How Do (Green) Innovators Respond to Climate Change Scenarios? Evidence from a Field Experiment *

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Abstract

This paper aims to unpack the pro-social motivations of green innovators. In a field experiment inviting SBIR grantees to learn more about and apply to MIT Solve, we provide scientifically valid scenarios varying the time-frame and scale of human cost of climate change. Innovators' response in clicks and applications increases with both scale and immediacy treatments. Our structural model estimates a welfare discount rate of 0.76%, providing a measure of innovators' value of future generations, and an elasticity to lives lost of 0.23, implying diminishing marginal concern to human loss.

Keywords: *innovation, motivation, pro-sociality, climate change, field experiment*

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1 Introduction

Green innovation is central to an appropriate response to climate change (Nordhaus, 2019). Economic research on the design of incentives for green innovation has been booming (Acemoglu et al., 2012, 2016; Gans, 2012; Akcigit and Stantcheva, 2020). However, this research has so far mostly focused on monetary incentives, and much less is known about the role of pro-social motivations of innovators themselves. That is, as innovators observe information on the scale of climate change impact and its effect on future generations, they may respond to address it for reasons beyond profits or tax incentives. Given the focus of recent work on social impact as an independent and important motivation for innovation (Cohen et al., 2020; Guzman et al., 2020), this gap is perhaps surprising. Understanding and unpacking pro-social motivations behind innovator response is crucial to devising strategy to address climate change. In particular, there is a need to quantify and rationalize fundamental parameters of innovator response to climate change scenarios such as the welfare discount rate (concern for future generations) and their elasticity of response to the number of lives lost.

Indeed, in climate economics models, the fundamental ambiguity about the right discount rate to use to evaluate climate investments, or how to adjudicate amongst multiple discount rates to consider both the future returns on investment and the well-being of future generations, has been a source of significant discussion.[1] In addition, psychological studies (Slovic, 2007; Peters et al., 2006) suggest a wide range of elasticities of response to lives lost, from elastic, where innovators would respond disproportionately more as the number of lives lost increases due to a higher risk of catastrophe, to inelastic, where innovator response would be attenuated due to numbing and inability to process large losses of life. The innovation literature has yet to offer a systematic way of conceptualizing and estimating innovator response to different dimensions of social issues, even within a specific problem like climate change.

In this paper, we tackle this problem by providing experimental evidence and devel-

[1] See Nordhaus (2007) and Drupp et al. (2018) for discussions of the sensitivity of climate estimates to the welfare discount rate.

oping a novel conceptualization of the response of innovators to climate change scenarios. We carry out a pre-registered field experiment on a large sample of highly skilled technology innovators. Working with MIT Solve, a premier competition focused on solving the world's problems, we email over 30,000 grantees of the Small Business Innovation Research (SBIR) award by the National Science Foundation (NSF) to encourage them to learn more and apply to the competition. Using different scientifically valid scenarios from climate science, we provide information through messages that randomly vary the time frame of climate change impact (to occur in 2020 vs. 2050) and the estimated number of lives at stake (150,000 vs. 400,000 deaths per year).

We then introduce a pre-registered stylized economic model of innovator response to the impact of climate change. In our model, the innovator's value of acting on climate change depends directly on the elasticity of action to number of lives lost, and a welfare discount rate for the timing of human loss. This welfare discount rate reflects the underlying concern for the well-being of future generations, rather than the cost of capital. We show that, under reasonable assumptions, these parameters can be estimated using simple experimental data that uses information messages, such as emails, and a private action on interest, such as clicks, that adequately captures personal motives without market or audience forces shaping them.

Our reduced-form experimental results show a substantial increase in clicks when the message describes the human cost of climate change to be greater (19.2% more clicks than the mean) and sooner (19.1% more). Using a surrogate index (Athey et al., 2019) for applications, we estimate more applications submitted when the human loss is described to be greater in scale (up to 9% of the mean) and occurring sooner (up to 8.7% of the mean). Finally, we use this data to estimate the parameters of our model. We estimate a welfare discount rate of 0.76%, and an elasticity to number of lives lost of 0.23, implying a diminishing marginal concern as the human toll of climate change increases.

Our paper contributes to three areas of research at the intersection of innovation economics, policy, and climate change. First and foremost, we contribute to recent work that emphasizes the importance of social impact as an incentive for innovation (Cohen

et al., 2020; Guzman et al., 2020) by unpacking innovators' pro-social interest into specific parameters of their private value to action on a potentially catastrophic problem. Our paper is therefore the first to open up the 'black-box' of innovators' pro-social motivations towards specific problems, especially for catastrophic scenarios like climate change. These results also complement prior work on various incentives for innovation, including financial incentives (Manso, 2011; Lerner and Wulf, 2007; Myers, 2019), individual and cultural factors (Kerr et al., 2019; Koning et al., 2019; Sauermann and Cohen, 2010; Mokyr, 2016; Azoulay et al., 2019b), organizational structures (Keum and See, 2017; Cockburn and Henderson, 1998; Azoulay et al., 2019a), and intrinsic motivations (Lakhani and Wolf, 2003; Stern, 2004).

Second, our paper connects to the long line of work in climate economics, where both financial incentives and the discount rate have long been considered fundamental parameters (Acemoglu et al., 2016; Gans, 2012; Stern, 2008; Nordhaus, 2019; Pindyck, 2020; Weitzman, 2009). We add to this work by focusing on the novel motive of social impact for innovation response, conceptualizing this response on a stylized model, and estimating its two key parameters, welfare discount rate and elasticity to lives lost. To the best of our knowledge, we are the first to use a revealed preference experiment to estimate these fundamental measures of climate response. Our estimates are at the mid-point of the range of existing estimates of 0.1% by Stern (2008) and 1.5% by Nordhaus (2007). Furthermore, a key distinction of our paper is that we focus directly on innovators and their value function, rather than a social planner problem, which directly leads to a different set of potential levers for action (i.e., targeting innovator behavior rather than tax policy). Given the importance of climate innovation in determining climate response (e.g. Nordhaus, 2007), our results add a complementary perspective to the public discussion.

Finally, our paper contributes to the broader literature using experiments to understand innovator incentives (Ganguli et al., 2018; Boudreau and Lakhani, 2011; Gallus et al., 2019; Guzman et al., 2020; Cowgill et al., 2020), by uniquely focusing on a more systematic sample of proven high-skilled innovators (SBIR grantees). Indeed, identifying and measuring the preferences of such innovators are important given survey evidence on

their distinct psychological traits (Kerr et al., 2019). Moreover, our email experimental approach is also complementary to existing studies using online experiments to measure economic and social preferences (Stantcheva, 2020).

2 Empirical Setting

2.1 MIT Solve Global Challenges

MIT Solve is an organization focused on solving world challenges through innovation. Its main program is their annual Global Challenges – thematic competitions to fund innovative solutions to specific problems. As of July 2020, Solve has received 6,500 applications from 157 countries, and has secured $25 million in funding and over 200 partnerships for winners (MIT Solve, 2020). Successful winners include companies such as ISeeChange, a startup using mobile technology to develop crowd-sourced micro-data on the impact of climate change, and Code Nation, an education company helping under-served students develop skills in software engineering. In 2020, the Solve Global Challenges focused on six areas, all of which have potential overlap with climate change challenges such as Sustainable Food Systems, Indigenous Communities, Good Jobs and Inclusive Entrepreneurship, and Maternal and Newborn Health. Figure A.5 contains a short description of each challenge from Solve's website.

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 events with local partners. We engaged with Solve in early 2019 and partnered with them for their 2020 Global Challenges to support their outreach activities. Specifically, 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.

2.2 Finding Innovators: SBIR/STTR Grantees

Our study focuses on highly skilled technological innovators who received a research grant from the Small Business Innovation Research (SBIR) or the Small Business Technology Transfer (STTR) federal programs. These are highly competitive programs that support the development of early-stage innovative technologies that need federal funding before they can be taken up by commercial financiers.[2] Run by the National Science Foundation (NSF) in partnership with the U.S. Small Business Administration, both programs are sponsored directly through several federal departments to advance American technological research priorities. To date, over $40 billion has been allocated through these programs to aid early-stage innovation. For simplicity, we hereafter refer to both programs together as SBIR.

The NSF releases public information online on all SBIR grantees, including project title and abstract, grantee address, awarded amount, and year of grant as well as contact information, which allows us to email them.

3 Experimental Design

Our experimental goal is to measure how innovator response varies across catastrophic scenarios in climate change. To accomplish this, following our pre-registration, we emailed SBIR innovators (from Solve's email account) randomly assigned messages varying the stated human toll of climate change across scientifically valid scenarios, and encouraged them to apply to 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' pro-social response to climate change scenarios.

Our treatments are structured as a 2x2 between-subject design, in which each innovator received one email with a climate change scenario of either low or high magnitude, framed as occurring either in the present or in the future. Based on the scientific literature, we used as either 150,000 or 400,000 lives as the estimated number of lives at stake each

[2] While SBIR focuses on supporting young innovative companies directly, STTR focuses on commercializing academic research through partnerships between small businesses and nonprofit research institutions.

year due to climate change, and framed the impact as occurring in either 2020 or 2050. These numbers are around the reasonable lower and upper bounds from the estimates in Patz et al. (2005), Springmann et al. (2016), and the World Health Organization (2014). Using these allowed us to have as much variance as we can while remaining 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 these four scenarios. The email subject was:

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

And the email 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 content in the email. The full email message is provided in Figure 1.

We ask innovators to save lives by solving climate change to clearly emphasize the pro-social incentives to mitigating the problem, without alluding to any potential market opportunities in green technologies. Such a pro-social message is in line with those used in Ganguli et al. (2018) and Guzman et al. (2020). As a simple sanity check, we also carried out a survey on Amazon Mechanical Turk asking individuals to identify the sentiment of our key message in the email as either pro-social or market-oriented. In particular, we asked them to rate "Save 400,000 lives in 2020 from Climate Change: Apply to MIT's Entrepreneurship Challenge!" as either pro-social ("The message intends to highlight the need to help people who are threatened by climate change") or market-oriented ("The message intends to highlight what climate change means for businesses and their profits"). We found that 90% of the 200 respondents chose the former, showing that our messages are generally perceived as engaging with pro-social motivations than market-oriented interests.

3.1 Sample Selection and Randomization

Our sample consists of all individuals who have received an SBIR grant since 2010.[3] This sample represents high-ability innovators who have created innovative technologies in relatively recent years, and provides a large enough sample size to run the experiment. We exclude 99 contacts whose email addresses had syntax errors or were invalid, resulting in our final sample of 31,666 individuals from 12,008 companies. We assign individuals randomly to one of the four treatment groups.

Table A.1 shows the summary statistics of the dependent variable and main pre-treatment observables available in our data. The click rate on email links is 1.5%, which is considerably higher than in similar settings with cold emails.[4] In Table A.2 in the appendix, we provide balance tests showing that the four treatment arms were well balanced in terms of pre-treatment covariates such as type of contact (principal investigator or not), award year, amount awarded, whether the individual invented a patent, whether the company is categorized as belonging to a disadvantaged population, 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. To ensure sufficient power in our empirical estimation, we pool treatments and estimate two parameters instead of four. In particular, we estimate one parameter comparing the responses to present vs. future framing and the other comparing messages with high vs. low number of lives saved.[5] Moreover, in the structural model we show that it is precisely these two parameters which are of theoretical consequence.

[3] All SBIR/STTR grants included were available on the government website, downloaded on May 3rd, 2020.

[4] In Guzman et al. (2020), the analogous click rate was 0.5% for emails sent to a list of entrepreneurs obtained from Dunn and Bradstreet emailed from a similar MIT account.

[5] Technically, we have one degree of freedom in terms of the treatment conditions since we only need three conditions to estimate these two parameters. The two "present" treatments, which vary in terms of high vs. low magnitude, would allow us to recover innovator motivations related to the scale of the problem. An additional treatment varying the timeline of climate change effects would allow the estimation of the time discount rate of the innovators.

3.2 Variables of Interest and Empirical Framework

Our empirical analyses focus on the treatment effects on clicks and applications. We begin by describing our reducted for estimates. For each individual i and outcome Y_i, we estimate the following model:

$$Y_i = \alpha + \rho \times Present_i + \gamma \times HighImpact_i + \zeta \times X_i + \epsilon_i \tag{1}$$

The main variables of interest are ρ, 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 is a random error term, and X_i represents a number of controls.

We estimate this model by focusing on two outcome measures. We review each of our measures in turn.

Clicked is a binary variable indicating whether an individual has clicked on any link in the email within 48 hours 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, thus representing an innovator's private, active interest in the climate change-related innovation competition. Clicks have been used to measure interest in related settings by Bapna and Ganco (2018), Bernstein et al. (2017) and Guzman et al. (2020) among others.

Application Probability represents the probability that the subjects actually apply to MIT Solve, constructed using the surrogate index method of Athey et al. (2019).[6] A surrogate index that estimates the mapping of intermediary outcomes (click behavior) to a final outcome (applications) can increase the precision of estimates and permit identification.

We introduce the predictive model used for our surrogate index in Table A.4. We regress whether a company applied to MIT Solve on a variety of measures related to click

[6] As is common in email experiments, measuring this outcome directly is difficult due to applications being sparse in our data. It is important to note that Solve has a multitude of outreach programs to solicit applications globally, well beyond the mailing list to which we have access.

behavior and innovator and firm level characteristics.[7] The *predicted* probability of this model constitutes our main dependent variable. Finally, for robustness, we also estimate a second surrogate index from a prior experiment we performed with the MIT Inclusive Innovation Challenge, a sister competition to MIT Solve (see Guzman et al., 2020). This allows us to ensure that the surrogate index is not unique to the intricacies of MIT Solve, but reflects actual innovator intent and also serves as an out-of-sample test of the index itself.

4 Results

We now proceed to our analysis, which uses experimental variation in our pro-social messages to identify innovator response in terms of clicks and a surrogate index to study its impact on applications. We present reduced form results and then take these estimates to implement a structural model of innovator response.

4.1 Baseline Estimates on Clicks and Heterogeneous Effects

We report the estimates from linear probability model regressions predicting *Clicked* in Table 1. We scale the dependent 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 impact leads to a higher probability of clicking on the email links. Specifically, innovators are 19.1% more likely to respond to messages framed in terms of the present rather than the future. Similarly, innovators are 19.2% more likely to respond to information with a high impact on lives relative to a low impact. Both effects are 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 results for both types of treatments are qualitatively and quantitatively similar. In column (3), we account for the possibility that some clicks may represent negative reactions to an unex-

[7] The different variants of click behavior are whether the email was clicked, 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 first award amount, whether it was phase I or phase II, and whether it was an SBIR or STTR grant.

pected email, by controlling for whether the individual unsubscribed after receiving our email. In column (4), we estimate the p-values of the treatment effects 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).

To ensure that our results are not driven by the use of linear probability models, we analyze our treatment effects under a variety of other assumptions. Figure 2 reports the treatment effects in terms of raw mean differences, and logit models with and without controls used in our baseline specification. These alternative specifications lead to almost identical results. Our preferred specification is the linear probability model controlling for pre-treatment covariates, for ease of interpretation and greater precision of estimates.[8] [9]

Next, we analyze heterogeneous treatment effects across levels of inventiveness, by comparing innovators who are patented inventors to those who are not, based on matching innovator names and locations to United States Patent and Trademark Office data. Using our preferred specification, Figure A.1 in the Appendix plots the main effects and a breakdown of the effects for patented inventors vs. others. It shows that patented inventors are more present-oriented as well as more responsive to a higher toll on human lives, compared to others. In other words, patented inventors respond differently from non-patented ones, and they seem to be driving our treatment effects. The finding that patented inventors are more present-oriented than others in these innovative firms aligns with Kerr et al. (2019), who find that inventors are more risk averse (in terms of both general and financial risk) than entrepreneurs or business leaders.

Finally, we carry out a series of robustness checks in Table A.3 in the Appendix to ensure that our baseline estimates are not driven by any idiosyncrasies in the data. We find estimates qualitatively and quantitatively similar to the baseline when we account for local political preferences captured by political donations, use alternative clustering

[8] For completeness, we report the disaggregated treatment effects in Figure A.2 in the Appendix.

[9] Technically, we note that a Logit model without controls estimates marginal effects like a linear probability model (with or without covariates). A Logit model with controls, on the other hand, estimates conditional effects.

of standard errors, as well as a double robust estimator.[10]

4.2 Baseline Estimates on Applications

Next, in Table 2, we examine the relationship between our emails and applications to the Solve Challenges. We proceed in two steps. First, following Bapna and Ganco (2018) and Guzman et al. (2020), we show that clicks and website visits do predict application activity. 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 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 made on a given day.

Column (3) uses a linear probability model to estimate treatment effects on our key outcome variable, *Application Probability*, which is the probability of applying estimated through a surrogate index comprised of multiple measures of click behavior as described in Section 3.[11] Both *Present* and *High Impact* treatments are significantly associated with submitting an application. As can be seen in the coefficients, which are scaled by the mean for ease of interpretation, the effect of *Present* is about a 4% increase from the mean and the effect of *High Impact* is about 3%. In column (4) we repeat our exercise using a different sample to build a surrogate index, using data from our previous experimental study with the MIT Inclusive Innovation Challenge (Guzman et al., 2020). 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 results are stronger, with our treatments increasing applications by approximately 9% relative to the mean.

[10] We also employ a keyword matching approach, based on text used by Solve and as well as the glossary of climate change keywords by the IPCC, to identify companies which might be more relevant to climate change as well as an alternative measure using the sponsoring federal agencies that are 'closer' to climate change. In Table A.5 in the Appendix, we show that companies that are 'closer' to climate change are more likely to click on our emails in general. This implies that we are capturing the attention of the most relevant innovators within the sample.

[11] It is also important to note that the website remain unchanged for all subjects and did not use the information in the emails again.

Together, our baseline results show a sizable difference in innovator response to treatment messages that vary the timeframe and scale of climate impacts. In terms of both clicks and applications, we find that innovators respond significantly more to climate change scenarios that are taking place sooner or are greater in scale. In the next section, we quantify these parameters in a structural model to assess how do the size of these treatment effects translate to the parameters of innovators' pro-social preferences.

5 A Structural Model of Innovator Response

We now proceed to estimate the parameters of innovator response in a stylized economic model. In our model, innovator interest is defined as their valuation of a climate issue, which is a function of their elasticity to the number of lives lost (concern for human loss) and welfare discount rate (concern for future generations). Innovators face a multinomial choice problem: they receive multiple messages and choose the one to learn more about, or do nothing. We show how under a simple assumption, the key parameters of this model can be estimated from our experiment. For our innovators, the elasticity to lives lost is 0.23 and the welfare discount rate is 0.76.

5.1 Theoretical Framework

Consider a population of innovators, indexed by i, who are presented four messages ($m = \{1...4\}$) about climate change impact. They can choose to learn more about any one of these messages or to do nothing. They have a private value of acting on each option $V_{i,m}$, and an opportunity cost of their time $V_{i,0}$.

The innovators choose an action m^* according to

$$m^* = \underset{m=\{0...4\}}{\arg\max}\ V_{i,m} \tag{2}$$

Each message contains two characteristics. A value L_m, which is the number of lives lost under climate change, and a time-delay T_m which is the time it will take for this human loss to occur.

For tractability, we assume that the two effects are separable and complementary, so that

$$V_{i,m} = A_i \; f(L_m) \; g(T_m) \; E_{i,m}$$

Where A_i represents is a baseline innovator interest in climate change, and $E_{i,m}$ is a random error term on the valuation of each choice distributed log-logistic (i.e., its logarithm has a logistic distribution).

Functions $f(\bullet)$ and $g(\bullet)$ depend on two parameters. The value of lives depends on an elasticity to lives lost β, and the response to timing is defined by exponential discounting with the welfare discount rate δ, reflecting the yearly discount rate of the well-being of future generations. These two parameters capture, at a first approximation, the two key dimensions of the human cost of any catastrophe.

$V_{i,m}$ can then be re-written as

$$V_{i,m} = A_i \; L_m^{\beta} \; \frac{1}{(1+\delta)^{T_m}} \; E_{i,m}$$

Taking logs on the value function, the innovator's problem can be re-formulated as

$$m^* = \underset{m=\{0...4\}}{\arg\max} \; a_i + \beta l_m + \gamma T_m + \epsilon_{i,m} \tag{3}$$

where $\gamma = -log(1+\delta)$ and l_m and $\epsilon_{i,m}$ are the logs of L_m and $E_{i,m}$, respectively.

5.2 Estimation Approach

Equation 2 represents a multinomial logit framework where each inventor evaluates all choices simultaneously. However, considerations such as the complexity of mentally evaluating multiple options, and the potential contamination of information from some options to others due to anchoring bias (and other types of biases) does not allow us to feasibly run this full experiment. To recover the underlying parameters, we first recognize that for a multinomial model with logistic error terms the log ratio of probabilities equals the

linear relationship of interest.

Given the two messages with high and low values of lives lost with click probabilities $P_{H,j}$ and $P_{L,j}$, respectively, a multinomial model implies:

$$log(\frac{P_{H,j}}{P_{L,j}}) = \beta \Delta l = \beta[l_H - l_L], \quad j \in \{P, F\} \tag{4}$$

where $j \in \{P, F\}$ reflects whether the message is future or present oriented. Removing j for simplicity,

$$\beta^* = \frac{log(\frac{P_H}{P_L})}{log(L_H) - log(L_L)}$$

And equivalently

$$\gamma^* = \frac{log(\frac{P_P}{P_F})}{T_P - T_F}, \quad \delta^* = e^{-\gamma^*} - 1 \tag{5}$$

To connect this estimand to our single message experiment, we impose an additional assumption of independence of irrelevant alternatives (IIA) between the outside option and a click. Note that this is not IIA amongst climate chance scenarios, but instead simply between the outside option (doing nothing) and choosing to click on any message. This makes the choice model equivalent to a nested logit model with the outside option in one nest and all messages in the other.

Representing the click probability of a message in single message experiment P_k^S, we can then use the ratio of clicks between any choice or not in this experiment to back out this ratio:

$$\frac{P(V_{i,H} > V_{i,0})/P(V_{i,H} < V_{i,0})}{P(V_{i,L} > V_{i,0})/P(V_{i,L} < V_{i,0})} = \frac{P_H^S/(1 - P_H^S)}{P_L^S/(1 - P_L^S)} = \frac{P_H}{P_L}$$

5.3 Parameter Estimates

We implement this approach on our data using 500 bootstrap samples. Figure 2 reports the distribution of β^* and δ^* for these samples and the Fisher exact test for the parameters being larger than zero.

The mean value of β^*, the elasticity to lives lost, is 0.23 and rejects the null of zero with an exact p-value of 0.04. The mean value of δ^*, the annual discount rate for 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.

5.4 Interpreting our Estimates within Climate Models

We have provided an original estimate of the welfare discount rate and the elasticity to lives lost using revealed private choices of innovators to climate messages. It is useful to frame these estimates with respect to the literature.

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. A zero or near-zero rate means that the welfare of future generations is weighted almost equally to nearer generations. Prior estimates have been produced through either expert surveys (Drupp et al., 2018), deductive methods that back out the welfare discount rate from observed returns of capital and growth in a Ramsey framework (Nordhaus, 2014), and inductive methods from moral principles (Stern, 2008). A takeaway from this literature is that even though welfare discount rate is central to climate modeling, its estimates vary widely across different approaches. For example, while Nordhaus (2007) estimates a value of 1.5% for the welfare discount rate, Drupp et al. (2018) report a large portion of climate policy experts would prefer a value of zero, and Stern (2008) recommends using 0.1% to guide policy. We provided the first 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 of zero (p=.032) and 0.1% (p=0.038) as too low, and 1.5% (p=.054) as too high.

The elasticity to lives lost, in contrast, does not have any direct equivalent in existing climate policy models, which are framed around the social planner's problem of discounting future utility, rather than deaths. 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 an attenuating concern as larger numbers of lives are affected by a catastrophe (Slovic, 2007), and provides novel evidence specifically in the context of innovators considering climate change.

6 Conclusion

In this paper, we carried out a pre-registered field experiment with MIT Solve to examine innovator response to different climate change scenarios. We emailed all grantees of the NSF's SBIR program with messages varying the timeline and magnitude of climate impact. Our main results are threefold. First, through email clicks, we find that innovators respond more when climate impact is framed as occurring sooner and in greater magnitude. Second, our treatments also have a sizable impact on the actual probability of applying to the competition. Finally, we construct a stylized structural model of innovator response to provide specific estimates of innovators' welfare discount rate and elasticity to lives lost.

These results shed light on innovators' pro-social interest by uncovering the parameters that determine their response. To the best of our knowledge, our paper is the first to open up the 'black box' of the extent of innovators' pro-social interest along fundamental dimensions and to do so experimentally. Our paper is also distinct in its choice to focus on innovators' pro-social interest in one specific problem of great significance, namely climate change. The revealed welfare discount rate for climate impacts closely relate to the broader debate around the adequate discount rate for climate change investments. Our experimental approach may potentially be applied beyond our sample to measure the response of other populations or to better understand the parameters of response to different types of problems facing society.

Finally, our paper also highlights the potential role of information in shaping innovator choices. Indeed, we show that different information on a problem, even in an email from an authoritative entity such as MIT, elicits a substantial difference in innovators' response

and interest. How information changes innovator choices to shift the rate and direction of innovation is a particularly important area for future work with significant policy implications.

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Figure 1: Email Treatment

MIT | SOLVE

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

Hi [First Name],

Did you know that an estimated [150,000/400,000] lives could be saved in [2020/2050] by mitigating climate change? To do so, we need innovative solutions to reduce emissions, increase adaptation efforts, and prevent natural and social disruptions. Transitioning to a more sustainable world requires us to innovate across multiple aspects of our lives, including energy, transportation, agriculture, and urban planning.

At Solve, we are committed to finding and supporting solutions to the world's most pressing challenges through open innovation. In response to the threat of climate change, we have launched a Solve Challenge focused on Sustainable Food Systems. This is one of five Global Challenges that Solve launched this year.

Food security is one of the most important issues of climate change, as disruptions from climate change-related disasters leads to lower production, more food insecurity and malnutrition. This demonstrates a need for more sustainable food systems: How do we produce and consume low-carbon, resilient, and nutritious food? With the Sustainable Food Systems Challenge, we are looking for technology-based solutions for achieving a low-carbon global food system that provides nutrition with minimal environmental impact.

Are you working on a relevant solution? Apply with your solution by June 18, 2020 at 12pm ET.

APPLY NOW

In addition, the Solve Indigenous Communities Fellowship seeks native-led solutions that provide healthy and sovereign food, sustainable energy, and safe water. Apply and spread the word by July 7.

Anyone, anywhere can apply with solutions at all stages of development. If you are selected as a Solver, you will:

- Receive access to over $1.5 million in prize funding for the 2020 Challenges;
- Join a supportive community of peers, funders, and experts to help advance your innovative work;
- Receive mentorship and strategic advice from Solve and MIT networks;
- Gain media and conference exposure for your solution.

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Table 1: Impact of Climate Scenarios on Innovator Response: Clicks

	Baseline	Restricted Clicks	Unsubscribed Control	Randomization Inference
	(1)	(2)	(3)	(4)
Variables	Clicked	Clicked	Clicked	Clicked
Present	0.191**	0.192**	0.190**	0.191**
	(0.0912)	(0.0916)	(0.0912)	[0.037]
High Impact	0.192**	0.193**	0.193**	0.192**
	(0.0928)	(0.0932)	(0.0928)	[0.038]
Observations	31,662	31,662	31,662	31,662
R-squared	0.024	0.024	0.024	0.024

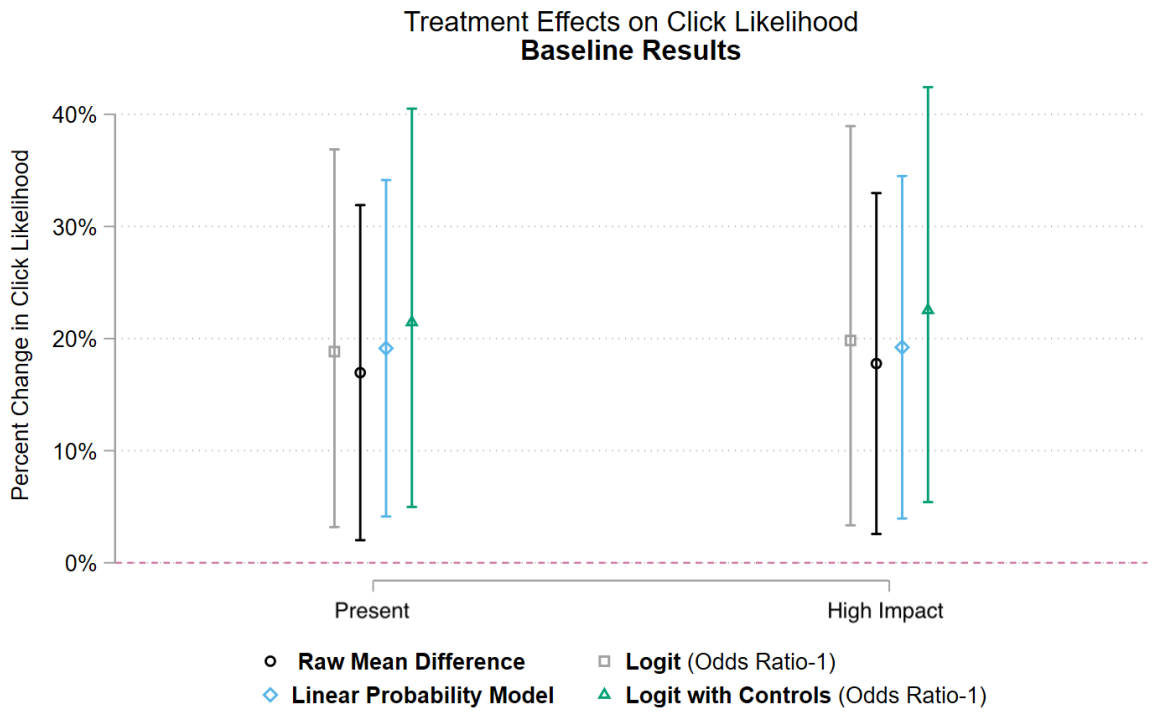
Robust standard errors in parentheses clustered by company in columns (1)-(3). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All columns use a linear probability model (LPM) and the unit of observation is at the individual level. The dependent variable is whether the individual recipient clicked on any 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, 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. Column (3) limits the outcome to clicks on links that take the individual straight to Solve's Challenges website. Column (2) additionally controls for whether the recipient unsubscribed from the list after clicking. Column (4) uses randomization inference to estimate the standard errors of the treatment effects for our baseline specification in column (1), with p-values reported in the square parentheses. Some observations are dropped due to collinearity with fixed effects.

Table 2: Impact of Climate Scenarios on Innovator Response: Applications

Variables	Solve Experiment (1) Application Submitted	Solve Website (2) Log(Applications)	Solve Surrogate (3) Application Probability	IIC Surrogate (4) Application Probability
Clicked	1.731***			
Number of Visitors		0.635***		
		(0.182)		
Sessions per Visitor		6.384**		
		(2.510)		
Present			0.041***	0.0899**
			(0.014)	(0.039)
High Impact			0.032**	0.087**
			(0.015)	(0.041)
Observations	30,878	115	31,463	30,955
R-squared			0.039	0.022

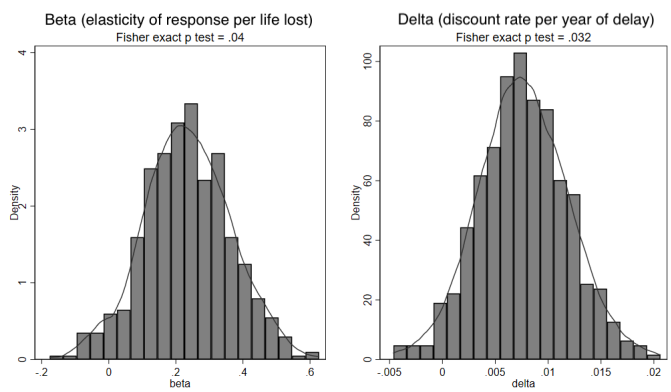
Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Column (1) uses a logit model while columns (2)-(4) use an OLS specification. The unit of observation is at the individual level in columns (1), (3) and (4) while it is at the day level in (2). The dependent variable is whether the individual recipient applied in column (1), the log number of daily applications to Solve in (2), the probability of applying predicted by a surrogate index based on the Solve experiment data in column (3), and that predicted using a surrogate index based on the IIC data in column (4). The dependent variable in columns (3) and (4) is divided by the mean for ease of interpretation. The independent variables in Column (2) are the log of the three-day moving average of the number of visitors and sessions per visitor. Controls include whether the individual is a business contact or principal investigator, award year, 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 in column (4) while column (3) uses 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.

Figure 2: Baseline Results: Alternative Functional Forms



Point estimates with 90% confidence intervals plotted for treatment effects under different assumptions. The linear probability model corresponds to our baseline estimate. The others are logit models with and without controls as well as the raw difference in means.

Figure 3: Baseline Structural Estimates



Appendix

Table A.1: Summary Statistics

	Mean	S.D.	Min	Max	Count
Clicked	0.015	0.121	0	1	31666
Applied	0.0013	0.036	0	1	31666
Has Patent	0.240	0.427	0	1	31666
Award Year	2015	3.077	2010	2020	31666
log(Award Amount)	12.578	0.971	7.24	16.30	31666
Phase I	0.639	0.480	0	1	31666
SBIR	0.842	0.365	0	1	31666
Less Than 5 Employees	0.265	0.441	0	1	31666
5-19 Employees	0.225	0.418	0	1	31666
20-49 Employees	0.123	0.329	0	1	31666
50 or More Employees	0.152	0.359	0	1	31666
Woman Owned	0.122	0.328	0	1	31666
Application Submitted	0.001	0.036	0	1	31666

Table A.2: Balance Table

	(1) Present-Low	(2) Present-High	(3) Future-Low	(4) Future-High	(5) Overall	(6) (1) vs. (2), p-value	(7) (1) vs. (3), p-value	(8) (1) vs. (4), p-value	(9) (2) vs. (3), p-value	(10) (2) vs. (4), p-value	(11) (3) vs. (4), p-value	(12) p-value from joint orthogonality test of treatment arms
Principal Investigator	0.46	0.46	0.46	0.46	0.46	1.00	0.99	1.00	0.99	0.99	1.00	1.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)							
Business Contact	0.30	0.30	0.30	0.30	0.30	0.99	0.99	1.00	1.00	1.00	0.99	1.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)							
Has Patent	0.24	0.24	0.24	0.24	0.24	0.53	0.15	0.42	0.41	0.86	0.52	0.55
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
Relevant Agency	0.19	0.19	0.18	0.19	0.19	0.382	0.302	0.930	0.874	0.336	0.262	0.56
	(0.40)	(0.39)	(0.39)	(0.40)	(0.39)							
Has Keyword	0.069	0.074	0.073	0.070	0.071	0.326	0.388	0.906	0.905	0.387	0.456	0.678
	(0.00)	(0.07)	(0.26)	(0.26)	(0.25)							
Award Year	2015.28	2015.22	2015.21	2015.22	2015.23	0.24	0.17	0.24	0.82	0.99	0.82	0.50
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)							
log(Award Amount)	12.58	12.58	12.58	12.57	12.58	0.77	0.66	0.90	0.88	0.67	0.57	0.94
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)							
Phase I	0.64	0.64	0.63	0.64	0.64	0.92	0.46	0.76	0.53	0.69	0.30	0.77
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)							
SBIR	0.84	0.84	0.84	0.85	0.84	0.90	0.81	0.30	0.91	0.24	0.20	0.56
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
Less Than 5 Employees	0.26	0.27	0.26	0.27	0.27	0.56	0.86	0.13	0.68	0.34	0.18	0.42
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)							
5-19 Employees	0.23	0.22	0.22	0.22	0.23	0.30	0.38	0.26	0.88	0.92	0.80	0.66
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
20-49 Employees	0.12	0.12	0.13	0.13	0.12	0.96	0.40	0.31	0.37	0.29	0.87	0.61
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
50 or More Employees	0.15	0.15	0.16	0.15	0.15	0.83	0.23	0.97	0.33	0.86	0.25	0.59
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
Woman Owned	0.13	0.12	0.12	0.12	0.12	0.94	0.21	0.43	0.23	0.48	0.63	0.54
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
N	7915	7917	7916	7918	31666							

Columns (1)-(4) show the means and standard deviations of the variables in each of the four conditions. Column (5) shows the same for the overall sample. Columns (6)-(11) show the p-value for pairwise tests of means across treatments while column (12) shows the joint orthogonality test of treatment arms. The unit of observation is at the individual level.

Table A.3: Robustness Checks

	Politcal Orientation	Political Orientation Ext.	City Level Std. Err	Double Robust Estimator
	(1)	(2)	(3)	(4)
Variables	Clicked	Clicked	Clicked	Clicked
Present	0.193**	0.195**	0.191**	0.191**
	(0.0911)	(0.0908)	(0.0904)	(0.0912)
High Impact	0.192**	0.189**	0.192**	0.192**
	(0.0928)	(0.0924)	(0.0886)	(0.0928)
Observations	31,661	31,661	31,658	31,661
R-squared	0.024	0.025	0.024	0.024

Robust standard errors in parentheses clustered by company except by city in column (3). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All specifications use a linear probability model. 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. Controls include whether the individual is a business contact or principal investigator, award year, 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. Column (1) uses political donations to Democrats and Republicans by zip-code as additional controls while in column (2) these are interacted with baseline controls. Column (3) clusters standard errors at city level while column (4) estimates Double Robust Treatment Effects. Some observations are dropped due to collinearity with fixed effects.

Table A.4: Extended Results for the Surrogate Index

VARIABLES	(Solve Data) (1) Application Submitted	(Solve Surrogate) (2) Application Probability	(IIC Data) (3) Application Submitted	(IIC Surrogate) (4) Application Probability
Present		0.041***		0.0899**
		(0.014)		(0.039)
High Impact		0.032**		0.087**
		(0.015)		(0.041)
Clicked	-7.896***		3.273***	
	(0.590)		(0.311)	
Restricted Clicks	8.903***			
	(0.782)			
Female Owner	1.247***			
	(0.357)			
Patented Innovator	0.254			
	(0.353)			
Disadvantaged Population	0.141			
	(0.495)			
Log(Award Amount)	0.310			
	(0.287)			
Phase 1	0.993**			
	(0.482)			
SBIR	0.632			
	(0.538)			
Opened	0.876**		0.937**	
	(0.412)		(0.468)	
Total Opens	-0.0109		0.0162	
	(0.0556)		(0.0205)	
Total Clicks	-0.00265		-0.0624	
	(0.0447)		(0.0611)	
Female			0.162	
			(0.242)	
Altruism			-0.760*	
			(0.428)	
Observations	31,467	31,463	7,317	30,955
R-squared		0.039		0.022

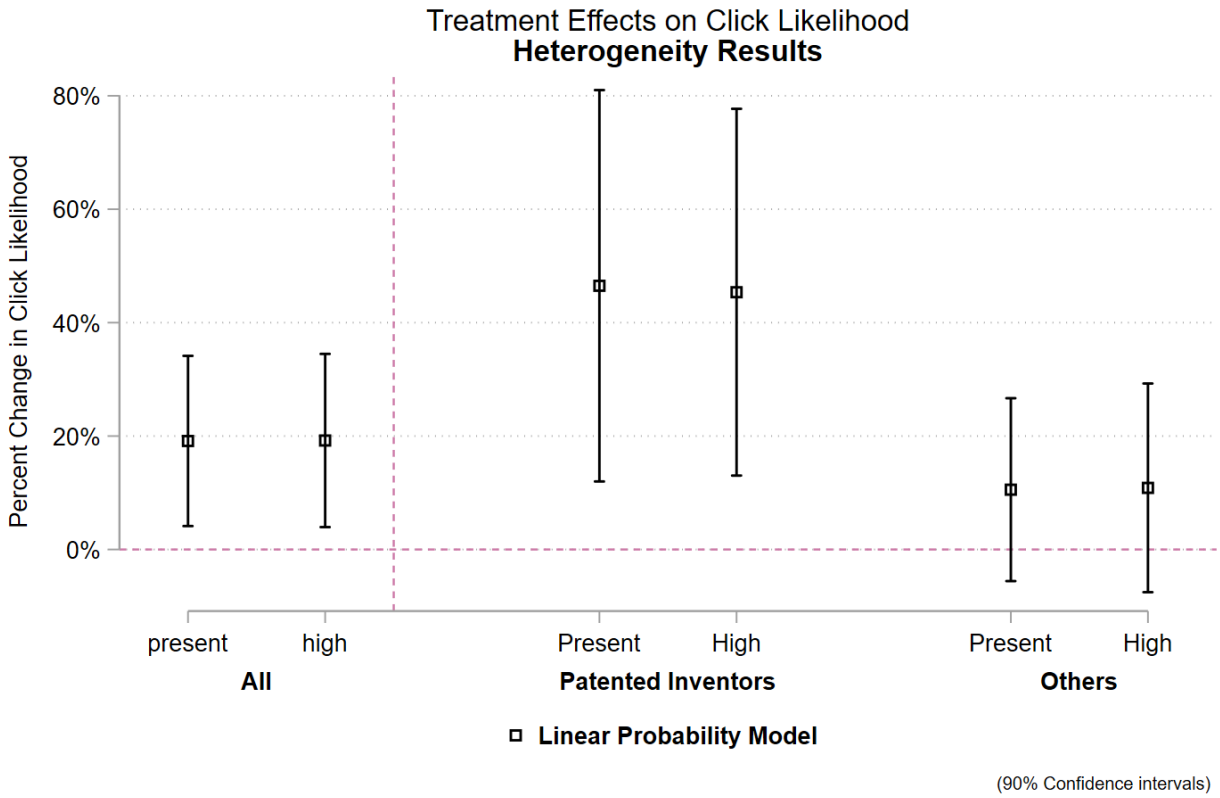
Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Column (1) and (3) use a logit model while columns (2) and (4) use an OLS specification. Column (2) uses the prediction from column (1), and column (4) uses the prediction from (3). The unit of observation is at the individual level. The dependent variable is whether the individual recipient applied in columns (1) and (3), the surrogate index based on the Solve experiment data in column (2), and the surrogate index based on the IIC data in column (4). Controls in column (4) include whether the individual is a business contact or principal investigator, award year, 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. In column (2) we control for award year, agency applied to, state fixed effects, and firm size since other covariates are utilized in column (1). Some observations are dropped due to collinearity with fixed effects.

Table A.5: Company Relevance to Climate Change and Clicks on Email Links

VARIABLES	(1) Clicked	(2) Clicked	(3) Clicked	(4) Clicked
Email Climate Keywords	1.765***			
	(0.580)			
IPCC Text Climate Keywords		0.431***		
		(0.167)		
Relevant Agencies			0.375**	
(Measure 1)			(0.184)	
Relevant Agencies				0.364**
(Measure 2)				(0.182)
Controls	Y	Y	Y	Y
Observations	30,465	30,465	30,465	30,465

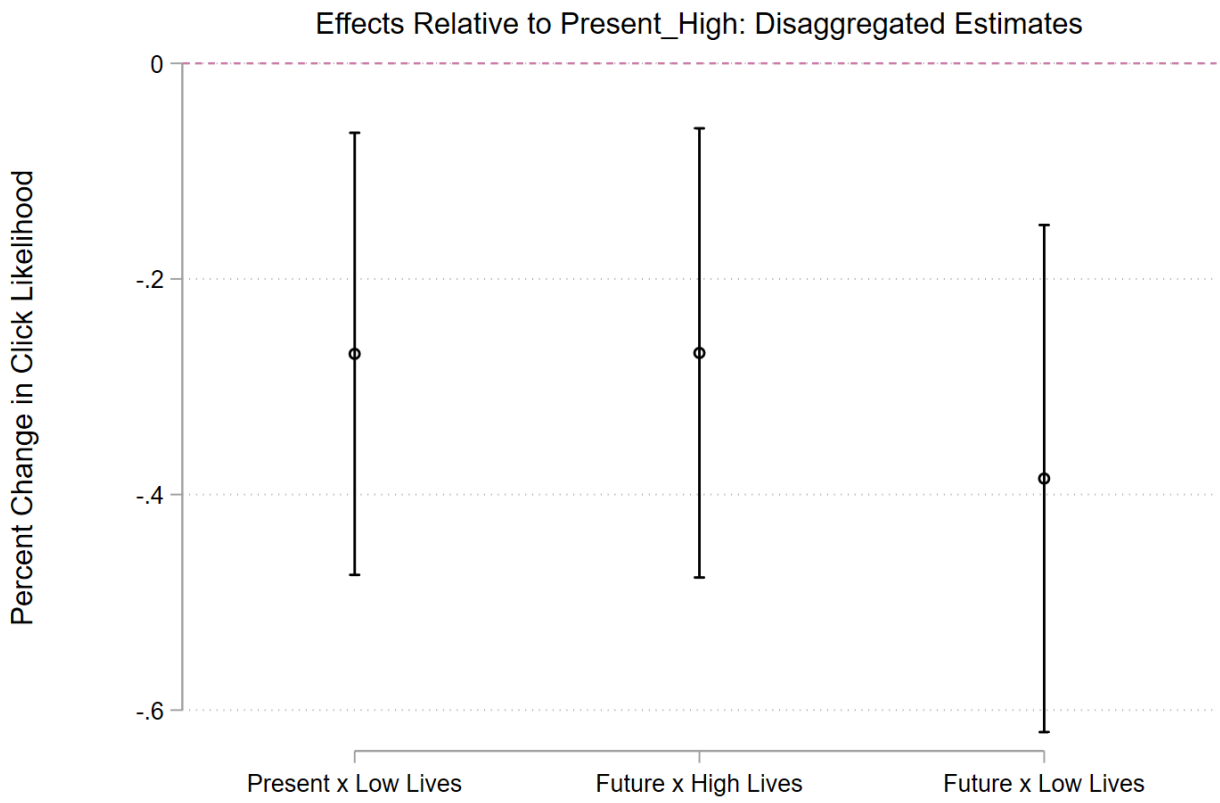
Robust standard errors in parentheses clustered by company. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All columns use a logit model. The unit of observation is at the individual level. The dependent variable is whether the individual recipient clicked on any link in the Solve email. Controls include whether the individual is a business contact or principal investigator, award year, and firm size. Column (1) uses keywords match between the award title and the Solve email sent out, and column (2) uses climate keywords from the IPCC glossary. Column (3) categorizes as climate change-relevant agencies the EPA, Department of Energy, Department of Agriculture, NASA and the NSF while column (4) drops NASA from the list as a robustness check. Some observations are dropped due to collinearity with fixed effects.

Figure A.1: Heterogeneity Results



Coefficients of linear probability models with 90% confidence intervals. The first two estimates correspond to the baseline while the next two are estimates for patented inventors. The last two estimates are for individuals who are not patented inventors.

Figure A.2: Disaggregated Estimates for Each Treatment Condition



Point estimates of linear probability models with 90% confidence intervals.

Figure A.3: Heterogeneous Structural Estimates

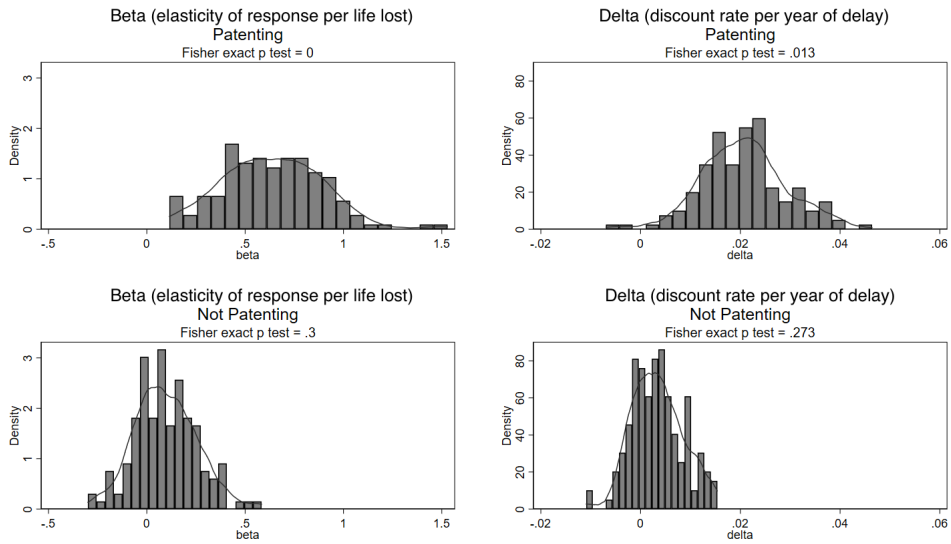


Figure A.4: Screenshot of MIT Solve's Impact

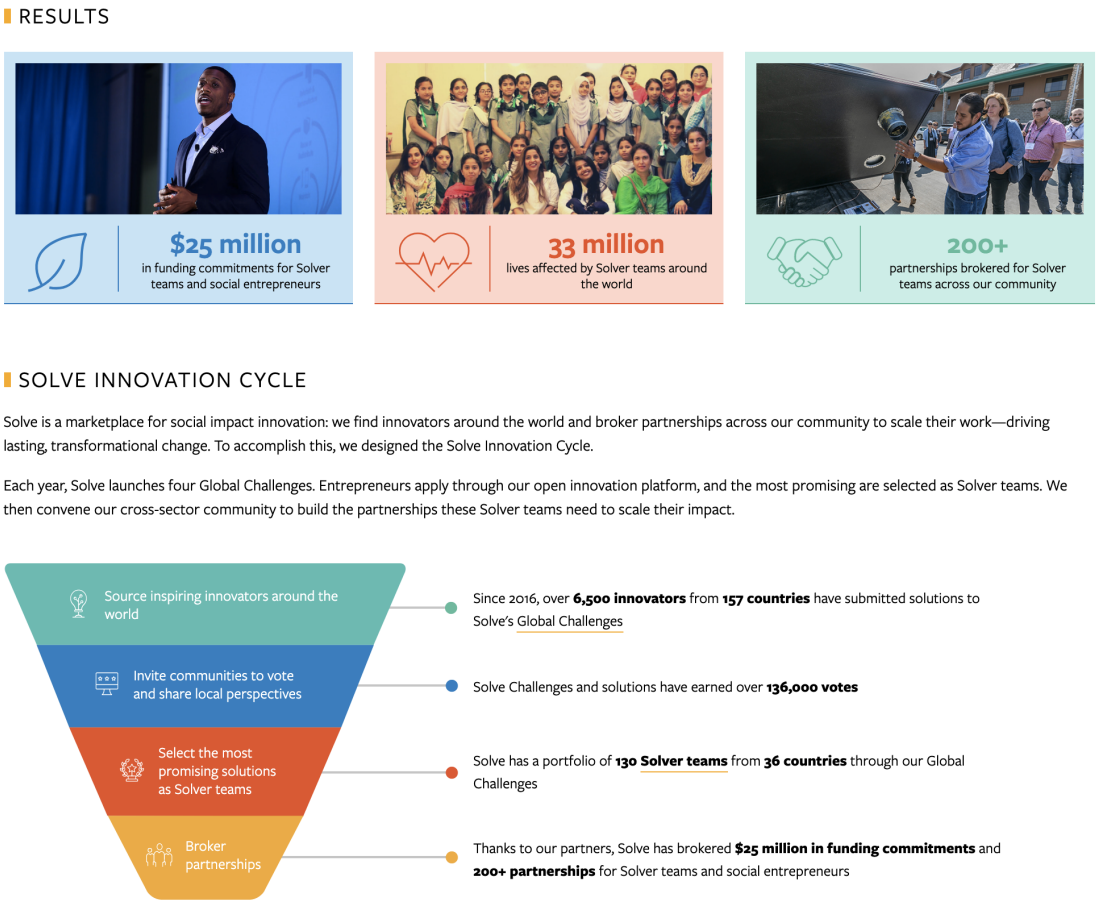


Figure A.5: Solve Challenges