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Big News: Climate Change and the Business Cycle

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News – anticipated changes of an economy's fundamentals – drive the business cycle. Climate change is big news: it will impact the economy profoundly, but its full effect will take time to materialize. To better understand the transmission of news, this paper focuses on climate-change expectations. First, we measure the expected economic impact of climate change in a representative survey of U.S. consumers. We find, in particular, that costly natural disasters are salient of climate change. Second, we calibrate a New Keynesian model with rare disasters to the survey results and find that shifts in climate-change expectations operate like adverse demand shocks.

Keywords

Climate Monetary policy Interest rates

JEL classification

E43; E52; E58

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Big News: Climate Change and the Business Cycle

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Abstract

News—anticipated changes of an economy's fundamentals—drive the business cycle. Climate change is big news: it will impact the economy profoundly, but its full effect will take time to materialize. To better understand the transmission of news, this paper focuses on climate-change expectations. First, we measure the expected economic impact of climate change in a representative survey of U.S. consumers. We find, in particular, that costly natural disasters are salient of climate change. Second, we calibrate a New Keynesian model with rare disasters to the survey results and find that shifts in climate-change expectations operate like adverse demand shocks.

Keywords: Climate change, Disasters, Expectations, Survey, Monetary policy, Business Cycle, Natural rate of interest
JEL-Codes: E43, E52, E58

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1 Introduction

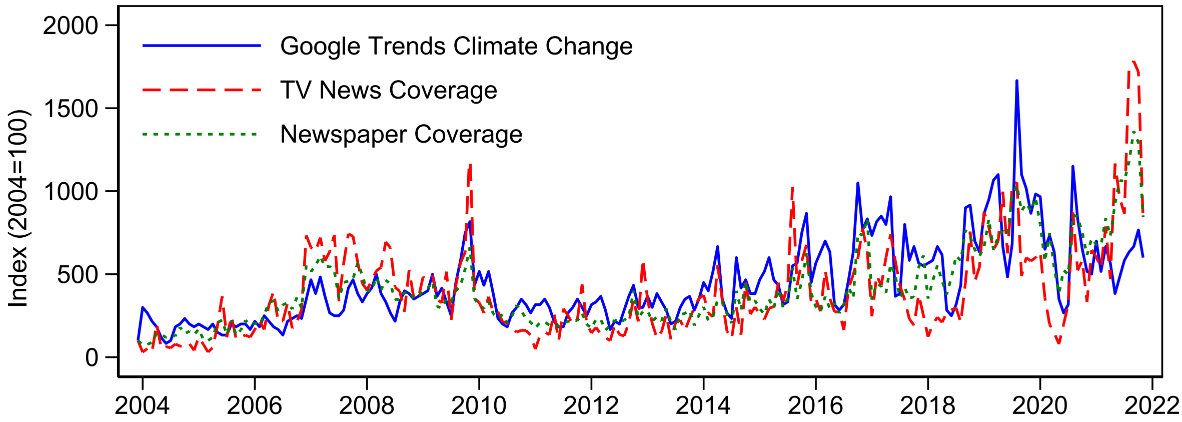
Climate change is on peoples' mind: With increasing intensity "climate change" is covered in the media and looked up online as Figure 1 illustrates. Also, there is an emerging consensus that climate change will profoundly alter peoples' way of life and, not least among it, the economy. Rising temperatures are, among other things, influencing productivity and growth; they are also making extreme weather events and rare disasters more likely (Dell et al., 2012; IPCC, 2012; Somanathan et al., 2021). But it will take a long time for the full impact of climate change to materialize. In this sense, the economic impact of climate change represents *news* about the future—anticipated changes of the economy's fundamentals. In business cycle theory, the distinct feature of news is that it matters already for current economic activity (Beaudry and Portier, 2006; Jaimovich and Rebelo, 2009; Schmitt-Grohé and Uribe, 2012). Against this background, we take up the following question: How do climate-change expectations impact economic activity at business-cycle frequency?

Measuring news and identifying their effect on business cycles is challenging and remains controversial to date (Barsky and Sims, 2012; Blanchard et al., 2013; Enders et al., 2021). After all, news is not directly observable and, what's more, it is equally difficult to see to what extent news captures peoples' attention. Against this background, we exploit the fact that climate-change expectations—perhaps the biggest news of all times—are rather tangible and can be measured fairly accurately. We attempt do so in this paper by means of a survey. We then calibrate a business cycle model to the findings of the survey and study the transmission mechanism of climate-change expectations in some detail.

Specifically, in the first part of the paper, we measure expectations about the economic impact of climate change in a large survey that is representative of U.S. consumers. We find that while expectations vary systematically with socioeconomic characteristics, media consumption and various information treatments, respondents tend to assign large probabilities to climate-change related natural disasters—a salient feature of climate change. Expectations of climate-change related natural disasters are an example of rare-disaster expectations, which in turn, have been identified as an important driver of asset prices and the business cycle (Barro, 2006; Gourio, 2012; Kozlowski et al., 2020).

In the second part of the paper, we therefore zoom in on climate-change related disaster expectations and study their business-cycle implications. For this purpose, we rely on a New Keynesian model with rare disasters as put forward by Fernández-Villaverde and Levintal (2018). We show analytically for a simplified version of the model that disaster expectations—along both, the intensive and the extensive margin—lower the natural rate of interest. Intuitively, an increase of disaster expectations amounts to bad news about the future and depresses—all else equal—current economic activity: consumption and inflation decline. The overall impact on the business cycle depends on how monetary policy adjusts to the shift in disaster expectations. We also map the results of the survey into a calibrated version of the full model which features capital accumulation and investment. We perform a quantitative analysis and flesh out the transmission mechanism of disaster expectations in some detail. In the last part of the paper we estimate a simple VAR model and provide external validation of the mechanism which operates at the heart of the model.

Figure 1: Climate Change in the Media



Notes: 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). All time series normalized to 100 in January 2004.

More particularly, in order to measure measure climate-change expectations, we rely on a representative survey of more than 20,000 U.S. consumers, conducted between October 2020 and July 2021. Among other things, we ask whether respondents expect climate change to impact output growth, either adversely, for example, due to stricter regulation or positively, for example, due to technological innovation. We find that on average the *expected* impact on growth is negligible.[1] At the same time, respondents expect median disaster costs due to climate change over the next 12 months that amount to 1.5 percent in terms of GDP. Moreover, the median respondent assigns a 10 percent probability to a large natural disaster with damages amounting to 5 percent of GDP. This number is very high in light of the historical record: In the period from 1980 to 2019, there was no natural disaster in the US of that size (NCEI, 2020). Still, we obtain very similar responses when we consider only respondents who display a high degree of probability literacy and when—in order to provide some context—we inform respondents of the fact that U.S. GDP declined by about 5 percent during the global financial crisis.

In our analysis, we focus on the probability of disasters as perceived by the respondents in the survey because disasters are salient of climate change. To see this, we remove any reference to climate change in the elicitation of probability beliefs about disasters and find that the reported probabilities decline considerably. Hence, respondents consider disasters *as such* less likely than disasters that are due to climate change. This is logically inconsistent and an instance of the conjunction fallacy (Tversky and Kahneman, 1983). It also suggests that disasters are a salient trait of climate change. For our baseline, we reference "climate change" when we elicit disaster probabilities so as to mimic the debates and narratives to which respondents are exposed in real life (Shiller, 2017).

We also verify that the responses likely represent genuine information rather than measurement error: they relate in a meaningful way to various respondent characteristics such as age,

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

gender, or political affiliations. Further validation of our survey responses as reflecting true subjective beliefs about the economic impact of climate change comes from the finding that respondents' perceived probabilities correlate with behavioral adjustments at the individual level in reaction to climate change. Respondents are more likely to report adjustment of their investments, mobility, and other decisions when they think that disasters due to climate change are more likely.

Second, while the measured probability of disasters may appear high, it may be so for a good reason. There are various possibilities: For instance, respondents may think we have been lucky in the past, just like in the case of "peso problems" and the past is therefore a bad guide for the future: in the relatively short sample under consideration, adverse events have simply materialized less often than one would find in a longer time series. Alternatively, natural disasters due to climate change may be more frequent in the future because we may have reached so-called "tipping points" where dynamics change in a highly non-linear way (Emanuel, 2018).

Third, and perhaps most likely, survey respondents may overestimate the probability of rare disasters, consistent with findings in other contexts which suggest that tail events and/or salient traits are assigned excessively large probability weights (Barberis, 2013b; Heimer et al., 2019; Lichtenstein et al., 1978). There are various attempts to operationalize this phenomenon (Bordalo et al., 2019, 2020; Tversky and Kahneman, 1973). Most important for our analysis is the finding in earlier work that peoples' subjective beliefs are relevant for their actions (Fox and Tversky, 1998; Tversky and Kahneman, 1992).

In the second part of the paper, we assess the business-cycle impact of climate-change expectations through the lens of a New Keynesian model with rare disasters, extended to allow for time-varying disaster expectations. As a limiting case, the model nests the textbook version of the New Keynesian model (Galí, 2015). For this case, we derive a number of results in closed form. In particular, we show that expectations of a rare disaster lower the natural rate of interest today, reflecting both the probability of a disaster and the extent of the disaster. Intuitively, as the expected costs of a disaster go up, people increase their savings. The natural rate has to fall for markets to equilibrate. This effect is first-order and obtains even in a linearized version of the model because disaster risk is one-sided. Shifts of disaster expectations thus operate very much like adverse belief or noise shocks (Enders et al., 2021; Lagerborg et al., 2022; Lorenzoni, 2009).

By tracking the natural rate, monetary policy can in principle fully stabilize the economy at its natural level in the face of disaster expectations. Under a conventional monetary policy rule, an adverse shift in disaster expectations instead is contractionary, and even more so if monetary policy is unresponsive to the shift. Because shifts in disaster expectations operate just like other adverse demand shocks, they call for monetary accommodation. Within the confines of the model, monetary policy simply needs to track the natural rate, irrespective of the nature of the shock, to achieve full stabilization. Still, as the natural rate is unobservable, policymakers need to understand the fundamental drivers of the business cycle, not least to get a sense of the likely persistence of the disturbances to which the economy is exposed. That this is particularly challenging in the context of climate change has been noted by central banks (Cœuré, 2018).

We study the transmission of shocks to disaster expectations in the full model which we calibrate to capture key aspects of the survey. In contrast to the simplified model, the full model allows for capital accumulation and investment dynamics. Yet, as with the simplified model, an increase of disaster expectations operates like an adverse demand shock, both consumption and investment contract. Inflation declines. Moreover, according to the calibrated model shifts in disaster expectations make a sizeable contribution to the business cycle. They account for 7 and 8 percent of the volatility of inflation and the output gap, respectively.

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

Our paper relates to the literature on the role of news shocks for business cycle fluctuations referenced above but also to work on the interaction of climate change and macroeconomic performance following the influential work by Nordhaus (1994), Mendelsohn et al. (1994), and Nordhaus (2006). Hassler and Krusell (2018) survey the "macroeconomics and climate" literature. This literature also studies the optimal policy response to climate change (e.g., Barro, 2015; Golosov et al., 2014; Hassler et al., 2021). We focus on the reverse: how (expected) climate change impacts the business cycle and what that means for policy. Related work investigates the extent of directed technological change in response to (actual) natural resource scarcity or to (actual) carbon taxes (Aghion et al., 2016; Heutel, 2012). Other work contrasts the effects of climate-change related risks to those of actual disasters, distinguishing demand and supply-side effects (Batten et al., 2020; Cantelmo, 2020). Related work on the implication of climate change for asset prices shares our focus on expectations (Bansal et al., 2019; Bauer and Rudebusch, 2021; Gollier, 2020). A recent survey of experts suggests that regulatory risk is also perceived as a key issue, at least in the short run (Stroebel and Wurgler, 2021).

There is also evidence that natural disasters trigger an adjustment of both expectations and economic behavior. While Baker et al. (2020) document the adjustment of professional forecasters to actual disasters on the basis of a large cross-country data set, Hu (2020) finds that households purchase more insurance policies in response to information about flood risk. Hong et al. (2020) study how the arrival of natural disasters affects disaster beliefs, disaster mitigation policy, and the economy. Fried et al. (2021) study the effect of climate policy risk on firm investment. Finally, we note that our results underscore the importance of news media for both the expectation formation process and, more generally, for understanding the business cycle (Carroll, 2003; Chahrour et al., 2021; Larsen et al., 2021).

The remainder of this paper is organized as follows: We introduce our survey in the next section and present the results. Section 3 outlines the model for which we present analytical results in Section 4. In Section 5, we map the main results from the survey into the full model and study the transmission of disaster expectations. Section 6 illustrates the external validity of the mechanism which operates at the heart of the model. A final section concludes.

2 The Survey

In what follows, we first provide some basic information about the survey. We subsequently present the main survey results which summarize peoples' beliefs regarding the near-term economic impact of climate change. Lastly, we show how these vary systematically and in a meaningful way with a range of socioeconomic indicators and information treatments.

2.1 Survey Design

Our data come from a large, nationally representative daily survey of consumers sponsored by the Federal Reserve Bank of Cleveland that has been running since March 10, 2020. The survey is described in detail in Dietrich et al. (2022) 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 the economic impact of the COVID-19 pandemic. These questions have been included during the period from October 1, 2020 to July 11, 2021. During that period, we collected 22,835 responses.

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

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

Table 1: Survey Respondent Characteristics

	Survey	US population		Survey	US population
Age			**Race**		
18-34	33.60%	29.8%	non-Hispanic white	72.69%	60.1%
35-55	34.58%	32.4%	non-Hispanic black	9.96%	12.5%
>55	31.82%	37.8%	Hispanic	9.84%	18.5%
			Asian or other	7.51%	8.9%
Gender					
female	50.16%	50.8%	**Household Income**		
male	49.46%	49.2%	less than 50k$	36.81%	37.8%
other	0.38%	-%	50$ - 100k$	41.23%	28.6%
			more than 100k$	21.96%	33.6%
Region					
Midwest	21.43%	20.7%	**Education**		
Northeast	21.04%	17.3%	some college or less	50.03%	58.3%
South	40.58%	38.3%	bachelor's degree or more	49.97%	41.7%
West	16.95%	23.7%			
			N=22,835		

Notes: Entries report statistics for the survey respondents and the US population, as obtained from the US Census Bureau (household income: CPS ASEC, 2021; gender, education: ACS, 2019 which does not report gender other than "male" and "female"; age, race, region: National Population Estimate, 2019).

perceive natural disasters to be. Specifically, we ask them about a large disaster causing damage of about 5 percent of GDP.[2]

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

The second set of complementary questions aims at validating that responses reflect economically relevant respondent beliefs. It also gauges the salient nature of natural disasters in the context of climate change. First, we use standard survey questions about socio-economic demographics to establish basic correlations with beliefs. Finding meaningful variation of beliefs with economic covariates can help rule out measurement error. Second, the survey also records respondent zip codes, which allows us to study the role of salient geographic features as

[2] In the past, years with high natural disaster damages were usually associated with one extremely large disaster, such as Hurricane Katrina in 2005.

Table 2: Survey Questions

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

Notes: Table outlines the main questions of the survey. Appendix A provides the full set of questions asked in the survey.

a potential driver of climate-change beliefs. We also measure media use which tends to relate natural disasters as salient features of climate change.

The third set of complementary questions, run as a separate robustness survey in November 2022 (N=1014), varies the setup of the questions to further establish the salient nature of natural disasters in the context of climate change, as well as the robustness to specifics of the setup. One variant for the question setup thus removes any reference to climate change in the elicitation of probability beliefs about rare natural disasters (Q3a). Another variant makes only a very brief reference to climate change in the elicitation of economic growth effects (Q1c) or asks about the growth effects of natural disasters, instead of climate change (Q1b). To avoid mechanically biasing estimates up or down, a third variant uses an equal-sized set of bins in the assessment of effects on GDP growth (Q1a). A final set of variants either removes or keeps the reference to climate change when allowing for longer horizons in the probability assessment (10, 20 and 30 years ahead, Q3d, Q3e, Q3f; Q3i, Q3j, Q3k) or when specifying lower as well as higher damages in terms of GDP (2 percent and 10 percent, Q3b, Q3c; Q3g, Q3h). Appendix A reports these

Table 3: Information Treatments

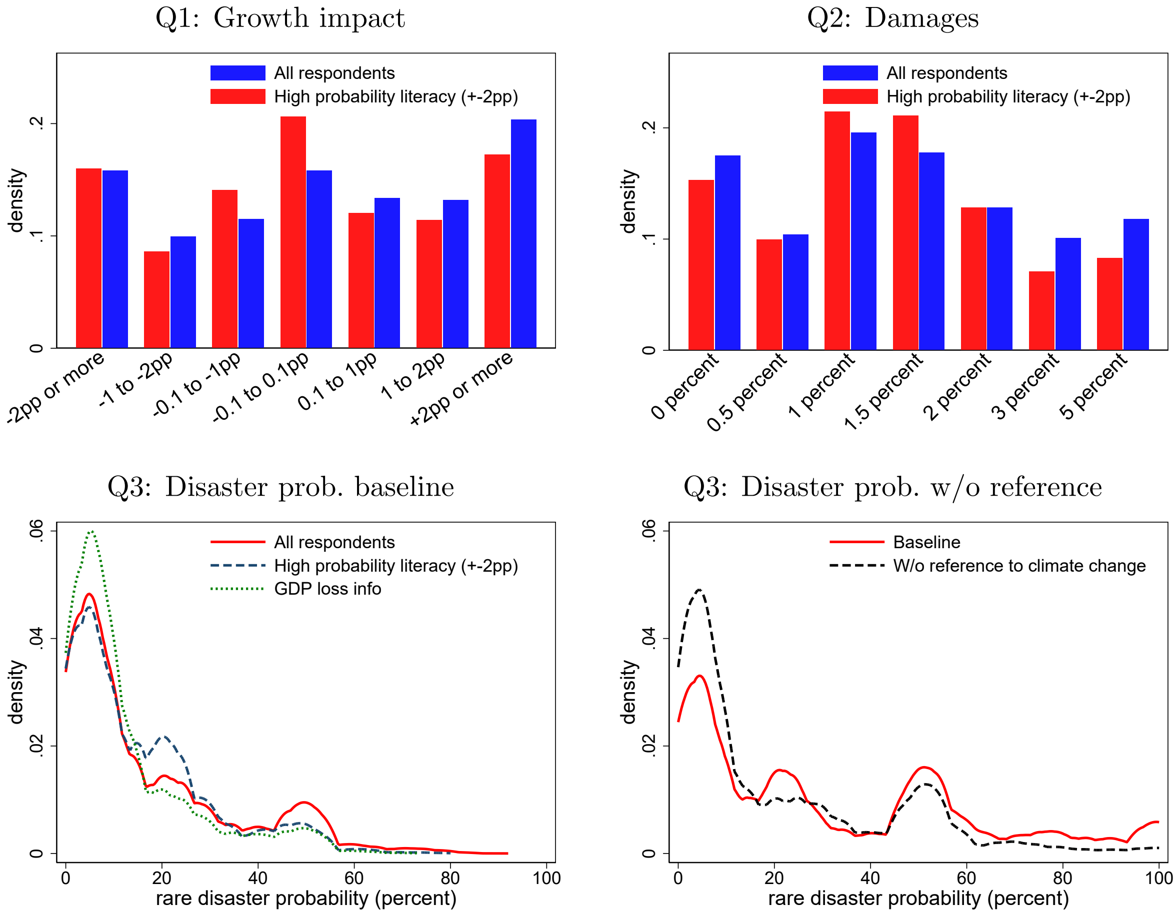
Control Group (T0)	No information treatment *(N=10.790)*
Newspaper Treatment (T1)	Extract from an USA Today article summarizing the 2020 hurricane season on the East Coast and in the Gulf region and the wildfires on the West Coast. The article links both developments to global warming. *(N=4.805)*
Historic 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)." *(N=4.847)*
Historic Disaster Frequency (T3)	"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)." *(N=1.065)*
GDP Loss Info (T4)	"The next question asks about potential damages due to climate change, expressed in percent of GDP. To put these damages in perspective, note that U.S. GDP declined by approximately 5 percent in 2008-09 in response to the global financial crisis." *(N=1.323)*

Notes: Table describes the information treatments used in the survey. Appendix A provides the full set of questions and information treatments.

additional question variants.

Finally, we also provide several information treatments before asking Questions 1 to 3. These treatments help gauge the extent to which pertinent information related to climate change and natural disasters can causally affect the formation of beliefs. The information treatment comes in several variants, summarized in Table 3. The "Newspaper treatment" shows to respondents sections of a USA Today newspaper article on the 2020 wildfire and hurricane season. The "Historic disaster probability treatment" informs respondents that in the past 20 years, there has been no disaster in the U.S. that has caused damage in the vicinity of 5 percent of GDP. A variant of this question is our "Historic disaster frequency treatment" which was only asked early on in the survey. It is therefore not included in all subsequent regression analyses. It informs respondents that in the past 20 years, there have been two large disasters in the U.S., both with damages of more than 0.5 percent of GDP. As a last treatment, we provide participants with information about an economic loss of similar magnitude, namely the Global Financial Crisis of 2008.

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). Bottom panels show the distribution of responses to Question 3: probability of a rare disaster with damage of 5 percent of GDP within the next 12 months (left: baseline, right: without reference to climate change). The red solid line represents the distribution for the full sample, other lines are based on subgroups with info treatments and/or numerical ability.

2.2 Survey Results

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 0.20 percentage points over the next 12 months. However, there is a lot of mass in the distribution for both positive and negative outcomes. We show this distribution in the top-left panel of Figure 2. The blue bars represent the answers of all respondents, while the red bars represent those of respondents with high probability literacy. For example, we find that nearly 20 percent of all respondents expect a boost to growth by more than 2 percentage points over the next 12 months due to climate change, while more than 15 percent expect a growth decline by more than 2 percentage points. For respondents with high probability literacy, there is somewhat less mass in the right tail. The standard deviation across all respondents is 1.30 percentage points.

Table 4: Survey Summary Statistics

All Respondents	Mean	Median	Std. Dev.	N
Growth Impact (Question 1)	0.20 pp	0.01 pp	1.30 pp	8393
Disaster Costs (Question 2)	1.47%	1.50%	0.81%	6919
Disaster Probability (Question 3)	16.36%	10.00%	17.24%	6839

High Probability Literacy Respondents	Mean	Median	Std. Dev.	N
Growth Impact (Question 1)	0.07 pp	0.00 pp	1.26 pp	806
Disaster Costs (Question 2)	1.36%	1.35 %	0.70%	782
Disaster Probability (Question 3)	14.42%	10.00%	14.18%	966

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

Table 4 provides summary statistics for all three main questions, both for all respondents (top panel), and respondents with high probability literacy (bottom panel). The first row in each panel summarizes the answers to Question 1.

This estimated effect of climate change on economic growth, moreover, also turns out to be small across variations of asking the question. We illustrate this in Appendix B: Whether the question uses equal-sized bins, is set up only in terms of natural disaster without mention of climate change, or only uses a brief reference to climate change makes no difference relative to the baseline, the average response to each of these variations of Question 1 is not statistically significantly different from the baseline.

Second, we find that survey respondents expect substantial economic damages due to climate change, amounting to approximately 1.5% of GDP on average over the next 12 months. The top-right panel in Figure 2 shows these responses, again for the full sample (in blue) and respondents with high probability literacy only (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 probability literacy. Approximately 15% of all respondents expect no loss, while the fraction among those with high numerical ability is slightly lower. Overall, the standard deviation of expected losses is at 0.81% as Table 4 summarizes.

Finally, turning to the third question, we find that respondents always perceive high probabilities for natural disasters due to climate change that inflict damages of 5 percent of GDP over the next 12 months. These beliefs are widely dispersed as was the case with the preceding questions. The mean probability is at 16.36 percent while the median is at 10 percent. In fact, as the high mean probability suggests, the distribution of responses is characterized by a heavy right tail. For example, almost 10 percent of respondents believe that such a rare disaster can occur with more than 75 percent probability.[3] Responses of survey participants with high probability

[3]The message from this third question is the same as when we elicit the probability of disaster costs by bins in Question 2 (top-right panel of 2): The probability of a large natural disaster is extremely large and statistically indistinguishable across the two questions. Respondents assign a 12.77 percent probability in Question 2 to a disaster bin that corresponds to damages amounting to 5 percent of GDP compared to the mean probability of

literacy do not differ much: As the lower-left panel of Figure 2 shows, for these respondents we obtain somewhat more mass on probabilities between 15 to 30 percent. But their median response is equal to the response in the full sample as Table 4 shows. At the same time, high probability literacy ability is associated with less mass in the extreme right tail bringing down the mean to 14.42 percent, but not in a statistically significant fashion relative to the full sample, once we control for demographic characteristics. It thus seems that understanding probabilities is not a major issue for respondents as the answers by high probability literacy respondents suggest across our three main questions.

The same conclusion emerges when we consider respondents which have been subjected to the information treatment that compares the magnitude of the probability event in Question 3 to the Great Recession. Clarifying the magnitude of the event in this way does not materially affect expectations. The distribution of responses is shown by the green dotted line in the bottom-left panel of Figure 2. While the treatment ("GDP loss info") draws mass from the extreme right tails to the left, the distribution has a similar shape as in the baseline. The Huber-robust weighted mean probability under the treatment is 11.88 percent compared to 16.37 percent in the full sample; however, the mode of distribution remains unchanged.

Natural disasters are salient of climate change—an aspect of climate change that is particularly noticeable. To see this, we run a wave of the survey where we drop the reference to climate change (as outlined in the preceding survey overview) and simply ask respondents what they think the probability of a large disaster is. We define "large" as before by damages of about 5 percent of GDP. We find that absent the reference to climate change, respondents perceive a lower disaster probability. We illustrate this in the bottom-right panel of Figure 2. The red solid line shows the distribution of responses for the baseline question while the black dashed line represents the distribution of responses for the question without reference to climate change.[4] Note that when we do not reference climate change, there is considerably more mass of responses concentrated at the left tail of the distribution. Instead, for our baseline question that does reference climate change the mass shifts to the right, illustrating that rare disasters are salient of climate change: When they are reminded of climate change, respondents tend to assign a higher probability to rare disasters than otherwise. For what follows, it is thus important to keep in mind that the answers to Q3 should not be understood as probabilities which respondents entertain unconditionally, but rather in the specific context of the climate change debate/narrative.[5]

In light of our results, it seems noteworthy that earlier work has documented overestimation of rare disaster probabilities in different contexts. Lichtenstein et al. (1978) show that individuals tend to overestimate the probability of potentially lethal events such as cancer or car accidents. Both Heimer et al. (2019) and Fischhoff et al. (2010) report similar results for

16.36 percent in direct response to Question 3.

[4]The follow-up sample underlying the bottom-right panel was obtained during one day, while the sample underlying the left-hand side panel ran considerably longer and thus smooths out day-to-day fluctuations.

[5]In Appendix B we report results for further variants of Q3. In particular, comparing the magnitude of the event to a 2 percent loss of GDP in the wording of the question does not lead to a statistically significantly different probability assessment. Only an increase in the comparison to a 10 percent GDP loss leads to an economically and statistically significant drop in the probability estimate, underlining the meaningful information contained in the responses. Compared to the baseline question for disasters during the next year, questions that ask about longer 10-, 20- and 30-year horizons reveal that respondents expect the probability of large disasters to increase.

general survival probabilities of young individuals. In a different setting, the probability of lung cancer for smokers is overestimated by the general public (Viscusi, 1990, 2016). Importantly, while individuals' subjective beliefs may, depending on the context, give too much weight to the risk of certain rare disasters, the two-stage model of rare events by Fox and Tversky (1998) suggests that it is those subjective beliefs that households act upon. Indeed, prospect theory implies that households might even overweight their expected probability for a rare negative event when making (financial) decisions (Barberis, 2013a).[6]

The availability heuristic put forward by Tversky and Kahneman (1973) has been understood to explain such overestimation of small objective rare disaster probabilities: Individuals overstate the probability of events for which they have a more frequent or salient recall from memory. Indeed, Lichtenstein et al. (1978) show that subjective probability judgements increase in media coverage of the respective event or personal experience. More recently, Bordalo et al. (2019) operationalize this heuristic based on a model for recall from a personal memory database. In a dynamic setting, their model of "diagnostic expectations" implies that the perceived probability of an event increases after realizations due to extrapolation (Bordalo et al., 2020).[7] Lastly, and more generally, recent work shows that expectations as measured in surveys impact economic decisions in various contexts (Coibion et al., 2021, 2022, 2019; Enders et al., 2022).

2.3 Covariates and Determinants of Climate-Change Expectations

In what follows, we document that responses vary in an intuitive way with a range of indicators and potential determinants of disaster expectations, such as media consumption habits, self-reported experiences, local conditions and socio-demographic characteristics as well as information treatments.

First, in line with earlier work cited above, we find an important role for media consumption—TV and newspapers—for the perception of disaster risks and other economic variables (see again, for example, Carroll, 2003). To establish this point, we relate the reported probability of a rare natural disasters to measures of respondents' preferred TV stations and newspapers and show results in Table 5. Respondents who consume news from neither a major TV station nor a major newspaper exhibit approximately 5 percentage points lower rare disaster probabilities. This effect corresponds to a reduction of the perceived mean disaster probability by almost a third. By contrast, respondents who watch the news instead have approximately 3.3 percentage point higher disaster beliefs. A more detailed breakdown shows that specific TV stations/newspapers impact the perceived disaster probability of respondents, even though systematic differences between different stations are not readily obvious, see Appendix B. For example, readership of the Wall Street Journal or the Los Angeles Times has a negative association with perceived

[6]Prospect theory suggest that individuals' overweight rare disaster probabilities in their real life actions. Barberis (2013b) provides a review of prospect theory and insurance decisions. At the same time, Barron and Yechiam (2009) suggest that rare disasters are often overestimated in their frequency but become under-weighted in decision functions by households, as individuals build their decision on the most recent realizations, where the disaster has probably not occurred.

[7]Moreover, Bordalo et al. (2022) show that selective, automatic memory can account for both over- and underestimation of novel risk: While younger individuals with an arguably low risk of a lethal Covid infection overestimate the risk, older respondents underestimate their personal death probability. Relevant experiences can help with simulating the scenario for which the probability is assessed while irrelevant experiences trigger interference in that simulation.

Table 5: Reported Probability of Disaster and Media Usage

	(1)	(2)	(3)
no major TV station	-3.299***		
	(-3.96)		
no major newspaper		-3.067***	
		(-5.17)	
consume major TV station×no major newspaper			-2.167***
			(-3.31)
no major TV station×consume major newspaper			0.785
			(0.38)
no major TV station×no major newspaper			-4.951***
			(-5.45)
Constant	17.14***	17.48***	17.81***
	(6.85)	(7.00)	(7.12)
State and Month FE	✓	✓	✓
Demographic Controls	✓	✓	✓
N	7141	7123	7123
R^2	0.0587	0.0608	0.0620

Notes: Regression relates reported probability of disaster to media usage; only data for respondents that did not receive any treatment considered 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.

disaster probabilities, but readership of USA Today has a positive association. Consumption of TV channels always tends to raise probabilities. When we consider economic damages and the growth impact of climate change as outcomes (instead of the perceived disaster probabilities), we find that respondents who do not watch TV and do not read newspapers expect significantly lower disaster costs and somewhat higher GDP growth, see Appendix B. By and large, these results support the relevance of the availability heuristic: reporting on climate change or natural disasters in the US and the rest of the world, these incidents are easier to recall for individuals that consume media.

Second, personal exposure to climate-change events also matters for climate-change expectations. For our data, in particular, we find a strong association between the exposure to certain types of rare natural disasters and climate-change beliefs. To measure such exposure, we rely on official data for natural disaster declarations at the county level for the last 10 years from the Federal Emergency Management Agency (FEMA, Federal Emergency Management Agency, 2020). Within our sample 15.7 percent of respondents live in a county with a wildfire-related disaster during the last 5 years, 28.4 percent with a hurricane, tornado, or typhoon event and 26.1 percent with a flood in the past. From the same data source, we also construct a more aggregate measure using the total number of events (fire, flood, and hurricane, etc.) within a state during the last 5 years, divided by the total land area of the state in square miles. We relate the reported probability of a disaster not only to respondents' disaster experience but also to a measure of "official" disaster risk. 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", or "High."

We report detailed results in Appendix B and summarize the main findings as follows: First, respondents within counties with a past record of natural disasters tend to expect higher disaster probabilities than respondents without a disaster experience, by more than 3 percentage points, for counties that have experienced a hurricane in the last 5 years. Similarly, respondents living in a state with a large number of reported wildfire events relative to their area report significantly higher disaster expectations. Second, concerning future risks, in particular the increased possibility of hurricanes drives up expectations of a future large disaster by up to 5 percentage points. These results suggest that exposure to disaster risk influences disaster expectations, consistent with findings from other contexts, such as inflation or house-price expectations (Kuchler and Zafar, 2019; Malmendier and Nagel, 2011).

Third, we provide evidence that demographic and socioeconomic characteristics relate to climate-change expectations (Appendix B). This insight is based on simple regressions which control for state and time fixed effects. We find that those aged 55 and above, relative to the youngest age group, expect climate change to boost growth, while highly educated respondents and those with middle and higher income tend to report an expected adverse impact of climate change on growth, though not significantly for high-income respondents. Relative to the youngest age group, those aged 55 and above instead expect significantly lower damages due to climate change in the future. Women tend to expect larger damages and report more more pessimistic expectations when it comes to disasters. For instance, on average they believe large disasters to be 4 percentage points more likely than men. This finding echos earlier findings according to which women tend to be more risk-averse than men (e.g., Borghans et al., 2009; Charness and Gneezy, 2012; Gustafson, 1998; Jianakoplos and Bernasek, 1998).[8] We also consider how self-reported disaster experiences and political attitudes impact expectations. Democrats, all else equal, believe that a very large rare disaster is more likely, by 1.6 percentage points, compared to independent voters. Republicans perceive damages to be 0.14 percentage points lower relative to Independents. There seems to be a clear division in beliefs between Democrats and Republicans, once it comes to natural disasters, with democrats holding more pessimistic beliefs. Survey participants that have experienced either a natural disaster or indicate that they have felt the impact of climate change report disaster probabilities that are 5.8 and 4.1 percentage points higher, respectively.

Our survey also features behavioral questions, and we find that they co-move with climate-change beliefs in an intuitive way. Notably, a substantial fraction of respondents indicates that they have changed their mobility or other lifestyle decisions due to climate change. For example, 31 percent of respondents say they have changed their mobility decisions and 25 percent indicate that they try to avoid products made from plastic, due to environmental concerns. A probit

[8]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 percent of the variance across respondents in an online survey.

Table 6: Reported Probability of Disaster and Information Treatment

	(1) Growth	(2) Disaster Costs	(3) Disaster Prob.	(4) Disaster Prob.
Newspaper (T1)	-0.0296	0.00931	0.741	0.874**
	(-0.77)	(0.35)	(1.60)	(2.73)
Historic Disaster Size (T2)	-0.0489	-0.0727**	-1.378**	-0.828**
	(-1.28)	(-2.73)	(-3.10)	(-2.72)
Historic Disaster Frequency (T3)			-1.652	-1.831**
			(-1.71)	(-2.76)
GDP Loss Info (T4)	-0.00245	0.0241	0.361	0.0989
	(-0.04)	(0.59)	(0.51)	(0.21)
Constant	0.158	1.411***	18.07***	13.85***
	(1.13)	(12.83)	(11.07)	(11.11)
State and Month FE	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
Drop largest 25% probabilities	×	×	×	✓
N	16834	15717	18644	16142
r2	0.0167	0.0483	0.0479	0.0468

Notes: regression relates reported probability of disaster to information treatment (one treatment per respondent); t statistics in parentheses, based on robust standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights and Huber-robust weights to ensure that sample is representative and independent of outliers, respectively. For the treatments, refer to table 3 or Appendix B. Column (4) drops respondents with the 25% highest disaster expectations (Q3) from the sample.

regression shows that decisions are statistically significantly related to the perceived probabilities of large natural disasters, reported in response to Question 3. A 1 percentage point higher perceived probability, for instance, is associated with a 0.25 percentage point higher probability of not taking a flight, see Appendix B.

The association of individual beliefs about natural disaster probabilities with financial decisions is of particular importance for macroeconomic trends, both on an intensive margin, that is, the riskiness of investments, as well as an extensive margin, that is, the consumption-savings decision. Indeed, we find on the intensive margin of investments that the individual disaster probability is significantly related to the probability of both refraining from investments that are considered harmful to the climate and to divesting one's portfolio, due to potential climate change risks. Balasubramaniam (2021) reports similar results, namely that households that have experienced natural disasters—either directly or indirectly via friends or relatives—shift their portfolio choices away from risky assets. In similar instances, Fier and Carson (2015) report a higher demand for life insurance polices. Likewise, several studies find that experienced disasters or disaster expectations increase the demand for disaster-related insurance, such as flood or home owner insurance policies (see, for example Gallagher, 2014).

Finally, Table 6 shows how specific information treatments alter the responses in the survey. Column 4 reports results when we remove extreme outliers with the top 25% of responses—who report a disaster probability of 50% or higher. Here, in response to the newspaper treatment, respondents show an up to 0.8 percentage points higher expected probability. The historic information treatments lower expected probabilities as expected. Once we perform these regressions on a subsample for respondents with high probability literacy, we find no effect of the treatments, except in the case in which we provide information about the size of disasters in the past. This lowers the reported probability of a large disaster considerably, by more than 1.6 percentage points, see Appendix B. These findings suggest that respondents with high probability literacy react more selectively to suggestive information in assessing disaster probabilities.

3 A New Keynesian Model with Rare Disasters

In what follows, we rely on a New Keynesian model to study how climate-change expectations can impact the business cycle. According to our survey, respondents do not expect much of an effect of climate change on growth. Yet they assign a high probability to climate-change related large disasters. For this reason, we abstract from growth effects and rely on a version of the New Keynesian model that features rare disasters, as put forward by Fernández-Villaverde and Levintal (2018).[9] We stress that even though the model assumes rational expectations, we do not require expectations about rare disasters to conform with the actual law of motion. Since we are only interested in the effect of disaster expectations, our setup could accommodate a range of behavioral distortions when it comes to disaster expectations.

We first establish a number of results in closed form using a simplified version of the model. While the full model features Epstein-Zin preferences and endogenous capital accumulation, 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, uses the simplified version of the model to derive analytical results. We specify and calibrate the full model and report simulation results in Section 5.

3.1 Households

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

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

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

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

[9] Earlier work on rare disasters assumes an exogenous process for output to study the implications of rare disasters for asset prices (Barro, 2006, 2015). Gourio (2012) uses a real business cycle model to show that variations in disaster risk can play a significant role for the business cycle.

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

$$\omega_t = \bar{\omega}^{(1-\rho_\omega)} \omega_{t-1}^{\rho_\omega} e^{\sigma_\omega \epsilon_{\omega,t}}, \tag{3.3}$$

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

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

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

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

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

as well as a solvency constraint. In the expression above, E_t is the expectations operator, $\beta \in (0,1)$ is the discount factor, $P_t(i)$ is the price of variety i, and D_t are dividends. The first term on the left of (3.5) captures all expenditures on goods used both for consumption and investment.

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

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

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

3.2 Firms

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

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

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

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

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

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

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

where $Y_{t+k|t}$ is the demand in period $t+k$, given prices set in period t, $Q_{t,t+k}$ is the stochastic discount factor, and $\mathcal{C}(\cdot)$ is the cost function. The parameter χ measures the extent of price indexation. Defining $\Pi_t = \frac{P_t}{P_{t-1}}$ and $\Pi_t^* = \frac{P_t*}{P_{t-1}}$, the price level evolves such that the following holds:

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

3.3 Market Clearing and Monetary Policy

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

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

The risk-free bond B_t is in zero net supply. Lastly, we specify monetary policy in terms of interest-rate feedback rules, considering different variants in what follows. 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 obtain a number of closed-form results. We solve the full model numerically in Section 5.

4.1 Canonical Representation

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

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

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

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

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. We also assume that capital is not subject to a disaster shock and constant over time: $K_t = \bar{K}$. Last, we assume that shocks to the disaster probability are purely transitory shocks ($\rho_\omega = 0$).

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

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

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

Equation (4.3) is the New Keynesian Phillips curve, with parameter restrictions $\kappa = \lambda(\sigma + \frac{\varphi+\alpha}{1-\alpha})$ and $\lambda = \frac{(1-\theta)(1-\beta\theta)}{\theta} \frac{1-\alpha}{1-\alpha+\alpha\epsilon}$. It links inflation, π_t, 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 be obtained 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. To characterize the nature of shocks to disaster expectations, we focus 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:*

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

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 ω_t and the size of a disaster μ, that is, in its extensive and intensive margins, respectively. Intuitively, the more likely and the larger a disaster, the larger the desire to save in order to stabilize consumption over time and across states of the world. Since there is no vehicle to save in the simplified economy—an assumption we relax in the next section—the natural rate of interest 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 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:

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

Here, the parameter $\phi_r \in \{0, 1\}$ captures the response of the policy rate to the natural rate. We focus on two limiting cases: the monetary authority either tracks the natural rate perfectly ($\phi_r = 1$) or not at all ($\phi_r = 0$). Results carry over to intermediate cases in a straightforward way. In addition, we assume throughout that the response of the interest rate to inflation is sufficiently strong to ensure the existence of a locally unique equilibrium. In case the response is constant over time, this requires $\phi_{\pi,t} = \phi_\pi > 1$ (Taylor Principle). But specification (4.5) is more general and allows the response to inflation to be time-varying. In this way, we can capture the possibility that monetary policy is temporarily unresponsive to inflation and set $\phi_{\pi,t} = 0$, but assume that it switches to being active with sufficiently high probability in a later period.[10] Such temporary inaction appears plausible in times of low interest rates when central banks are constrained by the effective lower bound (ELB) on the policy rate.

In order to solve the model under alternative scenarios for monetary policy, we rely on an approximation of the driving process for the disaster probability (3.3). In this way, we can define the deviation of the disaster probability from its mean, $\hat{\omega}_t \equiv \omega_t - \bar{\omega} = \bar{\omega}\sigma_\omega\epsilon_{\omega,t}$ and arrive at

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

$$\tilde{y}_t = \begin{cases} 0, \\ \Pi_y^0 + \Pi_y^1\hat{\omega}_t, \\ \Gamma_y^0 + \Gamma_y^1\hat{\omega}_t, \end{cases} \qquad \pi_t = \begin{cases} 0, & \text{if } \phi_r = 1 \text{ and } \phi_{\pi,t} = \phi_\pi > 1 \\ \Pi_\pi^0 + \Pi_\pi^1\hat{\omega}_t, & \text{if } \phi_r = 0 \text{ and } \phi_{\pi,t} = \phi_\pi > 1 \\ \Gamma_\pi^0 + \Gamma_\pi^1\hat{\omega}_t, & \text{if } \phi_r = 0 \text{ and } \phi_{\pi,t} = 0; \end{cases}$$

where $\Pi_y^0, \Pi_\pi^0, \Pi_y^1, \Pi_\pi^1 \leq 0$ *and* $\Gamma_y^0, \Gamma_\pi^0, \Gamma_y^1, \Gamma_\pi^1 \leq 0$*. It holds that* $\Gamma_x^0 < \Pi_x^0$ *and* $\Gamma_x^1 < \Pi_x^1$ *for* $x \in \{y, \pi\}$*. If* $\phi_\pi \to \infty$*,* $\Pi_y^0 \to 0$*,* $\Pi_y^1 \to 0$ *as well as* $\Pi_\pi^0 \to 0$ *and* $\Pi_\pi^1 \to 0$*.*
Proof. *See Appendix A.3.* ■

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 ($\phi_r = 1$), see the top line in the proposition. 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 (see Propostion 1).

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

[10] Specifically, in order to ensure the existence of a (locally) unique equilibrium we require $P(\phi_{\pi,t+1} > 1) = 1 - \zeta$, where ζ needs to satisfy the following inequalities: $(1 - \zeta)(1 - \beta\zeta)\sigma > \kappa\zeta > 0$. Note moreover that whenever the response to inflation is non-zero, we assume it to be sufficiently aggressive to satisfy local equilibrium determinacy, see Appendix C.3 for details.

case, monetary policy no longer responds to the natural rate, but only to inflation. The second line of Proposition 2 shows that the result is a contraction of output and inflation. Importantly, as the terms Π_y^0 and Π_π^0 indicate, there is a permanent downward effect on the output gap and inflation, even if disaster risk is at its mean value ($\hat{\omega}_t = 0$). This is because disaster risk is one-sided: A constant disaster risk depresses the economy permanently relative to a steady state which features no disasters in case monetary policy does not track the natural rate. Actual interest rates are too high. Time-varying upward shifts in the disaster probability, likewise induce a further contraction because they are not fully stabilized (and conversely for downward shifts), as the non-positive terms Π_y^1 and Π_π^1 indicate. Still, in the limiting case where the response to inflation is infinitely aggressive ($\phi_\pi \to \infty$), monetary policy does effectively insulate the economy from the adverse impact of disaster expectations.

A second complication is that 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 ($\phi_{\pi,t} = 0$), and sufficiently responsive only later (see again footnote 10). The result is a stronger decline of inflation and the output gap, as the third line in Proposition 2 shows: Note that the Γ-terms are more negative than the Π-terms. We conclude that the ELB will generally amplify the adverse impact of disaster expectations, a result that is akin to what has been established elsewhere, notably in the context of government spending shocks (e.g., Woodford, 2011).

More generally, and in line with the results of Gourio (2012), disaster expectations cause business cycle fluctuations—unless they are offset by monetary policy. The following proposition establishes this point formally by linking the volatility of disaster risk, $var(\hat{\omega}_t) = \sigma_\omega^2$, to the volatility of the output gap and inflation:

Proposition 3. *Given the simplified model, as represented by equations* (4.3) *and* (4.4)*, the variance of inflation and the output gap are functions of* σ_ω^2*:*

$$var(\tilde{y}_t) = \begin{cases} 0 \\ {\Pi_y^1}^2 \sigma_\omega^2, \\ {\Gamma_y^1}^2 \sigma_\omega^2, \end{cases} \qquad var(\pi_t) = \begin{cases} 0, & \text{if } \phi_r = 1 \text{ and } \phi_{\pi,t} = \phi_\pi > 1 \\ {\Pi_\pi^1}^2 \sigma_\omega^2, & \text{if } \phi_r = 0 \text{ and } \phi_{\pi,t} = \phi_\pi > 1 \\ {\Gamma_\pi^1}^2 \sigma_\omega^2, & \text{if } \phi_r = 0 \text{ and } \phi_{\pi,t} = 0; \end{cases}$$

where for $\phi_r = 0$ *it holds that* $\frac{\partial var(\pi_t)}{\partial \phi_\pi} < 0$ *and that* $\frac{\partial var(\tilde{y}_t)}{\partial \phi_\pi} < 0$*. The above follows directly from the solution for* $\tilde{y}_t$ *and* π_t *shown in Proposition 2.* ■

5 Quantitative Model Analysis

We now turn to the full model to flesh out the transmission mechanism of disaster expectation shocks. For this purpose, we calibrate the model to the main results of the survey. In a first step, we specify functional forms and discuss parameter values. Then we present simulation results.

5.1 Model Solution

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

$$E_t d_{t+1} = \omega_t = \bar{\omega}^{(1-\rho_\omega)} \omega_{t-1}^{\rho_\omega} e^{\sigma_\omega \epsilon_{\omega,t}}, \tag{5.1}$$

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

We run the model for $T = 10,000$ periods and report average results over 100 simulations. We report the mean of key variables and business-cycle statistics for the risky steady state, defined by the values to which variables converge in the absence of disaster shocks (see, for example Fernández-Villaverde and Levintal, 2018; Gourio, 2012). Specifically, we simulate shocks to the probability of disaster based on the exogenous process (3.3) while setting the actual disaster dummy to zero $\{d_t\}_{t=0}^{T} = 0$. This approach, in addition to allowing us to focus on the role of expectations, has two further advantages. First, it ensures consistency as we compare below the model predictions to actual time-series observations for a sample where no large disaster (with GDP losses of 5 percent) took place. Second, it allows us to remain agnostic about the objective probability of disasters which is arguably unknown. All that matters for our analysis are disaster expectations, as measured in our survey.

5.2 Calibration

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

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

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

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

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

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

Table 7: Model Calibration

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

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

adjustment costs $S(\cdot)$ in equation (3.2) take the form:

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

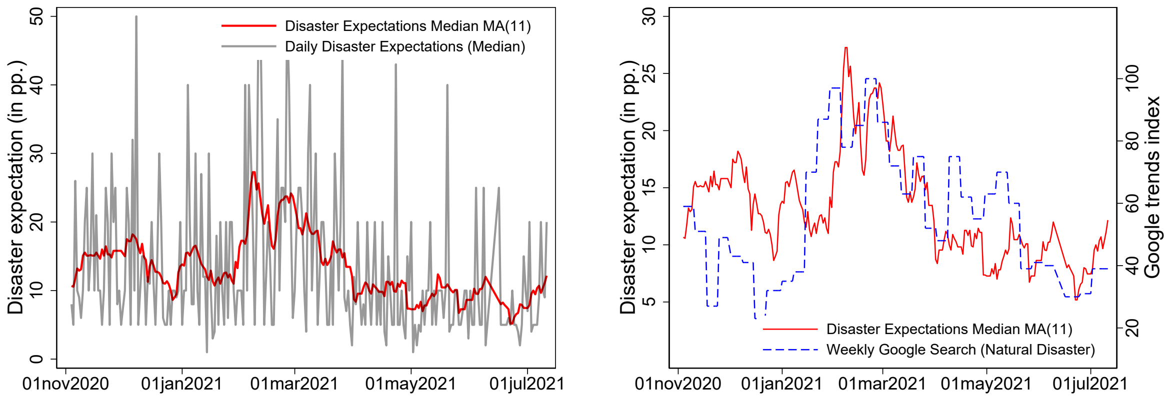
where κ_k is a positive constant. Last, we specify a fairly standard interest rate rule that allows for a response of the interest rate to output growth (with response coefficient ϕ_y) in addition to inflation as well as for interest-rate smoothing:

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

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

We calibrate the model to quarterly frequency and report parameter values in Table 7. In line with our survey, we set the disaster size to $\mu = 0.05$. Next, we set $\bar{\omega} = 0.025$, implying an annual average disaster probability of 10% in line with responses to our survey. We further assume $\rho_\omega = 0.9$, similar to the autocorrelation coefficient that Fernández-Villaverde and Levintal (2018)

Figure 3: Variation of disaster expectations over time



Notes: The left panel shows time series for the daily median of disaster expectations as measured in survey (black line) and 11-day moving average, based on Huber robust and survey weights (red line). The right panel shows the median disaster expectation (left axis) as well as a weekly index for Google searches for "Natural Disaster" (right axis). The unconditional correlation between the weekly Google Trends index and the weekly median of disaster expectations is 0.42.

use to specify the shock process for the disaster size. We set the standard deviation of the disaster probability shock, σ_ω, to 0.12, consistent with the extent of the time-series variation that we observe for Google search queries for "natural disaster" in the period from 2004 until 2021. We resort to Google search queries because for the 9-month period for which our survey ran daily there is a high degree of co-movement of these search queries and the probability assigned to rare disasters, as shown in Figure 3. The left panel shows the daily median of the reported probabilities of a large disaster in grey (Question 3). The series is very volatile, presumably reflecting the moderate number of daily responses. The red line in the same panel represents the 11-day moving average across daily medians. This series is much smoother, but still shows considerable variation over time. In the right panel, we reproduce this series jointly with a weekly Google search index for "natural disaster". Both series show a strong co-movement during our sample period.[14]

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

We further target the volatility of output, investment, and inflation for the pre-crisis period 1983Q1–2007Q4, computed based on quarterly time-series observations from which we remove

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

Table 8: Model Predictions

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

Notes: Standard deviation computed on pre-crisis sample 1983Q1—2007Q4; source: FRED (OUTNFB for real GDP, GPDIC1 for real investments, GDPDEF for inflation). GDP and Investment are in logs. Data are HP-filtered with filter weight of 1,600. Natural rate and inflation are average values for 2010–2019; estimate for natural rate by New York Fed based on approach by Laubach and Williams (2003). Model counterparts: average over 100 simulations for 10,000 periods each (standard errors in parenthesis). Statistics for the risky steady state are reported for annualized variables. For the simulated time series for output and investment, we apply an HP-filter with smoothing parameter of 1,600 before computing standard deviations (the process for TFP growth in equation (3.8) has a unit root even though we abstract from trend growth).

an HP-filtered trend. Setting $\kappa_k = 0.75$ allows the model to predict a volatility of investment in the right ballpark. The same holds for the volatility of output and inflation, as we set standard deviation of TFP growth to $\sigma_A = 0.013$ and the Calvo parameter to $\theta = 0.92$. This value implies an average price duration of 10 quarters. The value for σ_A is also in line with evidence by Fernald (2014). Lastly, we set the inflation target to 2% in accordance with Fed policies.

5.3 Simulation Results

We present the results of the model simulations in Table 8. The top panel reports the standard deviation of inflation, investment, output and the output gap. It contrasts the empirical moments (left) to the predictions of the model under the baseline calibration (second column). The predicted standard deviations align well with their empirical counterparts. This alignment is by construction: Our stylized model is calibrated to capture key features of the business cycles. This is the prerequisite for quantifying the contribution of climate-change related disaster expectations to the business cycle. A second purpose of our quantitative analysis is to establish that the mechanisms of the simplified model also operate in the full model, which allows for investment.

Given that the model can replicate key moments of the business cycle, we use it to quantify the contribution of climate-change related disaster expectations to the business cycle. Recall that we calibrate these expectations to capture the results of our survey. We now simulate a version of the model without disaster expectations and report results in the third column of Table 8. The rightmost column of the table shows the difference between the baseline and the model without disaster expectations: It turns out that climate-change related disaster expectations—as measured by our survey—make a non-trivial contribution to the business cycle. In particular, they raise the volatility of inflation and the output gap by 7-8 percent.[15]

Climate-change related disaster expectations also alter the first moments of key variables. We establish this formally in Proposition 2 above. Now we report key statistics for the risky steady of the full model in the bottom panel of Table 8. Again, the calibration of the model ensures that the natural rate of interest in the risk steady state is 0.68% on an annualized basis, in line with the evidence for the decade since the Global Financial Crisis. Quantitatively, the model without disaster expectations features a considerably higher natural rate in the risky steady state (Column 3): We find that disaster expectations lower the natural rate by about half a percentage point from 1.13 percent to 0.68 percent. This is a sizeable effect, given that the level of the natural rate is already quite low. We also observe that inflation in the risky steady state is quite a bit below the 2% target which rule (5.4) mandates, just like in the data for the period 2010–19. The output gap is also negative in the risky steady state because of disaster expectations (see our discussion of Proposition 2 in Section 4.2 above).[16]

Finally, we turn to the transmission of disaster expectations shocks—as a prototypical news shock. Figure 4 shows the impulse response functions assuming alternative scenarios for monetary policy. In each instance, we consider a one-standard-deviation shock to the perceived disaster probability, implying a temporary increase in the quarterly disaster risk from 2.5% to 2.8%. In the figure, the vertical axis measures deviations from the deterministic steady state, while the horizontal axis measures time in quarters.[17] The red solid line shows the responses for the baseline model in which monetary policy follows the interest rate rule specified in equation (5.4) above. The blue dashed lines, instead, show the adjustment under the assumption that monetary policy tracks the natural rate, a scenario analyzed in Section 4.2 above. Last, the black dotted line shows the adjustment for a scenario under which monetary policy does not respond to the shift in climate-change related disaster expectations, for instance, because it is constrained by the effective lower bound.[18]

As discussed in Section 4.2 above, the response of the natural rate is central to the transmis-

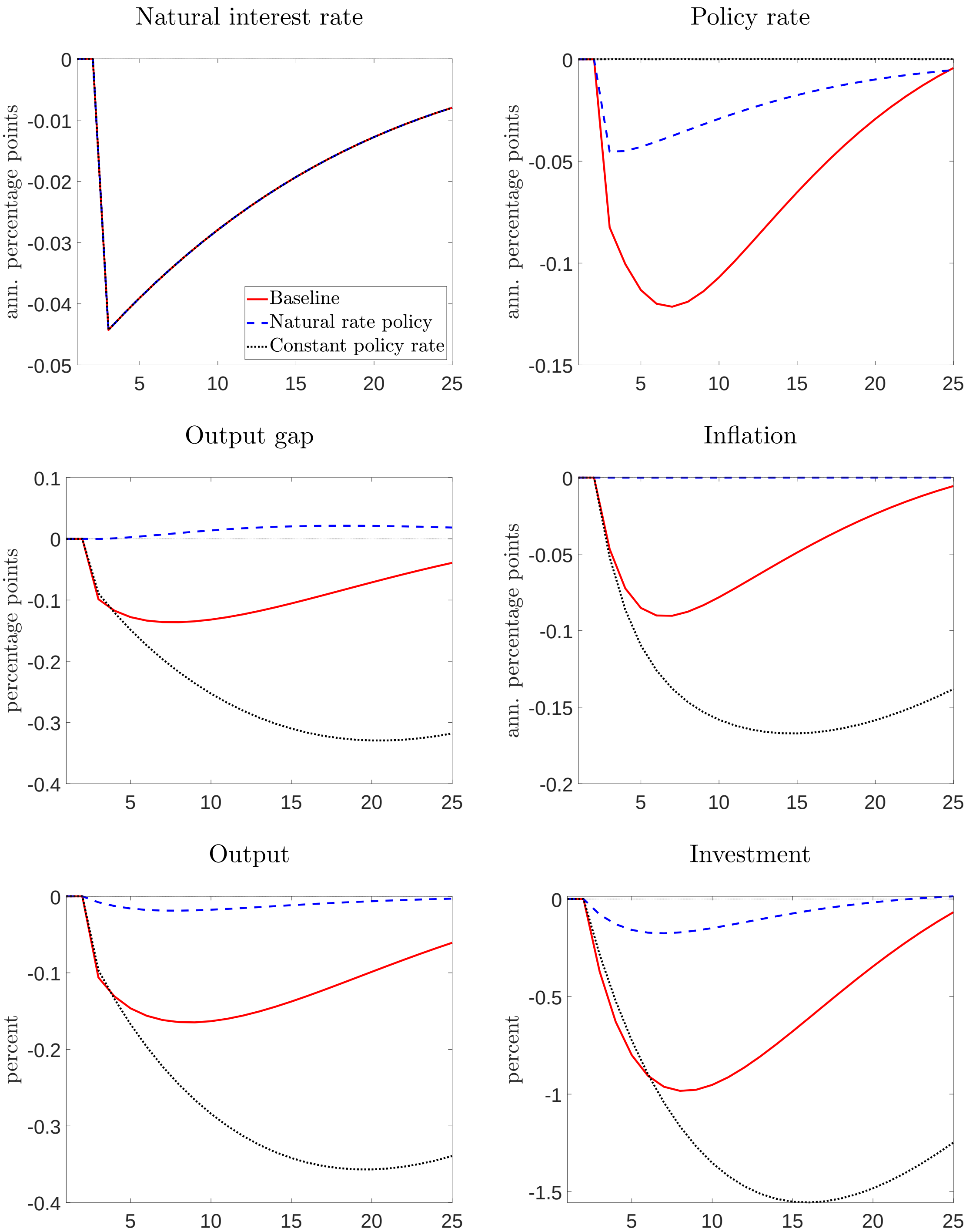
[15]Their contribution to the volatility of output is more limited. Nevertheless, they raise the volatility of the output gap while leaving the volatility of potential output almost unchanged (not shown). This is because shocks to disaster expectations lower the covariance of output and potential output because they mostly operate via aggregate demand.

[16]In the absence of disaster expectations, inflation is still below target because TFP shocks impact the economy asymmetrically.

[17]We compute impulse responses around the deterministic steady state to keep the analysis of a constant-interest-rate policy tractable. To study the constant-interest-rate policy case, we feed into the model a sequence of monetary policy shocks which offsets the endogenous response implied by the interest rate feedback rule.

[18]We approximate such a scenario by specifying a sequence of monetary policy shocks which offset the endogenous policy response to the disaster-probability shock.

Figure 4: Impulse responses to disaster expectation shock



Notes: Impulse responses to an increase of the disaster probability by one standard deviation. The vertical axis measures deviations from the deterministic steady state; the horizontal axis measures time in quarters. Red solid line: baseline policy as specified in Equation (5.4); blue dashed line: policy tracks natural rate; black dotted line: constant interest rate policy.

sion of the shock. It is shown in the upper-left panel of the figure and by definition independent of the monetary policy rule in place. The natural rate drops by some 4 basis points relative to the pre-shock level. The effect is gradually reversed as the expected probability of disaster converts back to its pre-shock level (with persistence parameter $\rho_\omega = 0.9$). The response of the rest of the economy crucially depends on how monetary policy adjusts short-term interest rates. We show the response of the policy rate in the upper-right panel. The case where monetary policy tracks the natural rate (blue dashed lines) provides a benchmark. Here inflation (shown in the middle-right panel) is perfectly stabilized, and the output gap remains almost closed (middle-left panel).[19] In contrast, we observe a sizeable response of the output gap and inflation under the baseline policy. This is the result of insufficient monetary accommodation under the baseline policy rule (5.4). While the short-term policy rate initially declines more strongly compared to what happens under the natural-rate policy, the order is later reversed.[20] And, eventually, it is the entire path of (real) short-term rates which determines the monetary stance in the New Keynesian model (e.g., Corsetti et al., 2012). In the last scenario under consideration, that is, when monetary policy is not responding to the shock at all, there is further amplification of the shock: The contraction of the output gap and inflation is even more pronounced.

These responses offer a quantitative illustration of the results established in Section 4.2 above, see Proposition 2 in particular. The bottom panels of Figure 4 provide additional insights. They display the adjustment of output and investment, respectively. Recall that the simplified model does not allow for investment dynamics. Now we observe for the full model that the shock triggers a sizeable contraction of investment. Intuitively, as disaster risk goes up, the expected return to capital declines. Hence the decline of investment. However, even though investment declines, this does not alter the transmission mechanism of disaster expectations in a fundamental way. First, we note that the natural rate declines in the full model just as in the simple model. Second, we observe that the adjustment of output and the output gap is very similar, implying that movements in potential output (not shown) are quite moderate in all policy scenarios. Against this background, we conclude that shifts in disaster expectations operate mainly via aggregate demand—not only in the simple but also in the full model.

6 External validation

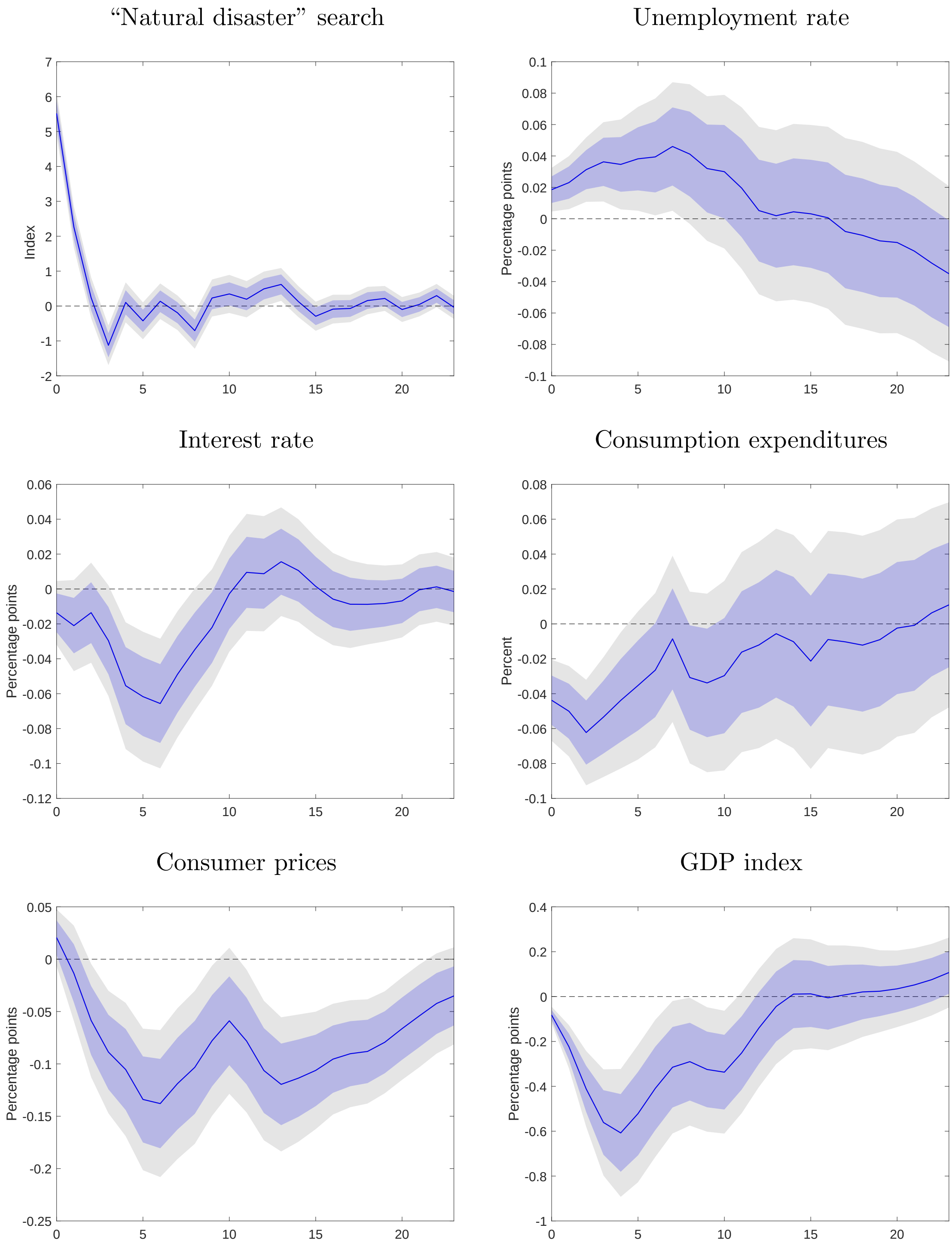
Our survey provides us which a well-defined measure of the expected economic impact of climate change. Our model, in turn, once calibrated to the survey, provides us with a quantitative account of the transmission of disaster expectation shocks. In what follows, we present further evidence based on a simple time-series analysis as a way to validate externally the mechanism which operates at the heart of the model.

Our survey only spans 9 months and is thus not suitable for a time-series analysis. However, as illustrated in Figure 3 above, the survey responses correlate strongly with Google search querries for "rare disasters", and the Google search index is available since 2004. In what follows, we exploit the variation in this variable as a proxy for the variation in disaster probability beliefs. In particular, we estimate a VAR model on monthly observations for the period 2004:M1 to

[19]In Section 4.2 the output gap is zero in case monetary policy tracks the natural rate. This is because divine coincidence is obtained in the New Keynesian model only when inflation is stabilized at exactly zero (Alves, 2014). In addition, reduced investment decreases the capital stock and thus potential output. Investment declines due to the increased expected risk of a disaster.

[20]At the end of the time horizon considered in Figure 4, the policy rate under the baseline rises considerably more than in the case of the natural-rate policy.

Figure 5: Macroeconomic Impact of Disaster Expectations



Notes: impulse responses to identified disaster expectation shocks. Solid line represents point estimate, shaded areas 68% and 90% confidence bounds. Shock size: one standard deviation; horizontal axis measures time in months, vertical axis deviation from pre-shock level.

2019:M12, that is, on data up until the COVID-19-induced recession. The baseline VAR model includes the Google search index for "natural disasters" as well as as three macroeconomic indicators: the unemployment rate (FRED: UNRATE) as a monthly measure of real activity, long-term interest rates (FRED: DGS10), and the log of real personal consumption expenditures (FRED: PCEC96). The VAR model includes 12 lags of the endogenous variables, a constant and a linear time trend. In addition, the model includes a time series of actual disaster costs as an exogenous variable, both its contemporary value as well as 12 lags. We obtain these data from NCEI (2020) and scale them by GDP.

We identify exogenous shifts in search queries for "natural disasters" through a recursive identification scheme where we order the search series first. In this way, we rule out a contemporaneous impact of macroeconomic indicators on search queries. This restriction appears fairly mild because there is no obvious link from the economy to the "natural disaster" search, notably at monthly frequency. However, because the VAR features current and lagged values of disaster costs, the innovations in disaster search are likely orthogonal to current disasters. Hence, our interpretation as shocks to disaster expectations. Under our identification scheme, these shocks may impact the macroeconomic indicators in the VAR immediately.

Figure 5 shows the impulse response functions to a shift in natural disaster expectations, as measured by the Google search query—that is, the responses to a shock to disaster expectations. In the figure, the vertical axis measures the deviation from the pre-shock level, the horizontal axis measures time in months. The solid line represents the point estimate to a one-standard deviation shock, while shaded areas indicate 68% and 90% confidence bounds, respectively. The shift in the search query, shown in the upper-left panel, is rather short-lived. It triggers a persistent increase of the unemployment rate (upper-right panel), which lasts for about a year. Interest rates, shown in the middle-left panel, decline during that year, and personal consumption expenditures also drop (middle-right panel). In sum, the shift in disaster expectations has a contractionary impact on the macroeconomy.

We further corroborate this notion as we reestimate the VAR model while replacing the time series for consumption with, in turn, the log of the CPI (FRED: CPIAUCSL) and an index for GDP that we compute based on the Brave-Butters-Kelley measure of monthly real GDP growth (FRED: BBKMGDP). Including these time series in the VAR rather than consumption does not alter the impulse responses of the other variables in a meaningful way but allows us to economize us on the degrees of freedom while fleshing out the transmission mechanism in more detail. We show the responses of the additional variables in the bottom row of Figure 5. We observe that consumer prices and GDP decline persistently as well in response to a shock to disaster expectations, just like the model predicts. In sum, the VAR evidence on the transmission of a disaster expectation shock conforms well with the predictions of the model, even though the underlying methodologies are fundamentally distinct.

7 Conclusion

How do climate-change expectations impact economic activity at business-cycle frequency? This question is interesting in itself but also because climate change represents news—anticipated changes about the economy's fundamentals. To address this question, we measure climate-change expectations, or more specifically, beliefs about the economic impact of climate change on the basis of a representative, high-frequency consumer survey in the U.S. 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. Our findings are consistent with the notion that natural disasters are salient of climate change and, hence, capture peoples' mind when thinking about climate change. In a second step, we calibrate a New Keynesian model with rare disasters to capture the main results of the survey. We hammer out, in closed-form and through simulations the nature of disaster-expectation shocks: they operate like adverse demand shocks. Monetary policy thus plays a key role when it comes to their business cycle impact.

Hence, our analysis has a direct bearing on the policy debate about climate change in which central banks have started to become involved recently. What comes out of this debate and what measures will play a significant role in the future is highly uncertain, just like the consequences 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.

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A Survey Questions

Demographic Questions

First, we ask all respondents the following demographic questions:

D1: Please enter your age.

D2 Please indicate your gender.

O Male
O Female
O Other

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

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

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

O Yes
O No

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

O Less than $10,000
O $10,000 - $19,999
O $20,000 - $34,999
O $35,000 - $49,999
O $50,000 - $99,999
O $100,000 - $199,999
O 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?

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

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.

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 months 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?

Alternative question setup

Q1a: 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 . . .

... 2.5 percentage points higher or more (say, more than 4.5 percent rather than 2)	__%
... 1.5 - 2.5 percentage points higher (say, between 3.5 and 4.5 percent rather than 2)	__%
... 0.5 - 1.5 percentage points higher (say, between 2.5 and 3.5 percent rather than 2)	__%
... different by -0.5 to 0.5 percentage points.	__%
... 0.5 - 1.5 percentage points lower (say, between 0.5 and 1.5 percent rather than 2)	__%
... 1.5 - 2.5 percentage points lower (say, between -0.5 and 0.5 percent rather than 2)	__%
... 2.5 percentage points lower or more (say, less than -0.5 percent rather than 2)	__%

Q1b: The average growth rate of real GDP in the US between 2009 and 2019 has been about 2 percent. Natural disasters might influence future growth rates negatively, say, because it of potential damage to the infrastructure or private property or positively because of reconstruction work and technological innovations.
What do you think is the overall impact of natural disasters on economic growth over the next 12 months? Please assign probabilities to each scenario listed below:
Due to natural disasters, 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)	____%

Q1c: Climate change may impact economic growth.
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)	____%

Q3a: Consider natural disasters in the US.
In 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.*

Q3b: Consider natural disasters in the US.
In the next 12 months, what do you think is the probability of a large disaster causing damage of about 2 percent of GDP?
The probability of a large disaster will be ______ *percent.*

Q3c: Consider natural disasters in the US.
In the next 12 months, what do you think is the probability of a large disaster causing damage of about 10 percent of GDP?
The probability of a large disaster will be ______ *percent.*

Q3d: Consider natural disasters in the US.
Ten years from now, in 2032, rather than this year, 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.*

Q3e: Consider natural disasters in the US.
Twenty years from now, in 2042, rather than this year, 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.*

Q3f: Consider natural disasters in the US.
Thirty years from now, in 2052, rather than this year, 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.*

Q3g: 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.
In the next 12 months, what do you think is the probability of a large disaster causing damage of about 2 percent of GDP?
The probability of a large disaster will be ______ *percent.*

Q3h: 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.
In the next 12 months, what do you think is the probability of a large disaster causing damage of about 10 percent of GDP?

The probability of a large disaster will be ______ percent.

Q3i: 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.
Ten years from now, in 2032, rather than this year, 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.

Q3j: 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.
Twenty years from now, in 2042, rather than this year, 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.

Q3k: 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.
Thirty years from now, in 2052, rather than this year, 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.

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: 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).

T4: The next question asks about potential damages due to climate change, expressed in percent of GDP. To put these damages in perspective, note that U.S. GDP declined by approximately 5 percent in 2008-09 in response to the global financial crisis.

A.1 Questions on Media Usage and Political Affiliation

Some respondents were additionally given the following questions:

P1: What would you say is your political affiliation?

O Democrat
O Independent
O Republican
O Other

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

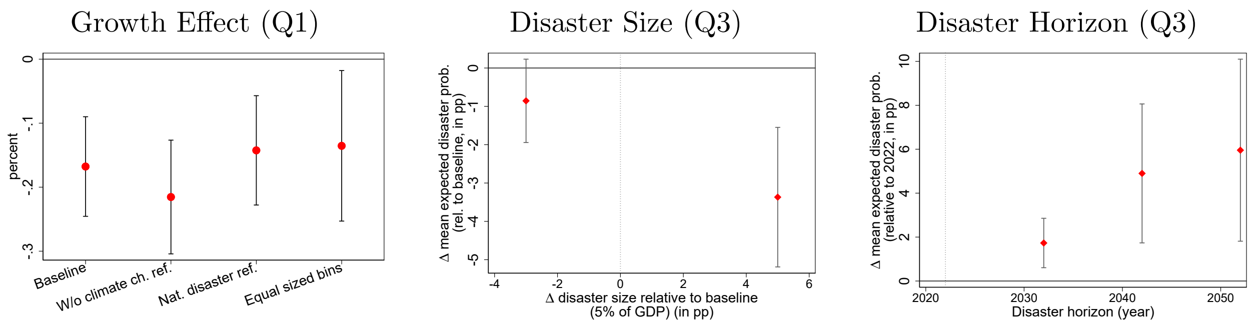
O ABC
O CBS
O CNN
O Fox
O MSNBC
O NBC
O PBS
O Other
O I do not watch any of these TV/news stations.

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

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

B Additional Survey Results

Figure B.1: Robustness: Growth Effect and Disaster Size and Horizon



Notes: The figure shows results of a complementary survey on climate change expectations. Left panel: Different question wordings on Q1 (growth effect of climate change). Relative to the baseline question (Q3), the middle panel varies the disaster size while right panel varies the disaster horizon. Middle panel: Mean difference in expected disaster probability, relative to baseline (5 percent of GDP damage) question. Right panel: Mean difference in expected disaster probability, relative to baseline (disaster in 2022) question.

Table B.1: Disaster Probability and Individual News Stations

	(1)	(2)	(3)
Multiple news stations	5.315***		3.641***
	(5.95)		(3.76)
Fox	0.0150		-0.251
	(0.01)		(-0.24)
CNN	1.637		1.626
	(1.35)		(1.27)
ABC	1.457		1.233
	(1.16)		(0.95)
MSNBC	2.526		2.370
	(1.32)		(1.20)
PBS	-0.224		-0.733
	(-0.11)		(-0.33)
NBC	3.204*		2.842
	(2.27)		(1.96)
CBS	4.720**		4.685**
	(3.10)		(2.96)
Multiple newspapers		5.563***	4.076***
		(7.85)	(5.24)
New York Times		0.331	-0.348
		(0.33)	(-0.33)
Washington Post		2.292	1.750
		(1.50)	(1.16)
Wall Street Journal		-2.462**	-3.042**
		(-2.58)	(-3.10)
USA Today		3.221**	2.563*
		(2.87)	(2.24)
Los Angeles Times		-2.326	-3.193
		(-1.17)	(-1.60)
Constant	13.74***	14.52***	13.44***
	(5.44)	(5.85)	(5.30)
State and month FE	✓	✓	✓
N	7160	7167	7193
R^2	0.0688	0.0736	0.0787

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 B.2: Expected Disaster Cost and Media Usage

	(1) Costs	(2) Costs	(3) Costs
no major TV station	-0.299***		
	(-5.29)		
no major newspaper		-0.127***	
		(-3.41)	
consume major TV station×no major newspaper			-0.0576
			(-1.51)
no major TV station×consume major newspaper			-0.135
			(-1.55)
no major TV station×no major newspaper			-0.363***
			(-5.59)
Constant	1.528***	1.481***	1.544***
	(8.48)	(8.17)	(8.52)
State and month FE	✓	✓	✓
Demographic controls	✓	✓	✓
N	4915	4916	4915
R^2	0.0692	0.0621	0.0713

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 B.3: Reported Growth Impact of Climate Change and Media Usage

	(1) Growth	(2) Growth	(3) Growth
no major TV station	-0.0333		
	(-0.42)		
no major newspaper		0.222***	
		(3.93)	
consume major TV station×no major newspaper			0.253***
			(4.21)
no major TV station×consume major newspaper			-0.117
			(-0.91)
no major TV station×no major newspaper			0.104
			(1.12)
Constant	0.142	0.0359	0.0710
	(0.53)	(0.14)	(0.27)
State and month FE	✓	✓	✓
Demographic controls	✓	✓	✓
N	4916	4916	4916
R^2	0.0492	0.0541	0.0546

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 B.4: Reported Probability of Disaster and Experience

	(1)	(2)	(3)	(4)	(5)
Wildfire experience	-2.781		-2.533*		-3.535*
	(-1.96)		(-2.36)		(-2.26)
Flood experience	1.748		0.964		1.023
	(1.95)		(1.29)		(1.13)
Hurricane experience	3.353***		1.426*		1.714
	(3.58)		(1.98)		(1.65)
Wildfire events in state		2993.3**	4709.8**		
(#/sqmi)		(2.62)	(2.98)		
Flood events in state		-63.66	-138.1		
(#/sqmi)		(-0.38)	(-0.69)		
Hurricane events in state		26.71	-171.6		
(#/sqmi)		(0.19)	(-0.95)		
High wildfire risk				0.569	1.235
				(0.51)	(1.06)
High flood risk				-0.661	-0.771
				(-0.88)	(-1.02)
High hurricane risk				5.010***	3.997***
				(4.39)	(3.30)
High landslide risk				2.289*	2.170*
				(2.20)	(2.05)
High earthquake risk				0.392	2.174
				(0.19)	(1.00)
Constant	16.78***	17.88***	17.58***	13.44***	13.08***
	(6.60)	(9.76)	(9.81)	(5.08)	(4.85)
State FE	✓	×	×	✓	✓
Month FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
N	7127	7024	7013	7145	7158
R^2	0.0657	0.0502	0.0529	0.0732	0.0751

Notes: Regression relates reported probability of disaster to personal experience; only respondents who did not receive any treatment used in regression; regressions control for state, month, demographics, media usage and political affiliation. The number of disaster events per state refers to the last 5 years and is normalized by the respective states' landmass in square miles. 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 B.5: Climate Change Expectations: Cross-Sectional Demographic Regressions

	(1) Growth	(2) Damage	(3) Disaster prob.
Female	0.0585	0.118***	3.978***
	(1.52)	(4.10)	(6.93)
35 to 44 years	0.0704	0.0521	1.017
	(1.36)	(1.21)	(1.32)
45 to 54 years	0.0272	0.0183	-1.282
	(0.44)	(0.39)	(-1.39)
above 55 years	0.277***	-0.163***	-0.984
	(5.47)	(-4.32)	(-1.29)
Highly educated	-0.0980*	0.0857*	0.312
	(-2.09)	(2.53)	(0.48)
Middle income	-0.0923*	-0.109**	-0.314
	(-2.11)	(-3.26)	(-0.49)
High income	-0.0167	-0.0657	0.524
	(-0.27)	(-1.44)	(0.61)
White	-0.162	-0.0487	0.343
	(-1.54)	(-0.71)	(0.24)
Black	-0.235*	-0.0315	0.926
	(-2.00)	(-0.39)	(0.56)
Asian	-0.171	-0.187*	-2.964
	(-1.41)	(-2.17)	(-1.79)
Hispanic	-0.0538	-0.0592	-1.394
	(-0.47)	(-0.75)	(-0.91)
Constant	0.410*	1.482***	16.16***
	(2.07)	(9.66)	(6.45)
State and month FE	✓	✓	✓
N	8393	7277	7133
R^2	0.0367	0.0418	0.0436

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 B.6: Climate Change Expectations: Cross-Sectional Regressions - Beliefs and Experiences

	(1) Growth	(2) Damage	(3) Disaster prob.
Republican	-0.0393	-0.135**	-0.585
	(-0.52)	(-2.84)	(-0.71)
Democrat	0.103	0.0269	1.625*
	(1.53)	(0.59)	(1.96)
Personal disaster experience	0.152*	0.232***	5.870***
	(2.02)	(4.91)	(6.70)
Personal climate change experience	-0.0911	0.213***	4.108***
	(-1.30)	(4.73)	(4.86)
Constant	-0.496	1.171***	13.03***
	(-1.61)	(6.00)	(3.70)
State and month FE	✓	✓	✓
Demographic controls	✓	✓	✓
N	4126	4126	3916
R^2	0.0523	0.0940	0.119

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. Personal climate change experience: Do you think your personal life has already been affected by climate change? Yes/No; Personal disaster experience: Do you think your personal life has already been affected by natural disasters? Yes/No

Table B.7: Behavioral Adjustments

	Probit regression		Descriptive statistics			
	Marginal effect	p-value	Yes	Sometimes	No	N
Investment						
Have you divested your investment decisions due to the fear of climate change related risk?	0.161***	0.000	27%	-	73%	10,981
Have you refrained from certain investments you consider harmful to the climate?	0.220***	0.000	33%	-	67%	10,981
Mobility						
Have you changed your decisions on personal mobility due to concerns about climate change?	0.247***	0.000	31%	-	69%	10,981
Has climate change altered your decision on owning a car?	0.212***	0.000	27%	-	73%	10,981
Do you refrain from flight travel due to concerns about climate change?	0.681***	0.000	20%	22%	58%	10,981
Other						
Did you stop eating meat due or reduce meat in your diet because of concerns about climate change?	0.483***	0.000	18%	26%	56%	10,981
Do you try to avoid products made from plastic?	0.627***	0.000	27%	35%	38%	10,981

Notes: Marginal effect of probit regression relates to the marginal effect of the subjective disaster probability; both disaster probability and probability for answers in percentage points. Only untreated respondents used in regressions; t statistics in parentheses, based on robust standard errors;* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; regression adjusted with survey weights to ensure that sample is representative. If respondents were able to choose a "Sometimes", an ordered probit model was estimated. Each regression controls for demographics and state as well as month-fixed effects. Questions on behavioral decisions asked before any treatments. Descriptive statistics on the right are computed on all answers, probit model only estimated on those respondents who did not receive a treatment before stating their disaster probability. $N = 4,093$ for probit regressions.

Table B.8: Treatment Regressions High Numerical Ability

	(1) Growth	(2) Disaster costs	(3) Disaster prob.	(4) Disaster prob.
Newspaper (T1)	0.100	0.103*	1.107	1.235
	(1.28)	(2.04)	(1.42)	(1.81)
Historic Disaster Size (T2)	0.0978	0.00474	-1.649*	-1.171
	(1.16)	(0.09)	(-2.05)	(-1.63)
GDP Loss Info (T4)	-0.122	0.141	-1.011	-0.711
	(-0.84)	(1.89)	(-0.75)	(-0.61)
Constant	-0.701*	1.292***	15.17***	14.93***
	(-2.18)	(6.97)	(5.53)	(5.83)
State and month FE	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Drop largest 25% probabilities	×	×	×	✓
N	2186	2121	2669	2530
R^2	0.0927	0.129	0.151	0.163

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 B.9: Risk Factors and Sources of Information

A) Risk Factors

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

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

B) Regional Expectations

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

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

C) Source of Information

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

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

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

C Details on Model

C.1 First Order Conditions of Simplified Model

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

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

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

Here we assume prohibitively high investment adjustment costs and no depreciation; specifically, we assume $K_t = \bar{K}$ 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:

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

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

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

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.

C.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 (C.3), it follows that the optimal price (in logs) is a constant markup over marginal costs:

$$p_t = \tau + \psi_t, \tag{C.6}$$

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

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

Inserting into (C.6) gives:

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

Combining this expression, the labor supply relation (C.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 $\Lambda = \frac{(1-\alpha)(\log(1-\alpha)+\alpha\log(\bar{K})-\tau)}{\sigma(1-\alpha)+\alpha+\varphi} > 0$.

Inserting the process for technology in logs $a_t = a_{t-1} + \sigma_A \epsilon_{A,t} - (1-\alpha) d_t \mu$ gives:

$$\hat{y}_t^n = \Xi_\mu d_t \mu + \Xi_a a_{t-1} + \Xi_a \sigma_A \epsilon_{A,t} + \Lambda.$$

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 (C.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:

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

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

C.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 μ and probability p_t, as formally shown in Proposition 1 and equation (C.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, $i_t = \rho + r_t^n + \phi_\pi \pi_t$. 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 $\phi_r = 0$ and that $\phi_{\pi,t} = \phi_\pi$ such that (4.5) implies $i_t = \rho + \phi_\pi \pi_t$. We first substitute in the expression for natural rate of interest using $\omega_t = \bar{\omega} + \hat{\omega}_t$. We next use the method of undetermined coefficients, starting from the observation that the output gap and inflation are linear functions of the disaster probability, that is, $\tilde{y}_t = \Pi_y^0 + \Pi_y^1 \hat{\omega}_t$ and $\pi_t = \Pi_\pi^0 + \Pi_\pi^1 \hat{\omega}_t$. Substituting in the equilibrium conditions, we obtain:

$$\begin{aligned}
\Pi_\pi^0 \bar{\omega} &= \beta \Pi_\pi^0 \bar{\omega} + \kappa \Pi_y^0 \bar{\omega}, \\
\Pi_y^0 \bar{\omega} &= \Pi_y^0 \bar{\omega} - \frac{1}{\sigma}\left(\Pi_\pi^0 \phi_\pi \bar{\omega} - \Pi_\pi^0 \bar{\omega} + \Omega(1-\alpha)\mu\bar{\omega}\right), \\
\Pi_\pi^1 \hat{\omega}_t &= \kappa \Pi_y^1 \hat{\omega}_t, \\
\Pi_y^1 \hat{\omega}_t &= -\frac{1}{\sigma}\left(\Pi_\pi^1 \phi_\pi \hat{\omega}_t + \Omega(1-\alpha)\mu\hat{\omega}_t\right).
\end{aligned}$$

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

$$\Pi_y^0 = -\frac{(1-\beta)}{\kappa(\phi_\pi - 1)}\Omega\mu(1-\alpha)\bar{\omega} < 0, \tag{C.8}$$

$$\Pi_\pi^0 = -\frac{1}{\phi_\pi - 1}\Omega\mu(1-\alpha)\bar{\omega} < 0, \tag{C.9}$$

$$\Pi_y^1 = -\frac{1}{\sigma + \kappa\phi_\pi}\Omega\mu(1-\alpha) < 0, \tag{C.10}$$

$$\Pi_\pi^1 = -\frac{\kappa}{\sigma + \kappa\phi_\pi}\Omega\mu(1-\alpha) < 0. \tag{C.11}$$

Note that as $\phi_\pi \to \infty$, the outcome for the Taylor rule is equivalent to full stabilization, since $\lim_{\phi_\pi \to \infty} \Pi_y^0 = 0$, $\lim_{\phi_\pi \to \infty} \Pi_y^1 = 0$, $\lim_{\phi_\pi \to \infty} \Pi_\pi^0 = 0$ and $\lim_{\phi_\pi \to \infty} \Pi_\pi^1 = 0$. Again, the solution in (C.8) and (C.11) 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 (C.8)-(C.11). 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:

$$\begin{aligned} E_t(\pi_{t+1}|U) &= \zeta E_t \pi_{t+1}^U + (1-\zeta)\left[\Pi_\pi^0\right], \\ E_t(\tilde{y}_{t+1}|U) &= \zeta E_t \tilde{y}_{t+1}^U + (1-\zeta)\left[\Pi_y^0\right]. \end{aligned}$$

due to $E_t \hat{o}mega_{t+1} = 0$. Using these expectations operators, we can express (4.3) and (4.4) in matrix form:

$$E_t \begin{bmatrix} \tilde{y}_{t+1}^U \\ \pi_{t+1}^U \end{bmatrix} = C + A \begin{bmatrix} \tilde{y}_t^U \\ \pi_t^U \end{bmatrix} + B\hat{\omega}_t,$$

where

$$A = \frac{1}{\zeta}\begin{bmatrix} 1 + \frac{\kappa}{\beta\sigma} & -\frac{1}{\beta\sigma} \\ -\frac{\kappa}{\beta} & \frac{1}{\beta} \end{bmatrix}, \quad B = \frac{1}{\zeta}\begin{bmatrix} \frac{(1-\alpha)}{\sigma}\Omega\mu \\ 0 \end{bmatrix}, \quad C = \frac{1-\zeta}{\zeta}\begin{bmatrix} -\Pi_y^0 + \frac{1-\alpha}{(1-\zeta)\sigma}\Omega\mu \\ -\Pi_\pi^0 \end{bmatrix}.$$

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 (C.12) holds:

$$(1-\zeta)(1-\beta\zeta)\sigma - \kappa\zeta > 0. \tag{C.12}$$

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 $\hat{\omega}_t$

and a constant, that is, we assume that $\tilde{y}_t^U = \Gamma_y^0 + \Gamma_y^1 \hat{\omega}_t$ and $\pi_t^U = \Gamma_\pi^0 + \Gamma_\pi^1 \hat{\omega}_t$. Solve for Γ_y^0, Γ_y^1, Γ_π^0 and Γ_π^1:

$$\begin{aligned}
\Gamma_y^0 &= \frac{(1-\beta\zeta)(1-\zeta)\sigma}{(1-\zeta)(1-\beta\zeta)\sigma-\kappa\zeta}\Pi_y^0 \\
&\quad + \frac{1-\zeta}{(1-\zeta)(1-\beta\zeta)\sigma-\kappa\zeta}\Pi_\pi^0 + \frac{(1-\beta\zeta)}{(1-\zeta)(1-\beta\zeta)\sigma-\kappa\zeta}\mu\Omega(1-\alpha), \\
\Gamma_\pi^0 &= \frac{(1-\zeta)\kappa\sigma}{(1-\zeta)(1-\beta\zeta)\sigma-\kappa\zeta}\Pi_y^0 \\
&\quad + \frac{1-\zeta}{1-\beta\zeta}\left[\beta + \frac{\kappa}{(1-\zeta)(1-\beta\zeta)\sigma-\kappa\zeta}\right]\Pi_\pi^0 + \frac{\kappa}{(1-\zeta)(1-\beta\zeta)\sigma-\kappa\zeta}\mu\Omega(1-\alpha), \\
\Gamma_y^1 &= -\frac{1}{\sigma}(1-\alpha)\mu\Omega\bar{\omega}, \\
\Gamma_\pi^1 &= -\frac{\kappa}{\sigma}(1-\alpha)\mu\Omega\bar{\omega}.
\end{aligned}$$

Using (C.8), (C.11) and (C.12), it can now also be shown that $\Gamma_y^0 < \Pi_y^0$ and $\Gamma_\pi^0 < \Pi_\pi^0$, as stated in proposition 2. $\kappa\phi_\pi > 0$ ensures that $\Gamma_y^1 < \Pi_y^1$ and $\Gamma_\pi^1 < \Pi_\pi^1$.

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