The Expectations Channel of Climate Change: Implications for Monetary Policy

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Abstract

Using a representative consumer survey in the U.S., we elicit beliefs about the economic impact of climate change. Respondents perceive a high probability of costly, rare disasters in the near future due to climate change, but not much of an impact on GDP growth. Salience of rare disasters through media coverage increases the disaster probability by up to 7 percentage points. We analyze these findings through the lens of a New Keynesian model with rare disasters. First, we illustrate how expectations of rare disasters impact economic activity. Second, we calibrate the model to capture the key aspects of the survey and quantify the expectation channel of climate change: disaster expectations lower the natural rate of interest by about 65 basis points and, assuming a conventional Taylor rule for monetary policy, inflation and the output gap by 0.3 and 0.2 percentage points, respectively. The effect is considerably stronger if monetary policy is constrained by the effective lower bound.

Keywords: Climate change, Disasters, Households Expectations, Survey, Media focus, Monetary policy, Natural rate of interest, Paradox of Communication
JEL-Codes: E43, E52, E58

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"I want to explore every avenue available in order to combat climate change."
— Christine Lagarde - ECB, *July 8, 2020*

"[...] 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."
— Lael Brainard - FED, *November 8, 2019*

1 Introduction

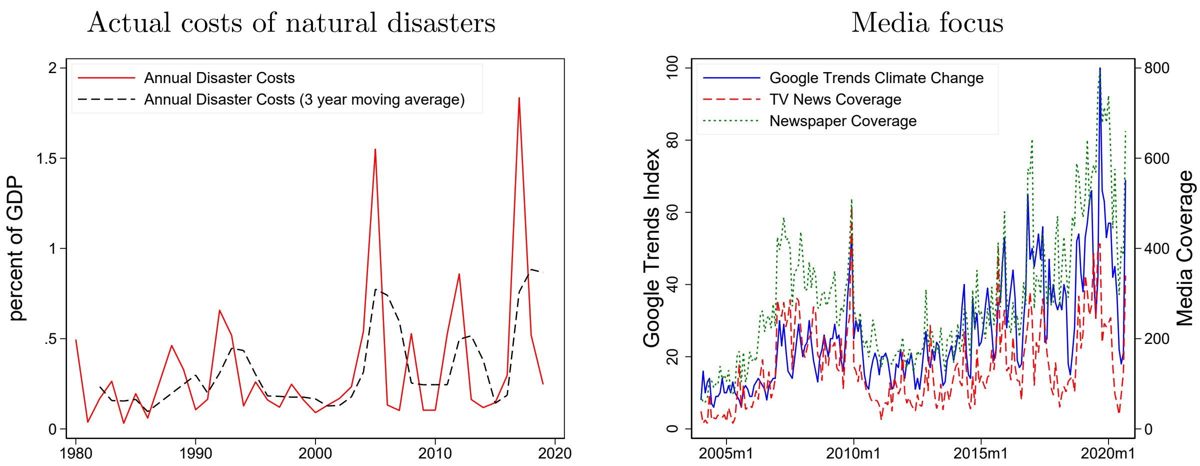
Climate change is a hotly debated topic and as such it presents a rising, complex challenge for policymakers. Even central bankers have recently begun to weigh in on this debate—as the quotes above illustrate. While some consider an active role in climate policy to be part of central banks' mandates, others argue that by assuming such a role, central banks run the risk of undermining their independence and their ability to maintain price stability (Weidmann, 2020). What seems less controversial is that central banks should make every effort to understand "the nature of climate disturbances to the economy." This, however, 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.

Against this background we offer a fresh perspective: irrespective of how climate change actually plays out, what matters for monetary policy is how people *expect* it to play out. After all, expectations feed back into economically relevant decisions today. Expectations about climate change, in turn, are bound to be influenced by the debate about climate change that has recently gained traction. Figure 1 illustrates the point. The left panel shows how the costs of natural disasters have evolved since the early 1980s. Measured as a fraction of GDP these costs have been very volatile, but they appear to be on a rising trajectory. These data are only suggestive and the debate to what extent natural disasters are caused by climate change has certainly not been settled yet (e.g., Coronese et al., 2019). But ultimately this does not matter, because as the right panel of Figure 1 shows, climate change is on peoples' minds and increasingly so over time: the panel displays an index for for TV and newspaper coverage of the topic as well as the Google Trends indicator for "climate change" search queries—all three showing consistently a considerable increase over time.

In the first part of the paper, we attempt to measure *expectations* of the near-term economic consequences of climate change. To this purpose, we rely on a large, representative consumer survey in the U.S. In the survey we elicit beliefs about climate change and more specifically its likely economic impact. Among other things, we ask respondents whether, going forward, they expect climate change to impact output growth, either adversely, say, because of increased regulation or positively, say, because of technological innovation. We find that on average the expected impact on growth is negligible.[1] We also ask respondents to assign

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

Figure 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).

a probability to natural disasters that cause significant economic damage in the near future. Here we find a high probability—in fact, it is much higher than what would seem justified given the historical record: the median response for the probability of climate-change related disaster causing a GDP loss of 5 percent within the next 12 months is 12 percent. The median response for the group of respondents with high numerical abilities turns out to be just as high, indicating that the ability to understand probabilities is not driving the results.

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": in the relatively short sample under consideration, adverse events have simply materialized less often than what the objective probability would imply. Alternatively, natural disasters due to climate change may be much more frequent in the future because we may have reached so-called "tipping points." Yet another possibility is that we are picking up a salient "Greta effect": people overestimate the risk of natural disasters because of a media focus on climate change, consistent with research that has documented that media focus can be an independent source of business cycle fluctuations (Chahrour et al., 2020).

In support of this last possibility we find in the survey that respondents that are not exposed to media at all report a significantly lower estimate for the probability of natural disasters. Moreover, we formally complement our survey analysis with several information treatments: a "Newspaper treatment," that shows respondents sections of a USA Today newspaper article on the 2020 wildfire and hurricane season; a "Lagarde treatment," which is a recent statement by ECB President Lagarde on the importance of climate change for the ECB's monetary policy; and two treatments that provide respondents with information about the frequency and extent of large disasters in the past. We find that in response to the newspaper treatment, respondents show a statistically significant, up to 3.4 percentage point higher expected disaster probability. When we remove extreme outliers, the Lagarde treatment also becomes significant. Relaying the intention of the ECB to tackle climate change raises the perceived probability of a large natural disaster by nearly 3 percentage points. Accurate information about past disasters lowers the expected probability of future disasters, but not significantly so. The reduction becomes more pronounced for a subset of individuals with high numerical ability.

In the second part of the paper, we illustrate how climate change expectations impact current economic activity and why this matters for monetary policy. We do so in a conventional New Keynesian model which allows for rare disasters (Fernández-Villaverde and Levintal, 2018). A special case of the model boils down to the textbook version of the New Keynesian model (Galí, 2015). For this version of the model, we are able to derive a number of results in closed form. In particular, we show that expectations of a rare disaster, both via the intensive and the extensive margin, lower the natural rate of interest today, and this—to the extent that it is unmatched by monetary policy—causes a contraction in economic activity and inflation. Intuitively, the expectations of a future disaster are "bad news" and induce an immediate contraction of aggregate demand because the desire to save increases (Barsky and Sims, 2012; Blanchard et al., 2013; Schmitt-Grohé and Uribe, 2012).

The change in the natural rate of interest provides a comprehensive measure for the demand contraction for a counterfactual scenario in which prices are flexible and serves as an important benchmark for monetary policy (Woodford, 2003). While the natural rate cannot be observed directly, several attempts have been made to estimate it following the seminal work of Laubach and Williams (2003). Recently, it has become clear that the natural rate is on a declining trajectory (e.g., Bauer and Rudebusch, 2020b; Holston et al., 2017; Jorda and Taylor, 2019) and a number of important factors that may account for this decline have been identified. The list of suspects includes the slowdown of productivity growth, demographic trends and an increase in the convenience yield (e.g., Del Negro et al., 2019).

To assess the quantitative effect of climate-change related disaster expectations on the natural rate, we calibrate the full model to the key figures from our survey and solve the model non-linearly using Taylor projections following Fernández-Villaverde and Levintal (2018). We find an effect that is not trivial: In our baseline calibration, we find that climate change related disaster expectations reduce the natural rate by about 65 basis points. This has important implications for monetary policy: it may insulate the economy from the adverse impact of climate-change related disaster expectations by lowering the policy rate in sync with the natural rate. But tracking the natural rate is notoriously hard. Assuming a conventional Taylor rule, we find that inflation declines by 0.29 percentage points and the output gap by 0.20 percentage points in response to climate change related disaster expectations. The contraction is even more severe if policymakers fail to accommodate the drop in the natural rate. This is a likely scenario to the extent that policy rates are low to begin with and policymakers are constrained by the effective lower bound (ELB) on policy rates.

To the extent that the ELB is a hard constraint, there is little central bankers can do using conventional monetary policy tools to contain the adverse effect of climate change expectations, an effect which operates via the natural rate of interest. A recent literature has emphasized the importance of central bank communication as a tool in such an environment. In this context our analysis points towards a "paradox of communication": to the extent that central bankers engage in the debate about climate change they may themselves contribute to the media focus on climate change which, in turn, may foster adverse expectations about future climate-change related disasters. In this way, by trying to tackle a major global challenge upfront, they actually make their current tasks harder today—because interest rates are low and further reductions in the natural rate may be hard to accommodate.

Hence, our analysis provides a new angle on the debate of whether and how monetary policy should respond to climate change. A central distinction in this regard is 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. The same holds for the growth impact of climate change which is the focus of the present paper. Instead, whether monetary policy should use its instruments actively to impact climate change, say, by twisting asset purchases towards "green assets" raises interesting questions regarding the (secondary) objectives and legitimacy of today's central banks (Honohan, 2019). To date there is no consensus on the quantitative relevance of this policy channel 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). This includes the analysis of how optimal policy can impact climate change via taxes on fossil fuels as well as the impact of the uncertainty about it (Golosov et al., 2014).[2] 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). Several studies also take an asset pricing perspective to analyze climate-change related issues (Bansal et al., 2019; Bauer and Rudebusch, 2020a; 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. Lastly, we stress that there is evidence that information about natural disasters triggers behavioral adjustments: Hu (2020) documents that households purchase more insurances in response to information about flood risk information.

The remainder of this paper is organized as follows. We introduce our survey in the next section; we present key features of the survey as well as the most important results. Section 3 outlines our model framework in general terms. We consider a simplified version of the model in Section 4 and present analytical results. 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. A final section offers some conclusions.

[2]See Hassler and Krusell (2018) for a recent review of the "macroeconomics and climate" literature.

2 The Survey

In what follows we first provide some basic information regarding the nature of the survey. We subsequently present the main survey results.

2.1 Survey Design

Our data come from a larger, 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. The appendix contains a detailed list of questions.

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 at least one response, or who complete the survey in less (more) than five (30) minutes. Our analysis uses a raking scheme to compute respondent weights ensuring that our sample is representative of the U.S. population by gender, age, income, education, ethnicity, and Census region.

Table 1: Survey Respondent Characteristics

	pct.	(Target)		pct.	(Target)
Age			**Race**		
18-34	33.61%	(33.3%)	non-Hispanic white	70.55%	(66%)
35-55	33.61%	(33.3%)	non-Hispanic black	12.03%	(12%)
older than 55	32.78%	(33.3%)	Hispanic	7.69%	(12%)
			Asian or other	9.73%	(12%)
Gender					
female	49.38%	(50%)	**Household Income**		
male	50.21%	(50%)	less than 50k$	46.23%	(30%)
other	0.41%	(-%)	50k$ - 100k$	29.08%	(35%)
			more than 100k$	24.69%	(30%)
Region					
Midwest	19.48%	(20%)	**Education**		
Northeast	20.03%	(20%)	some college or less	48.83%	(50%)
South	40.74%	(40%)	bachelors degree or more	51.17%	(50%)
West	19.75%	(20%)			
					N=14.162

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

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, these characteristics vary systematically with climate-change expectations.

We provide a list of all questions in Appendix B. In what follows we focus on the three main questions. Recall that our focus is on the impact of climate change expectations regarding the near term. In our first question we thus ask respondents how they expect climate change to impact economic growth over the next 12 months. Specifically, we ask:

"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)"*

The second question on climate change elicits respondents' beliefs about the economic damage due to natural disasters also over the next 12 months, as follows:

"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 on an order of 5% of GDP."*

Our third question asks respondents about their perceptions of natural disaster risks. Specifically, we ask them about a large disaster causing damage of about 5 percent of GDP. The disaster risk question is as follows:

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."

A fraction of respondents receives an information treatment before being asked Question 1 to 3, which is meant to gauge the extent to which official estimates, statements or public newspaper information related to climate change and natural disasters can affect responses. The info treatment comes in several variants, summarized in Table 2.

Table 2: 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)."

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

2.2 Survey Results

In what follows we present the results of the survey. We map the results of the survey into a model framework in Section 5 in order to quantify the effect of climate change expectations on macroeconomic activity in general and, in particular, on the natural rate of interest. However, the results of the survey are of interest outside the scope of a specific structural model. Thus, as a first 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 6.48 and COVID-19 7.72 out of 10 (see also Figure C.1 in the appendix). This perception is in line with a recent survey by the United Nations Development Program which documents that "the climate emergency" is globally recognized among respondents with a university degree, including in low-income countries.[3]

Because a correct understanding of probabilities is key to answering our main questions, we first present an brief assessment of respondents' numerical ability. For 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. We find that, when given the information that 14 out of 70 draws from the urn yielded black balls, 44 percent of respondents report expected probabilities of drawing a black ball next time within the range of 10-30 percent.

[3] 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).

We take this evidence as suggestive that respondents understand basic probabilities. For what follows, we also define a group of respondents with particularly high numerical ability, namely those 16.9 percent of respondents who state a probability in the range of 18-22 percent, that is, we allow for an error margin of 10 percent. As a way to verify that our results are not driven by lack of numerical abilities, we also report distinct results for this group of respondents.

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 by 0.16 percentage points over the next 12 months. However, there is a lot of mass in the distribution on both positive and negative ends. We show this distribution in the top-left panel of Figure 2. The blue bars represent the answers of all respondents, while the red bars represent those of respondents with high numerical ability. For example, nearly 20% of all respondents expect a boost to growth by more than 2 percentage points over the next 12 months while nearly 15% expect a growth decline by more than 2 percentage points. For respondents with high numerical ability there is considerably less mass in the tails. The standard deviation across all respondents is 1.24 percentage points. The first line in Table 3 provides summary statistics for Question 1, both for all respondents (top panel), and respondents with high numerical abilities (bottom panel).

Table 3: Survey Summary Statistics

All Respondents	Mean	Median	Std. Dev.	N
Growth Impact (Question 1)	0.16 pp	0.00 pp	1.24 pp	4344
Disaster Costs (Question 2)	1.51 %	1.50 %	0.81 %	3228
Disaster Probability (Question 3)	23.08 %	12.00 %	23.76 %	3223

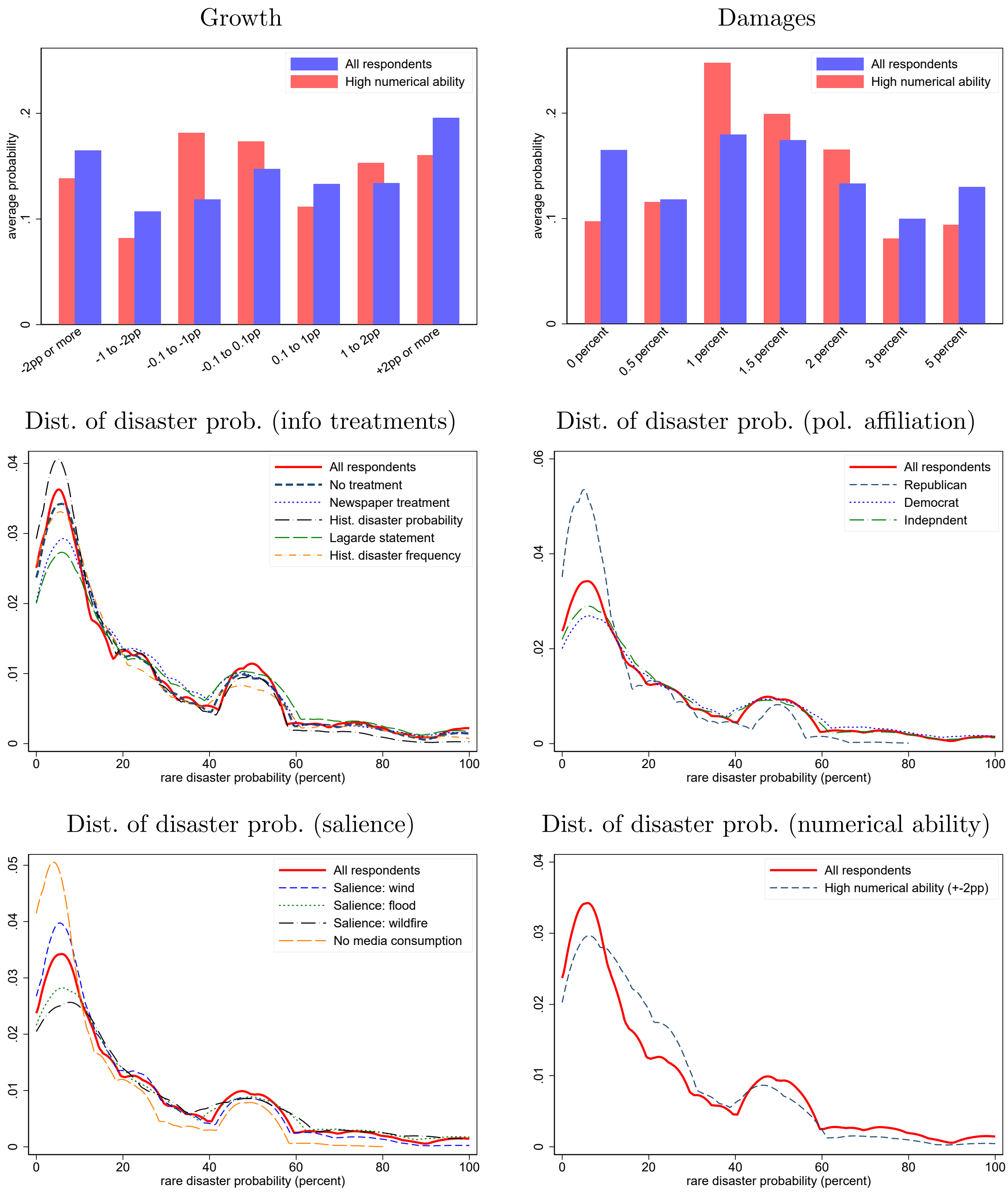
High Numerical Ability Respondents	Mean	Median	Std. Dev.	N
Growth Impact (Question 1)	0.11 pp	0.00 pp	1.18 pp	157
Disaster Costs (Question 2)	1.51 %	1.50 %	0.69 %	151
Disaster Probability (Question 3)	20.38 %	15.00 %	19.13 %	363

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

Second, respondents expect substantial economic damages, amounting to 1.51% of GDP on average over the next 12 months. The top right panel in Figure 2 shows the responses, again for the full sample (in blue) and respondents with high numerical ability (red). Again, expectations are widely dispersed over loss scenarios in both instances but, as before, there is less mass in the tails for respondents with high numerical ability. Approximately 15% of all respondents expect no loss, while this fraction among those with high numerical ability is lower, at slightly below 10%. Overall, the standard deviation of expected losses is at 0.81% as Table 3 summarizes.

Third, when we ask respondents about the probability of a climate-change related disaster with damages of 5% of GDP within the next 12 months, we again obtain a wide distribution of responses. The mean probability of such a rare disaster is at 23.08% while the median is at 12%. In fact, as the high median probability suggests, there is a substantial mass of respondents

Figure 2: 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 (middle-left panel), political affiliation (middle-right), exposure to actual disasters (lower-left), numerical ability (lower-right).

that assign large probabilities to such an event. For example, almost 15% of respondents believe that such a rare disaster can occur with more than 60% probability. The overall message, however, is the same as when we elicit the probability over various bins as in the top-right panel: respondents assign a 16.46% probability in the top-right panel to a disaster bin that corresponds to damages amounting to 5% of GDP, and a mean probability of 23.08% in direct response to a question about such damages. The probability of a large natural disaster is extremely large and statistically indeed indistinguishable. The middle and lower panels of Figure 2 show a kernel estimate of the probability distribution. We display the distribution of responses across all respondents (red line) along with the distribution for various subgroups.

In the middle-left panel we show the effect of alternative information treatments. As a result of these treatments, a lot of mass shifts to the right of the distribution. Hence, our information treatments tend to raise the expected probability of a disaster, an issue which we investigate in more detail in Section 2.3 below. In the middle-right panel we display the distribution of responses while conditioning on the political affiliation of respondents. We observe that, compared to the overall population, more Republicans assign smaller probabilities to large climate-change related disasters; the opposite holds for Democrats and Independent voters.

The lower-left panel, in turn, conditions on the possible exposure of respondents to actual, salient disasters. To measure such an exposure, we rely on official data for natural disaster declarations at the county level for the last 10 years provided by the Federal Emergency Management Agency (FEMA, Federal Emergency Management Agency, 2020). Within our sample 16.8% of respondents live in a county with a wildfire-related disaster over the last 10 years, 42.99% with a hurricane, tornado, or typhoon event and 40.64% with a flood in the past. From the same data source, we also construct data for the total number of events (fire, flood and hurricane, etc.) within a state in the given time span. An inspection of the lower-left panel shows that these experiences matter for peoples' disaster expectations, a finding that is familiar from other contexts (e.g., inflation expectations, see Malmendier and Nagel, 2011). It also suggests that we are indeed able to elicit respondents disaster expectations in a meaningful way.

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.[4] 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". Table C.2 in the appendix reports the results. 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 6.5 percentage points, depending on the disaster type. Second, concerning future risks, in particular the increased possibility of wildfires drives up expectations of a future large disaster by up to 8pp. 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, arguably most salient experience that drives the results.

In the the lower-right panel of Figure 2 we contrast the distribution of answers across

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

all respondents and the distribution of respondents with high numerical ability. We find the distributions are similar, although—perhaps surprisingly—a larger fraction of respondents with high numerical ability expects large disasters with even higher probability: there is considerably more mass for probabilities between 15 to 30 percent. As Table 3 shows, the median response is also higher in this case than for the full sample. It amounts to 15%, rather than 12%. At the same time, high numerical ability is associated with less mass in the extreme right tail.

Finally, we relate respondents' climate-change expectations to their demographic and socioeconomic characteristics through simple regression analysis while controlling for state fixed effects. Table C.1 in the appendix reports the results. In the case of the expected growth impact of climate change, we note that those aged 55 and above expect climate change to boost growth, while middle and high income is associated with an expected adverse impact of climate change on growth, though not significantly. Regarding expected damages, we obtain a negative effect of middle income respondents. Women, instead, 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.

Regarding disaster probabilities, three results emerge: first, we observe by far the largest effect for those who identify as ethnically white. Respondents in this category believe that a very large rare disaster is 4% more likely. Women also 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% 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). Republicans, all else equal, instead believe that a very large rare disaster is less likely, by 3.5%, compared to independent voters as illustrated in the bottom-right panel of Figure 2.[5]

2.3 Media Usage, Information and Expected Disaster Probability

In what follows, we provide further evidence regarding the formation of climate-change related disaster expectations that may be of particular interest to policymakers. Here, we establish a significant further role of salient information on expected disaster probabilities, consistent the notion that risk perception and expectation formation are governed by salience effects (Bordalo et al., 2016, 2012; Coibion et al., 2021). To be more specific, we find there is an important role of media consumption—TV and newspapers—for the perception of disaster risks. Indeed, information treatments can affect perceived disaster probabilities, implying a more causal relationship. To establish these points, we relate the reported probability of a disaster to either measures of respondents' preferred TV stations and newspapers, or information treatments while continuing to control for the same demographic and socio-economic variables as before.

Our main results can be summarized as follows: Respondents who consume news from neither a major TV Station nor a major newspaper exhibit approximately 6.9 percentage points lower rare disaster expectations. This effect corresponds to a reduction of the perceived mean disaster probability by 25%. Respondents who watch multiple news stations instead have more

[5] 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.

Table 4: Reported Probability of Disaster and Media Usage

	(1)	(2)	(3)
no major TV station	-5.185***		
	(-4.43)		
no major Newspaper		-3.348***	
		(-3.69)	
consume major TV station×no major newspaper			-1.476
			(-1.42)
no major TV station×consume major newspaper			0.673
			(0.23)
no major TV station×no major newspaper			-6.880***
			(-5.31)
Constant	14.03***	14.33***	14.68***
	(3.89)	(3.92)	(4.01)
State FE	yes	yes	yes
Demographic Controls	yes	yes	yes
N	3223	3223	3223
r2	0.0695	0.0684	0.0718

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.

than 7 percentage point higher disaster expectations. There is some evidence for individual TV Station/Newspaper impacts on the disaster probability of respondents, even though impacts as well as systematic differences between different stations are not readily obvious. For example, readers of the Washington Post or the Wall Street Journal have a negative association with disaster risks, but readers of USA Today exhibit a positive association. TV channels all tend to raise probabilities. Overall, the evidence strongly suggests that salience of disasters communicated (or not) in the news has strong effects on perceptions. Table 4 reports our main results, while Table C.3 in the appendix provides additional results for individual news stations. Tables C.4 and C.5 in the appendix present results for the questions on expected damages and the growth impact of climate change. Respondents who do not watch TV and do not read newspapers expect marginally lower disaster costs and a up to somewhat higher GDP growth.

Next, to give a more causal interpretation to these results, we study the effect of our information treatments related to media, public statements or factual information on natural disasters on the perceived disaster probability (see Table 2 above). The “Newspaper treatment” shows 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 tells 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.

Table 5: Reported Probability of Disaster and Information Treatment

	(1)	(2)	(3)	(4)
Newspaper (T1)	1.612*	0.943	1.837***	1.497**
	(2.36)	(1.20)	(3.75)	(2.75)
Historic Disaster Size (T2)	-1.624*	-1.808*	-0.728	-0.984
	(-2.43)	(-2.32)	(-1.57)	(-1.89)
Lagarde treatment (T3)	2.855***	2.557**	1.620**	1.383*
	(3.92)	(3.09)	(3.13)	(2.44)
Historic Disaster Freq (T4)	0.240		-1.123	
	(0.27)		(-1.95)	
Climate Change Scale		2.046***		1.026***
		(22.61)		(16.83)
Constant	14.62***	8.161***	12.46***	9.558***
	(7.77)	(3.80)	(8.64)	(6.00)
State Fixed Effect	yes	yes	yes	yes
Demographic Controls	yes	yes	yes	yes
Drop largest 25% probabilities	no	no	yes	yes
N	10603	8436	8678	6935
r2	0.0387	0.0992	0.0424	0.0862

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 2 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.

We find that in response to the newspaper treatment, respondents show a statistically significant, up to a 1.8 percentage points higher expected probability. Relaying the intention of the ECB to tackle climate change raises the probability of disaster risk by almost 2 to 3 percentage points. The newspaper treatment remains significant. The historic information treatments lower expected probabilities as expected, but only on a lower significance level. Table 5 presents the main results. 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.

Table C.6 in the appendix shows results for regressions on a subsample for respondents with high numerical abilities, that is, for those respondents for with a small error in answering Question 6 (probability of drawing a black ball). In this case 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 almost up to 3 percentage points. These findings suggest that respondents with high numerical abilities react less to suggestive information in assessing disaster probabilities. Table C.7 gives treatment effects on the growth impact and expected damage questions.

3 A New Keynesian Model with Rare Disasters

In order to study the economic implications of climate-change expectations we rely on a conventional New Keynesian model. According to our survey, respondents do not expect much of an effect of climate change on growth. Yet they assign a high probability of large disasters due to climate change. 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). In this model and in contrast to earlier models of rare disasters such as Gourio (2012), monetary policy plays a key role for how the economy adjusts to disaster expectations.

We establish this point formally through a number of closed form results for 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

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

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 with a probability of p and zero otherwise, with probability $1-p$. In the event of a disaster a possibly time-varying fraction μ_t of the capital stock is destroyed. Specifically, we assume that the extent of the disaster is fluctuating around mean $\bar{\mu}$ according to the following AR(1) process:

$$\mu_t = \bar{\mu}^{(1-\rho_\mu)} \mu_{t-1}^{\rho_\mu} e^{\sigma_\mu \epsilon_{\mu,t}}, \tag{3.3}$$

where $\epsilon_{\mu,t}$ are Gaussian innovations with zero mean.

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:

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

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 adjust prices infrequently. Instead, they adjust production in order to satisfy the demand for their goods given by the demand function (3.6). A generic firm i operates the following production function:

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

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

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

where Λ_A is trend growth of productivity and the term $d_t(1-\alpha)\log(1-\mu_t)$ captures the effect of a disaster on productivity.

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

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

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 price level evolves as follows:

$$P_t = \left[\theta(P_{t-1})^{1-\epsilon} + (1-\theta)(P_t^*)^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}. \tag{3.10}$$

3.3 Market Clearing and Monetary Policy

In our exposition above, we have already imposed market clearing 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 five 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. Third, we assume that there is no productivity growth in steady state ($\Lambda_A = 0$) and that the disaster size is constant by assuming $\sigma_\mu = 0$. Last, we assume that capital is not subject to a disaster shock. The law of motion for the capital stock is thus:

$$K_t = K_{t-1} + \left[1 - S\left(\frac{X_t}{X_{t-1}}\right)\right] X_t.$$

Under these assumptions, a log-linear approximation of the equilibrium conditions around a deterministic steady state yields the so-called canonical representation.[6] Specifically, using

[6]We state the first order conditions for the simplified model in Appendix A.1.

small-scale letters to denote logs, we obtain the following relationships:

$$\pi_t = \beta E_t \pi_{t+1} + \kappa \tilde{y}_t, \tag{4.3}$$
$$\tilde{y}_t = E_t \tilde{y}_{t+1} - \frac{1}{\sigma}(i_t - E_t \pi_{t+1} - r_t^n). \tag{4.4}$$

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.[7] 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:*

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

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 $\bar{\mu}$. 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:

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

[7]What makes the simplified model particularly tractable is that it features no endogenous state variables (up to first order). We use the method of undetermined coefficients to solve for the endogenous variables as linear functions of the exogenous states.

Here the parameter $\phi_r \in \{0, 1\}$ captures the response of the policy rate to the natural rate. We only consider 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 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.[8] Under these assumptions we obtain the following solution for inflation and the output gap for alternative scenarios for 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:*

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

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. and A.4.* ■

Proposition 2 shows that monetary policy can fully stabilize inflation and the output gap ($\pi_t = \tilde{y}_t = 0$) 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 responds no longer 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 accommodating the drag on demand. 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.

[8]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.

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).

5 Quantitative Model Analysis

We now turn to a quantitative model analysis in order to assess the impact of climate change expectations on the economy and, in particular, on the natural rate of interest. 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 discuss the results.

5.1 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:

$$U_t = C_t(1 - N_t)^{\nu}. \tag{5.1}$$

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 in (3.4) are given by

$$S\left(\frac{X_t}{X_{t-1}}\right) = \frac{\kappa_k}{2}\left(\frac{X_t}{X_{t-1}}\right)^2, \tag{5.2}$$

where κ_k is a positive parameter. Last, we specify an interest rate rule (in levels) that does not allow for a response of interest rates to the natural rate ($\phi_r = 0$), but allows for a response to the output growth (with response coefficient ϕ_y).

$$1 + i_t = (1 + i)\left(\Pi_t\right)^{\phi_\pi}\left(\frac{\frac{Y_t}{Y_{t-1}}}{e^{\Lambda_Y}}\right)^{\phi_y} e^{\sigma_m \epsilon_{m,t}} \tag{5.3}$$

Here, i is the nominal interest rate in steady state. The parameter Λ_Y is the trend growth of output (in turn, a function of the trend growth of productivity Λ_A). We also allow for a Gaussian monetary policy shock $\epsilon_{m,t}$ with standard deviation σ_m.

The impact of disaster expectations depends on both, the probability of a disaster and on its severity, captured by parameters p and $\bar{\mu}$, respectively. For the baseline, we set these parameters in line with our survey results, discussed in Section 2.2 above. Specifically, we set $p = 0.12$ and $\bar{\mu} = 0.05$. For the other parameters we stick to the choice of Fernández-Villaverde and Levintal (2018), but adjust parameters in such a way that a period in the model represents a year (rather than a quarter) in line with the time horizon for which we solicit disaster

Table 6: Model calibration

Parameters calibrated in line with Survey results (Section 2.2)		
$\bar{\mu}$	Mean disaster size	0.05
p	Disaster probability	0.12
Other parameters		
ρ_μ	Persistence of disaster risk shock	0.9
β	Discount factor	0.98
σ	Intertemporal elasticity of substitution	2
ν	Leisure preference	2.33
γ	Risk aversion	3.8
α	Capital share in production	0.21
δ	Depreciation	0.025
ϵ	Elasticity of substitution	10
Λ_A	Trend growth of technology	1.12%
κ_k	Capital adjustment costs parameter	9.5
θ	Calvo price setting parameter	1/2
ϕ_π	Taylor Rule parameter inflation	1.5
ϕ_y	Taylor Rule parameter output growth	0.5

Notes: parameter values used in model simulations. If not noted otherwise, parameters as in Fernández-Villaverde and Levintal (2018).

expectations in our survey. Table 6 lists all the parameter values used in the simulation.[9]

5.2 Simulation Results

Fernández-Villaverde and Levintal (2018) use the model to conduct a systematic analysis of alternative solution algorithms and find Talyor projections to perform particular well along the speed-accuracy trade-off. Hence, we solve the model using their algorithm based on Taylor projections. In the simulation, the equilibrium dynamics are approximated around the neighborhood of a steady state in which there are no disaster expectations. Because disaster expectations are a permanent feature in our analysis, the economy is permanently pushed out of the no-disaster steady state. Therefore, the deviation from the no-disaster-expectation steady state provides a direct measure of the quantitative impact of the disaster expectation.[10]

Overall, we find that the effect of these expectations can be quite sizeable. Put differently, the expectations channel of climate change can be quite powerful. Results are shown in Table 7. The left column corresponds to our baseline specification. Our key finding is that disaster expectations depress the natural rate of interest by almost 65 basis points. Because monetary policy does not track the natural rate directly, we find that there is negative output gap, that is, output falls below potential and inflation also drops permanently below the steady state level (by 0.29 percentage points). But, in contrast to the simplified model analyzed in Section 4

[9] We set the Calvo parameter to 1/2 which implies an average price duration of two periods. This is a high value given that period in the model represents one year. On the other hand there are several studies which assume a high degree of price stickiness to capture the fact that the Phillips curve is fairly flat (e.g., Corsetti et al., 2013).

[10] While our focus is on the effect of disaster expectations, we also illustrate the effect of an actual disaster in Figure C.2. Note that the natural rate increases while the economy contracts sharply in response to an actual disaster.

Table 7: The quantitative impact of disaster expectations

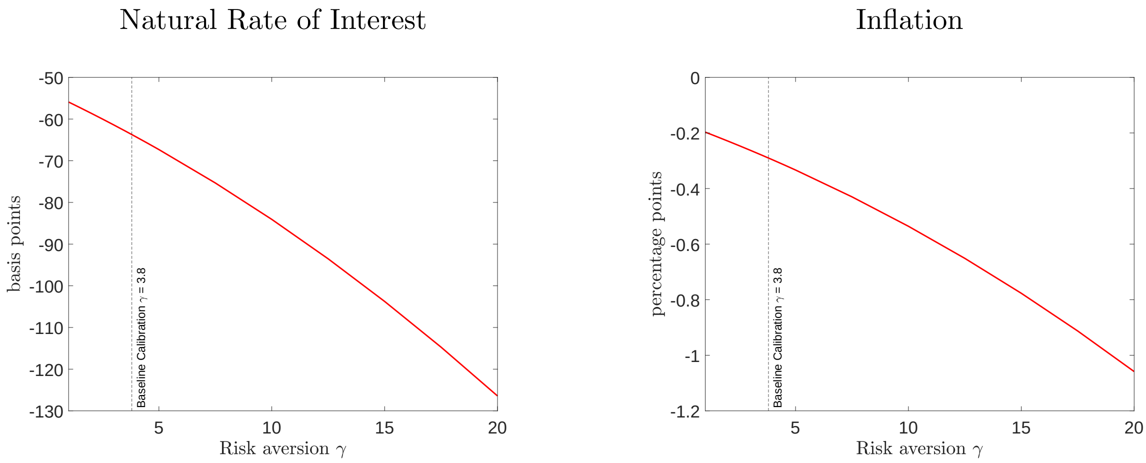
	Baseline	High p	Low p	Low $\bar{\mu}$
Disaster probability p	12%	**20%**	**10%**	12%
Mean disaster size $\bar{\mu}$	0.05	0.05	0.05	**0.025**
Natural rate of interest r^n	-0.64pp	-1.04pp	-0.53pp	-0.30pp
Output gap $\tilde{y}$	-0.20pp	-0.32pp	-0.17pp	-0.10pp
Inflation π	-0.29pp	-0.47pp	-0.24pp	-0.12pp
Nominal interest rate i	-0.66pp	-1.08pp	-0.56pp	-0.29pp
Rental rate of capital R^k	0.17pp	0.29pp	0.14pp	0.08pp
Output Y	-2.03%	-3.34%	-1.70%	-0.98%
Consumption C	-1.56%	-2.58%	-1.30%	-0.75%
Investment X	-5.27%	-8.66%	-4.40%	-2.53%
Capital K	-5.28%	-8.71%	-4.42%	-2.54%
Labor N	-0.56%	-0.86%	-0.44%	-0.25%

Notes: This table gives simulation results for different disaster calibrations. Numbers represent deviations from the no disaster steady state.

above, potential output also falls in response to disaster expectations because the capital stock declines permanently. Quantitatively these effects are large. The capital stock drops by more than 5 percent and actual output drops by about 2 percent.

We explore the robustness of these results as we vary both the probability and the size of the disaster. Columns 2 to 4 in Table 7 show these results. We find the effect of disaster expectations on the natural rate is fairly linear. For instance, if we raise p from 12% to 20% the drop in the natural rate also increases by approximately two thirds. Instead, if we reduce the extent of the disaster from 0.05 to 0.025, the effect on the natural rate also declines by approximately 50%, and similarly for the other variables. Hence, it seems that the extensive and the intensive margin of the disaster impact the economy in a fairly similar way.

Figure 3: The Impact of Disaster Expectations



Notes: model calibration as in baseline (see Table 6), except for risk aversion. Figure shows permanent effect on natural rate (left) and inflation (right). Dashed vertical line indicates risk aversion in baseline.

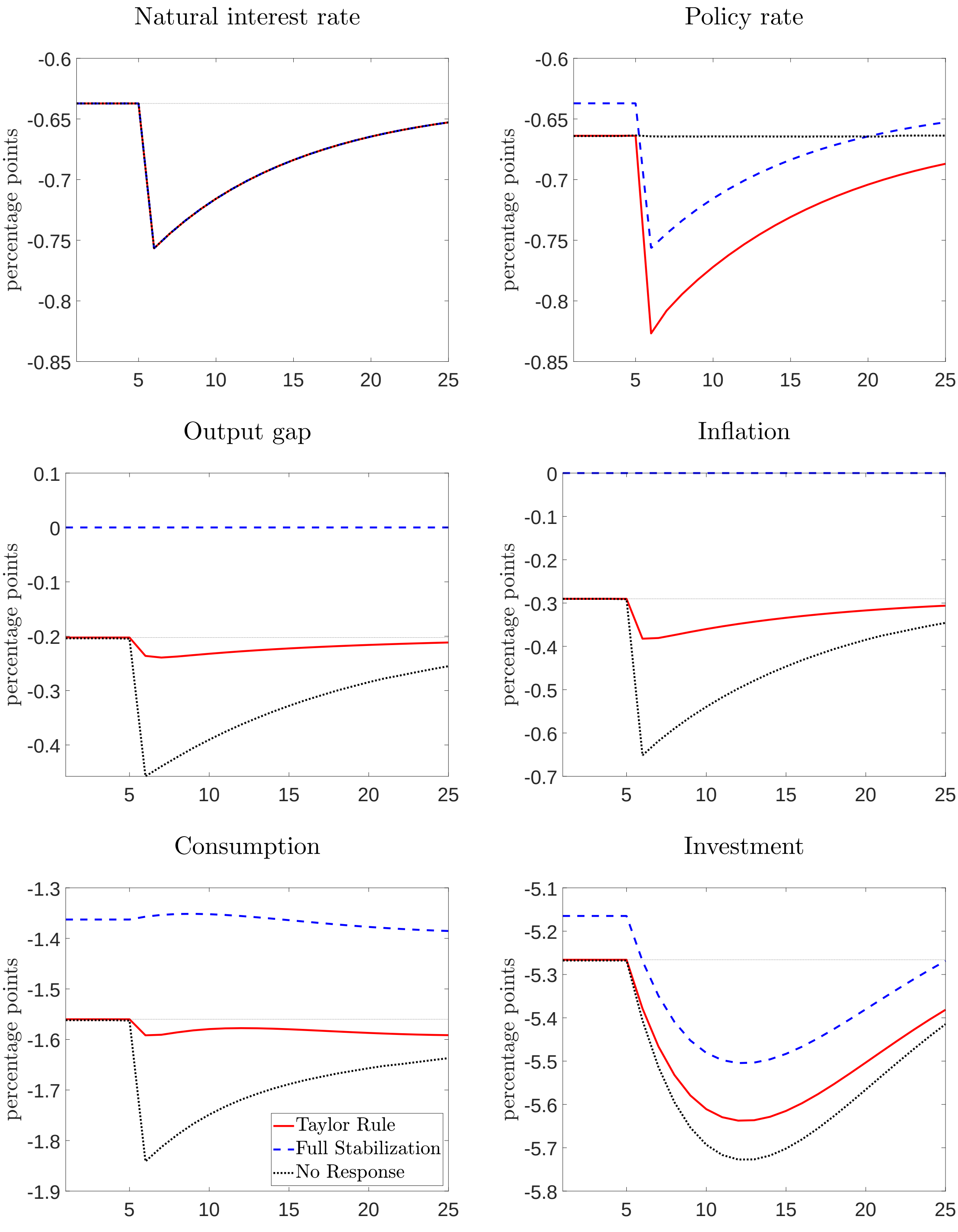
Figure 3 illustrates the extent to which the effect of disaster expectations depends on the degree of risk aversion, captured by parameter γ. This exercise is of particular interest because in the simplified model analyzed in Section 4 above, we implicitly impose certainty-equivalent behavior as we solve a log-linear approximation of the equilibrium dynamics. Instead, as we solve the model numerically via the Taylor projection, we no longer restrict policy functions to be linear and hence the impact of disaster expectations will generally depend on the degree of risk aversion. In the left panel we show the effect of disaster expectations on the natural rate as γ increases from 1 to 20. We see the effect on the natural rate increases almost linearly in the degree of risk aversion. For a value of $\gamma = 20$ the natural rate drops by about 125 basis points. Note that values for γ larger than 3.8 (our baseline calibration) are not uncommon in the literature. For instance, in an influential study Bansal and Yaron ("Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles") use a value of 10. The right panel of Figure 3 shows the effect on inflation. It also decreases strongly in the degree of risk aversion because we assume that monetary policy follows a conventional Taylor rule and does not track the natural rate directly.

So far we have solved the model assuming that disaster expectations are constant. Notably, we have kept the intensive margin of the expected disaster constant ($\mu_t = \bar{\mu}$). However, our model also permits the intensive margin of the expected disaster to vary over time. In fact, equation (3.3) specifies an AR(1) process which governs the expected loss in the event of a disaster. In order to study how a temporary shift in disaster expectations impacts the economy, we consider an innovation to process (3.3) such that μ_t increases temporarily from 0.05 to 0.059. From a quantitative point of view, this represents the effect of the information treatment we have been performed in our survey, albeit in a stylized way. Recall that the newspaper treatment and the Lagarde treatment both raise the probability of an expected disaster by about 1.5-2 percentage points. Given a median probability of 12 percent, this raises the expected value of the disaster by roughly 15 percent.

We show the dynamic adjustment of the economy to such an expectational shock in Figure 4. In the figure we display deviations from the no-disaster-expectations steady state and consider a scenario where the disaster expectations increase in year 5. Note that prior to the shock the economy is already outside the no-disaster-expectation steady state—this is the scenario for which we reported values in Table 7 above. Key to the dynamic adjustment is the response of the natural rate. The upper-left panel shows this response: relative to the pre-shock level it declines by another 10 to 15 basis points. The effect is gradually reversed as the expected extent of the disaster declines over time (with persistence parameter $\rho_\mu = 0.9$).

The response of the rest of the economy crucially depends on how monetary policy adjusts short-term interest rates, shown in the upper-right panel. Here, we distinguish three scenarios. The blue dashed line corresponds to the case where the central banks adjusts the policy rate in sync with the natural rate (which we approximate by assuming a very high value for ϕ_π). As a result, the output gap and inflation (shown in the second row) are perfectly stabilized—in line with our results in in Section 4.2 above. Instead, if monetary policy follows a conventional interest-rate feedback role à la Taylor (red solid line) the policy rate is lower to begin with because in this case inflation and the output gap are depressed relative to steady state even before the expectational shock hits. The Taylor rule calls for an adjustment of the

Figure 4: Dynamic adjustment to disaster expectation shock



Notes: Impulse response functions to a temporary increase in the disaster size from 0.05 to 0.062. Vertical axis measures deviation from no-disaster-expectation steady state, horizontal axis measures time in years.

policy rate which turns out to be insufficient to stabilize the output gap and inflation: they decline further in response to the shock. For the last scenario, captured by the black dashed line, we assume a sequence of monetary policy shocks which ensure that the policy rate does not adjust to the shock. This experiment is meant to illustrate what would happen in case monetary policy is unwilling or unable to accommodate the shock, say, because it is constrained by the ELB. In this case the effect of the shock on the output gap and inflation is largest: the output gap drops another 0.3 percentage points and inflation by another 40 basis points in response the shock (see again Proposition 2). These results illustrate that the adverse shifts in disaster expectations can have very detrimental effects on the economy if they are not accommodated by an appropriate policy response.

The bottom panels of the figure show the response of consumption and investment to the shock. Here we see again differences across monetary scenarios. In case monetary policy tracks the natural rate, in particular, we observe that consumption is fully stabilized, even though investment declines. The drop in consumption is particularly strong in case monetary policy remains unresponsive.

6 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 65 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.

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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 ($a_t = a_{t-1} - (1-\alpha)\bar{\mu} + \Lambda_A$) gives:

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

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:

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

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

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

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).

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) Growth	(3) Damage	(4) Damage	(5) Disaster Prob.	(6) Disaster Prob.
Female	0.00293	-0.0100	0.121**	0.119**	3.835***	4.005***
	(0.07)	(-0.22)	(3.29)	(3.27)	(4.46)	(4.60)
35 to 44 years	0.0291	0.0473	0.0697	0.0609	2.078	2.581*
	(0.54)	(0.88)	(1.43)	(1.25)	(1.87)	(2.27)
45 to 54 years	0.0116	-0.0211	0.000592	-0.0162	-1.288	-0.993
	(0.18)	(-0.32)	(0.01)	(-0.29)	(-0.97)	(-0.75)
above 55 years	0.219***	0.217***	-0.142***	-0.134**	0.234	0.602
	(4.17)	(4.10)	(-3.39)	(-3.20)	(0.22)	(0.57)
High Educated	-0.0860	-0.0868	0.0196	0.0296	-0.658	-0.631
	(-1.68)	(-1.68)	(0.47)	(0.70)	(-0.70)	(-0.67)
Middle Income	-0.0826	-0.0965	-0.116*	-0.108*	-0.518	-0.838
	(-1.49)	(-1.74)	(-2.53)	(-2.37)	(-0.50)	(-0.80)
High Income	-0.0946	-0.102	-0.0611	-0.0738	0.263	0.0417
	(-1.31)	(-1.43)	(-1.05)	(-1.26)	(0.21)	(0.03)
White	-0.114	-0.0975	-0.103	-0.0618	3.128	4.119*
	(-1.17)	(-1.01)	(-1.38)	(-0.85)	(1.78)	(2.48)
Black	-0.180	-0.156	-0.156	-0.145	-2.883	-2.003
	(-1.59)	(-1.40)	(-1.69)	(-1.58)	(-1.41)	(-1.00)
Asian	-0.104	-0.0990	-0.326***	-0.280**	-3.319	-2.852
	(-0.80)	(-0.78)	(-3.32)	(-2.87)	(-1.52)	(-1.34)
Hispanic	-0.0696	-0.0951	-0.187	-0.134	0.737	0.949
	(-0.56)	(-0.76)	(-1.87)	(-1.37)	(0.33)	(0.44)
Republican	-0.0363	-0.0244	-0.131**	-0.128**	-3.779***	-3.591***
	(-0.67)	(-0.45)	(-2.96)	(-2.92)	(-3.83)	(-3.61)
Democrat	0.0368	0.0574	0.209***	0.210***	3.468***	3.756***
	(0.74)	(1.16)	(5.08)	(5.08)	(3.40)	(3.65)
Constant	0.294**	0.591**	1.641***	1.794***	17.82***	12.92***
	(2.78)	(3.09)	(20.43)	(9.28)	(9.52)	(3.61)
State FE	no	yes	no	yes	no	yes
N	4344	4344	3222	3210	3223	3223
r2	0.00915	0.0388	0.0549	0.0856	0.0322	0.0629

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: Reported Probability of Disaster and Experience

	(1)	(2)	(3)	(4)	(5)
Fire experience	6.505**		3.582*		5.121*
	(2.93)		(2.01)		(2.13)
Flood experience	3.429*		4.151***		3.913**
	(2.56)		(3.46)		(2.92)
Hurricane experience	0.186		1.175		1.027
	(0.11)		(0.81)		(0.56)
Hurricane Events in State		0.00368	0.0123		
		(0.51)	(1.24)		
Flood Events in State		0.00589	0.00842		
		(0.46)	(0.57)		
Fire Events in State		0.0100	-0.00326		
		(1.23)	(-0.32)		
High wildfire risk				8.089***	6.708**
				(3.84)	(3.13)
High landslide risk				1.941	2.072
				(0.88)	(0.94)
High earthquake risk				-5.257	-7.628*
				(-1.61)	(-2.24)
High hurricane risk				-3.520	-3.409
				(-1.61)	(-1.43)
High flood risk				-0.625	-0.743
				(-0.38)	(-0.47)
Constant	5.993	15.97***	13.10***	7.861*	7.730*
	(1.69)	(7.33)	(5.35)	(2.11)	(2.03)
State FE	yes	no	no	yes	yes
Demographic Controls	yes	yes	yes	yes	yes
N	2167	2148	2148	2167	2167
r2	0.138	0.0463	0.0536	0.140	0.148

Notes: regression relates reported probability of disaster to personal experience; 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: Disaster Probability and Individual News Stations

	(1) Disaster Prob.	(2) Disaster Prob.	(3) Disaster Prob.
Multiple News Stations	7.178***		5.074***
	(5.56)		(3.55)
Fox	0.0929		-0.113
	(0.06)		(-0.07)
CNN	5.877**		6.476**
	(3.12)		(3.20)
ABC	0.418		0.477
	(0.23)		(0.25)
MSNBC	-1.422		-1.663
	(-0.56)		(-0.61)
PBS	11.77**		11.60**
	(2.91)		(2.83)
NBC	8.684***		8.705***
	(3.88)		(3.82)
CBS	9.094***		8.974***
	(3.80)		(3.64)
Multiple Newspapers		6.738***	4.700***
		(6.10)	(3.87)
New York Times		-0.263	-1.679
		(-0.17)	(-1.02)
Washington Post		1.849	0.944
		(0.82)	(0.41)
Wall Street Journal		-2.988	-4.279**
		(-1.91)	(-2.71)
USA Today		3.155	2.136
		(1.81)	(1.21)
Los Angeles Times		-1.831	-4.437
		(-0.55)	(-1.32)
Constant	11.51**	10.89**	10.71**
	(3.23)	(3.00)	(2.94)
State Fixed Effect	yes	yes	yes
Demographic Controls	yes	yes	yes
N	3223	3223	3223
r2	0.0858	0.0802	0.0951

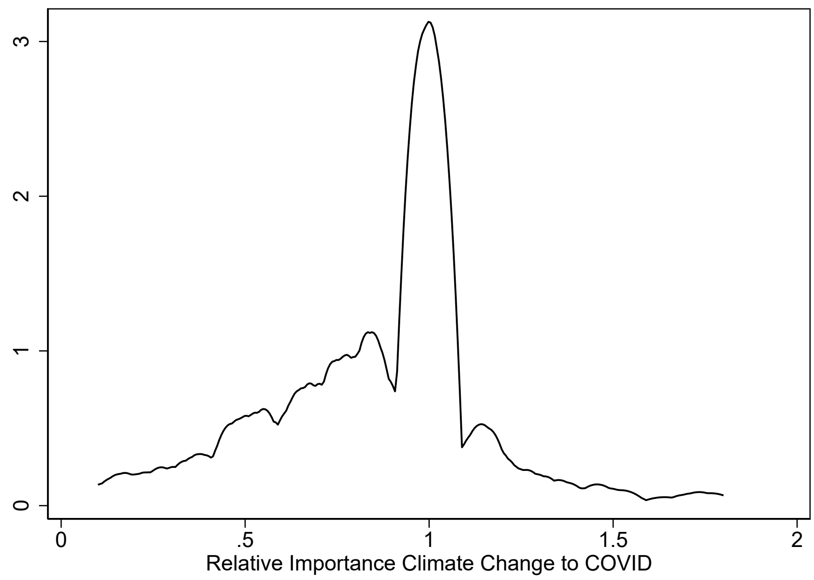
Notes: regression relates reported probability of disaster to use of specific news stations; only respondents who did not receive any treatment used in regression; t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey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

Table C.4: Expected Disaster Cost and Media Usage

	(1) Costs	(2) Costs	(3) Costs
no major TV station	-0.109		
	(-1.14)		
no major Newspaper		0.0276	
		(0.37)	
consume major TV station×no major newspaper			0.0830
			(0.98)
no major TV station×consume major newspaper			-0.0501
			(-0.25)
no major TV station×no major newspaper			-0.0948
			(-0.85)
Constant	2.177***	2.130***	2.142***
	(6.34)	(6.10)	(6.05)
State FE	yes	yes	yes
Demographic and Treatment Controls	yes	yes	yes
N	860	862	861
r2	0.150	0.148	0.150

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.

Figure C.1: 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.

Table C.5: Reported Growth Impact of Climate Change and Media Usage

	(1) Growth	(2) Growth	(3) Growth
no major TV station	0.0960		
	(0.73)		
no major Newspaper		0.253*	
		(2.23)	
consume major TV station×no major newspaper			0.260*
			(1.99)
no major TV station×consume major newspaper			-0.0162
			(-0.08)
no major TV station×no major newspaper			0.240
			(1.50)
Constant	0.108	-0.0252	-0.0207
	(0.38)	(-0.08)	(-0.07)
State FE	yes	yes	yes
Demographic and Treatment Controls	yes	yes	yes
N	867	867	867
r2	0.122	0.128	0.128

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.6: Treatment Regressions High Numerical Ability

	(1)	(2)	(3)	(4)
Newspaper (T1)	0.436	0.510	0.670	0.729
	(0.34)	(0.40)	(0.60)	(0.65)
Historic Disaster Size (T2)	-2.762*	-2.770*	-2.099*	-2.081*
	(-2.35)	(-2.37)	(-2.04)	(-2.04)
Lagarde treatment (T3)	-0.588	-0.259	-0.543	-0.438
	(-0.46)	(-0.20)	(-0.47)	(-0.38)
Climate Change Scale		1.031***		0.746***
		(7.24)		(6.00)
Constant	19.38***	14.58***	17.21***	13.45***
	(5.00)	(3.80)	(4.99)	(4.02)
State Fixed Effect	yes	yes	yes	yes
Demographic Controls	yes	yes	yes	yes
Drop largest 25% probabilities	no	no	yes	yes
N	1352	1360	1240	1240
r2	0.148	0.177	0.173	0.195

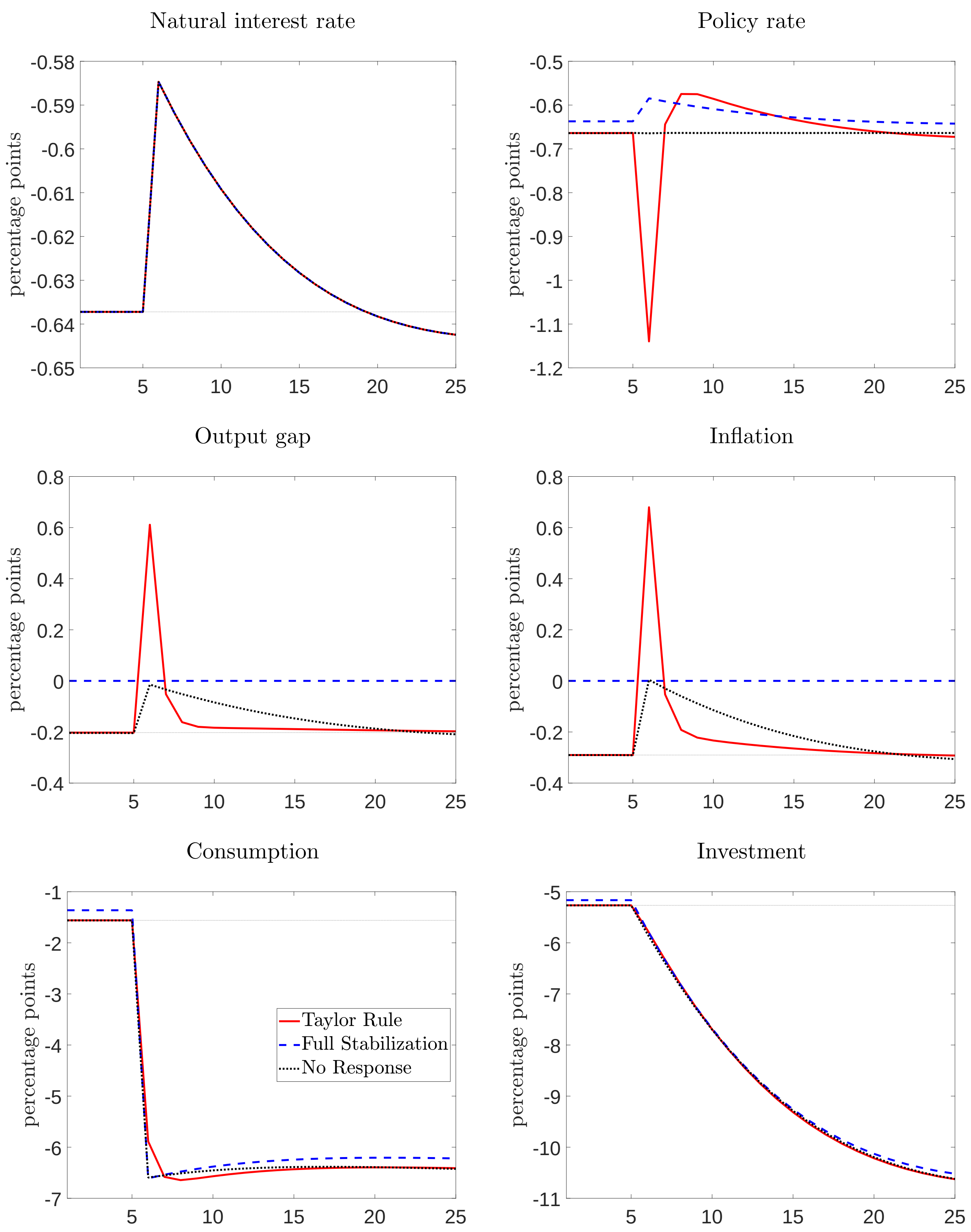
Notes: t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;This table presents regression results on the impact of several treatments on the expected disaster probability. Only data from respondents who were able to answer Q6 correctly by a margin of 2 percentage points was used. 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)	(2)	(3)	(4)
	Disaster Costs	Disaster Costs	Growth	Growth
Newspaper (T1)	0.0468	-0.0422	-0.0700	-0.0350
	(1.27)	(-0.86)	(-1.45)	(-0.51)
Historic Disaster Size (T2)	-0.0641	-0.146**	-0.0324	0.00855
	(-1.66)	(-2.90)	(-0.60)	(0.12)
Lagarde treatment (T3)	-0.00171	-0.102*	-0.130*	-0.0844
	(-0.05)	(-2.06)	(-2.49)	(-1.20)
Climate Change Scale		0.0638***		0.0495***
		(11.06)		(5.67)
Constant	1.686***	1.396***	0.0900	-0.696***
	(13.05)	(8.60)	(0.60)	(-3.30)
State Fixed Effect	yes	yes	yes	yes
Demographic Controls	yes	yes	yes	yes
N	5816	3444	6938	3462
r2	0.0642	0.115	0.0228	0.0523

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.

Figure C.2: Impulse Response Functions to a Disaster Shock



Notes: Figure shows impulse response functions to a disaster shock in period 6. Vertical axis measures deviation from no-disaster-expectation steady state, horizontal axis measures time in years.