior beliefs: confidence	4.37	4.43	0.663	4.38	0.907	4.33	0.784
Concerns about economic development	7.45	7.64	0.121	7.56	0.369	7.47	0.855
Risk attitude	4.78	4.79	0.889	4.97	0.131	4.74	0.746
Generalized trust	5.25	5.36	0.428	5.26	0.919	5.09	0.227
Trust in statistics and science	5.90	5.91	0.927	5.92	0.829	5.95	0.692
Trust in the media	5.49	5.53	0.769	5.63	0.299	5.45	0.778
Media consumption	189.41	166.07	0.002	164.36	0.001	179.20	0.201
News consumption	74.21	67.36	0.167	61.22	0.001	66.23	0.091
Political attitude	5.66	5.74	0.414	5.60	0.524	5.63	0.768
Financial concerns about COVID-19 crisis	3.64	3.56	0.603	3.80	0.315	3.87	0.165
Experience of COVID-19 testing	1.89	1.88	0.758	1.86	0.080	1.87	0.188
General concerns about COVID-19 crisis	7.04	6.95	0.517	6.96	0.569	6.93	0.433
Age	50.52	50.38	0.872	48.73	0.038	48.45	0.018
Female	0.50	0.50	0.919	0.50	0.837	0.48	0.571
East Germany	0.15	0.15	0.926	0.16	0.700	0.15	0.970
Education	1.92	1.94	0.778	1.98	0.219	1.98	0.214
Employed	0.47	0.51	0.167	0.52	0.035	0.50	0.253
Income	2.47	2.55	0.213	2.58	0.101	2.57	0.117
Household size	2.05	2.10	0.305	2.18	0.015	2.17	0.031
Partner	1.37	1.38	0.803	1.37	0.893	1.38	0.673
Migration background	1.71	1.67	0.091	1.69	0.290	1.68	0.209
Population size	3.29	3.16	0.078	3.24	0.505	3.19	0.185

Notes: Comparison table of active control group and treatment arms against passive control group.

Table B2: Tests for experimental balance: against active control group (baseline information) and between treatment arms.

			Treated		Between Treated		
	Control <i>I</i>	Treatment <i>I</i>	P-value	Treatment <i>II</i>	P-value	P-value	
33	Prior beliefs: future GDP growth	8.93	9.46	0.498	7.89	0.161	0.041
	Prior beliefs: confidence	4.43	4.38	0.755	4.33	0.490	0.703
	Concerns about economic development	7.64	7.56	0.511	7.47	0.173	0.478
	Risk attitude	4.79	4.97	0.172	4.74	0.642	0.066
	Generalized trust	5.36	5.26	0.488	5.09	0.050	0.191
	Trust in statistics and science	5.91	5.92	0.905	5.95	0.769	0.859
	Trust in the media	5.53	5.63	0.462	5.45	0.562	0.181
	Media consumption	166.07	164.36	0.795	179.20	0.063	0.034
	News consumption	67.36	61.22	0.111	66.23	0.803	0.160
	Political attitude	5.74	5.60	0.159	5.63	0.273	0.729
	Financial concerns about COVID-19 crisis	3.56	3.80	0.134	3.87	0.062	0.686
	Experience of COVID-19 testing	1.88	1.86	0.157	1.87	0.320	0.681
	General concerns about COVID-19 crisis	6.95	6.96	0.933	6.93	0.896	0.828
	Age	50.38	48.73	0.056	48.45	0.027	0.742
	Female	0.50	0.50	0.920	0.48	0.510	0.441
	East Germany	0.15	0.16	0.774	0.15	0.956	0.731
	Education	1.94	1.98	0.349	1.98	0.340	0.972
	Employed	0.51	0.52	0.487	0.50	0.811	0.348
	Income	2.55	2.58	0.711	2.57	0.765	0.942
	Household size	2.10	2.18	0.168	2.17	0.268	0.789
	Partner	1.38	1.37	0.906	1.38	0.865	0.772
	Migration background	1.67	1.69	0.515	1.68	0.667	0.830
	Population size	3.16	3.24	0.263	3.19	0.654	0.501

Notes: Comparison table of treatment arms against active control group and between treatment arms.

Appendix C: Original Newspaper Excerpts

Treatment I: Positive framing:

“The **German Council of Economic Experts** [economic experts] expect[s] an overall upturn in the coming year: It [the economic experts] expects significant growth again in the coming year **2021** after the COVID-19 recession. The gross domestic product will then increase by 3.7 percent [, write the five economists in their report for the German government].”

(*Die Zeit*, online: November 11, 2020)

Available online (German version): www.zeit.de/wirtschaft/2020-11/konjunktur-2021-corona-wirtschaft-wachstum-aufschwung-prognose.

Treatment II: Negative framing

“[Also] The **German Council of Economic Experts** [economic experts] fears a long shadow of the **COVID-19** crisis: Although it [they] no longer expects the collapse to be as severe as in the summer – it [they] also expects gross domestic product growth of only 3.7 percent in 2021.”

(*Der Spiegel*, online: November 10, 2020)

Available online (German version): www.spiegel.de/wirtschaft/unternehmen/coronakrise-wirtschaftsweise-heben-konjunkturprognose-an.

IMPRESSUM

Jena Economic Research Papers

ISSN 1864-7057

Friedrich Schiller University Jena

Faculty of Economics and Business Administration

Carl-Zeiss-Str. 3

D-07743 Jena, Germany

Email: office.jerp@uni-jena.de

Editor: Silke Übelmesser

Website: www.wiwi.uni-jena.de/en/jerp

© by the author