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JEL Classification: E43, E52, E58

Keywords: climate change, Disasters, Households Expectations, survey, Media focus, monetary policy, Natural rate of interest, Paradox of Communication

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The Expectations Channel of Climate Change: Implications for Monetary Policy

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1 Introduction

Climate change is a hotly debated topic and a rising, complex challenge for policymakers. This includes monetary policymakers who have been increasingly focusing on the issue while reviewing their strategies (see, for instance, ECB, 2021). And there is little doubt that "it is vital for monetary policymakers to understand the nature of climate disturbances to the economy, as well as their likely persistence and breadth, in order to respond effectively" (Brainard, 2019). Alas, this is a daunting task because the extent of climate change and its immediate consequences are highly uncertain—let alone their implications for, say, price and financial stability. What adds to the complexity of the task is that while the full impact of climate change is likely to materialize only over the course of several decades (if not centuries), people are increasingly concerned with climate change and maintain expectations about its economic impact.[1]

In this paper we ask how these expectations impact the economy today and assess the implications for monetary policy. Our analysis is centered around what we call the "the expectations channel of climate change" through which expectations about climate change—fundamentally warranted or not—feed back into the economy. In the first part of the paper, we measure expectations about the economic impact of climate change in a large survey representative of US consumers. We find that while expectations vary systematically with socioeconomic characteristics, media consumption and various information treatments, respondents tend to assign large probabilities to climate-change related natural disasters—a salient feature of climate change. Expectations of climate-change related natural disasters are an example of rare disaster expectations, which in turn, have been identified as an important driver of asset prices and the business cycle (Barro, 2006; Gourio, 2012; Kozlowski et al., 2020). In the second part of the paper, we thus zoom in on climate-change related disaster expectations and study their implications for monetary policy. For this purpose we rely on a New Keynesian model with rare disasters as put forward by Fernández-Villaverde and Levintal (2018). We show analytically for a simplified version of the model that disaster expectations—along both the intensive and the extensive margin—lower the natural rate of interest. Intuitively, a perceived increase of disaster risk represents bad news about the future and depresses current economic activity (Barsky and Sims, 2012; Blanchard et al., 2013; Schmitt-Grohé and Uribe, 2012). Once we map the results of the survey into a calibrated version of the model, we find that climate-change related disaster expectations make a sizeable contribution to the business cycle. Assuming a standard monetary-policy reaction function, we find that they account for close to 10 percent of the volatility of inflation and the output gap.

In order to measure climate-change expectations we rely on a representative survey of approximately 30,000 US consumers, conducted during the period from October 2020 through July 2021. Among other things, we ask whether respondents expect climate change to impact output growth, either adversely, for example, due to stricter regulation or positively, for example, due to technological innovation. We find that on average the expected impact on growth is negligible.[2] At the same time, respondents expect median disaster costs due to climate change over the next

[1]Various indicators testify to this such as, for instance, increasing media coverage of the topic as well as the Google Trends indicator for "climate change" search queries, as Figure C.1 in the appendix illustrates.

[2]For the actual impact of temperature on output and output growth, based on historical data, see the estimates of Dell et al. (2012), Burke et al. (2015), and Colacito et al. (2019).

12 months that amount to 1.50% in terms of GDP. Moreover, the median respondent assigns a 10% probability to a large natural disaster with damages amounting to about 5% of GDP. This number is very high in light of the historical record: in the period from 1980 to 2019 there was no natural disaster in the US of that size (NCEI, 2020). Still, we obtain very similar responses once we consider only respondents which display a high degree of probability literacy and once we inform respondents of the fact that US GDP declined by about 5% during the global financial crisis.

There are various possibilities for why the perceived probability of disaster is so high. For instance, respondents may think we have been lucky in the past, just like in the case of "peso problems" and the past is therefore a bad guide for the future: in the relatively short sample under consideration, adverse events have simply materialized less often than one would find in a longer time series. Alternatively, natural disasters due to climate change may be much more frequent in the future because we may have reached so-called "tipping points" where dynamics change in a highly non-linear way (Emanuel, 2018). Yet another possibility is that natural disasters are salient of climate change, that is, they are a very prominent aspect of climate change which captures peoples' attention. Salience also features prominently in recent accounts of risk-taking behavior and consumer choice (Bordalo et al., 2012, 2013, Heimer et al., 2019).[3]

Eventually, we are interested in how these expectations play out and do not take a stand as to what drives them. For this reason it is important to note that survey responses relate to various respondent characteristics such as age, gender or political affiliations in a meaningful way. This suggests that they represent genuine information rather than just measurement error. Moreover, experience also seem to matter, just like macroeconomic experiences influence financial risk taking (Malmendier and Nagel, 2011): we find that respondents exposed to wildfires or floods in their counties report 4 to 6 percentage point higher probabilities of future large disasters. Media consumption also correlates positively with disaster expectations. Further validation of our survey responses as reflecting true subjective beliefs about climate change comes from the finding that respondents' perceived probabilities correlate with behavioral adjustments at the individual level in reaction to climate change. Respondents are more likely to report adjustment of their investments, mobility and other decisions when they think that disasters due to climate change are more likely. Lastly, we run a number of information treatments which cause responses to shift in the expected direction. For instance, a "Newspaper treatment," provides respondents with sections of a USA Today newspaper article on the 2020 wildfire and hurricane season. We find that in response to this treatment, respondents show a statistically significant, up to 1.5 percentage point higher expected disaster probability. A "Lagarde treatment," confronts respondents with a recent statement by ECB President Lagarde on the importance of climate change for the ECB's monetary policy; this treatment, too, shifts perceived disaster expectations upwards. This finding is reminiscent of information effects that have been documented in the context of traditional monetary policy communications (Nakamura and Steinsson, 2018).

[3] In a recent review of the work on salience and economic behavior Bordalo et al. (2021) state: "Psychological research shows that salient stimuli attract human attention "bottom up" due to their high contrast with surroundings, their surprising nature relative to recalled experiences, or their prominence." It seems that as far as climate change is concerned natural disasters represent such salient stimuli. In our analysis we refer to salience effects in a strict sense when we interpret natural disasters as salient of climate change, although there are arguably a host of phenomena which relate to salience effects, more broadly understood.

Expectations about climate-change related natural disasters matter for monetary policy. This result emerges from our model-based analysis in the second part of the paper. Here we rely on a conventional New Keynesian model which allows for rare disasters, extended in order to account for time-varying disaster probabilities. As a limiting case the model nests the textbook version of the New Keynesian model (Galí, 2015). For this case, we derive a number of results in closed form. In particular, we show that expectations of a rare disaster lower the natural rate of interest today, reflecting both the probability of a disaster and the extent of the disaster. Intuitively, as the expected costs of a disaster go up, be it along the extensive or the intensive margin, people raise their savings. The natural rate has to fall for markets to equilibrate. This effect is first order and obtains even in linearized version of the model because disaster risk is one sided. Shifts of disaster expectations thus operate very much like sentiment or noise shocks (Enders et al., 2021; Lorenzoni, 2009).

We also rely on the simplified version of the model to spell out the implications for monetary policy in some detail: By tracking the natural rate, monetary policy can in principle stabilize the economy fully in the face of disaster expectations. Under a conventional monetary policy rule, an adverse shift in disaster expectations instead is contractionary, and even more so if monetary policy is unresponsive to the shift, say because it is constrained by the effective lower bound. Because shifts in disaster expectations operate just like other adverse demand shock they call for monetary accommodation. Within the confines of the model, monetary policy simply needs to track the natural rate, irrespective of the nature of the shock to achieve full stabilization. Still, as the natural rate is unobservable, monetary policymakers need to understand the fundamental drivers of the business cycle, not least to get a sense of the likely persistence of the disturbances to which the economy is exposed at a given point in time. Shifts in climate-change expectations are likely to become increasingly relevant in this regard.

We support this conjecture with a numerical analysis for which we map the responses of the survey into a calibrated version of the full model. We solve the model numerically using Taylor projections and verify that it captures key features of the business cycle. Under the baseline we assume that monetary policy follows a standard interest-rate feedback rule. A number of findings are noteworthy. First, climate-change related disaster expectations reduce the natural rate by 45 basis points in the risky steady state of the model. This is a sizable number given that recent estimates suggest an overall decline of the natural rate by about 2 percentage points in the wake of the global financial crisis (Federal Reserve Bank of New York, 2020). Moreover, shifts in climate-change related expectations (which we calibrate in line with a close proxy, google search queries for "natural disasters") make a sizeable contribution to the business cycle. They account for 7 and 8 percent of the volatility of inflation and the output gap, respectively.

Finally, we provide external evidence in support of the mechanism which operates at the heart of our model. Specifically we estimate a VAR model on monthly times-series observations for the period from 2004-2020. For this purpose we proxy climate-change related disaster expectation with google search queries for "natural disasters" because we find these to co-move strongly with the probability assigned to disasters by the respondents of our survey during the 9 months for which it has been running. We identify shocks to disaster expectations recursively as variations in google search queries and trace out their effects on other variables included in the VAR model, such as consumption, the CPI and unemployment. The dynamic adjustment to disaster expectations shocks apparent in the data confirms the predictions of our New Keynesian model as regards the effects of shifts in disaster expectations.

Our analysis thus provides a new perspective on the debate of how monetary policy should respond to climate change. So far, the literature has focused on the distinction between financial regulation and the implementation of monetary policy (Brunnermeier and Landau, 2020). That supervisors should take climate-change related risks into account in their risk assessment is uncontroversial. Instead, whether monetary policy should use its instruments actively to contain climate change, say, by twisting asset purchases towards "green assets" raises interesting questions regarding the (secondary) objectives and legitimacy of today's central banks as well as regarding their "market neutrality" (Honohan, 2019; Piazessi et al., 2021). To date there is no consensus on the quantitative relevance of such policies as recent studies based on DSGE models illustrate (Benmir and Roman, 2020; Ferrari and Landi, 2021).

More broadly, our paper also relates to the literature on the interaction of climate change and macroeconomic performance following the influential work by Nordhaus (1994), Mendelsohn et al. (1994) and Nordhaus (2006), see Hassler and Krusell (2018) for a recent review of the "macroeconomics and climate" literature. This literature also studies the optimal policy response to climate change (e.g. Barro, 2015; Golosov et al., 2014). We focus on the reverse: how (expected) climate change impacts policy, just like the work that investigates the extent of directed technological change in response to (actual) natural resource scarcity or to (actual) carbon taxes (Aghion et al., 2016; Hassler et al., 2020). Related work on the implication of climate changes for asset prices shares our focus on expectations (Bansal et al., 2019; Bauer and Rudebusch, 2020; Gollier, 2020). Batten et al. (2020), in turn, disentangle distinct channels through which climate-change related physical risks impact both aggregate demand—via increased uncertainty—and as well as aggregate supply through actual damages. A recent survey of experts suggests that regulatory risk is also perceived as a key issue, at least in the short run (Stroebel and Wurgler, 2021). There is also evidence that natural disasters trigger an adjustment of both expectations and economic behavior. While Baker et al. (2020) document the adjustment of professional forecasters to actual disasters on the basis of a large cross-country data set, Hu (2020) documents that households purchase more insurance policies in response to information about flood risk information. Fried et al. (2021) study the effect of climate policy risk on firm investment. Finally, we note that our results underscore the importance of news media for both the expectation formation process and, more generally, for understanding the business cycle (Carroll, 2003; Chahrour et al., 2021; Larsen et al., 2021).

The remainder of this paper is organized as follows. We introduce our survey in the next section and discuss the main results. Section 3 outlines our New Keynesian model. We present analytical results and spell out the implications for monetary policy using a simplified version of the model in Section 4. In Section 5 we map the main results from the survey into the full model to quantify the macroeconomic impact of climate-change related disaster expectations. Section 6 illustrates the external validity of the mechanism which operates at the heart of the model. A final section concludes.

2 The Survey

In what follows we first provide some basic information about the survey. We subsequently present the main survey results. Then, using the survey data, we study through the lens of climate change expectation what deeper factors and mechanisms affect the formation of expectations.

2.1 Survey Design

Our data come from a large, nationally representative daily survey of consumers sponsored by the Federal Reserve Bank of Cleveland that has been running since March 10, 2020. The survey is described in detail in Dietrich et al. (2020) and Knotek et al. (2020). We add a number of questions on climate change to the survey, complementing the regular survey questions on consumers' demographic characteristics, their expectations, and consumers' perceptions surrounding COVID-19 and its impact on their behavior. These questions have been included during the period from some 9 months, from October 1, 2020 to July 11, 2021. During that period we collected 28,284 responses.

The survey is administered by Qualtrics Research Services, which representatively draws respondents from several actively managed, double-opt-in market research panels, complemented using social media (Qualtrics, 2019). The survey includes filters to eliminate respondents who write in gibberish for one response or more, or who complete the survey in less (more) than five (30) minutes. Our analysis uses iterative proportional fitting to create respondent weights after completion of the survey ("raking", see for example Bishop et al. (1975) or Idel (2016)) to ensure that our sample is representative of the U.S. population by gender, age, income, education, ethnicity, and Census region. Table 1 provides a detailed breakdown of our sample. It shows that our sample even before weighting is approximately representative of the U.S. population according to the sampling criteria such as age, gender and race. It is also representative from a geographical point of view, as well as in terms of income and education. As we document below, climate-change expectations vary systematically with these characteristics. We provide a list of all questions in Appendix B.

In what follows we focus on the three main questions that relate to the effect of climate change on GDP growth, on the magnitude of economic damages and the probability of a costly large natural disaster. In doing so our focus is on the impact of climate-change expectations regarding the near term, as is relevant for business cycle analysis. Table 2 lists our main questions. Our first question asks respondents how they expect climate change to impact economic growth over the next 12 months. The second question on climate change elicits beliefs about economic damage due to natural disasters over the next 12 months. Respondent answer choices are both verbally described as well as numerically defined (for example, "more damage than in the past (say, 2% of GDP)"). Our third question asks respondents about how likely they perceive natural disasters to be. Specifically, we ask them about a large disaster causing damage of about 5 percent of GDP.[4]

[4]In the past, years with high natural disaster damages were usually associated with one extremely large disaster, such has 2005.

Table 1: Survey Respondent Characteristics

	pct.	(Target)		pct.	(Target)
Age			**Race**		
18-34	33.55%	(33.3%)	non-Hispanic white	72.81%	(66%)
35-55	34.78%	(33.3%)	non-Hispanic black	9.87%	(12%)
older than 55	31.67%	(33.3%)	Hispanic	9.95%	(12%)
			Asian or other/multiple	7.35%	(12%)
Gender					
female	50.12%	(50%)	**Household Income**		
male	49.49%	(50%)	less than 50k$	39.35%	(30%)
other	0.39%	(-%)	50k$ - 100k$	38.64%	(35%)
			more than 100k$	22.01%	(30%)
Region					
Midwest	20.80%	(20%)	**Education**		
Northeast	21.16%	(20%)	some college or less	50.09%	(50%)
South	40.54%	(40%)	bachelors degree or more	49.91%	(50%)
West	17.50%	(20%)			
					N=28,284

Notes: table reports unweighted population characteristics of survey participants administered by Qualtrics.

We add to these three main questions two sets of complementary questions. The first set of complementary questions aims at validating that respondent answers are not only measurement error and in fact relate to behavioral choices. For example, we elicit if climate change has lead respondents to adjust their investments, mobility or other choices. In addition, because a correct understanding of probabilities is key to answering our main questions, we assess respondent probability literacy. To this purpose, the survey features a question that requires respondents to infer the probability of drawing a black rather than a white ball from an urn, given a number of past observations and drawing with replacement. For what follows, we define a group of respondents with particularly high probability literacy, namely those respondents who answer the question with a error of margin of 2 percentage points. As a way to verify that our results are not driven by lack of probability literacy, we separately report results for this group of respondents.

The second set of complementary questions aims at validating that responses reflect economically relevant respondent beliefs. We do so in two ways: On the one hand, we use standard survey questions about media use and socio-economic demographics to establish basic correlations with beliefs. Finding meaningful variation of beliefs with economic covariates can help rule out measurement error while also shedding light on fundamental drivers of respondent beliefs about climate change. On the other hand, the survey also records zip codes, which further allows us to study the role of geography as a potential driver of climate-change beliefs.

Finally, we also provide several information treatments before asking Questions 1 to 3. These treatments help gauge the extent to which information related to climate change and natural disasters can causally affect the formation of beliefs. The information treatment comes in several variants, summarized in Table 3 and relates for example to historic data, official policy statements or public newspaper articles. One information treatment also compares the magnitude of the probability event to the magnitude of the Great Recession, thereby helping to further

Table 2: Survey Questions

Q1	The average growth rate of real GDP in the US between 2009 and 2019 has been about 2 percent. Climate change might influence future growth rates positively, say, because it triggers technological innovation or negatively because of regulation and taxes. What do you think is the overall impact of climate change on economic growth over the next 12 months? [...]	Due to climate change, economic growth, compared to what it would be otherwise, will be . . . *[Participants assign probabilities to 7 bins from more than 2% lower to more than 2% higher]*
Q2	Recently, the economic damage due to natural disasters amounted to about 1% of GDP per year (Source: National Center for Environmental Information). In your view, will these damages be larger or smaller because of climate change? [...]	Specifically, what would you say is the percent chance that, over the next 12 month there will be . . . *[Participants assign probabilities to 7 options (verbally described and numerically defined) from no damage to around 5% of GDP]*
Q3	As a result of climate change, the risk of natural disasters (such as hurricanes, tropical cyclones, droughts, wildfires, or flooding) is likely to increase. The economic damage of such disasters may be sizeable. Considering the next 12 months, what do you think is the probability of a large disaster causing damage of about 5 percent of GDP?	The probability of a large disaster will be ___ percent."

Notes: Appendix B provides the full set of questions asked in the survey.

validate the ability of respondents to deal with potentially rare events.

2.2 Survey Results

This subsection presents the results of the survey. As a background observation, we note that respondents consider climate change an important issue, almost as important as the COVID-19 pandemic. When asked to rank the importance of both on a scale from 0 to 10 (most severe), climate change scores 6.53 and COVID-19 7.75 out of 10 (see also Figure C.2 in the appendix). This perception is in line with a recent survey by the United Nations Development Program which documents that respondents with a university degree, including in low-income countries all recognize a "climate emergency."[5]

Turning to our main results, we first note that respondents on average expect a slightly positive impact of climate change on economic growth, with an average increase of GDP growth

[5] Among the 18 climate policies suggested to respondents "investing more money in green businesses and jobs" is approved by 50% of responds. This amounts to rank 4; "Conserve forests and land" is the most popular policy, supported by 54% of the respondents (UNDP and University of Oxford, 2021).

Table 3: Information Treatments

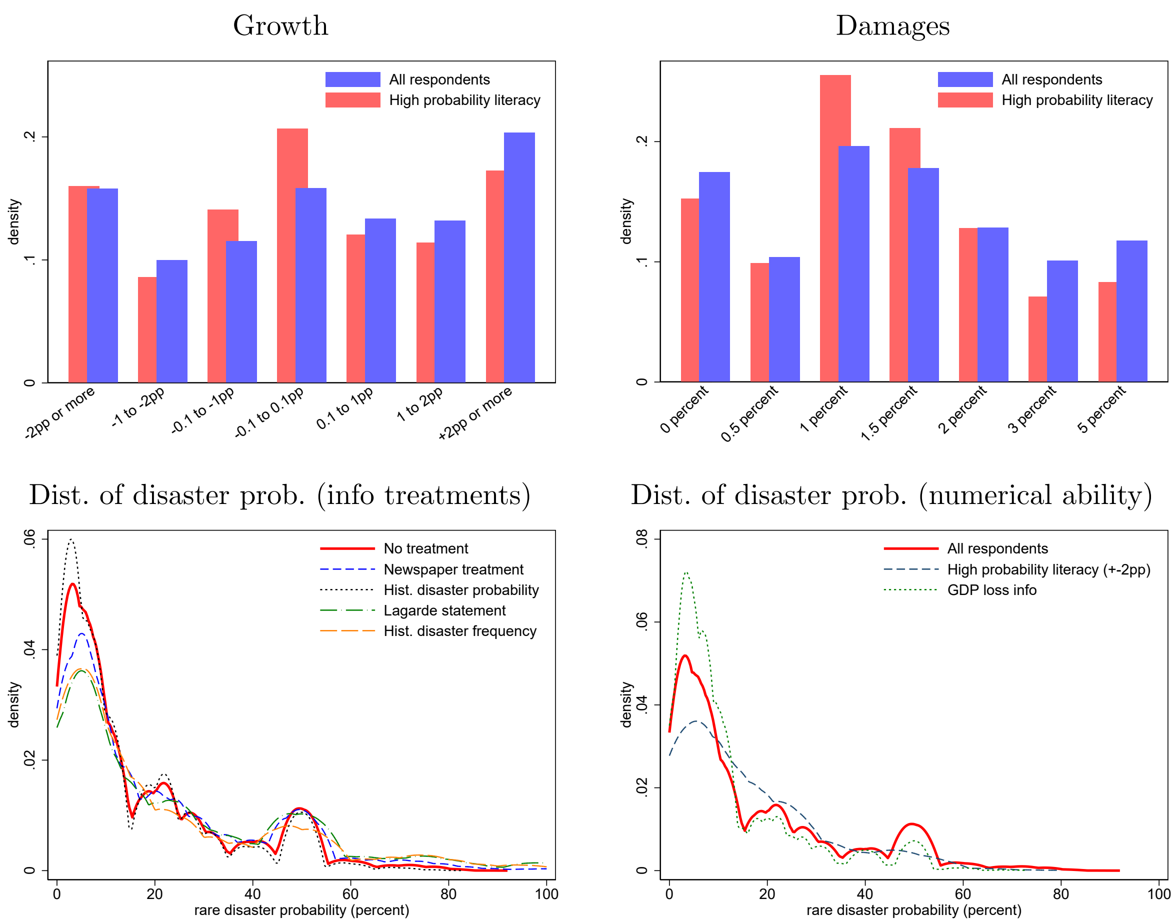
Newspaper treatment (T1)	Extract from an USA Today article summarizing the 2020 hurricane season on the east cost and in the gulf region and the wildfires on the west cost. The article links both developments to global warming.
Historic disaster size (T2)	"Over the past 20 years there have been 197 natural disasters in the United States, but even the largest caused damages of less than 1% of GDP (Source: National Center for Environmental Information)."
Lagarde treatment (T3)	Respondents are given the following quote by ECB President Lagarde: "I think when it comes to climate change, it's everybody's responsibility. Where I stand, where I sit here as head of the European Central Bank, I want to explore every avenue available in order to combat climate change."
Historic disaster frequency (T4)	"Over the past 20 years there have been 197 natural disasters in the United States. Two of them caused damage of more than 0.5 percent of GDP (Source: National Center for Environmental Information)."
GDP Loss Info (T5)	"The next question asks about potential damages due to climate change, expressed in percent of GDP. To put these damages in perspective, note that U.S. GDP declined by approximately 5 percent in 2008-09 in response to the global financial crisis."

Notes: Appendix B provides the full set of questions and information treatments.

by 0.20 percentage points over the next 12 months. However, there is a lot of mass in the distribution for both positive and negative outcomes. We show this distribution in the top-left panel of Figure 1. The blue bars represent the answers of all respondents, while the red bars represent those of respondents with high probability literacy. For example, we find that nearly 20% of all respondents expect a boost to growth by more than 2 percentage points over the next 12 months due to climate change while more than 15% expect a growth decline by more than 2 percentage points. For respondents with high probability literacy there is somewhat less mass in the tails. The standard deviation across all respondents is 1.30 percentage points. Table 4 provides summary statistics for all three main questions, including the first question, both for all respondents (top panel), and respondents with high probability literacy (bottom panel). The first row in each panel summarizes the answers to the Question 1.

Second, we find that survey respondents expect substantial economic damages due to climate change, amounting to approximately 1.5% of GDP on average over the next 12 months. The top right panel in Figure 1 shows these responses, again for the full sample (in blue) and respondents with high probability literacy only (red). Again, expectations are widely dispersed

Figure 1: Expected Impact of Climate Change



Notes: The top-left panel shows mean probability assigned to each scenario for Question 1, the top-right panel the mean probability assigned to each scenario for Question 2. High numerical ability respondents answer a question on probabilities with an error margin of at most 2 percentage points (Q6 in survey appendix). Remaining panels show the distribution of responses to Question 3: probability of a rare disaster with damage of 5% of GDP within the next 12 months. The red solid line represents the distribution for the full sample, other lines are based on subgroups with info treatments (lower-left panel) or numerical ability (lower-right).

over loss scenarios in both instances but, as before, there is less mass in the tails for respondents with high probability literacy. Approximately 15% of all respondents expect no loss, while the fraction among those with high numerical ability slightly is lower. Overall, the standard deviation of expected losses is at 0.81% as Table 4 summarizes.

Third, we find that respondents perceive very high probabilities for natural disasters due to climate change that inflict damages of 5% of GDP over the next 12 months. These beliefs are widely dispersed as was the case with the preceding questions. The mean probability is at 16.37% while the median is at 10%. In fact, as the high mean probability suggests, there is a heavy right tail of probabilities. For example, almost 10% of respondents believe that such a rare disaster can occur with more than 75% probability.[6] The same conclusions hold for this

[6]The message from this third question is the same as when we elicit the probability of disaster costs by bins in Question 2 (top-right panel of 1): The probability of a large natural disaster is extremely large and statistically

Table 4: Survey Summary Statistics

All Respondents	Mean	Median	Std. Dev.	N
Growth Impact (Question 1)	0.20 pp	0.01 pp	1.30 pp	8395
Disaster Costs (Question 2)	1.47%	1.50%	0.81%	6921
Disaster Probability (Question 3)	16.37%	10.00%	17.24%	6839

High Probability Literacy Respondents	Mean	Median	Std. Dev.	N
Growth Impact (Question 1)	0.07 pp	0.00 pp	1.26 pp	806
Disaster Costs (Question 2)	1.36%	1.35 %	0.70%	782
Disaster Probability (Question 3)	14.44%	10.00%	14.19%	966

Notes: statistics are weighted using survey weights as well as Huber-robust weights. High probability literacy respondents answer a question on probabilities with an error margin of at most 2 percentage points (Q6 in survey appendix).

third question if we consider high probability literacy respondents only. In fact, if anything, while distributions of all respondents and those with high probability literacy appear similar, perhaps surprisingly respondents with high probability literacy expects large natural disasters to have even *higher* probability: As the lower-right panel of Figure 1 shows, high probability literacy respondents place more mass on probabilities between 15 to 30 percent. Their median response is equal to the response in the full sample as Table 4 shows. At the same time, high probability literacy ability is associated with less mass in the extreme right tail bringing down the mean to 14.44%, but not in a statistically significant fashion relative to the full sample. It thus seems understanding probabilities is not a major issue for respondents as the answers by high probability literacy respondents suggest across our three main questions.

Likewise, our information treatment that compares the magnitude of the probability event in Question 3 to the Great Recession further suggests that the ability to understand magnitudes of large, rare disasters also does not affect the probabilities reported. The bottom-right panel of Figure 1 illustrates this finding. While the treatment ("GDP loss info") draws mass to the left from the extreme right tails, the distribution has a similar shape. The Huber-robust weighted mean probability under the treatment is 11.88% while it is 16.37% in the full sample.

The responses to the behavioral questions further validate that the survey elicits economically meaningful information, rather than capturing measurement error: perceived probabilities correlate with behavioral adjustments at the individual level in reaction to climate change. As Table C.8 shows, a substantial fraction of respondents indicates that they have changed their investments, mobility or other decisions due to climate change. For example, 27% of respondents say they have divested their portfolios. A probit regression indicates that all investment and mobility decisions are statistically significantly related to the perceived probabilities of large natural disaster, as captured by the responses to Question 3. A 1 percentage point higher perceived probability, for instance, is associated with a 0.25 percentage point higher probability of not taking a flight.

indistinguishable across the two questions. Respondents assign a 12.58% probability in Question 2 to a disaster bin that corresponds to damages amounting to 5% of GDP compared to the mean probability of 16.37% in direct response to Question 3.

2.3 Determinants of Climate-Change Expectations

In what follows we show that the survey responses vary in an intuitive way with a range of alternative factors and potential determinants. This serves two purposes. First, it suggests that the survey responses reflect genuine information. Second, our data also shed light on the formation of economic expectations more generally, exploiting climate change as a particular event that affects expectations about economic outcomes. Our results suggest in particular, that salience effects may play an important role in this process, along with demographic characteristics. Policy communication may also have large effects on respondents making them more pessimistic, a result that may be highly relevant for the design of policy communication and points to the need for further research on the effects general effects of policy communication, such as Gorodnichenko et al. (2021).

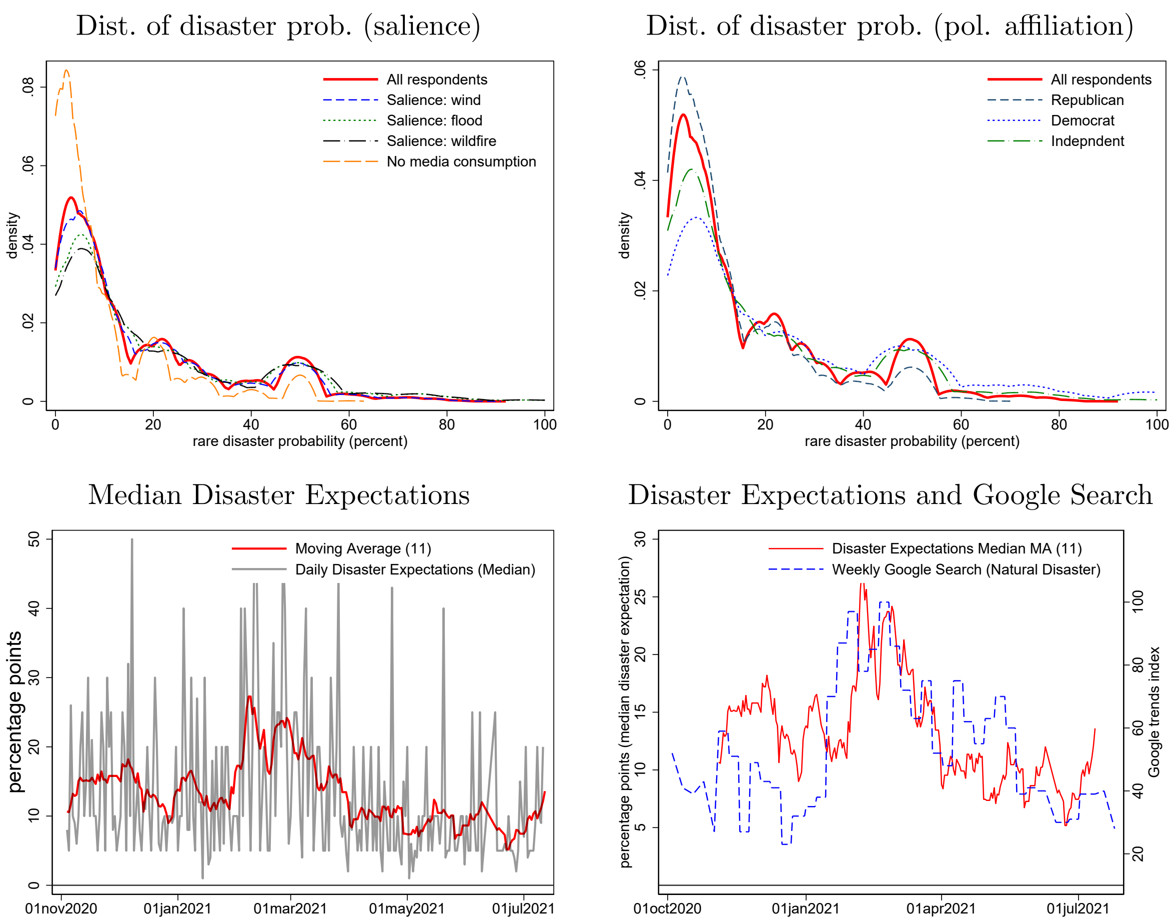
First, when we consider the impact of demographic and socioeconomic characteristics on economic expectations related to climate change, we find that some of them relate in a significant way to economic expectations in relation to climate change. To arrive at this result, our analysis regresses the expectations respondents hold with regard to climate change onto their demographic and socioeconomic characteristics while controlling for state as well as time fixed effects. Regarding the expected growth impact of climate change, we find that those aged 55 and above expect climate change to boost growth, while middle and high income categories are associated with an expected adverse impact of climate change on growth, though not significantly for high income respondents, see Table C.1 in the appendix for details. Regarding expected damages, we obtain a negative effect for middle income respondents. Women expect larger damages due to climate change in the future. Relative to the youngest age group, those aged 55 and above expect significantly lower damages, see again Table C.1. These findings are consistent with cohort effects documented by Malmendier and Nagel (2011) in the context of inflation.

Two results emerge regarding disaster probabilities: first, women report more pessimistic expectations. They do not only expect larger damages, but they also report higher probabilities. For instance, they believe very large rare disasters are 4 percentage points more likely than men. This finding echos earlier findings according to which women tend to be more risk averse then men (e.g., Borghans et al., 2009; Charness and Gneezy, 2012; Gustafson, 1998; Jianakoplos and Bernasek, 1998). Second, Republicans, all else equal, instead believe that a very large rare disaster is less likely, by 2.6 percentage points, compared to independent voters as we illustrate graphically in the top-right panel of Figure 2.[7] Democrats perceive a 2.8% higher probability relative to Independents.

Second, we also find that risk perception and expectations formation are governed by attention and salience effects, in line with earlier work (Bordalo et al., 2016, 2012; Coibion et al., 2021; Heimer et al., 2019). On the one hand, there is an important role of media consumption—TV and newspapers—for the perception of disaster risks. On the other hand, geographic exposure to natural disasters plays an important role. To establish these points, we relate the reported probability of a rare natural disaster to either measures of respondents' preferred TV stations

[7] Our findings are consistent with an earlier assessment of climate change risk perceptions, more broadly defined: according to van der Linden (2015) cognitive, experiential and sociocultural factors account for up to 70% of the variance across respondents in an online survey.

Figure 2: Expected Impact of Climate Change



Notes: Top row panels show the distribution of responses to Question 3: probability of a rare disaster with damage of 5% of GDP within the next 12 months. The red solid line represents the distribution for the full sample, other lines are based on subgroups with political affiliation (right) and exposure to actual disasters (left). Bottom row: left panel shows time series for the daily median of disaster expectations (black line). The red line gives a balanced 11 day moving average. Huber robust and survey weights applied. Right panel shows the weekly median disaster expectation (left axis) as well as an index for google searches for "Natural Disaster".

and newspapers, and to official data on the incidence of natural disasters at the county level, while continuing to control for demographic and socio-economic variables.

Table 5 reports the results for media consumption. We find that respondents who consume news from neither a major TV Station nor a major newspaper exhibit approximately 5 percentage points lower rare disaster probabilities. This effect corresponds to a reduction of the perceived mean disaster probability by almost a third. By contrast, respondents who watch the news instead have more than 3.3 percentage point higher disaster beliefs. There is also some evidence that individual TV Stations/Newspapers impact the perceived disaster probability of respondents, even though systematic differences between different stations are not readily obvious. For example, readership of the Wall Street Journal or the Los Angeles Times has a negative association with perceived disaster probabilities, but readership of USA Today has a positive association. Consumption of TV channels always tends to raise probabilities, see Table C.2 in

Table 5: Reported Probability of Disaster and Media Usage

	(1)	(2)	(3)
no major TV Station	-3.308***		
	(-3.98)		
no major Newspaper		-3.059***	
		(-5.16)	
consume major TV station×no major newspaper			-2.154***
			(-3.30)
no major TV station×consume major newspaper			0.762
			(0.37)
no major TV station×no major newspaper			-4.952***
			(-5.45)
Constant	17.10***	17.45***	17.77***
	(6.85)	(7.00)	(7.12)
State and Month FE	yes	yes	yes
Demographic Controls	yes	yes	yes
N	7143	7128	7125
r2	0.0587	0.0607	0.0619

Notes: regression relates reported probability of disaster to media usage; only respondents that did not receive any treatment used in regression; t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights and Huber-robust weights to ensure that sample is representative and independent of outliers, respectively.

the appendix for details. When we consider economic damages and the growth impact of climate change as outcomes (instead of the perceived disaster probabilities), we find that respondents who do not watch TV and do not read newspapers expect significantly lower disaster costs and somewhat higher GDP growth, see Tables C.3 and C.4 in the appendix for details.

Perhaps unsurprisingly, exposure to climate-change events also matters for climate-change expectations. For our data, in particular, we find a strong association between the exposure to certain types of rare natural disasters and climate-change beliefs. We first illustrate this finding graphically: The top-left panel of Figure 2 shows how the subjective probability of a rare natural disaster depends on the exposure of respondents' geographic region to actual disasters. To measure such exposure, we rely on official data for natural disaster declarations at the county level for the last 10 years from the Federal Emergency Management Agency (FEMA, Federal Emergency Management Agency, 2020). Within our sample 15.7% of respondents live in a county with a wildfire-related disaster over the last 5 years, 27.1% with a hurricane, tornado, or typhoon event and 28.1% with a flood in the past. From the same data source, we also construct a more aggregate measure using the total number of events (fire, flood and hurricane, etc.) within a state during the last 5 years, divided by the total land area of the state in square miles. We use this aggregate measure in regressions further below. An inspection of the lower-left panel in the figure based on the county-level measure shows that these experiences matter for peoples' disaster expectations, a finding that is familiar from other contexts, such as inflation or house-price expectations (Kuchler and Zafar, 2019; Malmendier and Nagel, 2011).

We run complementary regressions in order to systematically relate the reported probability of a disaster not only to respondents' disaster experience but also to a measure of "official" disaster risk.[8] For the latter we use the U.S. Natural Hazards Index, provided by the National Center for Disaster Preparedness of Columbia University (NCDP, 2020). For each county, the index categorizes the risk of a given type of natural disaster as either "None", "Low", "Medium" of "High." Three findings stand out: First, respondents within counties with a past record of natural disasters tend to expect higher disaster probabilities than respondents without a disaster experience, by up to 3 percentage points, for counties that experienced a hurricane in the last 5 years. Second, concerning future risks, in particular the increased possibility of hurricanes drives up expectations of a future large disaster by up to 4.7pp. Third, when we include the total number of disasters of a type for a given state—which should be a good proxy for how common a disaster type is within the state, both in the past and future—it is still the local, experience that drives the results. Only the frequency of wildfires within a state - relative to its size - seems to have an significantly positive impact on the expected disaster probability. See Table C.5 for details.

There is also sizeable variation of survey responses over time, which we illustrate in the bottom panels of Figure 2. The bottom left panel shows the daily time series for the reported probability of a large disaster caused by climate change in grey (median response) during our sample period. The series is very volatile, presumably reflecting the moderate number of daily responses. The red line represents the 11-day moving average across daily medians. This series still shows considerable variation over time. In the bottom-right panel of Figure 2 we reproduce this series jointly with a weekly google search index for "Natural Disaster" in the right panel. The series show a strong co-movement during our sample period, which we exploit further below in our model validation exercise.

We also look beyond correlations and present the causal effects of the information treatments on climate-change expectations. The "Newspaper treatment" shows to respondents sections of a USA Today newspaper article on the 2020 wildfire and hurricane season. The "Lagarde treatment" is a recent statement by ECB President Lagarde on the importance of climate change for the ECB's monetary policy. The "Historic disaster probability treatment" informs respondents that in the past 20 years, there was no disaster in the U.S. that caused damage in the vicinity of 5% of GDP. A variant of this question is our "Historic disaster frequency treatment" which was only asked early on in the survey. It is therefore not included in all subsequent regression analyses. It informs respondents that in the past 20 years, there were two large disasters in the U.S., both with damages of more than 0.5% of GDP. As a last treatment, we provide participants with information about an economic loss of similar magnitude, namely the 2008-2009 Great Financial Crisis, see again Table 3 above for more details on the treatments.

Table 6 presents the main results. We find that in response to the newspaper treatment, respondents show an up to 1.6 percentage points higher expected probability which is also significant if we remove extreme outliers. Relaying the intention of the ECB to tackle climate change raises the probability of disaster risk by almost 2 to 3 percentage points. This finding is consistent with recent work on monetary policy which has stressed the information effects ac-

[8] Due to data limitations, we focus on the reported disaster probability (Question 3), rather than our other expectation measures.

Table 6: Reported Probability of Disaster and Information Treatment

	(1)	(2)	(3)	(4)
Newspaper (T1)	0.732	1.159	0.810*	1.671**
	(1.56)	(1.35)	(2.48)	(2.73)
Historic Disaster Size (T2)	-1.466**	-1.955*	-0.875**	-1.219*
	(-3.24)	(-2.28)	(-2.81)	(-2.10)
Lagarde Treatment (T3)	1.376**	2.967**	0.906**	1.300*
	(2.90)	(3.25)	(2.75)	(2.09)
Historic Disaster Freq. (T4)	-1.558		-1.822**	
	(-1.57)		(-2.68)	
GDP Loss info (T6)	0.358		0.128	
	(0.50)		(0.27)	
Climate Change Scale		2.180***		1.054***
		(21.80)		(15.45)
Constant	18.80***	10.32***	14.67***	13.13***
	(12.75)	(3.71)	(12.69)	(6.17)
State Fixed Effect	yes	yes	yes	yes
Demographic Controls	yes	yes	yes	yes
Drop largest 25% probabilities	no	no	yes	yes
N	23775	8479	20126	6967
r2	0.0473	0.119	0.0453	0.104

Notes: regression relates reported probability of disaster to information treatment (one treatment per respondent); t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights and Huber-robust weights to ensure that sample is representative and independent of outliers, respectively. For the treatments, refer to table 3 or Appendix B. Climate Change Scale refers to question Q4, where respondents are asked to rate the threat of climate change for the U.S. on a scale from 0 to 10.

cording to which market participants update their view on the economy in response to monetary policy action and/or communication (Nakamura and Steinsson, 2018). The historic information treatments lower expected probabilities as expected. Columns 3 and 4 report results when we remove extreme outliers with the top 25% of responses—who report a disaster probability of 50% or higher.[9] Once we perform these regressions on a subsample for respondents respondents with high probability literacy, we find no effect of the treatments, except in the case in which we provide information about the size of disasters in the past. This lowers the reported probability of a large disaster considerably, by more than 3 percentage points, see Table C.6. These findings suggest that respondents with high probability literacy react less to suggestive information in assessing disaster probabilities.

Finally, before turning to our model-based analysis, we note that our data suggests that people act on their climate-change expectations, as already highlighted in the context of the discussion of the information content of our survey (page 10) . To make this point, we estimate a

[9] Table C.7 reports the effect of treatments on the expected growth impact and expected damages due to climate change.

probit model that links behavioral adjustment as reported by respondents to the reported probability of climate-change related natural disasters. We find that a higher perceived probability of disaster is positively associated with portfolio divestment due to "fear of climate change related risk" as well as refraining from "investment considered harmful to the climate." For example, a one percentage point increase in the probability of a large natural disaster is associated with a 0.22 percentage point higher probability of refraining form harmful investments. Similar results emerge for modes of travel, personal mobility choices, car ownership and flight travel, see Table C.8. Here, for example a one percentage point increase in the disaster probability is associated with a 0.25 percentage point higher probability of refraining from flights. Finally, respondents also report a general impact on their consumption choices. For example, a 1 percentage point higher probability of perceived disasters due to climate change is associated with a 0.68 percentage point higher probability of the decision to "stop eating meat due to or reduce meat in your diet because of concerns about climate change."

3 A New Keynesian Model with Rare Disasters

In what follows, we rely on a New Keynesian model to study how climate-change expectations can impact the business cycle. According to our survey, respondents do not expect much of an effect of climate change on growth. Yet they assign a high probability to climate-change related large disasters. For this reason we rely on a version of the New Keynesian model that features rare disasters, as put forward by Fernández-Villaverde and Levintal (2018). Earlier work on rare disasters assumes an exogenous process for output to study the implications of rare disasters for asset prices (Barro, 2006, 2015). Gourio (2012) uses a real business cycle model to show that variations in disaster risk can play a significant role for the business cycle. Our New Keynesian model, in turn, allows us to spell out the implications of climate-change related disaster expectations for monetary policy.

We first establish a number of results in closed form using a simplified version of the model. While the full model features Epstein-Zin preferences and an endogenous capital stock, the simplified version of the model does not. In fact, the simplified version of the model corresponds to the textbook version of the model as, for instance, developed in Galí (2015), except that it features rare disasters. In what follows, we provide a compact exposition of the general model. Section 4, in turn, introduces the simplified version of the model and presents analytical results. We specify and calibrate the full model and report simulation results in Section 5.

3.1 Households

A representative households purchases a consumption basket, C_t, and an investment good, X_t, both composite goods of the same varieties, $Y_t(i)$ with $i \in [0, 1]$:

$$C_t + X_t = \left[\int_0^1 Y_t(i)^{1-\frac{1}{\epsilon}} di \right]^{\frac{\epsilon}{\epsilon-1}} \equiv Y_t. \tag{3.1}$$

Here Y_t is aggregate output and $\epsilon > 1$ is the elasticity of substitution across varieties. The household saves via a nominally riskless bond, B_t, which trades at price Q_t, or by accumulating capital, K_t, which it rents to firms, earning the rental rate R_t^K. The law of motion for capital is given by

$$K_t = \left\{(1-\delta)K_{t-1} + \left[1 - S\left(\frac{X_t}{X_{t-1}}\right)\right] X_t\right\} e^{d_t \log(1-\mu)}. \tag{3.2}$$

Here the function $S(\cdot)$ represents investment adjustment costs which we assume to be prohibitively large in the simplified version of the model. $\delta \in (0,1)$ denotes the depreciation rate. Importantly, d_t is a binary random variable which takes the value of 1 in the event of a rare disaster and zero otherwise. A rare disaster in period t takes place with pre-determined probability p_{t-1} which follows an AR(1) process:

$$p_t = \bar{p}^{(1-\rho_p)} p_{t-1}^{\rho_p} e^{\sigma_p \epsilon_{p,t}}, \tag{3.3}$$

where $\epsilon_{p,t} \sim N(0,1)$ is a Gaussian innovation to the disaster probability. In the event of a disaster the fraction μ of the capital stock is destroyed.

Letting $U(C_t, N_t)$ denote period utility, the objective of the household is to

$$\max V_t^{1-\psi} \quad = \quad U(C_t, N_t)^{1-\psi} + \beta E_t \left(V_{t+1}^{1-\gamma}\right)^{\frac{1-\psi}{1-\gamma}} \tag{3.4}$$

subject to (3.1), (3.2), a budget constraint:

$$\int_0^1 P_t(i) Y_t(i) di + Q_t B_t \leq B_{t-1} + W_t N_t + R_t^K K_t + D_t, \tag{3.5}$$

as well as a solvency constraint. In the expression above E_t is the expectations operator, $\beta \in (0,1)$ is the discount factor, $P_t(i)$ is the price of variety i, and D_t are dividends.

The optimal intra-temporal allocation of expenditures across varieties implies that the demand function for a generic variety i is given by

$$Y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} (C_t + X_t) \tag{3.6}$$

where $P_t \equiv \left[\int_0^1 P_t(i)^{1-\epsilon} di\right]^{\frac{1}{1-\epsilon}}$ is the price index for the composite goods.

3.2 Firms

Varieties are produced by monopolistically competitive firms. Firms change prices only infrequently and adjust production in order to satisfy the demand at posted prices, given by (3.6). A generic firm i operates the following production function:

$$Y_t(i) = A_t K_t(i)^\alpha N_t(i)^{1-\alpha}, \tag{3.7}$$

where $N_t(i)$ and $K_t(i)$ are labor and capital employed by firm i, A_t is productivity common to all firms and $\alpha \in [0,1)$. For productivity we assume the following process

$$A_t = A_{t-1} e^{d_t (1-\alpha) \log(1-\mu) + \sigma_A \epsilon_A}, \tag{3.8}$$

where the term $d_t(1-\alpha)\log(1-\mu)$ captures the adverse effect of a disaster on productivity. The TFP growth shock $\epsilon_{A,t} \sim N(0,1)$ is a Gaussian innovation with zero mean.

In each period a fraction $\theta \in [0,1]$ of firms is unable to adjust its price. Firms which do adjust prices face an identical decision problem. Specifically, they set P_t^* to solve

$$\max \sum_{k=0}^{\infty} \theta^k E_t \left\{ Q_{t,t+k} \left[P_t^* \left(\frac{P_{t-1+k}}{P_{t-1}} \right)^{\chi} Y_{t+k|t} - \mathcal{C}(Y_{t+k|t}) \right] \right\}, \tag{3.9}$$

where $Y_{t+k|t}$ is the demand in period $t+k$, given prices set in period t, $Q_{t,t+k}$ is the stochastic discount factor and $\mathcal{C}(\cdot)$ is the cost function. The parameter χ measures the extent of price indexation. The price level evolves as follows:

$$1 = \theta \left(\frac{\Pi_{t-1}^{\chi}}{\Pi_t} \right)^{1-\epsilon} + (1-\theta)(\Pi_t^*)^{1-\epsilon}. \tag{3.10}$$

where $\Pi_t = \frac{P_t}{P_{t-1}}$.

3.3 Market Clearing and Monetary Policy

Good markets clear at the level of varieties. Labor market clearing, in turn, implies

$$N_t = \int_0^1 N_t(i)di = \left(\frac{Y_t}{A_t K_t^{\alpha}} \right)^{\frac{1}{1-\alpha}} \int_0^1 \left(\frac{P_t(i)}{P_t} \right)^{-\frac{\epsilon}{1-\alpha}} di. \tag{3.11}$$

The risk-free bond B_t is in zero net supply. Lastly, we specify monetary policy in terms of alternative interest rate feedback rules. In each instance the central bank is assumed to adjust the short-term nominal interest rate, given by $i_t = -\log Q_t$.

4 Analytical Results

In this section we consider a simplified version of the model and derive the familiar canonical representation of the New Keynesian model, based on a first-order approximation of the equilibrium conditions. Based on this representation we are able to obtain a number of closed-form results. We solve the full model numerically in Section 5.

4.1 Canonical Representation

To obtain the canonical representation of the model, we make a number of simplifying assumptions. First, we assume that $\psi = \gamma$ so that households maximize expected utility. At the same time, we assume for period utility:

$$U_t = \left(\frac{C_t^{1-\sigma} - 1}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi} \right)^{\frac{1}{1-\psi}}. \tag{4.1}$$

As a result, we can rewrite the household objective (3.4)

$$\max Z_t = \left(\frac{C_t^{1-\sigma} - 1}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi} \right) + \beta E_t Z_{t+1}, \tag{4.2}$$

where $Z_t \equiv V_t^{1-\psi}$. This specification boils down to the textbook version in Galí (2015). Second, we assume that investment adjustments costs are prohibitively high and that the capital stock does not depreciate. In this way we shut off any adjustment of investment and the capital stock over time. Moreover, we assume that shocks to the disaster probability are purely transitory shocks ($\rho_p = 0$). Last, we assume that capital is not subject to a disaster shock. The capital stock is thus:

$$K_t = K_{t-1} = \bar{K}$$

We list the optimality conditions for the simplified version of the model in Appendix A.1 and focus in what follows on the log-linear approximation of the equilibrium conditions around a deterministic steady state. Specifically, using small-scale letters to denote logs, we obtain the following familiar canonical representation of the model:

$$\pi_t = \beta E_t \pi_{t+1} + \kappa \tilde{y}_t, \tag{4.3}$$

$$\tilde{y}_t = E_t \tilde{y}_{t+1} - \frac{1}{\sigma}(i_t - E_t \pi_{t+1} - r_t^n). \tag{4.4}$$

Equation (4.3) is the New Keynesian Phillips curve, with parameter restrictions $\kappa = \lambda(\sigma + \frac{\varphi+\alpha}{1-\alpha})$ and $\lambda = \frac{(1-\theta)(1-\beta\theta)}{\theta} \frac{1-\alpha}{1-\alpha+\alpha\epsilon}$. It links inflation, $\pi_t \equiv p_t - p_{t-1}$, to expected inflation and the output gap, $\tilde{y}_t \equiv y_t - y_t^n$. Here y_t^n is potential output, that is, the output level that would obtain if prices were perfectly flexible. Equation (4.4) is the dynamic IS equation. In addition to the output gap and inflation it features the nominal interest rate, i_t, and the natural rate of interest, r_t^n, that is, the interest rate that would obtain if prices where fully flexible. It is a natural benchmark for the policy rate and takes center stage in the analysis and implementation of monetary policy (Woodford, 2003).

4.2 Model Solution

In what follows we solve the model starting from the canonical representation. Our focus is on the impact of disaster expectations on the natural rate of interest. The following proposition states the solution for the natural rate as well as for potential output.

Proposition 1 *Given the simplified model, as represented by equations* (4.3) *and* (4.4)*, the solution for the natural rate and for potential output is given by:*

$$r_t^n = \rho - \Omega(1-\alpha)p_t\mu \quad \textit{and} \quad y_t^n = \begin{cases} 0, & \textit{if } d_t = 0, \\ \Xi_\mu \mu, & \textit{if } d_t = 1, \end{cases}$$

where $\rho = -\log(\beta)$, $\Omega = \frac{\sigma(1+\varphi)}{\sigma(1-\alpha)+\alpha+\varphi} > 0$ *and* $\Xi_\mu = -\frac{\sigma(1-\varphi)(1-\alpha)}{\sigma(1-\alpha)+(\alpha+\varphi)} < 0$.
Proof. *See Appendix A.2.* ■

Proposition 1 shows that the natural rate declines in the probability p and the size of a disaster μ, that is, in its extensive and intensive margins, respectively. Intuitively, the more likely and the larger a disaster, the larger the desire to save in order to stabilize consumption over time and across states of the world. Since there is no vehicle to save in the simplified economy—an assumption we relax in the next section—the natural rate of interest rate declines in order for markets to clear (in the flex-price equilibrium). Potential output, in turn, declines only in the event of an actual disaster. The mere expectation of disaster does not impact the supply side of the (simplified) economy.

Instead, all else equal, disaster expectations impact aggregate demand adversely and monetary policy plays a key role for how the economy actually adjusts. To see this, we solve the model under a flexible interest rate rule which allows for a systematic response of the policy rate to both, the natural rate and inflation:

$$i_t = \phi_r r_t^n + \phi_{\pi,t}\pi_t. \tag{4.5}$$

Here the parameter $\phi_r \in \{0, 1\}$ captures the response of the policy rate to the natural rate. We focus on two limiting cases: the monetary authority may either track the natural rate perfectly ($\phi_r = 1$) or not at all ($\phi_r = 0$). Of course, intermediate cases are conceivable, but our results carry over to such cases in a straightforward way.

Moreover, specification (4.5) allows the response of monetary policy to inflation to be time-varying ($\phi_{\pi,t}$). In this way, we capture the possibility that monetary policy is unresponsive to inflation—at least for some time—and set $\phi_{\pi,t} = 0$. Such inaction appears plausible in times of low interest rates when central banks are constrained by the effective lower bound (ELB) on the policy rate. Still, we assume that monetary policy switches to an "active" role with a sufficiently high probability in the next period.[10] Under these assumptions we obtain the following solution for inflation and the output gap for alternative scenarios of monetary policy:

Proposition 2 *Given the simplified model, as represented by equations* (4.3) *and* (4.4) *and the interest-rate feedback rule given by* (4.5)*, the unique and stable solution for the output gap and inflation is given by:*

$$\tilde{y}_t = \begin{cases} 0 \\ \Pi_y r_t^n, \\ \Gamma_y r_t^n \end{cases} \qquad \pi_t = \begin{cases} 0, & \textit{if } \phi_r = 1 \\ \Pi_\pi r_t^n, & \textit{if } \phi_r = 0 \textit{ and } \phi_\pi \in (1, \infty) \\ \Gamma_\pi r_t^n, & \textit{if } \phi_r = 0 \textit{ and } \phi_{\pi,t} = 0; \end{cases}$$

where the natural rate r_t^n declines with disaster expectations (both along the intensive and the extensive margin), as established in Proposition 1. Also, $\Pi_y, \Pi_\pi \geq 0$ and $\Gamma_y, \Gamma_\pi \geq 0$. It holds that $\Gamma_y > \Pi_y$ and $\Gamma_\pi > \Pi_{\pi,t}$. If $\phi_{\pi,t} \to \infty$, $\Pi_y \to 0$ as well as $\Pi_\pi \to 0$.
Proof. *See Appendix A.3.* ■

Proposition 2 shows that monetary policy can fully stabilize inflation and the output gap

[10] Specifically, in order to ensure the existence of a (locally) unique equilibrium we require $P(\phi_{\pi,t+1} > 1) = 1 - \zeta$, where ζ needs to satisfy the following inequalities: $(1 - \zeta)(1 - \beta\zeta)\sigma > \kappa\zeta > 0$. Note moreover that whenever the response to inflation is non-zero, we assume it to be sufficiently aggressive to satisfy the Taylor principle.

($\pi_t = \tilde{y}_t = 0$) if it tracks the natural rate of interest perfectly ($\phi_r = 1$). This is a result well-known from the textbook version of the New Keynesian model (Galí, 2015). Here we show that it carries over to our setup. Intuitively, disaster expectations induce a contraction of aggregate demand which may be offset by monetary policy to the extent that the policy rate is lowered in sync with the natural rate.

This policy is challenging for two reasons. First, the natural rate is a counterfactual object and as such unobserved. We account for this complication by considering the case $\phi_r = 0$. In this case monetary policy no longer responds to the natural rate, but only to inflation. Proposition 2 shows that the result is a contraction of output and inflation in response to the disaster expectations (recall from Proposition 1 that the natural rate declines as disaster expectations increase). Intuitively, the policy rate is too high in this case and monetary policy is not sufficiently accommodative. Still, in the limiting case where the response to inflation is infinitely aggressive ($\phi_{\pi,t} \to \infty$), monetary policy can still insulate the economy from the adverse impact of disaster expectations.

Second, since the natural rate declines in response to disaster expectations, monetary policy may find itself constrained by the ELB. We capture this possibility in a stylized manner by assuming that upon impact monetary policy is not responsive to a shift in inflation ($\phi_{\pi,t} = 0$). The result is a stronger decline of inflation and the output gap, as Proposition 2 shows. We conclude that the ELB will generally amplify the adverse impact of disaster expectations, a result that is akin to what has been established elsewhere, notably in the context of government spending shocks (e.g., Woodford, 2011).

More generally, and in line with the results of Gourio (2012), disaster expectations cause business cycle fluctuations—unless they are offset by monetary policy. The following proposition establishes this point formally:

Proposition 3 *Given the simplified model, as represented by equations* (4.3) *and* (4.4)*, the variance of the natural rate is given by:*

$$\sigma^2_{r^n} = var(r^n_t) = \left[\Omega(1-\alpha)\bar{\mu}\right]^2 var(p_t) \tag{4.6}$$

with $var(p_t) = \bar{p}^2 var(e^{\sigma_p \epsilon_{p,t}})$. *It follows from Proposition 2 that the variance of inflation and the output gap are function of* $\sigma^2_{r^n}$*:*

$$var(\tilde{y}_t) = \begin{cases} 0 \\ \Pi^2_y \sigma^2_{r^n}, \\ \Gamma^2_y \sigma^2_{r^n} \end{cases} \qquad var(\pi_t) = \begin{cases} 0, & \text{if } \phi_r = 1 \\ \Pi^2_\pi \sigma^2_{r^n}, & \text{if } \phi_r = 0 \text{ and } \phi_\pi \in (1,\infty) \\ \Gamma^2_\pi \sigma^2_{r^n}, & \text{if } \phi_r = 0 \text{ and } \phi_{\pi,t} = 0; \end{cases}$$

where for $\phi_r = 0$ *it holds that* $\frac{\partial var(\pi_t)}{\partial \phi_\pi} < 0$ *and that* $\frac{\partial var(\tilde{y}_t)}{\partial \phi_\pi} < 0$. ■

5 Quantitative Model Analysis

We now turn to a quantitative analysis in order to assess the implications of climate-change expectations for monetary policy. For this purpose we map the results of the survey into the model. In a first step we specify functional forms and calibrate the model. Then we present results.

5.1 Model Solution

To solve the model, all equations are detrended with a measure for the level of technology. We then rely on the Taylor projection algorithm proposed by Fernández-Villaverde and Levintal (2018) to solve the model numerically.[11] We extend the original model by Fernández-Villaverde and Levintal (2018) in that we allow for time variation in the probability of a disaster.[12] As a result, the model features an additional state variable. Yet in our analysis, disaster risk only matters via the expected value of future disasters. Following Isoré and Szczerbowicz (2017), we may thus replace the expectations operator over future disasters in the first-order conditions in the following way:

$$E_t d_{t+1} = p_t = \bar{p}^{(1-\rho_p)} p_{t-1}^{\rho_p} e^{\sigma_p \epsilon_{p,t}}, \tag{5.1}$$

where the second equality uses equation (3.3). Our assumptions about the information flow is key to arrive at equation (5.1): While the realization of the disaster is only known in the respective period, the probability of a disaster in $t+1$ is known in period t.[13]

5.2 Calibration

In specifying functional forms we follow the original formulation of Fernández-Villaverde and Levintal (2018) as closely as possible. First, we assume for period utility:

$$U_t = C_t(1-N_t)^{\nu}. \tag{5.2}$$

Given the weight ν of leisure and the degree of risk aversion γ (in equation (3.4) above), the intertemporal elasticity of substitution is given by $\sigma = [1-(1+\nu)(1-\psi)]^{-1}$. The investment adjustment costs $S(\cdot)$ in equation (3.2) take to form:

$$S\left(\frac{X_t}{X_{t-1}}\right) = \frac{\kappa_k}{2}\left(\frac{X_t}{X_{t-1}}\right)^2, \tag{5.3}$$

where κ_k is a positive constant. Last, we specify a fairly standard interest rate rule that allows for a response of the interest rate to output growth (with response coefficient ϕ_y) in addition to

[11] Fernández-Villaverde and Levintal (2018) compare alternative strategies to solve rare-disaster models and find that Taylor projections perform particular well along the speed-accuracy trade-off. Under this approach, one first approximates the policy functions of the model with polynomial functions and inserts these into the system of first-order conditions. Next, one minimizes the resulting residual function in order to find the coefficients that best approximate the policy functions, see also Fernandez-Villaverde et al. (2016) for details further details.

[12] Their setup allows for time variation in the size of disaster which we keep constant. In addition, compared to the model by Fernández-Villaverde and Levintal (2018), we abstract from TFP trend growth.

[13] Isoré and Szczerbowicz (2017) employ perturbation methods to solve their disaster model.

Table 7: Model calibration

	Parameter	Value	Source/Target
Disaster expectations			
μ	disaster size	0.05	Survey
$\bar{p}$	Disaster probability	0.025	Survey, 10% p.a., see Table 4
ρ_μ	Persistence of disaster risk shock	0.9	FVL
σ_p	Standard deviation of (log) disaster prob.	0.12	Google search queries
Preferences			
β	Discount factor	0.99653	nat. rate ($r_n \approx 0.86\%$), see Table 8
σ	Intertemporal elasticity of substitution	2	FVL
ν	Leisure preference	2.33	FVL
γ	Risk aversion	3.8	FVL
Production			
α	Capital share in production	0.21	FVL
δ	Depreciation	0.0153	$X_t/Y_t \approx 0.15$
ϵ	Elasticity of substitution	10	FVL
κ_k	Capital adjustment costs parameter	0.75	Business cycle vol., see Table 8
σ_A	Standard deviation of technology shock	0.013	Business cycle vol., see Table 8
Monetary policy and pricing			
ϕ_π	Taylor rule parameter inflation	1.3	FVL
ϕ_y	Taylor rule parameter output growth	0.2458	FVL
γ	Interest rate smoothing parameter	0.5	FVL
$\bar{\Pi}$	Inflation target	1.005	2% annual inflation
θ	Calvo price setting parameter	0.92	Business cycle vol., see Table 8
χ	Price indexation parameter	0.6186	FVL

Notes: model calibrated to quarterly frequency. FVL: Fernández-Villaverde and Levintal (2018).

inflation as well as for interest-rate smoothing:

$$1 + i_t = \left[\frac{1 + i_{t-1}}{1 + i}\right]^{\gamma} \left[\left(\frac{\Pi_t}{\bar{\Pi}}\right)^{\phi_\pi} \left(\frac{Y_t}{Y_{t-1}}\right)^{\phi_y}\right]^{1-\gamma} . \tag{5.4}$$

Here, i is the nominal interest rate in steady state. $\bar{\Pi}$ is the inflation target. The parameter γ governs the degree of interest-rate smoothing.

We calibrate the model to quarterly frequency and report parameter values in Table 7. In line with our survey we set the disaster size to $\mu = 0.05$. Next, we set $\bar{p} = 0.025$, implying an annual average disaster probability of 10% in accordance with responses to our survey. We further assume $\rho_p = 0.9$ as in Fernández-Villaverde and Levintal (2018). We set the standard deviation of the disaster probability, σ_p, to 0.12, consistent with the extent of the time-series variation that we observe for google search queries for "natural disaster" over the period from 2004 until 2021. We opt for this strategy because for the 7-months period for which our survey ran there is a high degree of co-movement of these search queries and the probability assigned to rare disasters, as shown in Figure 2 above.[14]

[14] The standard deviation of the (log) Google search data, which we use as a proxy for the expected disaster probability is 0.27. We obtain $\sigma_p = std(\log(p_t))\sqrt{1 - \rho_p^2} \approx 0.12$.

For the other parameters we largely follow Fernández-Villaverde and Levintal (2018). We adjust a few parameters, however, such that the model predictions align well with a number of key empirical business cycle statistics, reported in Table 8 below. Most importantly in this regard, we want to make sure that the model predicts a plausible value for the natural rate of interest. The natural rate has been declining for some time and has been exceptionally low during the last decade. We set the discount factor β to match the average value of the estimate reported by the New York Fed for the period 2010–2019, based on the approach by Laubach and Williams (2003). Next, in order to match the investment to GDP ratio of $X/Y \approx 0.15$, we assume for the depreciation rate $\delta = 0.0153$.

We further target the volatility of output, investment, and inflation. Here we target the standard deviation for the pre-crisis period 1983Q1–2007Q4, computed based on quarterly time-series observations from which we remove an HP-filtered trend. Setting $\kappa_k = 0.75$ allows the model to predict the volatility of investment in the right ballpark. The same holds for the volatility of output and inflation, as we set standard deviation of TFP growth to $\sigma_A = 0.013$ and the Calvo parameter to $\theta = 0.92$. This implies an average price duration of 10 quarters, that is, a rather flat Phillips curve. The value for σ_A is also in line with evidence by Fernald (2014). Lastly, we set the inflation target to 2% in accordance with Fed policies.

We target the business cycle moments using simulation. We distinguish, as discussed in the next section, between two types of simulations: A simulation of a (disaster) risky steady state ("baseline"), and a simulation of a steady state without disaster risk. In both cases, we allow for productivity shocks. In the (disaster) risky steady state, we additionally allow for shocks to the probability of a rare disaster risk but exclude realizations from the simulated time series. By contrast, in the disaster-free steady state, the probability of a rare disaster is always equal to zero.

5.3 Simulation Results

We report the results of model simulations in Table 8. The top panel of Table 8 reports the standard deviations of inflation, investment, output and the output gap. The middle column reports the values as predicted by the baseline model for the (disaster) risky steady state. The predicted standard deviations align well with their empirical counterparts, reported in the left column. This is by construction. Our stylized model captures key features of the business cycles rather well and is thus fit for a quantitative analysis of the contribution of climate-change related disaster expectations to business cycle. For this purpose, we simulate the model in the absence of disaster expectations and report results in the third column. It turns out that climate-change related disaster expectations make a sizeable contribution: they raise the volatility of inflation and the output gap by 7-8 percent.

Climate-change disaster expectations also alter steady state means, as shown in the bottom panel of Table 8. Again, the calibration of the model ensures that the natural rate of interest in the risk steady state is 0.68% on an annualized basis, in line with the evidence for the decade since the Global Financial Crisis. A counterfactual in which there are no climate-change related disaster expectations (column 3) would result in a much higher natural rate. We find that disaster expectations lower the natural rate by about half a percentage point from 1.13% to

Table 8: Model predictions

	Standard deviation			
	Data	Model		
		Baseline, with disaster expectations	No disaster expectations	Contribution of disaster expectation
Inflation π_t	0.22	0.20	0.19	+7.03%
		(0.007)	(0.007)	
Investment X_t	3.86	3.43	3.18	+7.20%
		(0.092)	(0.096)	
Output Y_t	1.16	1.25	1.23	+1.31%
		(0.021)	(0.023)	
Output Gap $\tilde{y}_t$		1.23	1.13	+8.12%
		(0.039)	(0.037)	
	Means			
Natural rate of interest r^n	0.68%	0.68%	1.13%	-0.45pp
Inflation π	1.73%	1.43%	1.49%	-0.06pp
Output gap $\tilde{y}$		-0.19pp	0.00pp	-0.19pp

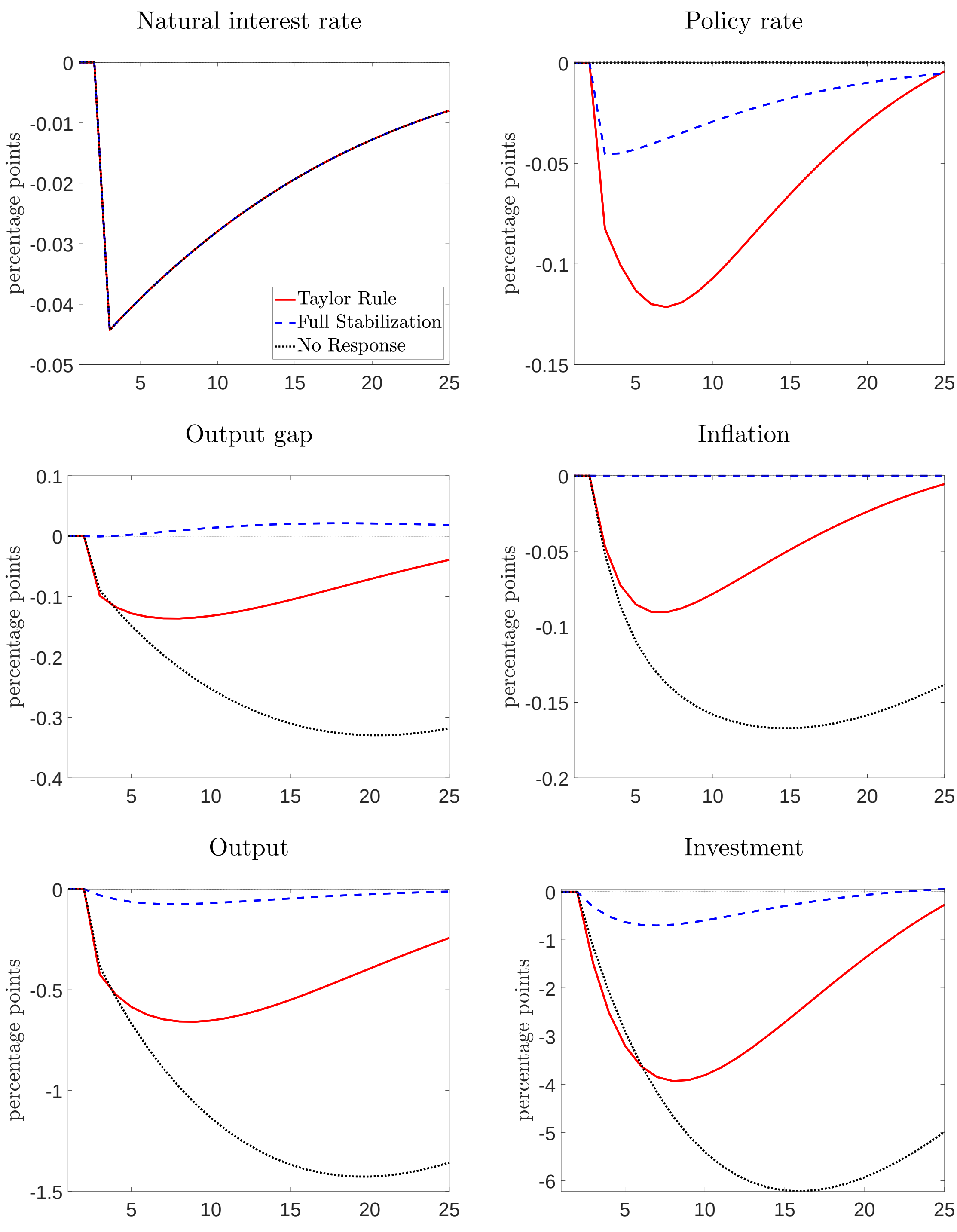
Notes: standard deviation computed on pre-crisis sample 1983Q1—2007Q4; source: FRED (OUTNFB for real GDP, GPDIC1 for real investments, GDPDEF for inflation). GDP and Investment are in logs. Data are hp-filtered with filter weight 1,600. Natural rate and inflation are average for period 2010–2019, estimate for natural rate by New York Fed based on approach by Laubach and Williams (2003). Model counterparts computed average over 100 simulations for 10,000 periods each. Standard errors of statistics in parenthesis. variables in risk steady state are annualized.

0.68%. This is a sizeable effect, given that the level of the natural rate is already quite low. Next, we observe that inflation in the risky steady state is quite a bit below its 2% target, just like in the data for the period 2010–19. The model captures this feature of the data because it is non-linear and TFP shocks impact the economy asymmetrically. Likewise, the output gap is negative in the risky steady state.

Next, in order to shed light on the transmission of disaster expectations we compute the impulse responses to a shock to the disaster probability. Figure 3 shows the results for alternative scenarios for monetary policy. In each instance, we consider a one-standard-deviation shock on the disaster probability, implying a temporary increase in the quarterly disaster risk from 2.5% to 2.8%. The figure displays the deviations from the risky steady state along the vertical axis in percentage points, and time in quarters along the horizontal axis. The red solid line shows the responses for the baseline model in which monetary policy follows the conventional Taylor rule specified above, see equation (5.4). The blue dashed lines, instead, show the adjustment under the assumption that monetary policy also tracks the natural rate, as scenario which analyzed in Section 4.2 above ("full stabilization"). Last, the black dotted line show the adjustment for a scenario under which monetary policy does not respond to the shift in the climate-change related disaster expectations, for instance, because it is constrained by the effective lower bound.[15]

[15]We approximate such a scenario by selecting monetary policy shocks which offsets the endogenous policy response to the disaster-probability shock.

Figure 3: Dynamic adjustment to disaster expectation shock



Notes: Impulse response functions to a one standard deviation shock on the disaster probability. Vertical axis measures deviation from risky steady state (see Table 8) measured in percentage points, horizontal axis measures time in quarters. Response of the natural rate, policy rate, inflation, output and investment are annualized. The output gap response is calculated as the deviation of the model from a flexible price version. The natural interest rate represents the real interest rate of the flexible price model.

The response of the natural rate, shown in the upper-left panel is central to the transmission of the shock. By definition its response is independent of the monetary policy rule in place.

The natural rate drops by some 4 basis points relative to the pre-shock level. The effect is gradually reversed as the expected extent of the disaster declines over time (with persistence parameter $\rho_p = 0.9$). The response of the rest of the economy crucially depends on how monetary policy adjusts short-term interest rates. The case where monetary policy tracks the natural rate (blue dashed lines) provides a benchmark. Here inflation (shown in the center right panel) is perfectly stabilized and the output gap remains almost closed.[16] Investment and output, however, nevertheless contract though only mildly. This adjustment is intuitive as the increased risk of disaster lowers the expected return on capital. We thus conclude that the main insights into the transmission of the shock established in Section 4.2 are robust once we allow investment dynamics in response to shocks—if anything the decline of investment reinforces the increase in savings which drives down the natural rate.

Consider next the response under the baseline scenario where monetary policy follows a conventional interest-rate feedback role à la Taylor (red solid line). In this case, the adjustment of the policy rate turns out to be insufficient to stabilize the output gap and inflation: both decline further in response to the shock. While initially the policy rate drops more than in the case when monetary policy tracks the natural rate, monetary policy does not provide sufficient accommodation in the baseline.[17] Inflation declines and hence the real rate does not decline as much as the natural rate does. In the last scenario under consideration, that is, when monetary policy is not responding to the shock at all, there is further amplification. In both instances, actual output drops with demand so does inflation. The shock induces a sizeable output gap as a result.

6 External Validation

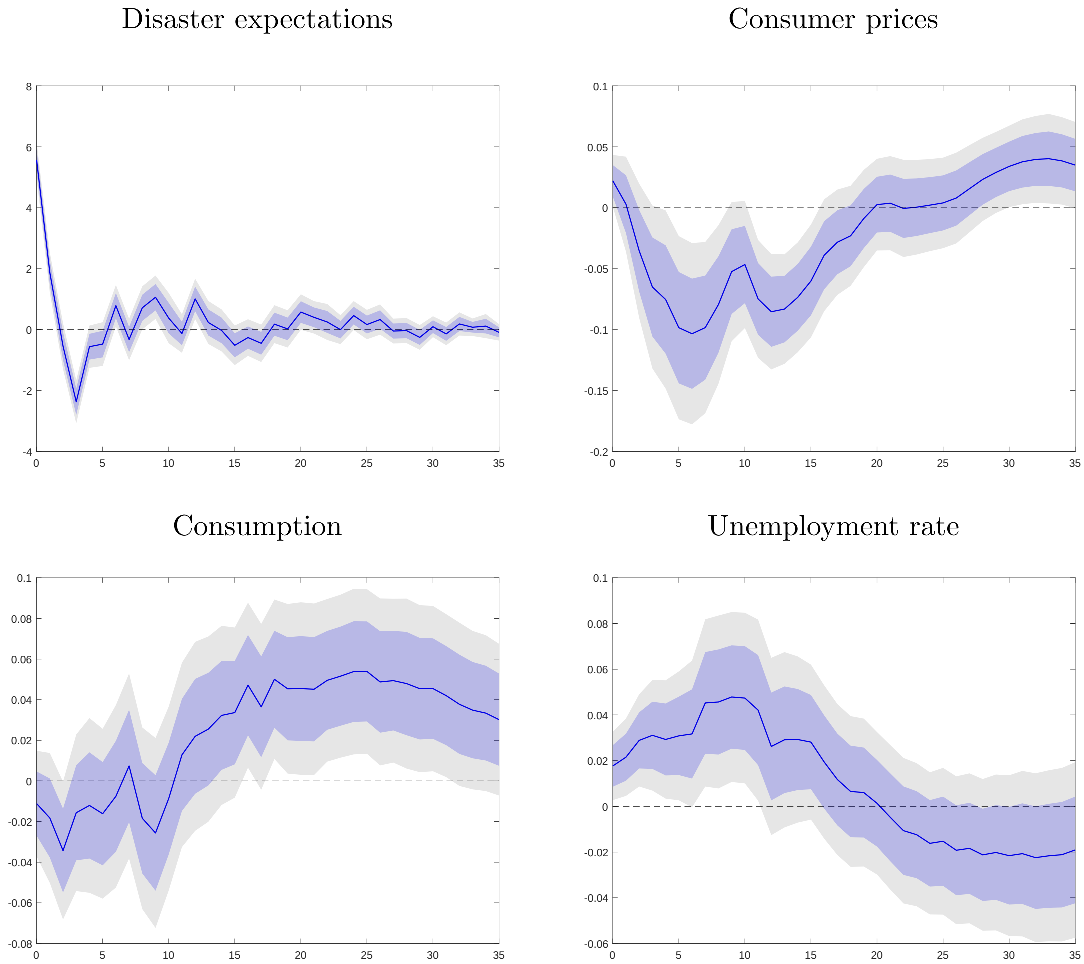
Our model-based analysis illustrates that shocks to disaster expectations induce a contraction of economic activity. At a fundamental level, this is unsurprising: in our model rising disaster expectations reflect bad news about the future which have been established to impact the business cycle adversely (Beaudry and Portier, 2006; Jaimovich and Rebelo, 2009; Schmitt-Grohé and Uribe, 2012). Against this background, we seek to validate our analysis with external evidence on the effects of disaster expectations. For this purpose we rely on a data that is both independent of the survey and our model-based analysis.

We start from the observation that the expectations regarding climate-change related natural disasters co-move strongly with the google search index for “natural disasters”, as illustrated in Figure 2 above. The google search index is available since 2004. In what follows we estimate a VAR model on monthly observation for the period 2004:M1 to 2020:12. In addition to the google search index as a proxy for disaster expectations, the model features four time series: actual disaster costs (see Figure C.1), the log of the CPI (FRED: CPIAUCSL), the log of real personal consumption expenditures (FRED: PCEC96), and, as a measure of real activity at monthly frequency, the unemployment rate (FRED: UNRATE). The VAR model includes 12 lags of the

[16] In Section 4.2 the output gap is zero in case monetary policy tracks the natural rate. This is because divine coincides obtains in the New Keynesian model only when inflation is stabilized at exactly zero (Alves, 2014).

[17] At the end of the time horizon considered in Figure 3 the policy rate under the Taylor rule rises considerably more than in the case of full stabilization. Eventually, it is the entire path of short term rates which determines the monetary stance in the New Keynesian model (e.g. Corsetti et al., 2012).

Figure 4: Responses to disaster expectation shock: VAR evidence



Notes: impulse responses to identified disaster expectation shocks. Disaster expectations measured google search index for "natural disasters". Solid line represents point estimate, shaded areas 68% and 90% confidence bounds. Response of actual disaster costs not shown. Shock size: one standard deviation, consumer prices, consumption are measured in percent, the unemployment rate in percentage points.

endogenous variables, a constant and a linear time trend. We order disaster expectations second and employ a recursive identification scheme, that is, we allow for a contemporaneous effect of the first variable (actual costs) on disaster expectations but not vice versa. The same holds for the other variables: they may respond contemporaneously to queries, but are ruled out to influence disaster expectations within months.

Figure 4 shows the response to a shock to disaster expectations to the extent that it becomes manifest in google queries for "natural disaster". The solid line shows the point estimate to a one-standard deviation shock, while shaded areas indicate 68% and 90% confidence bounds, respectively. In response to increased disaster expectations, consumer prices decline (upper-right panel), as do personal consumption expenditures (upper-left panel), at least initially; they rebound after about 10 months. Still, as the response of unemployment in the lower-right panel shows, the shock is clearly contractionary: the unemployment rate increases quickly and persistently.[18] Overall, the VAR evidence thus lends support to the transmission mechanism of disaster expectations that operates in our model.

7 Conclusion

Central banks have started to become involved in the debate about climate change and are devising measures in order to respond appropriately to new challenges. What comes out of this debate and what measures will play a significant role in the future is highly uncertain, just like the implications of climate change itself. Against this background, we stress a channel through which climate change impacts economic activity in a fairly conventional way—namely via expectations. Yet, while fairly conventional, the *expectations channel of climate change* has thus far been overlooked and central banks risk ignoring it at their own peril—as we illustrate in this paper.

In a first step, we run a representative consumer survey in the U.S. and elicit beliefs about the economic impact of climate change. We find that respondents perceive a high probability of costly, rare disasters due to climate change, but not much of an impact on GDP growth. Salience of rare disasters through media coverage increases the probability by up to 7 percentage points.

Expectations about climate-change related disasters matter for monetary policy because they lower the natural rate of interest. In a nutshell, bad news about the future are contractionary today. And the decline of the natural rate is an indicator of the extent of this contraction. We map the results from our survey into a New Keynesian model with rare disasters due to Fernández-Villaverde and Levintal (2018). Here we find that disaster expectations cause a drop in the natural rate by 45 basis points. This is a fairly large effect, notably if—as it happens to be the case in the current environment—the natural rate is already low. In particular, we show that, if monetary policy is unable or unwilling to accommodate the drop in the natural rate, its recessionary impact can be quite large.

[18]The response of actual disaster costs (not shown) in the VAR does not exhibit a systematic pattern. We still include it in the VAR as a control variable.

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A Details on Model

A.1 First Order Conditions of Simplified Model

The first order conditions for the household problem in the simplified model (Section 4) are given by:

$$\frac{W_t}{P_t} = C_t^\sigma N_t^\varphi \tag{A.1}$$

$$Q_t = \beta E_t \left\{ \left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \frac{P_t}{P_{t+1}} \right\} \tag{A.2}$$

Here we assume prohibitively high investment adjustment costs and no depreciation; we assume that $K_t = \bar{K}$ and $X_t = 0$ for all t. At the aggregate level, the goods market equilibrium collapses to $Y_t = C_t$.

The first order conditions of firms are given by:

$$0 = \sum_{t=0}^{\infty} \theta^k E_t \left\{ Q_{t,t+k} Y_{t+k|t} \left(P_t^* - \mathcal{M} \Psi_{t+k|t} \right) \right\} \tag{A.3}$$

$$\frac{\bar{K}}{N_t} = \frac{\alpha}{1-\alpha} \frac{W_t}{R_t^K} \tag{A.4}$$

$$\Psi_t = \left(\frac{1}{1-\alpha} \right)^{1-\alpha} \left(\frac{1}{\alpha} \right)^{\alpha} \frac{W_t^{1-\alpha} R_t^{K\alpha}}{P_t A_t} \tag{A.5}$$

where $\Psi_{t+k|t} = \mathcal{C}'_{t+k}(Y_{t+k|t})$ denotes marginal costs and $\mathcal{M} \equiv \frac{\epsilon}{\epsilon-1}$ is the markup in steady state.

A.2 Proof of Proposition 1

The proposition establishes the solution for the natural rate of interest and for potential output (or "natural output"). These are the outcomes if prices are flexible, that is, if $\theta = 0$. We solve the simplified model under this assumption. From (A.3), it follows that the optimal price (in logs) is a constant markup over marginal costs:

$$p_t = \mu + \psi_t \tag{A.6}$$

where μ is the log of the steady state markup. ψ_t gives the log marginal costs. Using equations (A.4) and (A.5), we obtain:

$$\psi_t = w_t - p_t - a_t + \alpha n_t - \log(1-\alpha) - \alpha \log(\bar{K})$$

Inserting into (A.6) gives:

$$\mu = -w_t + a_t - \alpha n_t + \log(1-\alpha) + \alpha \log(\bar{K})$$

Combining this expression the labor supply relation (A.1) and the goods market clearing condition, we obtain the following solution for potential output:

$$\hat{y}_t^n = \Xi_a a_t + \Lambda$$

where $\Xi_a = \frac{1+\varphi}{\sigma(1-\alpha)+(\alpha+\varphi)} > 0$ and $\Lambda = \frac{(1-\alpha)(\log(1-\alpha)+\alpha\log(\bar{K})-\mu)}{\sigma(1-\alpha)+\alpha+\varphi} > 0$.
Inserting the process for technology in logs ($a_t = a_{t-1} - (1-\alpha) d_t \bar{\mu}$)gives:

$$\hat{y}_t^n = \Xi_\mu d_t \bar{\mu} + \Xi_a a_{t-1} + \Lambda$$

With $\Xi_\mu = -\frac{\sigma(1-\varphi)(1-\alpha)}{\sigma(1-\alpha)+(\alpha+\varphi)} < 0$. Potential output thus depends on d_t, that is, the realization of the disaster.

Linearizing the Euler equation (A.2) and substituting for consumption using goods market clearing yields:

$$y_t = E_t y_{t+1} - \frac{1}{\sigma}(i_t - E_t\pi_{t+1} - \rho)$$

Defining the output gap as $\tilde{y}_t = y_t - y_t^n$ and using the solution for the potential output, we obtain the dynamic IS equation (4.4) as well as the expression for the natural rate of interest which is stated in Proposition 1:

$$\begin{aligned} r_t^n &= \rho + \Omega E_t \Delta a_{t+1} \\ &= \rho + \Omega\Lambda_A - \Omega(1-\alpha)p_t\bar{\mu}. \end{aligned} \tag{A.7}$$

where $\Omega = \frac{1+\varphi}{\sigma(1-\alpha)+\alpha+\varphi} > 0$.

A.3 Proof of Proposition 2

The proposition considers three alternative scenarios for monetary policy. For each, we solve the model given by (4.3), (4.4) and (4.5). We use the method of undetermined coefficients to solve for the endogenous variables as linear functions of the natural rate of interest r_t^n, which itself depends on the exogenous parameters of the model, namely the disaster size $\bar{\mu}$ and probability p, as formally shown in Proposition 1 and equation (A.7)

Full Stabilization First, we assume that the central bank stabilizes the economy by tracking the natural rate of interest, that is, the interest rate rule is given by (4.5) with $\phi_r = 1$, that is, $i_t = r_t^n + \phi_{\pi,t}\pi_t$. Using this in (4.4) and combining with (4.3), we find that $\{\tilde{y}_t, \pi_t\} = 0$ for all t is a stable solution. The solution is unique, provided the Taylor principle is satisfied: $\phi_\pi > 1$.

Taylor Rule Second, we assume $\phi_r = 0$ such that (4.5) implies $i_t = \phi_{\pi,t}\pi_t$. To solve the model under this assumption we, we use the method of undetermined coefficients, starting from the observation that the output gap and inflation will linear functions of the natural rate of interest, that is, $\tilde{y}_t = \Pi_y r_t^n$ and $\pi_t = \Pi_\pi r_t^n$. Substituting in the equilibrium conditions, we obtain:

$$\begin{aligned} \Pi_\pi r_t^n &= \beta\Pi_\pi r_t^n + \kappa\Pi_y r_t^n, \\ \Pi_y r_t^n &= \Pi_y r_t^n - \frac{1}{\sigma}(\Pi_\pi\phi_{\pi,t} r_t^n - \Pi_\pi r_t^n - r_t^n). \end{aligned}$$

Solving for the undetermined coefficients Π_y and Π_π gives the solution stated in proposition 2:

$$\Pi_y = \frac{1}{\sigma + \kappa\phi_{\pi,t}} > 0 \tag{A.8}$$

$$\Pi_\pi = \frac{\kappa}{\sigma + \kappa\phi_{\pi,t}} > 0 \tag{A.9}$$

Note that as $\phi_{\pi,t} \to \infty$ the outcome for the Taylor rule is equivalent to full stabilization, since $\lim\limits_{\phi_{\pi,t}\to\infty} \Pi_y = 0$ and $\lim\limits_{\phi_{\pi,t}\to\infty} \Pi_\pi = 0$. Again, the solution in (A.8) and (A.9) is unique given that the Taylor principle holds, that is $\phi_\pi > 1$.

Unresponsive Monetary Policy Here we assume that monetary policy is unresponsive to the disaster expectations ($\phi_{\pi,t} = 0$) in period t and with probability ζ for another period. With probability $1 - \zeta$ monetary policy reverts back to follow a Taylor rule in the next period. In that case, since there are no endogenous state variables, the solution in period $t + 1$ is given by (A.8)-(A.9). In terms of notation, we use superscript U to index variables to the state in which monetary policy is unresponsive. We write, for instance, π_t^U. Using the Markov structure for the responsiveness of monetary policy outlined above, we can rewrite the expectations operators in (4.3) and (4.4) - given that monetary policy is unresponsive in t - as:

$$\begin{aligned} E_t(\pi_{t+1}|U) &= \zeta E_t \pi_{t+1}^U + (1-\zeta)\Pi_\pi r_t^n \\ E_t(\tilde{y}_{t+1}|U) &= \zeta E_t \tilde{y}_{t+1}^U + (1-\zeta)\Pi_y r_t^n \end{aligned}$$

Using these expectations operators, we can express (4.3) and (4.4) in matrix form:

$$E_t \begin{bmatrix} \tilde{y}_{t+1}^U \\ \pi_{t+1}^U \end{bmatrix} = A \begin{bmatrix} \tilde{y}_t^U \\ \pi_t^U \end{bmatrix} + B r_t^n$$

where

$$A = \frac{1}{\zeta} \begin{bmatrix} 1 + \frac{\kappa}{\beta\sigma} & -\frac{1}{\beta\sigma} \\ -\frac{\kappa}{\beta} & \frac{1}{\beta} \end{bmatrix}, \quad B = \frac{1-\zeta}{\zeta} \begin{bmatrix} \frac{\zeta}{1-\zeta} - \frac{2}{\sigma}\Pi_\pi - \Pi_y \\ \Pi_\pi \end{bmatrix}$$

Following the method proposed by Woodford (2003) it can be shown that in our model a solution is determinate as long as both eigenvalues of A are outside the unit circle. This condition is fulfilled if (A.10) holds:

$$(1-\zeta)(1-\beta\zeta)\sigma - \kappa\zeta > 0 \tag{A.10}$$

Given that result, we solve again by the method of undetermined coefficients. To find the solution for the period t, we assume that the output gap and inflation are linear functions of the natural rate of interest, that is, we assume that $\tilde{y}_t^U = \Gamma_y r_t^n$ and $\pi_t^U = \Gamma_\pi r_t^n$. Solve for Γ_y and Γ_π gives

$$\begin{aligned} \Gamma_y &= \frac{(1-\beta\zeta)(1-\zeta)\sigma}{(1-\zeta)(1-\beta\zeta)\sigma - \kappa\zeta}\Pi_y \\ &\quad + \frac{(1-\zeta)}{(1-\zeta)(1-\beta\zeta)\sigma - \kappa\zeta}\Pi_\pi + \frac{(1-\beta\zeta)}{(1-\zeta)(1-\beta\zeta)\sigma - \kappa\zeta} \\ \Gamma_\pi &= \frac{(1-\zeta)\kappa\sigma}{(1-\zeta)(1-\beta\zeta)\sigma - \kappa\zeta}\Pi_y \\ &\quad + \frac{(1-\zeta)}{1-\beta\zeta}\left[\beta + \frac{\kappa}{(1-\zeta)(1-\beta\zeta)\sigma - \kappa\zeta}\right]\Pi_\pi + \frac{\kappa}{(1-\zeta)(1-\beta\zeta)\sigma - \kappa\zeta} \end{aligned}$$

which establish a unique and stable solution given that the condition for determinacy holds. Using (A.8), (A.9) and (A.10) it can now also be shown that $\Gamma_y > \Pi_y$ and $\Gamma_\pi > \Pi_\pi$, as stated in proposition 2.

B Survey Appendix

B.1 Demographic Questions

First, we ask all respondents the following demographic questions:

D1: Please enter your age.

D2 Please indicate your gender.

- *Male*
- *Female*
- *Other*

D3: How would you identify your ethnicity? Please select all that apply.

- *Asian/Asian American*
- *Black/African American*
- *White/Caucasian*
- *Other*
- *Prefer not to say*

D4: Do you consider yourself of Hispanic, Latino or Spanish origin?

- *Yes*
- *No*

D5: Please indicate the range of your yearly net disposable income.

- *Less than $10,000*
- *$10,000 - $19,999*
- *$20,000 - $34,999*
- *$35,000 - $49,999*
- *$50,000 - $99,999*
- *$100,000 - $199,999*
- *More than $200,000*

D6: In which state do you currently reside?

D7: What is the postal (zip) code for the address of your permanent residence?

D8: What is the highest level of school you have completed, or the highest degree you have achieved?

- *Less than high school*
- *High school diploma or equivalent*
- *Some college, but no degree*
- *Bachelor's degree*
- *Master's degree*
- *Doctorate or Professional Degree*

D9: How many children do you have?

D10: What is the percent chance that you will leave any inheritance?

B.2 Questions on climate change

Q1: The average growth rate of real GDP in the US between 2009 and 2019 has been about 2 percent. Climate change might influence future growth rates positively, say, because it triggers technological innovation or negatively because of regulation and taxes.
What do you think is the overall impact of climate change on economic growth over the next 12 months? Please assign probabilities to each scenario listed below:
Due to climate change, economic growth, compared to what it would be otherwise, will be

- *2 percentage points higher or more (say, more than 4 percent rather than 2)*
- *1 - 2 percentage points higher (say, between 3 and 4 percent rather than 2)*
- *0.1 - 1 percentage points higher (say, between 2.1 and 3 percent rather than 2)*
- *different by -0.1 to 0.1 percentage points.*
- *0.1 - 1 percentage points lower (say, between 1 and 1.9 percent rather than 2)*
- *1 - 2 percentage points lower (say, between 0 and 1 percent rather than 2)*
- *2 percentage points lower or more (say, less than 0 percent rather than 2)*

Q2: Recently, the economic damage due to natural disasters amounted to about 1% of GDP per year (Source: National Center for Environmental Information). In your view, will these damages be larger or smaller because of climate change? Please assign probabilities to each scenario listed below:
Specifically, what would you say is the percent chance that, over the next 12 month there will be . . .

- *no damage.*
- *less damage then in the past. (say, around 0.5% of GDP)*
- *the same as in the past. (say, 1% of GDP)*
- *more damage than in the past. (say, 1.5% of GDP)*
- *considerably more than in the past (say, 2% of GDP)*
- *much more than in the past (say, 3% of GDP)*
- *extremely rare disasters, with damage in an order of 5% of GDP.*

Q3: As a result of climate change, the risk of natural disasters (such as hurricanes, tropical cyclones, droughts, wildfires, or flooding) is likely to increase. The economic damage of such disasters may be sizeable. Considering the next 12 months, what do you think is the probability of a large disaster causing damage of about 5 percent of GDP?
The probability of a large disaster will be ___ percent.

Q4: On a slider from 0 (not important at all) to 10 (very important) how severe a problem do you consider climate change?

Q5: On a slider from 0 (not important at all) to 10 (very important) how severe a problem do you consider the COVID-19 pandemic?

Q6: Imagine there are white and black balls in a ballot box. You draw a ball for 70 times. 56 times, you have drawn a white ball, 14 times a black ball.
Given this record, what would you say is the probability of drawing a black ball the next time?
The probability is ___ percent.

B.3 Treatments

T1: We have just a few more questions. But next, before you give us your responses, we would like you to know the following. On September 17, 2020, USA Today summarized information about wildfires and hurricanes as follows:
This extraordinarily busy Atlantic hurricane season – like the catastrophic wildfire season on the West Coast – has focused attention on the role of climate change. [...]
Federal government forecasters from the National Oceanic and Atmospheric Administration announced La Niña's formation last week. It's expected to exacerbate both the hurricane and wildfire seasons.
In the West, climate scientists say rising heat and worsening droughts in California consistent with climate change have expanded what had been California's autumn wildfire season to year-round, sparking bigger, deadlier and more frequent fires like the ones we've seen this year. [...]
And as for hurricanes, scientists also say global warming is making the strongest of them, those with wind speeds of 110 mph or more, even stronger. Also, warmer air holds more moisture, making storms rainier, and rising seas from global warming make storm surges higher and more damaging.

T2: Over the past 20 years there have been 197 natural disasters in the United States, but even the largest caused damages of less than 1% of GDP. (Source: National Center for Environmental Information).

T3: You are doing well with the survey. We have just a few more questions. But before you give us your responses, we would like you to read the following extract from an interview with Christine Lagarde, president of the European Central Bank (ECB) from July 08, 2020:
"I think when it comes to climate change, it's everybody's responsibility. Where I stand, where I sit here as head of the European Central Bank, I want to explore every avenue available in order to combat climate change."

T4: Over the past 20 years there have been 197 natural disasters in the United States. Two of them caused damage of more than 0.5 percent of GDP. (Source: National Center for Environmental Information).

T5: The next question asks about potential damages due to climate change, expressed in percent of GDP. To put these damages in perspective, note that U.S. GDP declined by approximately 5 percent in 2008-09 in response to the global financial crisis.

B.4 Questions on Media Usage and Political Affiliation

Some respondents were additionally given the following questions:
P1: What would you say is your political affiliation?

- *Democrat*
- *Independent*
- *Republican*
- *Other*

P2: Please select your preferred news station from the list below: (you might pick more than one answer)

- *ABC*
- *CBS*
- *CNN*
- *Fox*
- *MSNBC*
- *NBC*
- *PBS*
- *Other*
- *I do not watch any of these TV/news stations.*

P3: Please select your preferred newspaper (print or online) from the list below: (you might pick more than one answer)

- *Washington Post*
- *Wall Street Journal*
- *New York Times*
- *USA Today*
- *Los Angeles Times*
- *Other*
- *I do not read any of those newspapers.*

C Tables and Figures

Table C.1: Climate Change Expectations: Cross-Sectional Demographic Regressions

	(1) Growth	(2) Damage	(3) Disaster Prob.
Female	0.0568	0.106***	4.038***
	(1.46)	(3.73)	(7.06)
35 to 44 years	0.0694	0.0441	0.861
	(1.34)	(1.02)	(1.11)
45 to 54 years	0.0289	0.0245	-1.373
	(0.46)	(0.52)	(-1.48)
above 55 years	0.278***	-0.146***	-0.632
	(5.47)	(-3.87)	(-0.82)
High Educated	-0.107*	0.0578	-0.320
	(-2.27)	(1.71)	(-0.49)
Middle Income	-0.0883*	-0.0914**	0.0842
	(-2.00)	(-2.76)	(0.13)
High Income	-0.0161	-0.0514	0.834
	(-0.26)	(-1.14)	(0.97)
White	-0.161	-0.0202	0.550
	(-1.52)	(-0.30)	(0.38)
Black	-0.269*	-0.0896	-0.316
	(-2.27)	(-1.11)	(-0.19)
Asian	-0.174	-0.184*	-3.047
	(-1.43)	(-2.19)	(-1.81)
Hispanic	-0.0646	-0.0561	-1.689
	(-0.57)	(-0.73)	(-1.08)
Republican	-0.0215	-0.169***	-2.553***
	(-0.45)	(-4.88)	(-3.83)
Democrat	0.0996*	0.134***	2.752***
	(2.33)	(4.08)	(4.02)
Constant	0.397*	1.511***	16.21***
	(2.00)	(10.05)	(6.55)
State FE	yes	yes	yes
N	8395	7279	7160
r2	0.0376	0.0586	0.0557

Notes: t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; This table presents cross section regression results on the impact of demographics on the climate change expectations. We use weighted regressions with robust standard errors. Weights used are the product of survey weights and calculated Huber robust weights.

Table C.2: Disaster Probability and Individual News Stations

	(1) Disaster Prob.	(2) Disaster Prob.	(3) Disaster Prob.
Multiple News Stations	5.324***		3.654***
	(5.97)		(3.78)
Fox	0.0192		-0.244
	(0.02)		(-0.23)
CNN	1.657		1.645
	(1.37)		(1.28)
ABC	1.470		1.245
	(1.17)		(0.96)
MSNBC	2.558		2.398
	(1.34)		(1.22)
PBS	-0.185		-0.702
	(-0.09)		(-0.31)
NBC	3.234*		2.869*
	(2.29)		(1.98)
CBS	4.734**		4.692**
	(3.11)		(2.97)
Multiple Newspapers		5.547***	4.056***
		(7.84)	(5.23)
New York Times		0.340	-0.340
		(0.34)	(-0.33)
Washington Post		2.305	1.761
		(1.52)	(1.17)
Wall Street Journal		-2.473**	-3.052**
		(-2.60)	(-3.12)
USA Today		3.210**	2.545*
		(2.87)	(2.23)
Los Angeles Times		-2.306	-3.173
		(-1.16)	(-1.59)
Constant	13.72***	14.49***	13.40***
	(5.43)	(5.85)	(5.29)
State Fixed Effect	yes	yes	yes
Demog. and Pol. Affiliation Controls	yes	yes	yes
N	7166	7169	7193
r2	0.0686	0.0734	0.0785

Notes: regression relates reported probability of disaster to use of specific news stations; only respondents who did not receive any treatment used in regression; t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights and Huber-robust weights to ensure that sample is representative and independent of outliers, respectively.

Table C.3: Expected Disaster Cost and Media Usage

	(1) Costs	(2) Costs	(3) Costs
no major TV Station	-0.299***		
	(-5.34)		
no major Newspaper		-0.128***	
		(-3.47)	
consume major TV station×no major newspaper			-0.0592
			(-1.56)
no major TV station×consume major newspaper			-0.136
			(-1.56)
no major TV station×no major newspaper			-0.364***
			(-5.65)
Constant	1.529***	1.483***	1.545***
	(8.55)	(8.24)	(8.60)
State and Month FE	yes	yes	yes
Demographic Controls	yes	yes	yes
N	4915	4916	4915
r2	0.0691	0.0620	0.0711

Notes: regression relates reported probability of disaster to media usage; only respondents who did not receive any treatment used in regression; t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights and Huber-robust weights to ensure that sample is representative and independent of outliers, respectively.

Table C.4: Reported Growth Impact of Climate Change and Media Usage

	(1) Growth	(2) Growth	(3) Growth
no major TV Station	-0.0353		
	(-0.45)		
no major Newspaper		0.217***	
		(3.91)	
consume major TV station×no major newspaper			0.251***
			(4.20)
no major TV station×consume major newspaper			-0.119
			(-0.92)
no major TV station×no major newspaper			0.101
			(1.10)
Constant	0.138	0.0320	0.0675
	(0.52)	(0.12)	(0.26)
State and Month FE	yes	yes	yes
Demographic and Treatment Controls	yes	yes	yes
N	4916	4916	4916
r2	0.0490	0.0538	0.0543

Notes: regression relates reported probability of disaster to media usage; only respondents who did not receive any treatment used in regression; t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights and Huber-robust weights to ensure that sample is representative and independent of outliers, respectively.

Table C.5: Reported Probability of Disaster and Experience

	(1)	(2)	(3)	(4)	(5)
Fire experience	-1.672		-2.480		-1.941
	(-1.14)		(-1.67)		(-1.18)
Flood experience	1.795*		1.723		1.187
	(2.02)		(1.92)		(1.32)
Wind experience	3.078**		3.060**		1.404
	(3.27)		(3.22)		(1.36)
Hurricane Events in State		225.0	169.5		
		(0.95)	(0.70)		
Flood Events in State		-10.36	-30.49		
		(-0.06)	(-0.19)		
Fire Events in State		6947.0*	8011.8*		
		(2.25)	(2.47)		
High wildfire risk				1.121	1.344
				(1.02)	(1.19)
High landslide risk				2.061*	1.896
				(2.02)	(1.84)
High earthquake risk				-0.654	0.384
				(-0.32)	(0.18)
High hurricane risk				4.737***	3.923***
				(4.20)	(3.31)
High flood risk				0.0503	-0.00201
				(0.07)	(-0.00)
Constant	16.90***	18.12***	17.20***	12.95***	12.74***
	(6.68)	(7.22)	(6.76)	(4.85)	(4.73)
State FE	yes	no	no	yes	yes
Demographic Controls	yes	yes	yes	yes	yes
N	7127	7084	7082	7156	7155
r2	0.0645	0.0643	0.0676	0.0702	0.0711

Notes: regression relates reported probability of disaster to personal experience; only respondents who did not receive any treatment used in regression; regressions control for state, month, demographics, media usage and political affiliation. t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights and Huber-robust weights to ensure that sample is representative and independent of outliers, respectively.

Table C.6: Treatment Regressions High Numerical Ability

	(1)	(2)	(3)	(4)
Newspaper (T1)	1.009	0.309	1.131	0.798
	(1.26)	(0.22)	(1.63)	(0.65)
Historic Disaster Size (T2)	-1.652*	-3.622**	-1.169	-2.723*
	(-2.03)	(-2.81)	(-1.63)	(-2.41)
Lagarde Treatment (T3)	0.650	-0.943	0.348	-0.942
	(0.78)	(-0.68)	(0.49)	(-0.77)
GDP Loss info (T6)	-1.754		-1.241	
	(-1.27)		(-1.06)	
Climate Change Scale		0.954***		0.699***
		(6.40)		(5.39)
Constant	15.31***	12.37**	14.69***	11.95***
	(6.14)	(3.18)	(6.45)	(3.43)
State Fixed Effect	yes	yes	yes	yes
Demographic Controls	yes	yes	yes	yes
Drop largest 25% probabilities	no	no	yes	yes
N	3478	1366	3253	1246
r2	0.142	0.190	0.141	0.211

Notes: t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;This table presents regression results on the impact of several treatments on the expected disaster probability. Only data from respondents who were able to answer Q6 correctly by a margin of 2 percentage points was used. We use weighted regressions with robust standard errors. Weights used are the product of survey weights and calculated Huber robust weights.

Table C.7: Treatment Regressions Damage Cost and Growth Impact

	(1) Disaster Costs	(2) Disaster Costs	(3) Growth	(4) Growth
Newspaper (T1)	0.00961	-0.0631	-0.0308	-0.0662
	(0.37)	(-1.21)	(-0.80)	(-0.87)
Historic Disaster Size (T2)	-0.0731**	-0.144**	-0.0506	-0.0284
	(-2.75)	(-2.71)	(-1.32)	(-0.37)
Lagarde Treatment (T3)	-0.0595*	-0.0756	-0.0930*	-0.123
	(-2.27)	(-1.45)	(-2.39)	(-1.59)
GDP Loss info (T6)	0.0299		-0.00408	
	(0.74)		(-0.07)	
Climate Change Scale		0.0676***		0.0515***
		(11.08)		(5.14)
Constant	1.398***	1.141***	0.0738	-0.646**
	(14.75)	(4.98)	(0.56)	(-2.63)
State Fixed Effect	yes	yes	yes	yes
Demographic Controls	yes	yes	yes	yes
N	19279	3491	20397	3505
r2	0.0524	0.132	0.0152	0.0617

Notes: t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;This table presents regression results on the impact of several treatments on the expected disaster costs and the growth impact of climate change. We use weighted regressions with robust standard errors. Weights used are the product of survey weights and calculated Huber robust weights.

Table C.8: Behavioral Adjustments

	Probit regression		Descriptive Statistics			
	Marginal effect	p-value	Yes	Sometimes	No	N
Investment						
Have you divested your investment decisions due to the fear of climate change related risk?	0.161***	0.000	27%	-	73%	14.433
Have you refrained from certain investments you consider harmful to the climate?	0.220***	0.000	33%	-	67%	14.433
Mobility						
Have you changed your decisions on personal mobility due to concerns about climate change?	0.247***	0.000	31%	-	69%	14.433
Has climate change altered your decision on owning a car?	0.212***	0.000	27%	-	73%	14.433
Do you refrain from flight travel due to concerns about climate change?	0.253***	0.000	18%	23%	59%	14.433
Other						
Do you think your personal life has already been affected by climate change?	0.303***	0.000	42%	-	58%	14.433
Do you think your personal life has already been affected by natural disasters?	0.483***	0.000	39%	-	61%	14.433
Did you stop eating meat due or reduce meat in your diet because of concerns about climate change?	0.682***	0.000	17%	26%	57%	14.433
Do you try to avoid products made from plastic?	0.628***	0.000	25%	37%	38%	14.433

Notes: marginal effect of probit regression relates to the marginal effect of the subjective disaster probability; both disaster probability and probability for answers in percentage points. only untreated respondents used in regressions; t statistics in parentheses, based on robust standard errors;* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights to ensure that sample is representative. If respondents were able to choose a "Sometimes", an ordered probit model was estimated. Each regression controls for demographics and state as well as month fixed effects. Questions on behavioral decisions asked before any treatments. Descriptive statistics on the right are computed on all answers, probit model only estimated on those respondents that did not receive a treatment before stating their disaster probability. $N = 4.093$ for probit regressions.

Table C.9: Risk Factors and Sources of Information

A) Risk Factors

"When you assessed the overall disaster probability, to what extent did you place weight on the following risk factors? (0 to 100 Scale)"

	raw weights			**normalized weights**		
	mean	median	std dev	mean	median	std dev
Hurricanes	51.38	53	29.98	14.99	14.62	4.37
Severe wind events	49.92	50	28.54	14.81	14.50	3.82
Floods	50.87	52	29.05	15.20	14.72	4.06
Wildfires	52.00	53	30.22	15.23	14.68	4.66
Meteorite impacts	34.60	26	31.81	9.56	11.69	6.30
Extreme snowfall	43.53	43	30.89	12.67	13.95	4.85
Earthquakes	45.50	47	30.89	13.34	14.15	4.43

B) Regional Expectations

"When you thought about these risk factors, did you relate to disaster risks in your own region or in other parts of the US? (-10 only own region, 10 only other parts of US)"

	raw weights		
	mean	median	std dev
Hurricanes	0.22	0.20	6.56
Severe wind events	-0.05	0.00	5.60
Floods	0.26	0.40	5.83
Wildfires	0.56	0.60	6.39
Meteorite impacts	-1.42	-0.20	6.50
Extreme snowfall	-0.27	0.00	6.21
Earthquakes	-0.11	0.20	6.40

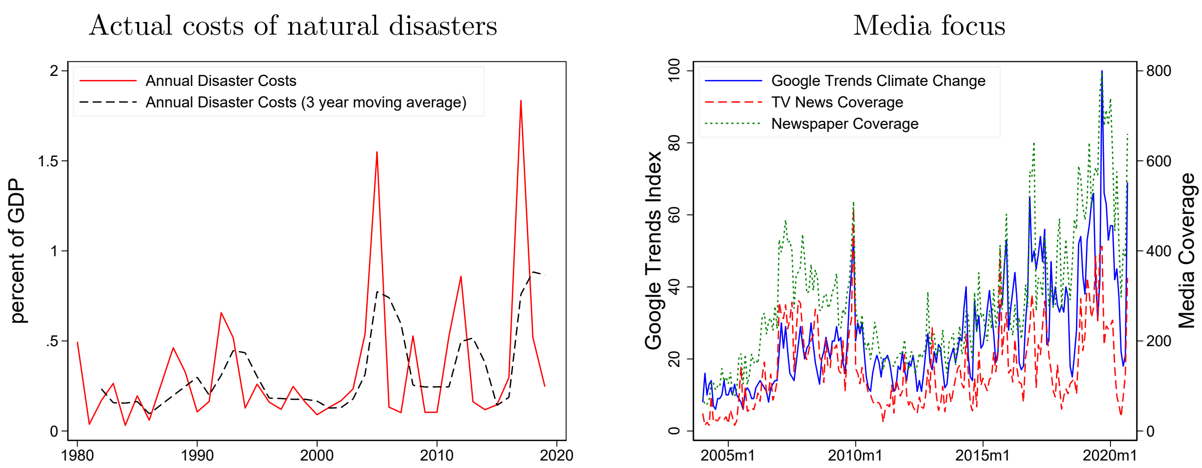
C) Source of Information

"When you assessed the overall disaster probability, to what extent did you place weight on the following sources of information? (0 to 100 Scale)"

	raw weights			**normalized weights**		
	mean	median	std dev	mean	median	std dev
Experiences w. disasters in the past	46.43	49	31.13	9.87	10.46	4.46
Articles I read in newspapers	44.83	47	30.03	10.11	10.55	4.14
Programs on TV/ the news	50.33	51	30.11	11.26	11.12	4.05
Statements by elected officials	40.49	41	30.67	8.96	10.00	4.12
Statements by experts in the media	46.93	49	30.41	10.61	10.90	4.01
Information by friends or family	42.49	43	31.25	9.28	10.24	4.36
Own projections based on past	50.27	51	29.80	10.77	11.01	3.79
Information from statistical agencies or the government	46.45	49	30.28	10.48	10.87	3.85
Activist campaigns	40.37	40	32.34	8.74	10.17	4.66
Others	9.65	0	24.42	1.75	0.00	4.51

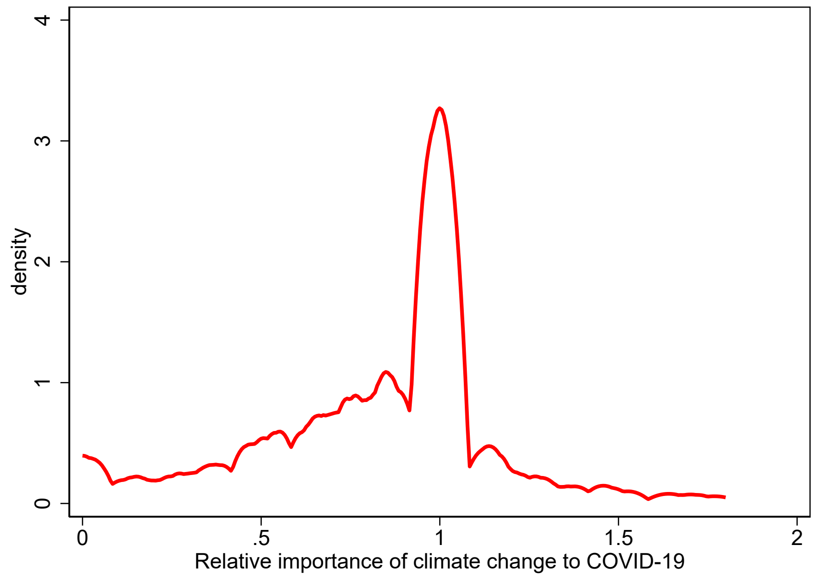
Notes: Weights displayed are weighted with demographic and Huber robust weights. Normalization done within each respondent.

Figure C.1: Climate Change Makes Itself Felt



Notes: left panel shows annual damages due to natural disasters in the U.S. between 1980 and 2019 in percent of GDP (red solid line), black line is a three year moving average, Source: NCEI (2020). In the right panel, the blue solid line shows monthly averages of Google search queries for "climate change", source: Google Trends; the red dashed (green dotted) line shows media coverage of climate change by seven major news stations (five major newspapers), Source: Boykoff et al. (2020).

Figure C.2: Relative Importance Climate Change to COVID-19



Notes: Figures shows the relative importance assigned to climate change relative to the COVID-19 pandemic by respondents. Respondents were asked to rate on a scale from 0 to 10 how severe Climate Change or COVID-19 is a problem to the US.