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Climate change framing and innovator attention: Evidence from an email field experiment

Jorge Guzman[a,b,1,2], Jean Joohyun Oh[a,1], and Ananya Sen[c,1]

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Drawing the attention of innovators to climate change is important for green innovation. We report an email field experiment with MIT using messages about the impact of climate change to invite innovators (SBIR grantees) to apply to a technology competition. We vary our messages on the time frame and scale of the human cost of climate change across scientifically valid scenarios. Innovator attention (clicks) is sensitive to climate change messaging. These changes in clicks also predict higher application rates. The response varies by individual characteristics such as location-based exposure to climate change risks and whether innovators have climate-related innovations. Finally, using a structural model of innovator attention, we provide estimates of the implied discount rate of time and the elasticity of attention to lives at stake.

attention | green innovation | climate change | field experiment

Green innovation is central to an appropriate response to climate change (1–3). For green innovation to take place, however, the first step is for innovators to pay attention to climate change amid the myriad of problems in which they can invest their time and effort. Without this initial engagement, there is little hope for any further action that may lead to green innovation. As argued by Brooks et al. (4), managing the attention of innovators is one of the main challenges in transitioning to an environmentally sustainable society.

In this paper, we provide experimental evidence on the impact of climate change messages on the attention and initial action of innovators. To do so, we implement a preregistered field experiment at the Massachusetts Institute of Technology using messages about the social impact of climate change to invite proven innovators to apply to the technology competition MIT Solve. We focus on over 30,000 innovators who received a Small Business Innovation Research (SBIR) grant, a federal seed fund for high-potential technologies. We randomize messages across several scientifically valid scenarios varying the time frame and scale of the human loss of climate change and study the difference in the clicks and predicted applications from innovators across these messages. Using this approach, we document four interrelated insights.

First, innovator attention is sensitive to climate change messaging. Email messages that state a higher annual number of lives at stake (400,000 vs. 150,000) or a sooner impact (2020 vs. 2050) are both about 20% more likely to be clicked.

Second, these changes in messaging also predict higher application rates. Using a surrogate index (5), we estimate that each of our treatments leads to between 3% and 9% increase in the probability of applying to the technology competition (depending on the specification).

Third, innovator response to climate change messages varies by individual characteristics. Innovators in locations with higher climate change risk are more sensitive to lives lost and more future oriented. On the other hand, innovators who have already developed climate-related technologies (as implied in the language they use in their SBIR grants) seem slightly less sensitive to lives and more present oriented. Interestingly, however, we do not find a difference in our estimates between Democrat-leaning and Republican-leaning locations. Innovator response toward climate change appears to operate separately from local partisanship.

Finally, we provide a framework to analyze innovator attention within a choice model of the value to learn more about different aspects of large-scale problems. Based on the experimental setup, we utilize a structural model to focus on two fundamental dimensions of most problems, the scale of impact, and its timing. We apply this framework to the problem of climate change through our data. We estimate an elasticity of attention to lives at stake at 0.23 and a discount rate at the time of such an event at 0.76%.

Significance

Addressing climate change critically depends on innovation. However, there is little work on understanding how to shift the attention of innovators (who have particularly specialized skillsets) toward climate change. We perform a field experiment with successful innovators to understand how sensitive they are to climate change scenarios. Innovators increase their attention when stated climate change impact is more imminent or has the potential for greater human casualties, partly depending on their location characteristics and technological focus. Our results suggest that messaging experiments, emphasizing the cost of climate change, can shift attention (and potentially action) toward this problem.

Author affiliations: [a]Columbia University, New York, NY 10027; [b]NBER, Cambridge, MA 02138; and [c]Carnegie Mellon University, Pittsburgh, PA 15213

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[1]J.G., J.J.O., and A.S. contributed equally to this work.

[2]To whom correspondence may be addressed. Email: jag2367@gsb.columbia.edu.

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Together, our results provide evidence on the important role messaging can play in focusing innovator attention on the problem of climate change. These results contribute to several areas of the literature. First, our results uncover how messaging and innovator attention may shape the direction of innovation as a social problem worsens. Indeed, attention has been an underappreciated area in the large work on innovation incentives (6–16). Second, our study also connects to the broader literature on the role of scarce attention in decision-making (17, 18). Our approach using clicks is not only an effective method to elicit individual preferences (19), but it also complements prior work that has measured the attention of managers using surveys and public-facing statements (20). Because clicks are a private response, they offer a more direct measure of attention allocation without potential confounding. Finally, our paper contributes to the broader literature using experiments to understand innovator incentives (16, 21–24), by uniquely focusing on a sample of proven high-skilled innovators (SBIR grantees).

Empirical Setting

MIT Solve Global Challenges. We implement our experiment by partnering with an organization within the Massachusetts Institute of Technology (MIT) named MIT Solve. MIT Solve is a marketplace for innovation focused on solving the world's challenges. Its main program is their annual Global Challenges—thematic competitions to fund innovative solutions to specific problems. Since its launch in 2015, MIT Solve has received 6,500 applications from 157 countries and has secured $25 million in funding and over 200 partnerships for winners (25, *SI Appendix*, Fig. A.1). Successful winners include companies such as ISeeChange, a startup using mobile technology to develop crowd-sourced microdata on the impact of climate change, and Code Nation, an education company helping underserved students develop skills in software engineering.

MIT Solve seeks applications from companies around the world with technology-based solutions at all stages of development. To its winners, Solve provides various types of support to help advance and scale their innovations, including large cash prizes (which total more than $2 million annually across winners), access to an MIT-backed network of mentors, funders, and experts, and public recognition at the annual flagship event. In 2020, Solve sought applications for six Global Challenges, all of which have potential overlap with climate change challenges such as Sustainable Food Systems, Good Jobs and Inclusive Entrepreneurship, and Maternal and Newborn Health.*

Finding innovators capable of solving the world's problems is no easy task, which is why Solve devotes substantial effort to marketing and outreach, including a professional website, email marketing campaigns, and outreach efforts with various partners. We partnered with Solve to support their outreach for the 2020 Global Challenges. We were granted full control over the initial email that went out to our sample of innovators from their email account on May 6th, 2020. To apply, individuals were asked to submit a full application by the deadline, June 18, 2020. The application form included approximately 50 long- and short-form questions that together amounted to a short business plan consisting of five parts: overview, detailed description, team information, business model and funding, and partnership opportunities. We estimate that it would take a serious applicant at least two to three hours to complete an application.

*[*SI Appendix*, Fig. A.2](#) contains a short description of each challenge from Solve's website.

Finding Innovators: SBIR Grantees. We focus on highly skilled technological innovators by studying grantees of the Small Business Innovation Research (SBIR) or the Small Business Technology Transfer (STTR) programs. Coordinated by the U.S. Small Business Administration (SBA) and funded by several federal agencies, the SBIR/STTR programs aim to advance American technological research priorities by funding the development of early-stage innovative technologies directly through several federal departments, before they can be taken up by private financiers. To date, over $40 billion has been allocated through these programs. For simplicity, we hereafter refer to both programs together as SBIR.

The SBA releases public information online on all SBIR grantees, including project title and abstract, award amount, company information, and email addresses of the principal investigator and business contact. We download this public information and use these publicly released email addresses to contact SBIR grantees.

Methods

Following our preregistration,† we emailed all SBIR grantees receiving a grant since 2010 with randomly assigned messages varying the time frame and scale of the human toll of climate change across scientifically valid scenarios and encouraged them to apply to MIT Solve's Global Challenges to address the problem. We then studied how these treatments changed the likelihood of clicks and applications, from which we inferred variation in innovators' attention to climate change scenarios.‡ The study was approved under the Columbia Institutional Review Board (IRB) number AAAS3430 and the Carnegie Mellon University IRB number 2020_00000197, with a waiver of informed consent. We requested this waiver to allow us to observe behavior in a real-world context and thus observe revealed preferences and behavior, rather than stated preferences and behavior.

Our treatments are structured as a 2×2 between-subject design, in which each innovator received one email with a climate change scenario.§ This scenario included either low or high impact on human lives and framed the impact as occurring either in the present or in the future. Based on the scientific literature, we used either 150,000 or 400,000 lives as the estimated number of lives at stake each year due to climate change and framed the impact as occurring in either 2020 or 2050. These numbers are well within the reasonable lower and upper bounds based on prior estimates from Patz et al. (26), Springman et al. (27), and the World Health Organization (WHO) (28). These numbers allowed us to have as much variance as possible while remaining

†Our study is preregistered at the AEA RCT Registry under AEARCTR-0005743, which can be found at https://www.socialscienceregistry.org/trials/5743.

‡We have one deviation from our preregistration: We had originally envisioned including an additional experiment with a noninnovator sample on Amazon Mechanical Turk (MTurk). While our treatment in the paper encouraged people with technological expertise to expend effort to develop solutions to climate change, it was unlikely that individuals recruited through MTurk would consider applying to innovate toward climate change solutions. Hence, we would have to elicit clicks from individuals on MTurk in a different (climate change-related) context. After receiving feedback from different sources, it became clear that the interpretation of a "click" may be quite different between innovators and noninnovators and might even be two separate papers. Hence, we did not carry out the experiment with an MTurk sample but, unfortunately, did not update this information in our preregistration.

§We chose not to have a pure control condition that simply encourages participants to apply because our interest was in the intensive margin changes of the framing (time frame and scale) of a problem, rather than the effect of having such a framing or not. Additionally, we also wanted to ensure sufficient statistical power to detect our main effects of interest. Our power analyses suggested that we have three or four treatment arms at most, given the typical click rates in emails and the total number of innovator contacts that were available to us.

scientifically grounded, thus presenting variation that is both realistic and possible.

Across treatment conditions, we varied both the email subject and the body to include one of the four scenarios. The subject was

"Save [150,000/400,000] lives in [2020/2050] from Climate Change: Apply to MIT Solve's Challenge"

And the body varied the first sentence as follows:

"Did you know that an estimated [150,000/400,000] lives could be saved in [2020/2050] by mitigating climate change?"

Outside of these treatment messages, we kept constant all other aspects of the email as shown in *SI Appendix*, Fig. A.3.

Sample Selection and Randomization. Our sample consists of all individuals who have received an SBIR grant since 2010. After excluding 99 contacts whose email addresses had syntax errors or were invalid, our final sample included 31,666 individuals from 12,008 companies. We assign individuals randomly to one of the four treatment groups. *SI Appendix*, Table A.1 shows the summary statistics of the dependent variable and main pretreatment observables. The click rate on email links is 1.5%, which is considerably higher than in similar settings with emails.[¶] In *SI Appendix*, Table A.2, we provide balance tests showing that the four treatment arms were well balanced in terms of pretreatment covariates such as type of contact (principal investigator or not), whether the individual invented a patent, award year, amount awarded, number of employees, and whether the company is woman owned, among others. Such balance in key observables across treatment conditions lends credibility to our randomization.

While we have four treatment conditions, we are interested in estimating two fundamental parameters: the time preference around present- and future-orientation and the sensitivity to high vs. low number of lives saved. Focusing on these two parameters also allows us to ensure sufficient statistical power by pooling treatments. Moreover, as we emphasize in our structural model and in our preregistration, it is precisely these two parameters which are of theoretical consequence.

Variables of Interest and Empirical Framework. Our empirical analyses focus on the impact of treatment on clicks and applications. We begin by describing our reduced form estimates. For each individual i and outcome Y_i, we estimate the following two models:

$$Y_i = \alpha_0 + \beta \times Present_i + \zeta' \times \mathbf{X_i} + \epsilon_i. \quad [1]$$

$$Y_i = \alpha_1 + \gamma \times High\ Impact_i + \theta' \times \mathbf{X_i} + \nu_i. \quad [2]$$

The main variables of interest are β, representing the change in the likelihood of response when a message is the present rather than the future impact of climate change, and γ, which is the change in the likelihood of response when the message is the high impact of climate change instead of the low one. α is a constant, ϵ_i and μ_i are random error terms, and $\mathbf{X_i}$ represents a vector of individual- and firm-level controls.

Our main outcome, Clicked, is a binary variable indicating whether an individual has clicked on any link in the email within 48 h of receiving it. Clicking is a spontaneous response carried out privately, as far as the subjects are concerned, to acquire more information on Solve's Challenges and therefore better represents the private innovator response to our treatment. Clicks have been used to measure interest in related settings (16, 29, 30).

Our second outcome is applications. While applications are a more active response than clicks, they are not as natural or private since they also require considering the "audience," i.e., MIT Solve. Applications also suffer from several disadvantages for statistical analysis. In particular, they are sparse and noisy because the time lapse between treatment and application can span more than a month. To address this issue and have higher statistical power, we use the surrogate index method of Athey et al. (5) that has been shown to improve the precision of estimates with later-on outcomes that are rare and noisy. This method combines several short-term proxies into a "surrogate index," which is the predicted value of the long-term outcome (in our case, applications) given the short-term proxies (click behaviors). The surrogate index thus eliminates any noise in the long-term outcome that is orthogonal to the treatment, leading to greater precision.

The surrogate approach requires four key assumptions to be valid. The first is unconfounded treatment, which is automatically provided in our setting through an experiment. The second is surrogacy or that the intermediate measures fully capture the causal link to the outcome of interest. We think that this assumption is particularly valid in our setting: Email clicks and opens capture quite well the causal pathway between our email treatments and eventual applications. The third and fourth are comparability of samples and overlap. Both of these are not an issue in our setting since we use only a secondary sample to train the surrogate index as a robustness test.[#] Using this method, we can identify the treatment effect on applications under the identifying assumption that applications are independent of our treatment message conditional on click behaviors.[‖]

We define our outcome Application Probability as the predicted value estimated from a logit model mapping applications to a variety of intermediary click behaviors as well as pretreatment covariates at the individual and firm level.[**]

$$Application\ Probability_i = \alpha + \delta' \times Surrogates_i + \mu_i. \quad [3]$$

We estimate this model on two samples for additional robustness: our main sample of MIT Solve applicants and data from a prior experiment that we conducted with the MIT Inclusive Innovation Challenge (IIC), a sister competition that later merged with MIT Solve, see ref. 16. This second surrogate index allows for an out-of-sample prediction, ensuring that our surrogate index results are not unique to the intricacies of MIT Solve.

Results

Baseline Estimates on Clicks and Heterogeneous Effects. Table 1 reports estimates from linear probability models where the dependent variable is Clicked. We scale the dependent

¶In ref. 16, the analogous click rate was 0.5% for emails sent to a list of entrepreneurs obtained from Dunn and Bradstreet from a similar MIT account.

#A surrogate approach is valid independent of the length of time passed between intermediate and final outcomes. Our approach is similar to the pioneering implementation of surrogates by Athey and Stern (31).

‖In other words, individuals' click behaviors must be the only causal pathway between our treatment emails and applications, which we believe is a reasonable assumption. Our use case also follows the suggestion of ref. 5 and a prior empirical study by ref. 32 that use online user behaviors as surrogates for longer-term engagement.

**The different measures of click behavior are whether the email was opened, clicked, number of clicks restricted to those other than social media links, and the total number of clicks and opens. The six innovator- or firm-level characteristics are whether the innovator is a patented inventor, whether the company is woman owned, whether the company is owned by a disadvantaged population, the log of the award amount, whether it was phase I or phase II, and whether it was an SBIR or STTR grant.

Table 1. Impact of present framing on innovator response: Clicks

Variables	Baseline (1) Clicked	Restricted clicks (2) Clicked	Unsubscribed control (3) Clicked	Randomization inference (4) Clicked
Present	0.191**	0.193**	0.190**	0.191**
	(0.0912)	(0.0914)	(0.0912)	[0.0315]
Observations	31,662	31,662	31,662	31,662
R-squared	0.024	0.024	0.024	–

Robust standard errors in parentheses clustered by company in Columns (1)–(3). $*P < 0.10$, $**P < 0.05$, $***P < 0.01$. All columns use a linear probability model (LPM), and the unit of observation is at the individual level. The dependent variable is whether the individual recipient clicked on any link in the Solve email scaled by the mean for ease of interpretation. All specifications have controls which include whether the individual is a business contact or principal investigator, award year, log award amount, agency applied to, whether the company is woman owned, whether SBIR or STTR, whether the company is in phase 1, state fixed effects, and firm size.

variable by its mean so that the coefficients can be interpreted in percentage terms. In Column (1), we see that a present-oriented framing of climate change leads to a higher probability of clicking on email links. Innovators are 19.1% more likely to respond to messages framed in terms of the present rather than the future. This effect is significant at the 5% level. In Column (2), we restrict our clicks measure to direct links to Solve's website as opposed to other potentially less relevant social media pages. The result for the future treatment is qualitatively and quantitatively similar. In Column (3), we account for the possibility that some clicks may represent negative reactions to an unexpected email, by controlling for whether the individual unsubscribed after receiving our email. In Column (4), we estimate the *P*-values using randomization inference, which allows us to analyze what would have happened under all possible random assignments and not only the random assignment used in the experiment. Both results are extremely close to those in Column (1).

We carry out the same empirical exercise for the High Impact framing with the results in Table 2. The results mirror those found for future vs. present framing. In particular, Column (1) shows that innovators react significantly more to a high impact framing relative to a low impact one. The increase in the probability of clicking is 19.2% higher for a high impact framing. This effect persists even after looking at restricted clicks Column (2), controlling for unsubscribing behavior Column (3), as well using randomization inference to compute *P*-values Column (4).

We decompose these effects into each possible treatment cell in *SI Appendix*, Table A.6. As expected, relative to the baseline *Present* × *High Impact* condition, the lowest treatment effect comes from messages that include both Future and Low Impact framings, while the other two treatments that have only one of these framings are also negative and significant but have a less negative effect size.

To ensure that our results are not driven by the use of linear probability models, we analyze our treatment effects under a variety of assumptions. *SI Appendix*, Fig. A.4 reports the treatment effects in terms of raw mean differences and logit models with and without controls used in our baseline specification, which all lead to nearly identical results. Our preferred specification is the linear probability model controlling for pretreatment covariates, for ease of interpretation and greater precision.[††]

Finally, we carry out a series of robustness checks for the present framing treatment in *SI Appendix*, Table A.4 to ensure that our results are not driven by any idiosyncrasies in the data. We find estimates qualitatively and quantitatively similar to the baseline when we explicitly control for local political preferences captured by political donations, use alternative clustering of standard errors, as well as a double robust estimator. In *SI Appendix*, Table A.5, we use the same checks for the high impact framing to find the baseline results unchanged.

Next, we analyze heterogeneous treatment effects across different dimensions that may be correlated with an individual's interest in solving climate change in Fig. 1. We include our main coefficients for comparability.

First, we look at the subsample of individuals with greater location-based exposure to climate change risks. These are individuals located in areas predicted to have high coastal damage from sea level rise.[‡‡] The coefficients show that at-risk individuals respond more to the scale of climate change impacts (higher number of lives at stake) and do not reduce their interest when the impact occurs in the future. That is, they value future impact as much as the present.

Second, we consider people whose technology appears to be more related to climate change. To measure whether a technology relates to climate change, we created a measure of relevance to climate change using word-embeddings (34) and defined High Tech Relevance to Climate Change as the top 20% of grants whose abstract is most similar to a list of relevant climate keywords.[§§] The effect of lives on climate response for this group is close to the main estimate, though the estimate is less precise. The impact of timing has a higher point estimate than the main estimate, though the differences are not statistically significant. We conclude that innovators who are already working on climate change-related technologies do not respond much differently to

Table 2. Impact of high impact framing on innovator response: Clicks

Variables	Baseline (1) Clicked	Restricted clicks (2) Clicked	Unsubscribed control (3) Clicked	Randomization inference (4) Clicked
High impact	0.192**	0.184**	0.193**	0.192**
	(0.0928)	(0.0930)	(0.0928)	[0.0355]
Observations	31,662	31,662	31,662	31,662
R-squared	0.024	0.024	0.024	–

Robust standard errors in parentheses clustered by company in Columns (1)–(3). $*P < 0.10$, $**P < 0.05$, $***P < 0.01$. All columns use a linear probability model (LPM), and the unit of observation is at the individual level. The dependent variable is whether the individual recipient clicked on any link in the Solve email scaled by the mean for ease of interpretation. All specifications include the same controls as Table 1.

[††] Using a seemingly unrelated regressions model (SUR), we find that the impact of the future treatment is not statistically different across high and low treatments with a *P*-value of 0.50 and that the impact of the high treatment does not vary with the time horizon with a test that does not reject equality of coefficients with a *P*-value of 0.46. While not conclusive, this does provide suggestive evidence in line with limited interaction effects across treatments.

[‡‡] We categorize High Risk of Coastal Damage as individuals whose company is located in an area where the predicted coastal damage due to climate change is higher than the median, based on county-level prediction data by ref. 33 for coastal states in the North-East and South.

[§§] Briefly, the measure was created as follows. First, we trained a Word2Vec (34) model on the text corpus of all SBIR applications in our sample (including the title, keywords, and abstract). Second, we used this model to estimate the most similar words to a list of initial keywords related to climate change. We expanded the list of keywords, iterating until we converged on a final set of keywords ("climate change," "global warming," "carbon emission," "reduce emission," "carbon footprint," "greenhouse gas," "reduce greenhouse," "environmental impact," "environmental sustainability," "sustainable," "clean energy," "renewable," and other variations of these terms). Then, we calculated the cosine similarity between the mean vector representation of this final set of keywords and that of all words in each SBIR grant. We categorize High Tech Relevance to Climate Change as the subsample of individuals whose SBIR grant ranked in the top quintile of this cosine similarity measure.

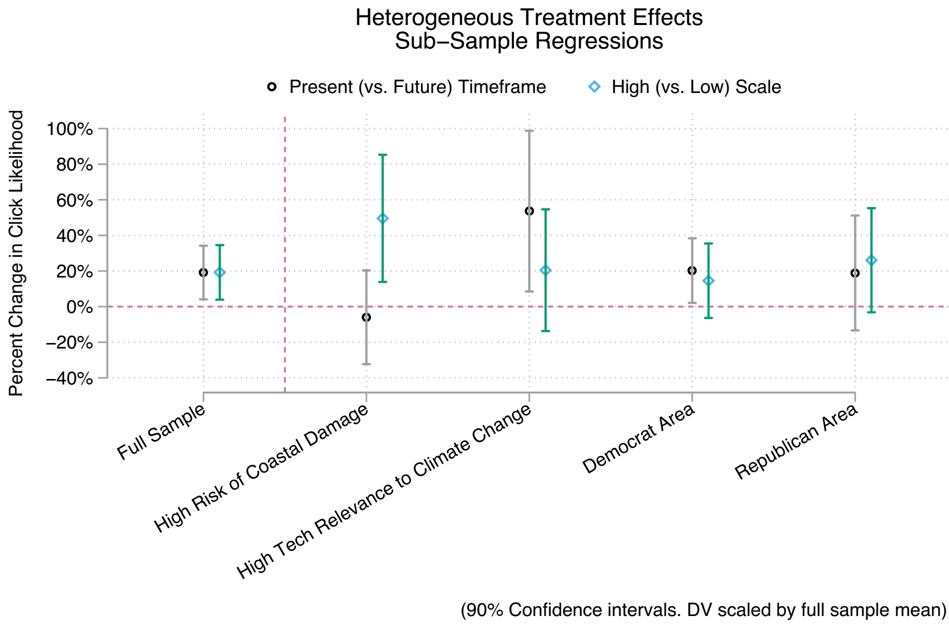

Fig. 1. Heterogeneity results.

the time frame and scale of the problem than other innovators. Importantly, this is not to say that their level of interest in climate change is similar: They were more likely to click in general. Rather, the results imply that the variation in responding to the framing effects from climate oriented innovators is similar to other innovators.

Finally, we analyze political orientation at the ZIP Code level in which the company is located.[¶¶] We do not observe any meaningful differences across political orientation. Innovator response toward climate change appears to operate separately from local partisanship.

Together, these estimates indicate striking differences in the responses of innovators to the treatment messages, as revealed through their clicks. The results show that to pique an innovator's interest in large-scale problems whose impacts occur over the long term, it may be more effective to highlight impacts that are occurring in the present. Moreover, innovators are in fact responsive to differences in the estimated magnitude of the impact; thus, to call them to action, the exact statistics matter.

Baseline Estimates on Applications. We proceed to examine in Table 3 the relationship between our emails and applications to MIT Solve by using a surrogate index. Following prior work (16, 29), we first show that clicks and website visits do predict applications. First, we look at the 41 applications that were started on Solve's platform by individuals who received our emails. In Column (1), we report that an individual who clicks on the email is more likely to apply, both statistically and economically. In Column (2), we take this a step further and look at all 2,683 applications submitted to Solve by individuals both within and outside of our sample. Using web analytics data on Solve's website, we find that daily website visits (three-day moving averages of both the number of website visitors and sessions per visitor) are highly correlated with the number of applications submitted on a given day.

Columns (3) and (4) then estimate the impact of our framing treatments on applications. Columns (3) and (4) report an OLS regression with Application Probability—the probability of applying to Solve estimated through a surrogate index, as described in *Result*—as the dependent variable.[##] Both Present and High Impact treatments are significantly associated with submitting an application. The effect of Present is about a 4% increase from the mean, and the effect of High Impact is about 3%.

Columns (5) and (6) repeat our exercise using data from our previous experimental study with the MIT Inclusive Innovation Challenge (16) to build the surrogate index. This index serves as an important robustness test because it uses out-of-sample data to train our surrogate measure, thus avoiding any spurious correlation between the index and predictions in the data. The IIC experiment followed a similar design to our current study, where we emailed a large sample of innovative entrepreneurs and encouraged them to apply to the competition (We believe that it is reasonable to assume that the two experiments involve a similar mapping between individuals' click response to our email and their likelihood of submitting an application, allowing us to train a surrogate index using the IIC data to predict the likelihood of applying in our current study.). The results are stronger with the Future framing treatment increase applications by approximately 9% relative to the mean. Similarly, in Column (6), the High Impact framing leads to an increase in the probability of an application by 8.8%.

A Structural Model of Innovator Response

Finally, we provide structure to our results by studying our messages through a structural model of innovator attention. The fully fledged model is provided in *SI Appendix*, Appendix *B*. We provide a simplified description below.

In our model, innovators choose whether or not to click on a given message based on the scale of climate change impacts

[¶¶] In line with Gentzkow and Shapiro (35), a zip code is defined as Republican (Democratic) if residents have made more political donations to Republican (Democratic) congressional candidates over 2010 to 2018.

[##] *SI Appendix*, Table A.3 shows the predictive models for our surrogate indices, using either data from the current experiment (Columns 1 and 2) or from the IIC experiment (Columns 3 and 4).

Table 3. Impact of climate scenarios on innovator response: Applications

Variables	Solve experiment (1) Application	Solve website (2) Log (Applications)	Solve surrogate (3) Application probability	Solve surrogate (4) Application probability	IIC surrogate (5) Application probability	IIC surrogate (6) Application probability
Clicked	1.731***					
	(0.609)					
Number of visitors		0.635***				
		(0.182)				
Sessions per visitor		6.384**				
		(2.510)				
Present			0.041***		0.090**	
			(0.015)		(0.039)	
High impact				0.030**		0.088**
				(0.015)		(0.041)
Observations	30,878	115	31,463	31,463	30,955	30,955
R-squared		0.718	0.039	0.039	0.022	0.022

Robust standard errors in parentheses. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. Column (1) uses a logit model, while Columns (2)–(6) use an OLS specification. The unit of observation is at the individual level in all columns except for Column (2), where it is at the day level. The dependent variable is whether the individual recipient applied in Column (1), the log number of daily applications to Solve in Column (2), the probability of applying predicted by a surrogate index based on the Solve experiment data in Columns (3) and (4), and that predicted using a surrogate index based on the IIC data in Columns (5) and (6). The dependent variable in Columns (3)–(6) is divided by the mean for ease of interpretation. In Column (2), independent variables are the log of the three-day moving average and the number of visitors and sessions per visitor and controls for average session duration and the percentage of single-page sessions. Controls in Columns (5) and (6) include whether the individual is a business contact or principal investigator, award year, log award amount, agency applied to, whether the company is woman owned, whether SBIR or STTR, whether the grant was for phase 1, state fixed effects, and firm size dummies while Columns (3) and (4) use award year, agency applied to, state fixed effects, and firm size since they are not used in the construction of the surrogate index. Column (1) does not use state fixed effects and year fixed effects because they lead to a substantial loss in observations, but results are robust to their addition. Some observations are dropped due to collinearity with fixed effects.

(i.e., number of lives at stake), the time frame of this loss, and their own preferences regarding these two dimensions. These preferences are captured in two parameters, namely the elasticity of attention to lives lost (or concern for human loss, which we call β) and the time discount rate (concern for future generations, which we call δ). First, the elasticity to lives lost captures how an innovator's marginal attention changes to saving an additional life. Innovators may exhibit diminishing marginal attention as the total human toll of climate change increases (inelastic or β smaller than 1), disproportionately increases due to a higher risk of catastrophe (elastic or β larger than 1), or changes exactly proportional to the changes in lives lost (β equals 1). Second, the time discount rate, also called the welfare discount rate or the pure rate of social time preference, is the discount rate on future generational welfare. The larger the time discount rate, the more discounted the future welfare compared to the present and the less attention an innovator pays to future-oriented framing.

Using this value function, we start with a multinomial choice model. To be able to apply our structural estimators to our single message experiment, we assume the independence of irrelevant alternatives (IIA) between clicking on each message and the outside option of doing nothing (We do this because the multinomial model would require each inventor to evaluate all four messages simultaneously, choosing to act on one of them or do nothing. We are not able to feasibly run this within-subjects experiment due to the complexity of mentally evaluating multiple options and the potential contamination of information across options due to anchoring bias (and other types of biases).). Note that this is only IIA between the outside option and each message but still allows correlation between the messages themselves. We are then able to use the proportions of click-through rates in the between-subjects experiment to recover the two underlying parameters of our model.

Parameter Estimates. We implement this approach on our data using 500 bootstrap samples. Fig. 2 reports the distribution of $\hat{\beta}$ and $\hat{\delta}$ for these samples.

The mean value of $\hat{\beta}$, the elasticity of attention to the number of lives lost, is 0.23 and rejects the null of zero with an exact P-value of 0.04.

The mean value of $\hat{\delta}$, the annual discount rate of attention to future lives lost, is 0.76% with a P-value of 0.032. This implies that changing the time frame from 2020 to 2050 reduces innovator response by 21.4%, an estimate close to our reduced form estimates.

Together, this model and estimates provide a generalizable characterization of the way attention is directed toward a specific problem and a characterization of the core parameters of innovator attention for climate change. Expanding on this model to estimate the parameters of attention for other populations or with regard to other important problems is a promising area for future work.

Interpreting Our Estimates Within Climate Models. To make better sense of these estimates, we consider how they compare with respect to the literature. We highlight, nonetheless, that they are distinctly different from other values as they represent directly the preferences of innovators rather than the public at large.

The welfare discount rate on climate change (also called the time discount rate or the pure rate of social time preference) is the discount rate on future generational welfare in evaluating long-term public investments. Prior research has produced a wide range of estimates through either expert surveys (36), deductive methods that back out the welfare discount rate from observed returns of capital and growth in a Ramsey framework (37), and inductive methods from moral principles (38). While (39) estimates a value of 1.5% for the welfare discount rate, (36) report that a large portion of climate policy experts prefer a value of zero and (38) recommends using 0.1% to guide policy. We provide an approach to estimate the welfare discount rate under revealed preference. Within our sample of innovators, our estimate lands at the mid-point of prior estimates, at 0.76%. Using Fisher exact tests, we show that our value has relatively tight standard errors. Indeed, within our sample, we can conclusively reject both values

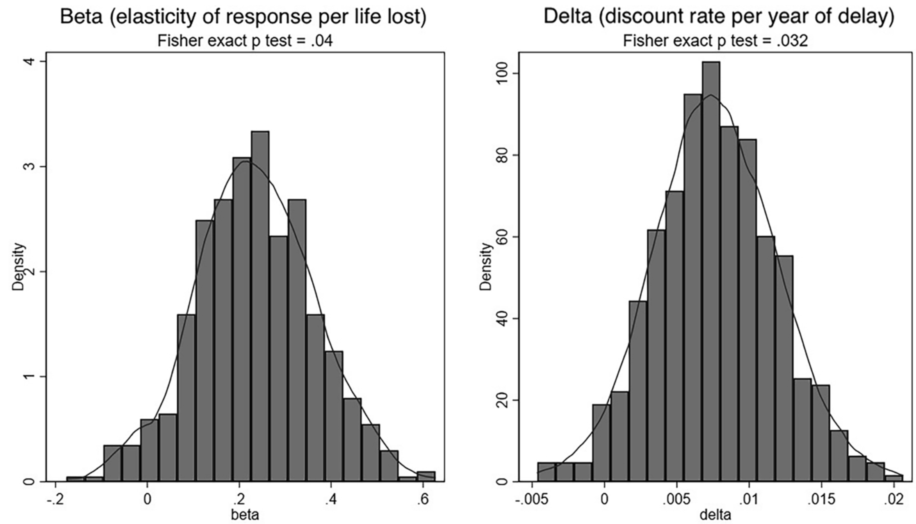

Fig. 2. Baseline structural estimates.

of zero (P = 0.032) and 0.1% (P = 0.038) as too low and 1.5% (P = 0.054) as too high.

This value is also lower than the social discount rate used to discount the welfare payoff of public investments (40), which prior work proposes should be at 3.5% (41). The core difference between our estimate and the social discount rate is that we are measuring only the level of social time preference (how much less the future should matter compared to the present), but we do not incorporate the opportunity cost of capital, the risk of future payment problems or default, or any other element determining the nature of the return to public finance projects beyond time preference itself.

The elasticity to lives lost, in contrast, does not have any direct equivalent in existing climate models, which are framed around the social planner's problem of discounting future utility rather than the number of lives lost. However, some observations can be made on our estimate. Most significantly, while $\beta^* = 0.23$ indicates a significant response to the change in the number of human lives affected, the fact that this value is smaller than 1 shows that the marginal value of saving an additional life diminishes as the total human toll of climate change increases. This result suggests that the concern for catastrophic human loss attenuates as larger numbers are affected (42) and provides evidence specifically in the context of innovators considering climate change.

Conclusion and Discussion

In this paper, we carried out a preregistered field experiment with MIT Solve to examine innovator response to different climate change scenarios. We emailed all grantees of the SBIR program with messages varying the timeline and scale of climate impact. Our main results are fourfold. First, through email clicks, we find that innovators respond more when climate impact is framed as occurring sooner and in greater scale. Second, our treatments also have a sizable impact on the actual probability of applying to the competition. Third, innovator response varies by their characteristics such as their location-based exposure to climate change risk and existing technological relevance to climate change. Finally, we construct a stylized structural model of innovator attention to provide specific estimates of innovators' elasticity to lives lost and discount rate on time.

Our paper highlights the potential role of messaging and attention in shaping innovator choices. We show that different messages framing a problem, even in a low-touch email communication, elicit a substantial difference in innovators' level of interest and initial response. Nonetheless, we add a note of caution that it is not advisable to exaggerate a problem as negatively as possible in the hopes of garnering more attention. To be clear, our treatment messages were based on scientifically valid scenarios, despite the uncertainty around climate change. While we do not test cases outside of this range in our field experiment, exaggerating the time frame or scale of climate change (or any other problem) may lead to backlash or unintended consequences due to potential nonlinear effects in edge cases. The audience may disbelieve the claim and lose trust in the information source, especially in the case of knowledgeable audiences like innovators. Deception produces distrust and undermines the general effectiveness of similar types of communications, as shown in research on advertising (43). Furthermore, we believe that exaggeration may also make the audience overwhelmed and disengage from a seemingly impossible situation due to psychic numbing effects or the inability to appreciate losses of life as they become larger (42, 44).

To extrapolate beyond our setting, it is worth considering the time necessary for any innovative effort to have an impact. Climate change action would take time to have an effect, given the complexity of Earth climate systems. More immediate problems (e.g., COVID-19 vaccines) are likely to have, ceteris paribus, larger effects as the payoff to innovative effort increases in present value. However, this is reduced to the extent the problem is also already more present in the innovator's attention beforehand, in which case the amount of attention shifted by a present-framing may be weaker, leading to a smaller effect. Understanding the balance between these two effects is critical to move beyond our results to think about soliciting innovators from different fields to pay attention to large-scale societal problems.

More broadly, our results also speak to prior work that shows how public support for taking action on climate change varies by how the issue is communicated (45, 46). We provide a complementary focus on innovators, a distinct group of people with a key potential to develop technological solutions. Our findings on heterogeneous effects also suggest that the messaging effect on innovators' attention to climate change varies by their personal exposure to climate change-related events.

These findings also provide practical implications on innovation policy for climate change. While much of the policy discussions on climate change center on financial incentives such as carbon taxes and research subsidies, carefully drafted communications to inventors and entrepreneurs may provide a cost-effective way to draw attention to the issue of climate change and motivate related innovation efforts.

Data, Materials, and Software Availability. Anonymized Stata data have been deposited in a publicly accessible and persistent repository at OSF Home, https://osf.io/fzjua/.

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