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Abstract

Willingness to vaccinate and test are critical in the COVID-19 pandemic. We study the effects of two measures to increase the support of vaccination and testing: defaults and monetary compensations. Some organizations, such as restaurants, fire departments, hospitals, or governments in some countries, use these measures. Yet there is the concern that compensations could erode intrinsic motivation and decrease vaccination intentions. We show that, in the early stages of the pandemic, both approaches, compensations and defaults, significantly increased COVID-19 test demand and vaccine intentions. For vaccines, compensations need to be large enough because low compensations can backfire. We estimate heterogeneous treatment effects to document which groups are more likely to respond to these measures. The results show that defaults and avoidance of small compensations are especially important for individuals who are more skeptical of the vaccine, measured by their trust in the vaccine and their political views. Hence, both measures could be used in a targeted manner to achieve stronger results.

JEL-Codes: D010, D040, I120.

Keywords: choice architecture, defaults, incentives, Covid-19, vaccine hesitancy, test avoidance.

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1. Introduction

Vaccination and testing play fundamental roles in overcoming the COVID-19 pandemic. Yet both require peoples' time investment and, in the case of testing, may come at a direct cost if tests must be paid for. We study the impact of two widely discussed interventions, monetary incentives and defaults, on COVID-19 vaccination intentions and test demand. As vaccine and test scarcity decrease, the main goal of many businesses and policymakers has shifted from who should get access (Goldstein et al., 2021) to how to motivate as many people as possible to take part in vaccination and testing (Mandavilli, 2021).

A classic tool for behavior change proposed by many economists are monetary incentives (see, e.g., Litan, 2020, for an early proposal to pay those getting the COVID-19 vaccine). Several employers and governments have provided compensation to their employees for vaccinating themselves against COVID-19 (Dailey, 2021). Employers using compensations include hospitals, telecommunications and train companies, restaurants, and supermarket chains. Incentives offered by employers and governments vary drastically: from smaller monetary amounts like \$25, going up to \$750 in some companies, or much larger lottery prizes offered by local governments of some cities and states in the US.

An important concern is that low monetary incentives may commodify goods and behaviors of moral relevance (Gneezy and Rustichini, 2000; Bowles, 2008; Gneezy et al., 2011). Testing and vaccination are behaviors that protect the individual engaging in them, but also have externalities on others, because they can decrease the spread of COVID-19. While testing does not have long-term consequences, the long-term safety of COVID-19 vaccines is unknown (Kim et al., 2021).

Compensating individuals for taking the vaccine could lead to a loss in intrinsic motivation or a higher perception of associated risk, which could lower vaccination rates below those without compensation (Cryder et al. 2010, Loewenstein and Cryder, 2020). Moreover, a compensation could be seen as a price tag by people, and a low price may indicate the item is not of good quality. In other domains, such as blood donation decisions, monetary incentives can lead to crowd-out (e.g., Mellstrom and Johannesson, 2008), though positive effects have been documented (e.g., Lacetera et al., 2014).

We conduct an experiment to evaluate the impact of compensations and defaults on vaccination intentions and test demand, at the individual level, between December 2020 and February 2021. At this early stage of the vaccine roll-out, the data shows that crowd-out can occur for COVID-19 vaccines: we find that low monetary compensations of $10 or 20 *reduce* vaccine intentions compared to no compensation. Thus, employers must be cautious not to set too low incentives when it comes to vaccination. Only compensations of at least $100 significantly *increase* vaccine intentions.

Our finding is consistent with contemporaneous work focusing on vaccine intentions in the US asking whether incentives would make individuals more or less likely to take the vaccine (Vavreck, 2021). In Germany, Kluever et al. (2021) also find that vaccine intentions increase with large incentives. While we find negative effects of compensations of less than $20, they do not find negative effects, but very small positive effects for a 25-Euro compensation (approximately $30). While there are many differences across the studies, one possible explanation may be that incentives in their study started at a higher level and were seen as more meaningful in Germany than in the US.

As the pandemic has evolved, later work has studied the effect of financial incentives on vaccination behavior, revealing mixed findings. In a large-scale experiment in Sweden, a $24 incentive increased vaccination rates during the Spring and Summer of 2021 (Campos-Mercade et al., 2021a). By contrast, in the US, first evidence on the effects of large lottery incentives, with a small expected payoff, on aggregate COVID-19 vaccination rates shows no significant increases in take-up (Gandhi et al., 2021; Thirumurthy et al., 2021). Focusing on the vaccine hesitant in the US, Chang et al. (2021) find directionally negative impacts of financial incentives of $10 and $50. Hence, a finding that arises from our study and other research in the US is that small compensations may not increase (and could, for some, decrease) vaccination rates.

If prevention of infection and outbreaks is a major goal, this investment can pay for itself. Our data show that compared to no compensation, about 1 in 6 people can be motivated to take the vaccine for $500. For some employers, like nursing homes or hospitals, this increase in vaccination rates may be crucial to save many lives. Moreover, for many other businesses, such as factories, it may be fundamental to avoid larger outbreaks, in order to stay economically healthy.

Testing, by contrast, does not exhibit crowd-out. We study the demand for PCR tests, the so-far gold standard for detecting active infections with COVID-19 (Centers for Disease Control and Prevention, 2020; Robert Koch-Institut, 2021). Demand *increases monotonically* with compensations, even if compensations are small. A reward of $5 leads to a significant increase in demand compared to zero compensation. Likewise, a cost of $5 leads to a significant reduction in demand, even though the market price for PCR tests in non-symptomatic people can be much higher. Of course, when it comes to testing, people do not have to worry about potentially serious health effects. With the vaccine, hopefully, its health consequences will be beneficial long-term for almost all people who take it. But some risks cannot be ruled out, and with a new vaccine, it may be appropriate to speak of ambiguity.

Choice architecture encompasses alternative interventions that have proven successful in a variety of domains, including health-related behaviors (Thaler and Sunstein, 2008). The idea is to nudge decision-makers into a direction, e.g., the socially desired direction. One way of "nudging" is by making a behavior the default, without changing the options that decision-makers have. Defaults could be a pre-scheduled vaccine appointment or an assigned infection test that decision-makers could still choose not to take. Defaults have proved effective for influenza immunization (Chapman et al., 2010, Milkman et al., 2011 and 2021, Patel 2021). Yet, COVID-19 vaccines are new and have raised hesitancy among many. Widespread regular testing for an infectious disease is new as well. The effect of interventions could be fundamentally different for these new contexts. Video messages can increase vaccination uptake (Dai et al., 2021), but conflicting risk information about vaccines could decrease it (Thunstrom et al., 2021). Encouragingly, our data show that defaults significantly increase COVID-19 vaccine intentions and test demand. The increase in intentions is of 5 to 6 percentage points for the vaccine, where the baseline intentions are close to 70%, while it is of 11 to 12 percentage points for testing, where the baseline demand for a free test is 50%.

Many scientists argue this pandemic will not be the last one within the next decades (Mahajan, 2020). The mutations in 2021 can be seen as a new Coronavirus pandemic compared to the original one from 2020 (Rourke, 2021). For businesses and governments aiming to increase vaccination and testing it is of major importance to understand how to motivate people to take up preventative measures. Vaccination and testing are likely to also play fundamental roles in future pandemics. As with every new medical treatment, there will be an ambiguity regarding health consequences associated with new vaccines. Accepting this ambiguity may be necessary for the vaccine if people want to protect themselves and others against the disease. Testing, in contrast, may not come with as much ambiguity regarding its long-term health and safety impact. Our data demonstrates that interventions need to be evaluated for these different measures separately.

Pandemics have been shown to increase inequality (Wade, 2020). This also seems to be the case in this pandemic, with people of black ethnicity, lower education background, and older age suffering disproportionately (Abedi et al., 2020). Further, vaccine intentions seem to be low for Black people (Funk and Tyson, 2020). We oversampled Black participants to study ethnic differences with sufficient statistical power. We document that Black participants' lower vaccine intentions can be explained by distrust of the vaccine. Nevertheless, they were equally motivated by the measures investigated.

Our data show that defaults have a specifically strong effect on groups of the population who are less inclined or more uncertain about taking the vaccine. Using causal forests (Athey, Tibshirani and Wager, 2019; Athey and Wager, 2018), we estimate conditional average treatment effects of defaults on vaccine intentions and examine which groups are predicted to exhibit stronger reactions to defaults. We find that defaults more strongly affect vaccine intentions in individuals who trust the vaccine less and whose political views are less supportive of Dr. Fauci's and more supportive of Trump's approach to the pandemic. These groups also display a lower intention to take the vaccine. We also document that those who believe to have been infected with COVID-19 already are more likely to react to defaults. The latter group does not display a lower intention to take the vaccine but may be more uncertain about whether they should take the vaccine.

We also explore which groups are more likely to react negatively to small monetary compensations for taking the vaccine, using the same approach based on causal forests. Consistent with the interpretation that small compensations may crowd-out intrinsic motivation, we find that those who are less supportive of the vaccine (who trust it less or whose political views support Trump) exhibit a higher likelihood of reacting negatively to a small compensation. In all, these insights offer guidance to what kinds of measures may increase vaccine uptake for specific groups, which can save resources and avoid eroding intrinsic motivation.

2. Experimental Design and Procedures

We designed and conducted an online experiment in which participants were assigned to decide about taking the COVID-19 vaccine (N=1,544) or an at-home PCR saliva-based test (N=583). Decisions about PCR testing decisions were incentivized, as explained below. COVID-19 vaccine decisions were based on self-reported intentions. For both vaccines and testing, each participant was either randomly assigned to the "Opt-out", the "Opt-in" or the "Active choice" condition. In the Opt-out condition, participants were asked whether they would take the vaccine, if an appointment had been scheduled for them to receive it; or whether they would keep a PCR test, if they had been randomly assigned one. They could opt-out from their “default” option. In contrast, in the Opt-in conditions, not taking the test or vaccine was the default, but participants were asked whether they wanted to receive it. In the Active Choice condition, participants had to decide what they wanted without a default.

At the participant level, self-reported intentions about taking the vaccine were measured for both when there was no compensation (N=615) and for 8 different compensation levels (from $0 to $500, N=929). For testing, each participant made 8 decisions, each involving different monetary levels. These were compensations for taking the test, or cost reductions compared to the market price (ranging from an additional $25 gift card for taking the test to forgoing a $119 gift card, the listed test price). One testing decision was implemented for 1 of each 25 participants. Specifically, selected participants could additionally receive an Amazon gift card and/or a PCR test, depending on their choice in one randomly selected decision. The PCR test was a saliva-based test, provided by the company Vault. As it was a saliva-based test, no deep nasal swab was necessary for taking this test. If participants wanted the test, they got a personalized URL so that they could order the test at Vault themselves. Since the test is at-home, we do not observe actual take-up, but the participants’ willingness to give up an Amazon gift card for the Vault PCR test. The instructions presented in the study are shown in Online Appendix B, in addition to the pre-registrations.

After pre-registration (on aspredicted.org, #55138 and #57775), data collection took place between December 2020 and February 2021 on Prolific Academic (Palan and Schitter, 2018). At this stage of the pandemic, vaccine access was highly restricted. By focusing on this early stage, we study the effect of financial incentives and defaults prior to a broad roll-out. Marginal individuals who are affected by these interventions may differ from those who are marginal at later stages of roll-out.

We first recruited 200 subjects per condition, which detects a 12 percentage-point (p.p.) effect on a 70% baseline with 80% power. We added ca. 300 subjects per condition for vaccination decisions, five weeks later, to detect a 7-p.p. effect with 80% power. In this wave we also specified that the vaccine offered to individuals would be the Pfizer vaccine, i.e., an mRNA vaccine. At the time the studies were run, mRNA vaccines were the standard in the US. Decisions were stable over time (t-test, p-value=0.4927).

In addition to vaccine intentions and testing decisions, we also simultaneously elicited demand for antibody tests under defaults and active choice (N=591) and air quality monitors (N=597) on the same Prolific sample. In Online Appendix C, we describe the results for these decisions in detail. Defaults (Opt-out) significantly increase demand for antibody tests by 10 p.p. and demand for air quality monitors by 14 p.p. (p-value<0.01 in both cases). We also compare decisions regarding antibody testing in the Active Choice condition on Prolific to a quota-representative sample of the US (N=1,984), based on a separate study (Serra-Garcia and Szech, 2020) conducted in June of 2020. We find that demand levels are qualitatively similar across the Prolific and the U.S. quota-representative sample (as shown in Online Appendix C).

Participants in the experiments were required to be individuals born and residing in the United States, whose participation in previous studies had been approved in more than 95% of the cases. Participants received a fixed fee of $1.00 for a ca. 5-minute study. The study platform allows to target studies to participants based on their demographic and socioeconomic characteristics. We oversampled Black participants so that we could study ethnic differences with sufficient statistical power. We targeted and achieved an overall share of Black participants of 34 to 36%, to detect a 13-p.p effect on this group with 80% power.

At the end of the experiment, we included a questionnaire (shown in Online Appendix B) that elicited each participant's age, gender, ethnicity, and household income (among 6 categories). The questionnaire also included several questions regarding the participant's experiences and beliefs about COVID-19. It asked how often the participant had been tested for a COVID infection at the time of the experiment, whether she had been tested for COVID antibodies, whether she believed she has had COVID in the past (on a scale from 0-100 chance), and how many friends or acquaintances had died of COVID. The survey also included two experimentally validated measures of generosity (Falk et al., 2016), which have been shown to correlate with COVID-19 prevention behaviors (Campos-Mercade et al., 2021b). The first question asked about the individual's willingness to give to good causes without expecting anything in return, on a scale from 0 "completely unwilling" to 10 "completely willing." The second question asked about an intended donation to charity, should the individual unexpectedly receive $10,000 today. The standardized principal component of the answers to these two questions is used to measure an individual's generosity. The survey measured the individuals' political views, in addition to political party, by eliciting the rating of Dr. Fauci's and of Trump's approaches to the Coronavirus pandemic. We again used a standardized principal component of the answers to these two questions, where higher values reflect more support for Trump (and less support for Dr. Fauci), to measure an individual's political views. Since trust in the vaccine is considered a centrally important predictor of vaccine intentions, we asked individuals to report their trust of the vaccine and doctors, by selecting whether she "does not trust at all", "not very much", "somewhat" trusts or "completely" trusts each of these.

The sample is balanced in terms of gender, ethnicity and age across treatments as shown in Online Appendix A. For PCR testing decisions, between 48% and 54% of the participants were female, the average age of participants was between 35 and 37 years old. Between 44% and 51% of participants were white, while 34% to 36% were Black. For COVID-19 vaccine decisions, between 48% and 57% of participants were female, of 33 to 34 years of age. Between 47% and 51% of participants were white, while 35% to 36% were Black.

3. Hypotheses

We expected and pre-registered that both measures, defaults and compensations, could increase vaccine intentions and test demand. Most countries provide vaccines against COVID-19 for free (European Commission, 2021; GOV.UK, 2021; U.S. Department of Health & Human Services, 2021). Therefore, we consider the case of no compensation versus positive monetary compensations, ranging from $25 to $500. This is in line with what many employers have started to implement (Dailey, 2021; Scipioni, 2021). Compensations may operate in the neoclassical way – the more money people receive, the more they want a vaccine. Yet two qualifications are in order. First, new vaccines come with ambiguity. Potential health consequences, specifically in the long run, are unclear. People may perceive a low compensation as a price tag (Sandel, 2013;

Satz, 2012), or assume the low price indicates a low quality (Zhao, 2000). If so, smaller compensations could backfire, reducing demand compared to no compensation at all. Second, there has been an ongoing discussion of markets and money in morally relevant domains. Gneezy and Rustichini (2000) show that a low pay can reduce intrinsic motivation to collect donations compared to when there is no pay at all. Similarly, payments for blood donations can decrease donations, especially among women (e.g., Mellstrom and Johannesson, 2008), though the effects may vary depending on how the incentive is implemented, and could be positive (e.g., Lacetera et al., 2014).

If taking the vaccine is seen as a morally relevant act, as it also protects others, commodification (Sandel, 2013; Satz, 2012) could reduce vaccine intentions. For these two reasons, we extended our hypothesis (relative to the pre-registration) to acknowledge that vaccine intentions may be lower for small compensations compared to no compensations.

Hypothesis 1 (Vaccines and Compensations):

1a. Vaccine intentions increases in compensations.

1b. For small compensations, a crowd-out in intentions may occur.

It has been shown that pre-scheduled appointments increase the uptake of influenza vaccines (Chapman et al., 2010; Lehmann et al., 2016).[1] Based on this evidence, we hypothesized that an opt-out default would increase vaccine intentions. Yet a change in the default may mostly affect people who are rather indifferent towards taking a vaccine or not. With COVID-19 vaccines,

[1] Relatedly, Beshears et al. (2016) show that reducing effort to get an influenza shot increases take-up.

people may have stronger preferences. COVID-19 appears to be a more dangerous disease than the regular influenza (Piroth et al., 2021; Xie et al., 2020). Moreover, studies indicate there may be severe long-term consequences from infection. Therefore, on one hand, quite some people may have a strong preference in favor of the vaccine. On the other hand, the vaccines are new. Thus, there may be a stronger hesitancy in some people than with other vaccines that have been investigated over longer time periods. Therefore, there are reasons that point towards the opt-out default in the form of a pre-scheduled appointment having a rather small impact on COVID-19 vaccine intentions.

In the experiment, we also study the impact of active choice. Imposing an active choice outperforms Opt-in when it comes to the delivery of prescription drugs (Beshears et al., 2021). Further, some countries enforce an active choice on willingness to donate organs when people get their driver's license (Thaler & Sunstein, 2009). Since in our experiment Opt-in set a clear default but Active choice elicited a decision, we hypothesized that Active choice would be in between Opt-in and Opt-out.

Hypothesis 2 (Vaccines and Defaults):

2a. Vaccine intentions are higher in Opt-out than in Opt-in.

2b. Vaccine intentions in Active choice are in between those of Opt-in and Opt-out.

Tests for COVID-19 can help detect infections even if people are asymptomatic. The PCR test is the gold standard (CDC, 2020; Robert Koch-Institut, 2021). Yet, without documented contact to other infected people or symptoms, people may have to pay for the test themselves. Therefore, we test demand at the market price versus price reductions and compensations. People provide a saliva sample themselves, at home, with live (online) guidance from a health-care professional. Thus, the test is not very invasive. We cannot think of any risks in health providing a saliva sample, if people stick to the instructions. There is uncertainty about the test result, which could lead to test avoidance, though recent work suggests limited evidence of test avoidance for COVID-19 infection tests (Thunstrom et al., 2020) and antibody tests (Serra-Garcia and Szech, 2020). Hence, we expect test demand to increase if people must pay less for the test. We hypothesize it further increases with compensation, since tests do not appear to carry any health risk, and small compensations would not signal low quality or crowd-out intrinsic motivation to get tested.

Hypothesis 3 (Test Demand and Compensations):

3a. Test demand increases as the cost of testing falls.

3b. Test demand increases further with positive compensations.

Moreover, we hypothesize that making the test the default option will increase demand compared to when not taking the test is the default. We also hypothesized that Active choice would increase demand relative to Opt-out, but be less effective than making testing the default option, as in Opt-in.

Hypothesis 4 (Test Demand and Defaults):

4a. Test demand is higher in Opt-out than in Opt-in.

4b. Under Active choice, test demand is in between Opt-out and Opt-in.

In addition to examining the effects of compensations and defaults on vaccine intentions and test demand, we also explore heterogeneity in levels as well as in the effect of these treatments. We expected Black participants to exhibit lower intentions to take the vaccine, but we did not have specific hypotheses for potential heterogeneity in the reaction to compensations and defaults. In addition to exploring heterogeneous treatment effects for Black participants, we use causal forests to explore heterogeneity according to other individual characteristics (including demographics, beliefs and experiences with COVID-19, generosity, and political views).

4. Results

4.1. Average Effects of Compensations and Defaults on Vaccine

Figure 1 provides an overview of our main results, presenting vaccine intentions and testing demand under Opt-in versus Opt-out for various compensations levels.

Compensations increased vaccine intentions by 4.5 pp. with $100 compensation and 13.6 pp. with $500 ($p$-value<0.001 in all cases). However, a $20 compensation decreased intentions by 5 pp. relative to no compensation (p-value<0.001). Thus, small compensations can erode an intrinsic motivation to vaccinate or commodify the vaccine (Marx, 1904; Gneezy & Rustichini, 2000; Loewenstein & Cryder, 2020; Satz, 2012; Sandel, 2013; Falk & Szech, 2013; Ziegler et al., 2021).

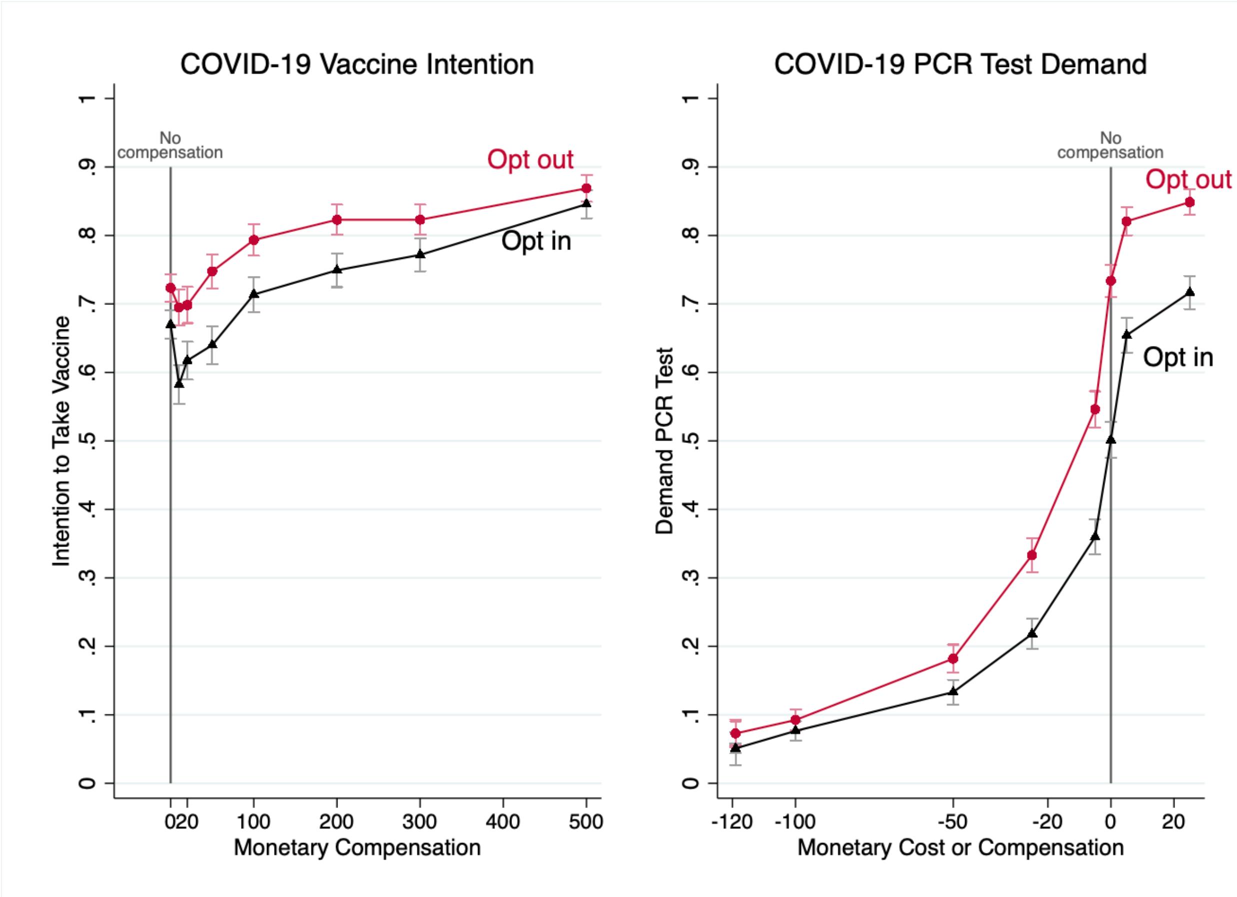
Result 1 (Vaccines and Compensations):

1a. Vaccine intentions increase for compensations equal to or above $100.

1b. For the smallest compensation of $20, intentions are lower than without compensation.

Larger incentives, of more than $100, significantly increase intentions to take the vaccine. In Table 1, we examine the effect of compensations, as well as the Opt-in and Opt-out treatments, for vaccine intentions and test demand. We use linear probability models to estimate the effects on vaccine intentions and test demand using demographic controls (gender, age, ethnicity, and income) in columns (1) and (2). We also add a larger set of control variables using the post-double-selection methodology proposed by Belloni et al. (2014), which uses the lasso estimator to select among the following controls included in the post-experimental questionnaire: work status, political views (standardized index), experiences with and beliefs regarding COVID19, (standardized) trust in the vaccine and doctors. This methodology estimates the causal impact of the treatments, allowing for many controls, where the "right" set of controls is not known. It first estimates a lasso regression on vaccine intentions and test demand, and then a lasso regression on the treatments and demographic characteristics (age, gender, ethnicity, and income). The set of controls included in the model is the union of controls selected in the first and second step. We examine the role of ethnicity and income, which are significant predictors of vaccine intentions and test demand, as well as additional covariates in Section 4.2. Alternative regression specifications using probit regressions and estimating the separate effect of each compensation level are provided in Online Appendix A.

Figure 1. COVID-19 Vaccination Intentions and PCR Test Demand, by Default and Compensation



Notes: Percentage of participants who report an intention to take the COVID-19 vaccine (left panel) and who demand an at-home PCR test (right panel). The red line shows percentages in the Opt-out condition and the black line shows percentages for the Opt-in condition. +/- 1 Standard error bars are shown.

As shown in column (1) of Table 1, compensations of more than $50 increase vaccine intentions by 6 percentage points on average. This effect increases with the magnitude of the incentive, as shown in columns (2) and (3) of Table 1. The largest incentive (of $500) increases support by about 15 to 20 pp. This implies that vaccine intentions grow above 80% and combined with an Opt-out default it gets closer to 90%. This could make a big difference for the spread of COVID-19. If employees have close contact to each other or to clients or patients, it may make sense for employers to think about large compensations (possibly combined with an opt-out default.)

The analysis in Table 1 also shows that small compensations may not yield a positive effect, and may even result in a negative one, on vaccine intentions. Overall, the results suggest that, if employers and governments want to increase vaccine intentions, incentives need to be large enough. Four qualifications to these results are in order. First, each organization or local government may face a different culture and composition of individuals. Second, we only study vaccine intentions. Third, gifts may work differently than monetary incentives (Kube, Maréchal, & Puppe, 2012). Fourth, in our design, getting no compensation can be seen as an anchor by participants, and it is clear that $10 is the lowest compensation possible. This may be different in a real-life situation. Still, our results suggest that a careful evaluation should be done if employers want to work with incentives for vaccination.

Columns (1) through (3) of Table 1 also show that the Opt-out treatment increases vaccine intentions by 5 to 6 percentage points. Since the Opt-out treatment in practice implies prescheduling appointments and, hence booking appointments that get rescheduled or missing, more often than under Opt-in, such default could come with a "cost". Nevertheless, more people end up taking the vaccine under the Opt-out condition, as shown by Chapman et al. (2010) for influenza vaccination. Our data is in line with this finding. Active choice also leads to a directional increase in vaccine intentions, of 4 percentage-points, which is 2 percentage points smaller than Opt-out, but not significantly different (*p*-value>0.10 in all cases). The effects of Active choice, however, are only statistically significant if additional control variables are included, as we do in column (3).

Result 2 (Vaccines and Defaults):

2a. Vaccine intentions are higher in Opt-out than in Opt-in.

2b. Vaccine intentions in Active Choice are in between those of the Opt-in and the Opt-out treatments.

4.2. Average Effects of Compensations and Defaults on Test Demand

The reaction to compensations and defaults is somewhat different for PCR testing. First, the data show demand for a PCR test increases as the costs go down, as expected. It increases further if there is a positive compensation associated with the test. One reason for the difference to vaccine intentions could be that PCR tests do not come with any larger health risks for participants. Therefore, even a small compensation may feel attractive. In case of the vaccine, a very small compensation may instead devalue the act of taking the vaccine.

Result 3 (Test Demand and Compensations):

3a. Test demand increases as the cost of testing falls.

3b. Test demand increases further with positive compensations.

Table 1. Vaccine Intentions and PCR Test Demand

	(1)	(2)	(3)	(4)	(5)	(6)
	COVID-19 Vaccine Intentions			COVID-19 Test Demand		
	LPM	LPM	Post-lasso	LPM	LPM	Post-lasso
Opt-out	0.0672**	0.0672**	0.0487**	0.1210***	0.1210***	0.1192***
	(0.0277)	(0.0277)	(0.0196)	(0.0255)	(0.0255)	(0.0247)
Active	0.0417	0.0415	0.0435**	0.0805***	0.0805***	0.0768***
	(0.0288)	(0.0288)	(0.0195)	(0.0247)	(0.0247)	(0.0241)
Low compensation (<$50)	-0.0566***	-0.0566***	-0.0567***	0.1449***	0.1449***	0.1449***
	(0.0091)	(0.0091)	(0.0091)	(0.0151)	(0.0151)	(0.0151)
Large compensation (>=$50)	0.0634***	-0.0001	-0.0001			
	(0.0090)	(0.0093)	(0.0093)			
Large compensation (>=$50) X $ Amount		0.0003***	0.0003***			
		(0.0000)	(0.0000)			
Cost				-0.4154***	-0.2728***	-0.2728***
				(0.0187)	(0.0190)	(0.0190)
Cost X $ Amount					-0.0024***	-0.0024***
					(0.0002)	(0.0002)
Constant	0.8279***	0.8280***	0.6597***	0.5495***	0.5495***	0.5142***
	(0.0536)	(0.0536)	(0.0414)	(0.0457)	(0.0457)	(0.0470)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	Yes	No	No	Yes
Observations	7,996	7,996	7,996	4,664	4,664	4,664
Number of clusters	1,544	1,544	1,544	583	583	583

Notes: This table reports coefficients from linear probability models (columns 1-2 and 4-5) and linear regression models using the post-double-selection methodology proposed by Belloni et al. (2014), columns (3) and (6), which use the lasso estimator to select among the following controls: work status, political views (standardized principal component), generosity (standardized principal component), experiences with and beliefs regarding COVID19, (standardized) trust in the vaccine and doctors. All regressions include age, gender, ethnicity and household income (below $75,000 per year) as controls. Robust standard errors are estimated. Indicator variables are shown for each treatment and compensation level. Low compensation indicates a compensation for taking the vaccine or a test of less than $50. Large compensation indicates a compensation of $50 or higher. Cost indicates a positive cost for taking the COVID-19 test. The omitted categories are the Opt-in treatment without a compensation ($0). Robust standard errors shown in parentheses. ***p<0.01, **, p<0.05, * p<0.10

In line with Hypothesis 4, test demand is higher in Opt-out than in Opt-in. The effect of Opt-out is also almost double in size for testing than for vaccine intentions. One reason is that the baseline demand for testing is lower, and hence there is a larger potential to observe default effects. Under Active choice, test demand is 8 percentage points higher than in Opt-in. It is not significantly different from Opt-out, though directionally smaller (p-value>0.10 in all cases).

Result 4 (Test Demand and Defaults):

4a. Test demand is higher in Opt-in than in Opt-Out.

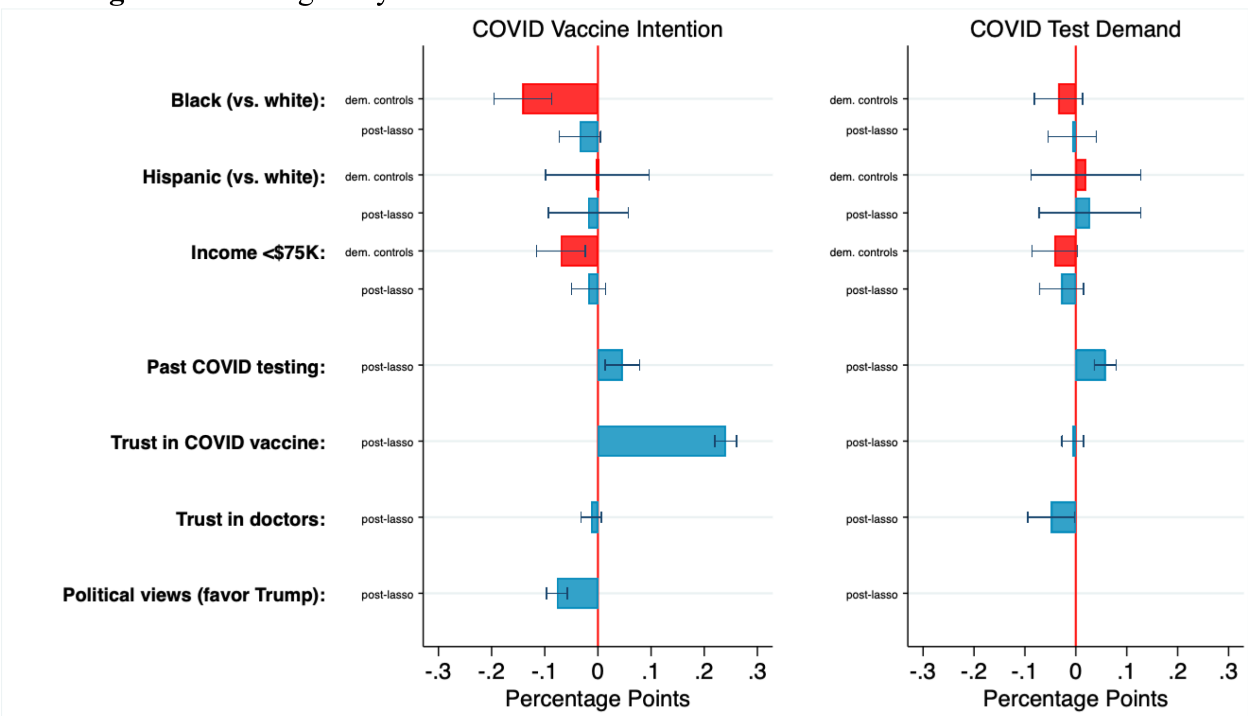
4b. Under Active choice, test demand is in between Opt-in and Opt-out.

4.3. Heterogeneity in Vaccine Intentions and Test Demand

Existing studies have indicated that Blacks exhibit unequal access to immunization and have lower intentions to take the COVID-19 vaccine (Funk and Tyson, 2020). In this section, we examine whether there is a significant difference in vaccine intentions and test demand for Black participants, and explore heterogeneity in levels depending on income and other relevant covariates. In Section 4.4, we explore whether there are heterogeneous treatment effects of compensations and defaults depending on the individual's demographic characteristics.

The analysis in Table 1 includes covariates for ethnicity (Black, Hispanic, Other, relative to white), age, gender, and household income (below or above $75,000 a year, which is the median in the sample). There are no significant differences in vaccine intentions and test demand by age and gender. If the only controls included are demographic characteristics, vaccine intentions (but not test demand) are significantly lower among Black participants and those with an annual household income below $75,000. This result is shown in the red bars of Figure 2.

Figure 2. Heterogeneity in COVID-19 Vaccination Intention and PCR Test Demand



Notes: This Figure reports coefficients from the models (columns 1, 3, 4, and 6) presented in Table 1. The label "dem. controls" refers to models presented in columns (1) and (4) that only include demographic controls (ethnicity, age, gender, and income), while the label "post-lasso" refers to the models presented in columns (3) and (6) of Table 1. The covariates selected using the post-lasso methodology but not shown are related to work status, "not working" (such as student) and "other work situation". Past COVID testing indicates how often the individual has taken a COVID test in the past (ranging from 0 to 7 times). Trust in the vaccine and doctors are standardized measures of trust in each. Political views indicates the standardized principal component of participants' evaluation of Trump and Dr. Fauci during the pandemic (with higher scores indicating higher support for Trump and lower support for Dr. Fauci). 95% confidence intervals are shown.

However, when additional controls are included, both ethnicity and income differences are no longer predictive of lower vaccine demand. Figure 2 includes the selected covariates using the post-lasso methodology, excluding covariates for work status (not employed and other work situation are also selected). Instead, Figure 2 reveals that individuals who have (been) tested more often for COVID-19 in the past are more likely to demand both the vaccine and the test. Additionally, trust in the vaccine is the largest predictor of vaccine intentions (but not test demand). Its inclusion reduces (and makes insignificant) the relationship between Black ethnicity and vaccine intentions, as Blacks trust the vaccine significantly less than white (0.44 standard deviations, p-value<0.001).

In addition, Figure 2 shows that political views are important for vaccine intentions (though not selected or "relevant" for test demand). Individuals who favor Trump (and are less supportive of Dr. Fauci) are significantly less likely to intend to take up the vaccine. These results are consistent with related evidence showing that COVID-19 vaccine support is highly polarized depending on individuals' political party affiliation.

4.4. Heterogeneity in the Effects of Compensations and Defaults on Vaccine Intentions

An important question when designing interventions to increase test demand and vaccine intentions is whether they equally affect all groups in the population, or rather advantaged (or disadvantaged) ones. As pre-registered, we examined whether the effects of defaults or compensations on vaccine intentions and test demand were different for Black relative to white individuals. We do not find evidence of heterogeneous effects (p-value>0.05 in all cases), indicating that both types of measures could increase demand among different ethnicities (detailed results provided in Appendix A).[2]

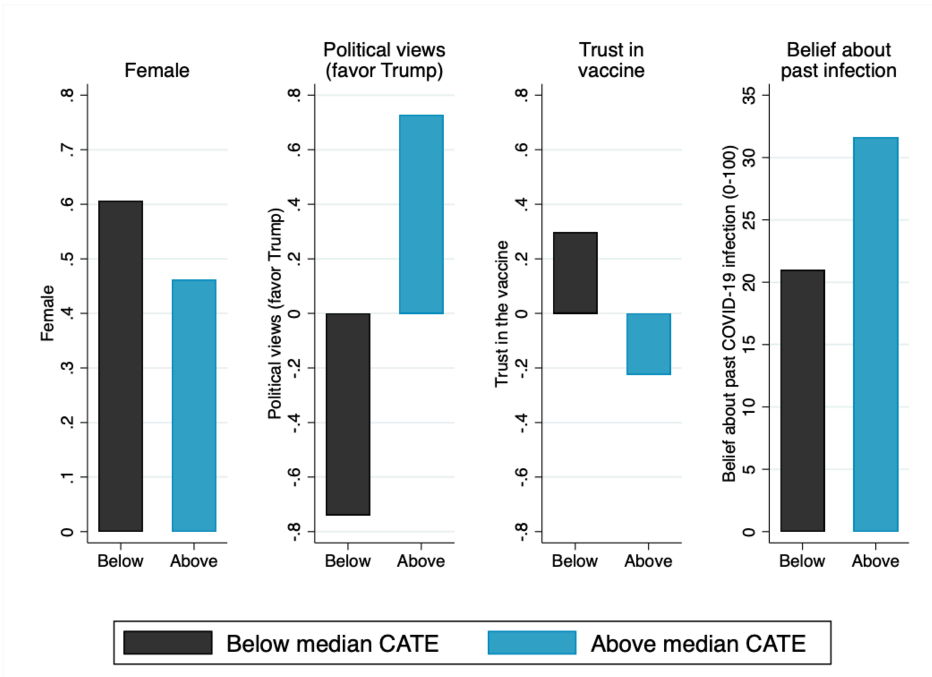
[2] When we examine heterogeneous treatment effects for COVID-19 testing, we observe that, when interaction effects are included for all treatments and compensation levels, Black participants demand testing significantly less often in the Opt-in condition without compensation (13 p.p.) relative to white participants. However, no interaction effect between default and compensation is statistically significant.

Yet, the previous results raise two open questions regarding the effects of interventions on vaccine intentions. First, are certain demographic groups more likely to strongly respond to defaults (Opt-in vs. Opt-out)? If so, prescheduled appointments could potentially be targeted to these groups. Second, is the effect of crowd-out (for small monetary compensations) more likely to be observed on certain demographic groups?

A new approach to explore heterogeneous treatment effects, without excessive data mining, is to use causal forests (Athey and Wager, 2018; Athey, Tibshirani, and Wager, 2019). Broadly speaking, causal forests extend random forests, a classification method typically used to predict outcomes, to instead predict average treatment effects. We first use causal forests to examine whether individuals who are predicted to respond more strongly (above-median) to the Opt-out treatment, for the case in which there is no compensation for intentions to take the vaccine, have different demographic characteristics than those predicted to respond less (below-median).

Following the methodology in Athey and Wager (2019) (and using the "grf" R package), we first split the dataset between the training sample, on which the forests are estimated, and the test sample, for prediction. The training sample is 66.7% of the dataset. This sample is then further separated into the "splitting sample", which is then further split into subsamples that are used to build trees in the forest, and the "estimation sample", which is used to compute the average treatment effect across the trees. After fitting the forest, for each observation the forest makes an "out-of-bag" prediction (including the point estimate and its standard error). To derive these out-of-bag predictions, it uses the output of trees whose training data did not include the observation which is being predicted. Details on the parameters used for prediction and an excerpt of the code are provided in Online Appendix A. As shown in Appendix A, the distribution of the out-of-bag conditional average treatment effect (CATE) for the Opt-out treatment is bimodal, suggesting that some individuals may exhibit a rather small reaction to the Opt-out treatment of less than 5 percentage points, while others may exhibit a larger reaction of close to 10 percentage points.[3]

Figure 3. Heterogeneous Treatment Effects of Opt-out Treatment



Notes: This figure shows the average share of female participants, political views (standardized principal component), trust in the vaccine (standardized) and belief about past COVID-19 infection for those exhibiting below and above median CATE.

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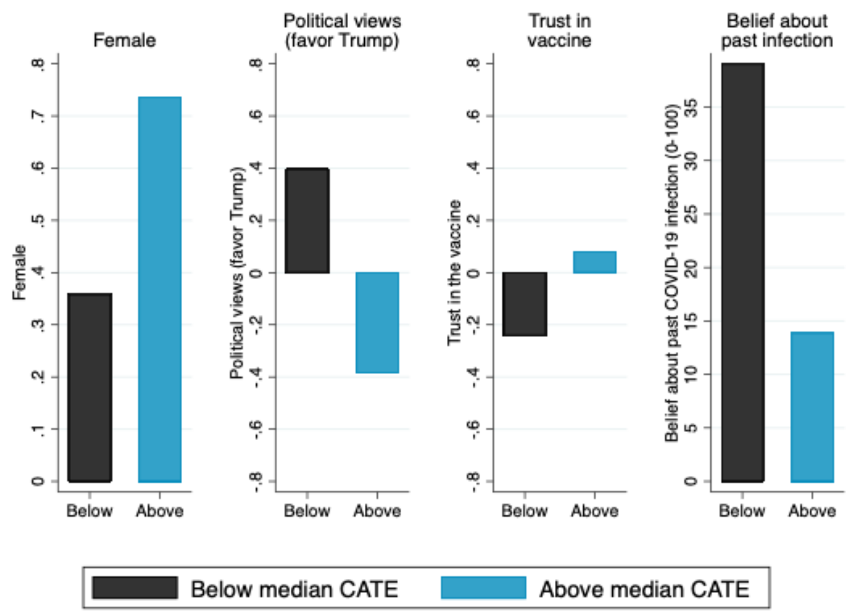
[3] We then examine heterogeneity in demographics by splitting the sample depending on whether the predicted CATE is below or above median. We then compute the Augmented Inverse-Propensity Weighted (AIPW) Average Treatment Effects (see Athey, Tibshirani and Wager, 2019), which is a method to estimate conditional treatment effects, including a correction for any biases that arise if unconfoundedness is not satisfied (Glynn and Quinn, 2010). The estimated AIPW average treatment effect is 0.03 (s.e.=0.027), for those below-median observations, while it is 0.11 (s.e.=0.035) for those above-median observations (Wald test, p-value<0.01), which suggests there is substantial heterogeneity in the effect of the Opt-out treatment.

We explore whether those who have above-median estimated conditional average treatment effects also have different covariate levels than those who have below-median estimated CATE. We observe strong heterogeneity according to gender, political views, belief about past infection, and trust in the vaccine (detailed results for all covariates are shown in Online Appendix A). As shown in Figure 3, individuals with estimated higher effects of the Opt-out treatment are more likely to be male, have political views that are more supportive of Trump, trust the vaccine less, and believe it is more likely that they may have had a COVID-19 infection in the past. We observed that political views and trust in the vaccine are important predictors of intentions, and these results suggest that some groups with lower vaccine intentions could be “nudged” into taking the vaccine with the Opt-out treatment. For individuals who believe they were infected in the past, vaccine intentions were not significantly higher. But these individuals may have doubted whether they “should” take the vaccine, since they may have antibodies. In Online Appendix A, we show the results of the same analysis focusing on testing decisions, rather than vaccine intentions. We find evidence suggesting very similar patterns of heterogeneity: the same groups (based on gender, political views, trust in the vaccine and past infections) exhibit qualitatively similar heterogeneity.

Next, we follow the same approach, but this time focusing on better understanding the potentially negative effects of small compensations on vaccine intentions. For this reason, we focus on the effect of no compensation, compared to offering a $10 compensation for taking the vaccine in the Opt-in treatment, clustering observations at the individual level. As shown in Online Appendix A, the effects of the small compensation are generally negative, and between a

5 and a 20 percentage-point drop in vaccine intentions, and in this case the distribution has one mode.[4]

Figure 4. Heterogeneous Treatment Effects of Small Monetary Incentives



Notes: This figure shows the average share of female participant, political views (standardized principal component), trust in the vaccine (standardized), and belief about past COVID-19 infection for those exhibiting below and above median CATE.

Those individuals who are estimated to exhibit more negative effects (below-median CATE) in response to a small compensation for the vaccine are more likely to be male, exhibit political views more supportive of Trump, trust the vaccine less, and hold a higher belief that they may have had a COVID-19 infection in the past. This heterogeneity suggests that those who are less

[4] The estimated AIPW average treatment effect is -0.104 (s.e.=0.04), for those with below-median estimated CATE, while it is -0.077 (s.e.=0.03) for those above-median (Wald test, *p*-value<0.01), which suggests there is some heterogeneity in the negative effect of a small compensation, though the difference is small in magnitude.

supportive of the vaccine, as measured by their trust or political views, may also be more susceptible to crowd-out.

5. Discussion and Conclusion

Compensations and defaults can increase vaccine intentions and test demand. The effects of these measures are not substitutes to each other, so both approaches could be successfully combined. In the case of the COVID-19 vaccine, compensations need to be large enough. A compensation of $10 or $20 backfired and reduced vaccine intentions. Yet compensations of at least $100 increased vaccine intentions compared to when no compensation was offered. Test demand, by contrast, increased monotonically with monetary compensations.

A broader discussion of both "nudges" and compensations in the present context is necessary. Both measures can be controversial from a cost and moral perspective. Pre-scheduled appointments may be called off or more likely become postponed than when patients schedule appointments themselves. Indirectly, this could create additional costs. The way in which appointments and similar nudges are worded may matter as well, as has been documented for flu shots (Milkman et al., 2021). Compensations come with an obvious direct cost as compensations need to be paid for, e.g., by employers, insurance companies, or states. Moreover, many people may profit from a compensation or price-reduction, even though they would test or vaccinate without them. Further, in the case of the vaccine, it is likely that the lowest possible compensation we tested, $10 upon completion of the second dose, devalued the vaccine or eroded intrinsic motivation. The phenomenon of commodification and moral erosion from market mechanisms has been discussed for centuries (Simmel, 1990; Fiske, 1992; Roth, 2007; Falk and Szech, 2013). Yet the benefits of market design in this pandemic have been pointed out (Cramton et al., 2020). In our data, larger compensations prove successful at increasing vaccine intentions. Compensations from $100 on seem to offset and overpower the detrimental effects of commodification. Given the huge social benefits of vaccination in this pandemic, even much larger compensations seem to be justifiable from an economic perspective (Castillo et al., 2021).

In implementing measures to increase vaccination rates, organizations and policymakers could gain from targeting their efforts to groups that are more likely to react positively (and strongly) to these measures. We found significant heterogeneity in response to the Opt-out treatment, and stronger responses among those individuals who trust the vaccine less and were more supportive of Trump (and less of Dr. Fauci). In areas where support for the vaccine is low, due to a lack of trust or limited support of the health policies recommended by Dr. Fauci, using prescheduled appointments and compensations of at least $100 could be effective in increasing vaccine take-up.

When it comes to the vaccine, it may not be surprising that some people costly forego it as they may dislike vaccines in general or fear bad health consequences from a newly introduced vaccine. Some people may further hope to free-ride on herd immunity once enough others are vaccinated. But we also see limited costly aversion to the test (in line with Thunstrom et al., 2020), and small incentives around zero have pronounced impact on test demand.[5] This is

[5] See also Carrillo and Mariotti (2000), Caplin and Leahy (2001, 2004), Eliaz and Spiegler (2006), Ganguly and Tasoff (2017), Baucells and Bellezza (2017), Rosar (2017), Schweizer and Szech (2018) and Mariotti et al. (2020) on test and information avoidance.

qualitatively comparable to the demand function for moral information in Serra-Garcia and Szech (2021).[6] Indeed, taking a PCR test without having symptoms may be mostly a social and moral activity, in order to prevent spreading the virus to other people. Some people may not want to bear the costs of self-quarantine should they test positive, and therefore avoid the test. Small monetary costs or incentives may transport a normative signal, thereby affecting demand around prices of zero. Further, taking the test comes with some uncertainty, as tests can make mistakes. This could render the test unattractive for some, even if it comes with a positive monetary incentive.

A limitation of our experiment is that, for vaccination, intentions were measured. For testing, we could measure incentivized decisions to obtain an at-home PCR test. Employers that have already implemented compensations for vaccinations should be careful to evaluate the success of their programs. If compensations are small, they could be paying for a business policy that does not have any significant impact, or even does more harm than good.

[6] Dana et al. (2007)'s moral wiggle room paradigm is seminal for showing that people avoid moral information in order to justify selfish behaviors. Relatedly, Exley (2020) documents that people use uncertainty about charities as an excuse not to give.

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ONLINE APPENDIX

Incentives and Defaults Can Increase COVID-19 Vaccine Intentions and Test Demand

A. Additional Results

A.1. Balance Checks

This section provides a comparison of participant characteristics across decisions and treatments (Tables A.1 and A.2.).

Table A.1.: Balance Check for Sample Characteristics in PCR and Vaccine Decisions

	(1)	(2)	(3)	(4)	(5)
	Opt-in	Opt-out	Active Choice	*p*-value	Sample
Panel A: PCR Test					
Female	0.482	0.539	0.533	0.467	583
Age	36.805	35.741	35.354	0.538	583
White	0.513	0.508	0.436	0.235	583
Black	0.338	0.347	0.359	0.914	583
Hispanic	0.041	0.036	0.072	0.276	583
Other	0.108	0.109	0.133	0.689	583
Panel B: Vaccine Intention (First wave)					
Female	0.479	0.527	0.503	0.623	615
Age	33.443	37.083	33.801	0.008	615
White	0.466	0.498	0.429	0.396	615
Black	0.356	0.356	0.361	0.993	615
Hispanic	0.059	0.049	0.089	0.287	615
Other	0.119	0.098	0.120	0.704	615
Panel C: Vaccine Intention (Second wave)					
Female	0.569	0.551	0.565	0.648	929
Age	33.897	33.777	33.607	0.898	929
White	0.511	0.538	0.521	0.512	929
Black	0.354	0.321	0.326	0.396	929
Hispanic	0.042	0.062	0.032	0.253	929
Other	0.093	0.079	0.121	0.520	929

Notes: This table shows the fraction of female participants, participants who are white, Black, Hispanic or other ethnicities, for each treatment, as well as their average age. For vaccine intention, Panel B presents the descriptive statistics for the first wave of the study and Panel C presents those for the second wave. Column (4) indicates the *p*-value for a *t*-test of the difference in each individual characteristic across the three treatments, from a linear regression on each individual characteristic.

Table A.2.: Balance Check for Sample Characteristics in Vaccine Decisions: First and Second wave

	(1) First wave	(2) Second wave	(3) *p*-value	(4) Sample
Vaccine Intention	0.653	0.682	0.491	1544
Female	0.479	0.569	0.042	1544
Age	33.443	33.897	0.662	1544
White	0.466	0.511	0.303	1544
Black	0.356	0.354	0.954	1544
Hispanic	0.059	0.042	0.371	1544
Other	0.119	0.093	0.353	1544

Notes: This table shows the fraction of participants who stated they would take the COVID-19 vaccine, the fraction of female participants, participants who are white, Black, Hispanic or other ethnicities as well as their average age. Column (4) indicates the *p*-value for a *t*-test of the difference in each individual characteristic across the two waves treatments, from a linear regression that includes treatment fixed effects and their interaction.

A.2. Additional Regression Results

This section provides additional regression results for each treatment and compensation level, for vaccine and test decisions (Tables A.3, A.4 and A.5). The results in tables A.4 and A.5 also include specifications in which each treatment and compensation level is interacted with an indicator for Black ethnicity, to examine the presence of heterogeneous treatment effects of Black participants, as pre-registered.

Table A.3. Extended Regression Results (for Table 1)

	(1)	(2)	(3)	(4)	(5)	(6)
	COVID-19 Vaccine Intentions			COVID-19 Test Demand		
	LPM	LPM	Post-lasso	LPM	LPM	Post-lasso
Opt out	0.0672**	0.0672**	0.0487**	0.1210***	0.1210***	0.1192***
	(0.0277)	(0.0277)	(0.0196)	(0.0255)	(0.0255)	(0.0247)
Active	0.0417	0.0415	0.0435**	0.0805***	0.0805***	0.0768***
	(0.0288)	(0.0288)	(0.0195)	(0.0247)	(0.0247)	(0.0241)
Low compensation (<$50)	-0.0566***	-0.0566***	-0.0567***	0.1449***	0.1449***	0.1449***
	(0.0091)	(0.0091)	(0.0091)	(0.0151)	(0.0151)	(0.0151)
Large compensation (>=$50)	0.0634***	-0.0001	-0.0001			
	(0.0090)	(0.0093)	(0.0093)			
Large compensation (>=$50) X $Amount		0.0003***	0.0003***			
		(0.0000)	(0.0000)			
Cost				-0.4154***	-0.2728***	-0.2728***
				(0.0187)	(0.0190)	(0.0190)
Cost X $ Amount					-0.0024***	-0.0024***
					(0.0002)	(0.0002)
Age	-0.0023**	-0.0023**	-0.0002	-0.0003	-0.0003	0.0002
	(0.0011)	(0.0011)	(0.0007)	(0.0009)	(0.0009)	(0.0008)
Female	-0.0417*	-0.0418*	-0.0297*	0.0030	0.0030	0.0150
	(0.0230)	(0.0230)	(0.0159)	(0.0212)	(0.0212)	(0.0213)
Race: non-Hispanic Black	-0.1414***	-0.1414***	-0.0341*	-0.0341	-0.0341	-0.0071
	(0.0276)	(0.0276)	(0.0199)	(0.0242)	(0.0242)	(0.0244)
Race: Hispanic	-0.0012	-0.0012	-0.0184	0.0198	0.0198	0.0277
	(0.0498)	(0.0498)	(0.0383)	(0.0547)	(0.0547)	(0.0508)
Race: Asian or other	0.0764**	0.0764**	0.0625**	0.0341	0.0341	0.0288
	(0.0339)	(0.0339)	(0.0250)	(0.0333)	(0.0333)	(0.0330)
Household income $<$75k in 2019	-0.0698***	-0.0697***	-0.0178	-0.0417*	-0.0417*	-0.0280
	(0.0234)	(0.0234)	(0.0165)	(0.0228)	(0.0228)	(0.0220)
Tests for COVID in the past			0.0460***			0.0304
			(0.0165)			(0.0221)
Trust in vaccine			0.2404***			0.0581***
			(0.0104)			(0.0110)
Trust in doctors			-0.0126			-0.0062
			(0.0098)			(0.0107)
Political views (favoring Trump)			-0.0770***			
			(0.0100)			
Not employed (e.g., student, retired)			0.0074			-0.0482**
			(0.0180)			(0.0235)
Other work situation			0.0150			
			(0.0232)			
Constant	0.8279***	0.8280***	0.6597***	0.5495***	0.5495***	0.5142***
	(0.0536)	(0.0536)	(0.0414)	(0.0457)	(0.0457)	(0.0470)
Observations	7,996	7,996	7,996	4,664	4,664	4,664
R-squared	0.0613	0.0670		0.2931	0.3225	

Notes: This table reports the individual covariates included in Table 1. See Table 1 in the main text for details.

Table A.4. Vaccine Intentions Decisions

	(1)	(2)
	Vaccine Intention(=1)	
Opt-out	0.068**	0.063*
	(0.029)	(0.037)
Active	0.045	0.021
	(0.029)	(0.037)
Compensation $10	-0.062***	-0.056***
	(0.009)	(0.012)
Compensation $20	-0.044***	-0.042***
	(0.009)	(0.012)
Compensation $50	-0.006	-0.014
	(0.009)	(0.013)
Compensation $100	0.046***	0.037***
	(0.010)	(0.014)
Compensation $200	0.071***	0.065***
	(0.011)	(0.015)
Compensation $300	0.084***	0.075***
	(0.012)	(0.016)
Compensation $500	0.156***	0.133***
	(0.014)	(0.018)
Black	-0.136***	-0.173***
	(0.027)	(0.041)
Opt-out X Black		0.011
		(0.059)
Active X Black		0.063
		(0.060)
Compensation $10 X Black		-0.016
		(0.024)
Compensation $20 X Black		-0.005
		(0.024)
Compensation $50 X Black		0.021
		(0.024)
Compensation $100 X Black		0.024
		(0.025)
Compensation $200 X Black		0.016
		(0.026)
Compensation $300 X Black		0.025
		(0.027)
Compensation $500 X Black		0.058*
		(0.031)
Clusters	1544	1544
Observations	7,996	7,996

Notes: This table reports marginal effects, calculated at the means of all covariates, for a probit regression on the intention to take the vaccine. Indicator variables are shown for each treatment and compensation. The omitted categories are the Opt-in treatment without a compensation ($0). The regressions include age, gender, ethnicity and income group as controls. Robust standard errors shown in parentheses. ***p<0.01, **, p<0.05, * p<0.10

Table A.5. PCR Test Demand

	(1)	(2)
	PCR Test Demand	
Opt-out	0.163***	0.130***
	(0.034)	(0.042)
Active	0.108***	0.081**
	(0.033)	(0.041)
Compensation $25	0.165***	0.155***
	(0.017)	(0.020)
Compensation $5	0.113***	0.103***
	(0.015)	(0.019)
Cost $5	-0.191***	-0.193***
	(0.019)	(0.023)
Cost $25	-0.355***	-0.366***
	(0.023)	(0.028)
Cost $50	-0.510***	-0.529***
	(0.027)	(0.033)
Cost $100	-0.575***	-0.591***
	(0.030)	(0.038)
Cost $119	-0.672***	-0.676***
	(0.034)	(0.042)
Black	-0.041	-0.130**
	(0.032)	(0.055)
Opt-out X Black		0.101
		(0.072)
Active X Black		0.084
		(0.070)
Compensation $25 X Black		0.031
		(0.034)
Compensation $5 X Black		0.029
		(0.031)
Cost $5 X Black		0.003
		(0.038)
Cost $25 X Black		0.033
		(0.048)
Cost $50 X Black		0.057
		(0.058)
Cost $100 X Black		0.050
		(0.063)
Cost $119 X Black		0.009
		(0.074)
Clusters	583	583
Observations	4,664	4,664

Notes: This table reports marginal effects, calculated at the means of all covariates, for a probit regression on the decision to take the PCR test. Indicator variables are shown for each treatment and compensation. The omitted categories are the Opt-in treatment without a compensation ($0). The regressions include age, gender, ethnicity, and income group as controls. Robust standard errors shown in parentheses. ***p<0.01, **, p<0.05, * p<0.10

A.3. Heterogeneous Treatment Effects Estimated Using Causal Forests

We estimate heterogeneous treatment effects using the R package "grf" (generalized random forests, version 1.2.0), following the tutorial provided by Susan Athey titled "Estimation of Heterogeneous Treatment Effects and Optimal Treatment Policies," (November 2019).[1] We perform the analysis to address two separate questions. First, whether there are heterogeneous treatment effects of the Opt-out treatment relative to the Opt-in treatment for taking the vaccine, when there is no compensation. Second, whether there are heterogeneous treatment effects of a small compensation (of $10) relative to no compensation for taking the vaccine, in the Opt-out treatment.

In both cases, 66.7% of the data is used for training purposes, while the remaining observations are part of the test dataset. We split 50% of the training dataset into the "splitting" dataset and 50% into the "estimation" dataset. After loading the data, and creating the training dataset (labelled df_train)

A.3.1. Heterogeneity in the Effect of Defaults for Vaccine Intentions

We estimate the causal forest using the following command.

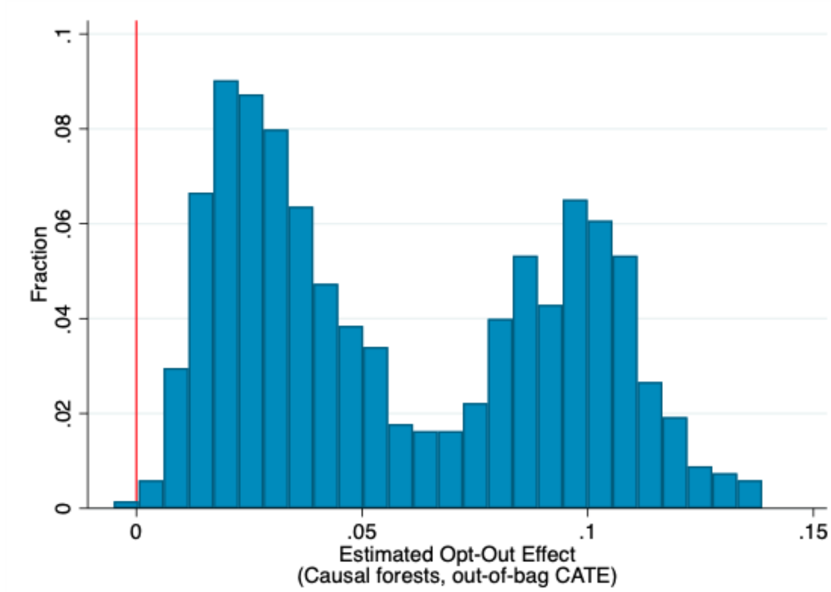
```
cf = causal_forest(as.matrix(df_train[covariate_names]),
             Y = df_train$Y,
             W = df_train$W,
             Y.hat = Y.hat , W.hat = W.hat,
             seed=1234,
             num.trees = 2500,
             min.node.size = 9,
             sample.fraction=0.50,
             alpha = 0.40,
)
```

The outcome variable, Y, is an indicator for whether the individual intends to the vaccine. W is the treatment assignment (Opt-out or Opt-in). The covariates in the dataset are the following. They include the age, gender, ethnicity, income (above/below median) of the participant. They also include how often the participant has been tested for a COVID infection at the time of the experiment, whether she has been tested for COVID antibodies, whether she beliefs she has had COVID in the past (0-100), how many friends have died of COVID, her trust of vaccines and doctors (standardized), her generosity (standardized principal component), her political views (standardized principal component) and whether she is not working. Following Athey and Wager (2019), we train a forest for Y and W using default settings and use their predictions as inputs for the causal forest, Y.hat and W.hat. As they discuss, the nuisance components Y.hat and W.hat need not be estimated using a regression forest and specified in the command, since the command would also silently estimate them.

[1] An updated version can be found here: https://gsbdbi.github.io/ml_tutorial/hte_tutorial/hte_tutorial.html (accessed April 27, 2021).

In addition to setting a seed for replicability, we also set several tuning parameters. The forest grows 2,500 trees (num.trees), and set the minimum number of observations in each tree leaf to 9 (min.node.size). The sample size used for building each tree (sample.fraction) is 0.5, the default. Finally, we specify the maximum imbalance of each split (alpha) to be 0.4. We perform a test calibration of the forest using the forest prediction (on held-out data) as well as the mean forest prediction as the only regressors, using the command test_calibration. The mean forest prediction is very often correct, as the coefficient for it is 0.98 (close to 1). The forest also captures quite some heterogeneity in the underlying heterogeneity, in that the coefficient for the forest prediction is 0.67 (though not significantly different from zero). The distribution of CATE is shown in Figure A.1 below.

Figure A.1 Distribution of CATE for the Opt-out Treatment



Notes: Figure A.1. shows the distribution of the estimated out-of-bag CATE for the Opt-out treatment, relative to Opt-in, in the absence of compensation.

We then divide the sample in two, by its median, and compute the AIPW treatment effect on each group, as reported in the main text. For each group, those with below and above median, we estimate the average level of each covariate, as shown in Table A.6. We also conduct *t*-tests in each case to test for the difference (*N*=676, which is the number of observations in the training sample dataset).

Table A.6. Covariate Heterogeneity by above and below median CATE of the Opt-out treatment

	(1) Above-median CATE	(2) Below-median CATE	(3) *p*-value
Age	34.382	34.935	0.552
Female	0.459	0.609	0.000
Race (1-4)	1.689	1.701	0.866
Income low	0.607	0.618	0.753
Past testing frequency	0.462	0.402	0.121
Past test for antibodies (=1)	0.115	0.062	0.015
Nr. of friends died of COVID-19	0.574	0.660	0.380
Belief about past infection	31.382	21.192	0.000
Political views (favor Trump)	0.731	-0.743	0.000
Generosity	0.123	-0.002	0.101
Trust vaccine (standardized)	-0.231	0.304	0.000
Trust doctors (standardized)	-0.040	0.158	0.010

Notes: This table reports the average value of each covariate, by whether the estimated CATE of the Opt-out treatment is below or above median. The results of *t*-tests on each covariate by whether they are above or below median are shown in column (3). N=676.

A.3.2. Heterogeneity in the Effect of Small Compensations (Crowd-out) for Vaccine Intentions

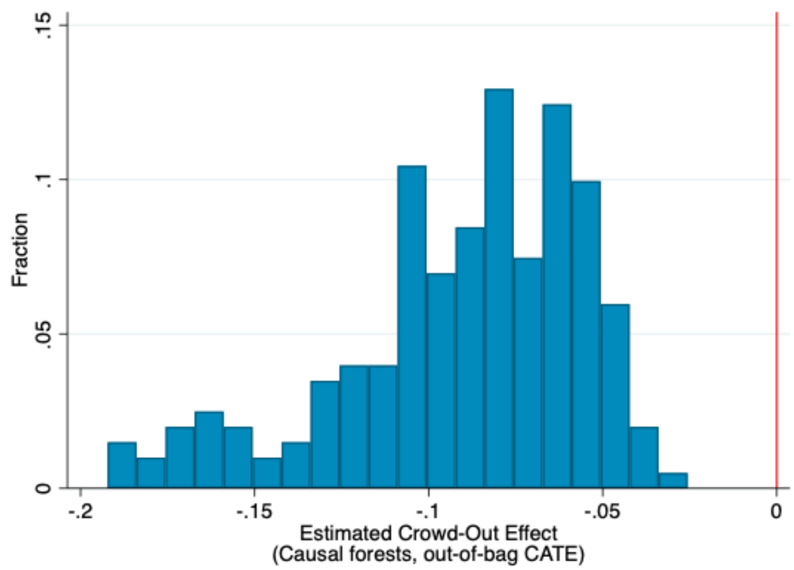
We follow the same approach to estimate heterogeneity in treatment effects for offering small compensations, relative to no compensations, to individuals who intend to take the vaccine, focusing on the Opt-in treatment. The code includes a cluster indicator for each individual.

```
cf = causal_forest(as.matrix(df_train[covariate_names]),
                Y = df_train$Y,
                W = df_train$W,
                Y.hat = Y.hat , W.hat = W.hat,
                seed=1234,
                clusters = df_train$vid,
                alpha = 0.40,
                num.trees = 3000,
                sample.fraction=0.45,
                min.node.size = 2,
)
```

In addition to setting a seed for replicability, we also set several tuning parameters, to achieve high test calibration. The forest grows 3,000 trees (num.trees), and set the minimum number of observations in each tree leaf to 2 (min.node.size). The sample size used for building each tree (sample.fraction) is 0.45. Finally, we specify the maximum imbalance of each split (alpha) to be

0.40. We perform a test calibration of the forest using the forest prediction (on held-out data) as well as the mean forest prediction as the only regressors, using the command test_calibration. The mean forest prediction is very often correct, as the coefficient for it is 1.00 (close to 1). The forest also captures some heterogeneity in the underlying heterogeneity, in that the coefficient for the forest prediction is 0.20 (though not significantly different from zero). The distribution of CATE is shown in Figure A.2 below.

Figure A.2. Distribution of CATE



Notes: This figure shows the distribution of the estimated out-of-bag CATE for the $10 compensation, relative to no compensation, in the Opt-in treatment.

We then divide the sample in two, by its median, and compute the AIPW treatment effect on each group, as reported in the main text. For each group, those with below and above median, we estimate the average level of each covariate, as shown in Table A.7. We also conduct *t*-tests in each case to test for the difference (*N*=402, which is the number of observations in the training sample dataset).

Table A.7. Covariate Heterogeneity by above and below median CATE of the low compensation in the Opt-in treatment

	(1) Above-median CATE	(2) Below-median CATE	(3) *p-value*
Age	33.866	32.910	0.419
Female	0.736	0.348	0.000
Race (1-4)	1.587	1.796	0.005
Income low	0.622	0.662	0.407
Past testing frequency	0.547	0.408	0.005
Past test for antibodies (=1)	0.139	0.070	0.022
Nr. of friends died of COVID-19	0.577	0.587	0.937
Belief about past infection	13.886	39.050	0.000
Political views (favor Trump)	-0.384	0.397	0.000
Generosity	0.010	0.048	0.613
Trust vaccine (standardized)	0.080	-0.241	0.001
Trust doctors (standardized)	0.091	-0.018	0.262

Notes: This table reports the average value of each covariate, by whether the estimated CATE of the small compensation for taking the vaccine is below or above median. The results of t-tests on each covariate by whether they are above or below median are shown in column (3). N=402.

A.3.3. Heterogeneity in the Effect of Defaults for Test Demand

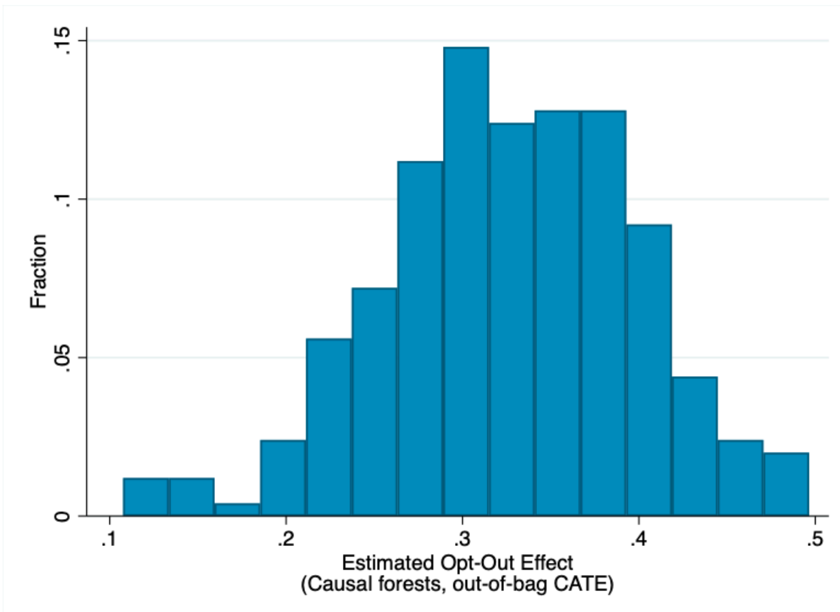
We follow the same approach to estimate heterogeneity in the treatment effect of the Opt-out treatment on COVID-19 PCR test demand. This analysis should be considered suggestive as the number of observations is limited (N=375). The main code command is as follows:

```
cf = causal_forest(as.matrix(df_train[covariate_names]),
        Y = df_train$Y,
        W = df_train$W,
        Y.hat = Y.hat , W.hat = W.hat,
        seed=1234,
        alpha = 0.45,
        num.trees = 500,
        sample.fraction=0.45,
        min.node.size = 1,
)
```

In addition to setting a seed for replicability, we also set several tuning parameters, to achieve high test calibration. The forest grows 500 trees (num.trees), and set the minimum number of observations in each tree leaf to 1 (min.node.size). The sample size used for building each tree (sample.fraction) is 0.45. Finally, we specify the maximum imbalance of each split (alpha) to be

0.45. We perform a test calibration of the forest using the forest prediction (on held-out data) as well as the mean forest prediction as the only regressors, using the command test_calibration. The mean forest prediction is very often correct, as the coefficient for it is 1.03 (close to 1). The forest also captures limited heterogeneity, in that the coefficient for the forest prediction is 0.37 (though not significantly different from zero). The distribution of CATE is shown in Figure A.3 below.

Figure A.3. Distribution of CATE

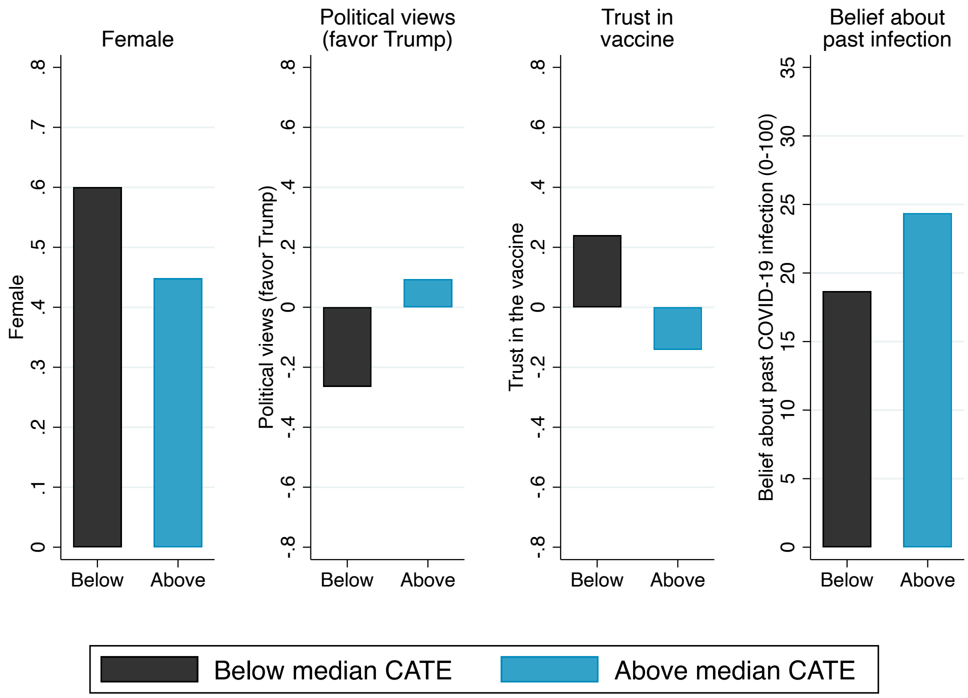


Notes: Figure A.3. shows the distribution of the estimated out-of-bag CATE for the Opt-out treatment, relative to Opt-in, in the absence of compensation for COVID-19 Test Decisions.

We then divide the sample in two, by its median, and compute the AIPW treatment effect for those below and above median. For those with below and above median CATE, we estimate the average level of each covariate, as shown in Figure A5. We also conduct t-tests in each case to test for the difference (*N*=250, which is the number of observations in the training sample dataset).

Relative to the heterogeneity found for the Opt-out Treatment on vaccine intentions, we find similar results. Individuals with estimated higher effects of the Opt-out treatment are more likely to be male, have political views that are more supportive of Trump, trust the vaccine less, and believe it is more likely that they may have had a COVID-19 infection in the past.

Figure A.4. Heterogeneous Treatment Effects of Opt-out Treatment



Notes: This figure shows the average share of female participant, political views (standardized principal component), trust in the vaccine (standardized) and belief about past COVID-19 infection for those exhibiting below and above median CATE.

Table A.8. Covariate Heterogeneity by above and below median CATE of of the Opt-out treatment for COVID-19 Test Demand

	(1)	(2)	(3)
	Above-median CATE	Below-median CATE	*p*-value
Age	31.408	41.888	0.000
Female	0.448	0.6	0.016
Race (1-4)	1.936	1.488	0.000
Income low	0.632	0.48	0.015
Past testing frequency	0.344	0.36	0.792
Past test for antibodies (=1)	0.04	0.072	0.273
Nr. of friends died of COVID-19	0.464	0.584	0.435
Belief about past infection	24.368	18.664	0.056
Political views (favor Trump)	0.093	-0.26437	0.004
Generosity	-0.062	0.036	0.480
Trust vaccine (standardized)	-0.141	0.240	0.003
Trust doctors (standardized)	-0.0495	0.211	0.020

Notes: This table reports the average value of each covariate, by whether the estimated CATE of the small compensation for taking the vaccine is below or above median. The results of t-tests on each covariate by whether they are above or below median are shown in column (3). N=250.

B. Instructions

In the following section, we provide the instructions for the Vaccine Decisions (B.1.), the PCR Testing Decisions (B.2.) and the End-of-Experiment Survey (B.3.).

B. 1. Vaccine Decisions

*Below, we present the instructions for **vaccine** decisions. Some questions differentiate between three treatments (opt-in, opt-out, active choice) as indicated in square brackets. Furthermore, the experiment was conducted in two waves (first and second wave), differences in the instructions between these are indicated in brackets as well. As stated in the main text, for vaccine decisions without compensation (elicited in both waves) no significant differences in decision-making were found.*

Decisions about the Coronavirus vaccine
We would like to ask you to make a decision about the **Coronavirus vaccine**. The vaccine is currently being rolled out across the US.

[*Second wave:* You would get the Pfizer vaccine which is one of the recommended vaccines in the USA (more information from the CDC). Two doses of the vaccine are necessary for best protection, with 21 days inbetween.]

[*Opt-in treatment*] Suppose the vaccine becomes available to you in 2021, and you can schedule an appointment to receive it. What would you choose?

- Leave as is and not receive the vaccine
- Opt in to receive the vaccine

[*Opt-out treatment*] Suppose the vaccine becomes available to you in 2021, and an appointment has been scheduled for you to receive the vaccine. What would you choose?

- Leave as is and receive the vaccine
- Opt out to not receive the vaccine

[*Active treatment*] Suppose the vaccine becomes available to you in 2021, and you can schedule an appointment to receive it. What would you choose?

- Receive the vaccine
- Not receive the vaccine

*The following questions were included only in the **second wave**.*
If you could choose between the following types of gift cards to receive a compensation, which one would you prefer? Please select one gift card:

- Gas gift card
- Amazon gift card
- Pharmacy store gift card (e.g., CVS, Walgreens, Walmart)

Page break ―――――――――――――――――――――――――――――――――――

In the following, we ask you to make seven decisions regarding the vaccine. In these decisions, you receive an additional gift card as a thank-you if you decide to get vaccinated. You would receive the gift card **after having received the second dose.**

[*Opt-in treatment*] Suppose the vaccine becomes available to you in 2021, and you can schedule an appointment to receive it. Please indicate your choice for each of the seven cases below.

- Leave as is and not receive the vaccine
- Opt in to receive the vaccine and receive a $10/$20/$50/$100/$200/$500 [gift card placeholder]

[*Opt-out treatment*] Suppose the vaccine becomes available to you in 2021, and an appointment has been scheduled for you to receive the vaccine. Please indicate your choice for each of the seven cases below.

- Leave as is, receive the vaccine and a $10/$20/$50/$100/$200/$500 [gift card placeholder]
- Opt out to not receive the vaccine

[*Active treatment*] Suppose the vaccine becomes available to you in 2021, and you can schedule an appointment to receive it. What would you choose?

- Receive the vaccine and a $10/$20/$50/$100/$200/$500 [gift card placeholder]
- Not receive the vaccine

B.2. PCR Testing Decisions

*Below, we present the instructions for the **PCR Testing Decisions**. Some questions differentiate between three treatments (opt-in, opt-out, active) as indicated.*

Decisions about Coronavirus infection (PCR) tests

[*Opt-in treatment*: You have been randomly allocated to possibly receive **an Amazon gift card.**]

[*Opt-out treatment*: You have been randomly allocated to possibly receive a **saliva-based Coronavirus infection (PCR) test and possibly an additional Amazon gift card.**]

[*Active treatment:* We would now like to ask you to make decisions about **saliva-based Coronavirus infection (PCR) test and possibly an additional Amazon gift card**.]

[*Opt-in / Opt-out treatment*: We would now like to ask you to make decisions about Coronavirus infection tests.]

[*Opt-in treatment:* **You can choose to change the gift card, and take a saliva-based Coronavirus PCR test, and possibly an additional Amazon gift card.**]

The accuracy of saliva-based tests is very high, with a 1% rate of false-positive and false-negative results, respectively. It is very similar to that of tests based on nasal swabs (more information can be found here).

[*Active treatment:* **In each decision below you choose between the Coronavirus test and an Amazon gift card value.**]

If one of your decisions below is randomly chosen to be implemented, and you choose [*Opt-in:* **to change the Amazon gift card for the Coronavirus infection test] [***Opt-out:* **to keep the Coronavirus infection test] [***Active:* **the Coronavirus infection test], you will get a personalized URL (link) for the test. We will have prepaid for the test and you will face no costs whatsoever.** Once you receive the personalized URL (link), you will:

- Create an account with Vault Health
- Request that a testing kit be mailed to your address of choosing via overnight shipping
- Complete a saliva test over Zoom
- Mail the kit to Vault Health's lab via overnight shipping
- Receive results through their Vault Health account within 48-72 hours

The value of the test kit is $119 per test kit. We will pay this amount for you, and it will cover all taxes, credit card processing fees, and prepaid overnight shipping to each individual tester and to our laboratory.

[*Opt-out treatment:* **You can choose to change the test, and take an Amazon gift card, instead. In that case, you will get the Amazon gift card.**]

[*Active treatment:* **If you choose an Amazon gift card, you will get the Amazon gift card.**]

In each row, please choose between the two options:

[Opt-in treatment]

- Keep $5/$5/$5/$5/$25/$50/$100/$119 Amazon gift card
- Change for Coronavirus infection test [& $30/$10/$5 Amazon gift card]

[Opt-out treatment]

- Keep Coronavirus infection test [& $30/$10/$5 Amazon gift card]
- Change for $5/$5/$5/$5/$25/$50/$100/$119 Amazon gift card

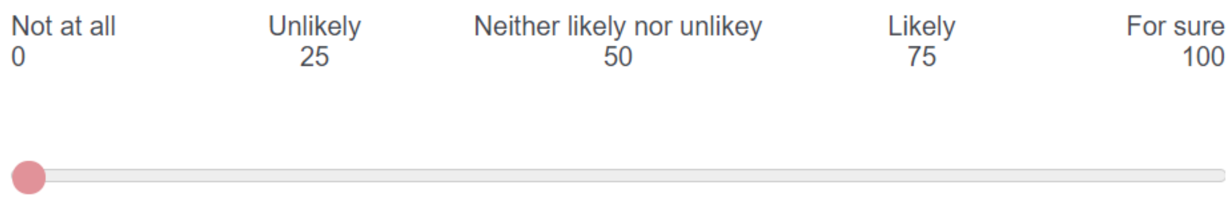
[Active treatment]

- Coronavirus infection test [& $30/$10/$5 Amazon gift card]
- $5/$5/$5/$5/$25/$50/$100/$119 Amazon gift card

B.3. End-of-Experiment Survey

Below, we present the instructions for the ***End-of-Experiment Survey****. Those questions were asked across all treatments.*

Do you think you have had Coronavirus already? Please select how likely you think it is you had Coronavirus, from 0% chance to 100% chance.



Page Break
Have you been tested for Coronavirus infection already?

- Yes, more than 5 times
- Yes, 4 times
- Yes, 3 times
- Yes, 2 times
- Yes, once
- No, I have not been tested for Coronavirus infection yet.

Page Break
The following two questions were displayed if participants previously indicated that they had been tested.

What was the reason for taking the Coronavirus test (for the most recent test you took)?

- I had symptoms and/or had been in contact with someone who tested positive for Coronavirus
- I was asymptomatic but needed the test. For what reason?

Page Break
What was the result of your Coronavirus test (for the most recent test you took)?

- It was positive, indicating I had Coronavirus
- It was negative, indicating I did not have Coronavirus
- I don't know, I am currently waiting for the results

Page Break
Have you gotten tested for Coronavirus <u>antibodies</u>?

- Yes
- No
-

Page Break
How worried are you about getting infected with Coronavirus?

- A great deal

- A lot
- A moderate amount
- A little
- Not at all

Page Break
How many people in your family, friends and acquaintances circle have died from Coronavirus, that you know of?

Page Break
What do you think is the chance, from 0% chance to 100% chance, that the Coronavirus pandemic will be over, and most economic and social activity return to normal, by...[Sliders for March 2021, June 2021, September 2021, December 2021, March 2022, June 2022]

Page Break
Suppose all high-risk individuals and health-care workers have received the vaccine. You can then choose in which order to receive the vaccine. Which place in line would you like to be? [Slider from 0 to 100, among the first…among the last]

Why did you choose the place in line above? Please explain briefly.

Page Break
What is the chance, from 0% chance to 100% chance, that you would take the **Coronavirus vaccine**, if 0%/ 20%/ 40%/ 60%/ 80%/100% of others in your community took it?

Page Break
If the vaccine would protect from infecting others, should people who received the vaccine be excluded from lock-downs and travel restrictions?

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Page Break
How willing are you to give to good causes without expecting anything in return?
Please again indicate your answer on the scale from 0 to 10, where 0 means you are "completely unwilling to do so" and a 10 means you are "very willing to do so".

Imagine the following situation: **You receive unexpectedly $10,000 today. How much of that sum would you donate to a charitable cause?**

Page Break
What is your gender?

- Male
- Female

- Other

What is your age?

What is your ethnicity?
- Non-Hispanic White
- Non-Hispanic Black
- Hispanic
- Asian
- Other Race

What was your household income in 2019?
- Less than $25,000
- $25,000-$49,999
- $50,000-$74,999
- $75,000-$99,999
- $100,000-$149,999
- More than $150,000

What is your current employment situation?
- I am an essential worker and I am currently working outside of my home
- I am not an essential worker and I am currently working outside of my home
- I am currently working from home
- I have been put on furlough or lost my job due to the Coronavirus pandemic
- I am not currently working (e.g., retired, student, etc.)
- Other. Please specify

How do you position yourself politically?
- Democrat
- Republican
- Independent

Page Break
On a scale from 0 to 10, how would you rate President Trump's performance during the Coronavirus crisis?

On a scale from 0 to 10, how would you rate Dr. Fauci's performance during the Coronavirus crisis?

Page Break
Do you have health insurance?
- Yes
- No
- Prefer not to answer

How much do you trust doctors?

- Do not trust at all
- Do not trust very much
- Trust somewhat
- Trust completely

How much do you trust that the Coronavirus vaccine will be effective and safe to take?

- Do not trust at all
- Do not trust very much
- Trust somewhat
- Trust completely

B.3. Pre-registrations

As Predicted:"*Willingness to receive health information about COVID-19*" (#55138)

Created: 12/30/2020 07:33 AM (PT)

Author(s)

1) Have any data been collected for this study already?
No, no data have been collected for this study yet.

2) What's the main question being asked or hypothesis being tested in this study?
We study individuals' willingness to learn about their health status and take preventive measures for their health and those of others around them, in the context of Coronavirus (COVID-19). Specifically, we measure willingness to get tested for Coronavirus (COVID-19) infection, for Coronavirus antibodies, invest in devices that provide information related to the risk of Coronavirus infection, and stated willingness to get the Coronavirus vaccine. This project will build on Projects #40547 and #54101. We hypothesize that willingness to learn about one's health status, such as testing for Coronavirus antibodies, Coronavirus infection, willingness to learn about healthiness of the environment (via an air monitor), and willingness to get vaccinated against Coronavirus, may depend on whether getting information is the default behavior or not.

3) Describe the key dependent variable(s) specifying how they will be measured.
For three Coronavirus-related products, people will decide between the products (Coronavirus infection test, Coronavirus antibody test, air quality monitor) versus Amazon gift cards. They know that, with some probability, one of their decisions may materialize. For the vaccine, they will decide whether they would be willing to take it or not.

4) How many and which conditions will participants be assigned to?
To understand the willingness to receive health information and take preventive health measures, we will use the strategy method for the three Coronavirus-related products. Subjects will decide for different dollar values of Amazon gift cards between the product and the gift card.
Participants will be assigned to one of three conditions. In the first condition, they will be endowed with a test, vaccine, or air quality monitor (opt-out). In the second condition, they will be endowed with the Amazon gift card (opt-in). In the third condition, they will make an active choice without an endowment (active choice).

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
We plan to analyze the impact of being endowed with health information products on willingness to pay (or willingness to receive) for these products. Our project #40547 showed significant differences in willingness to pay for the products depending on ethnicity. We plan to test whether there are heterogeneous treatment effects by ethnicity. If the impacts of the endowment conditions are not significant, we plan to merge the data across conditions for the analysis. We also plan to merge the opt-in and active choice conditions in the analysis, if their impacts do not differ significantly.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
We will exclude subjects who fail to provide consistent answers.

7) How many observations will be collected or what will determine sample size?
No need to justify decision, but be precise about <u>exactly</u> how the number will be determined.
We plan to collect approximately 2400 observations (approximately 200 per condition, since there are 3 conditions and 4 products), from participants on Prolific Academic. As we saw differences according to ethnicity, we will try to oversample non-Hispanic black participants.

8) Anything else you would like to pre-register?
(e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)
We aim to examine whether the willingness to pay for testing and air monitoring devices depends on individuals' educational background, income, own beliefs about whether they have had Coronavirus, cases of Coronavirus among friends or family, a higher degree of being scared of Corona, gender, and ethnicity. We also plan to test whether the willingness to pay for testing and monitoring devices depends on the individuals' degree of prosociality, political position and evaluation of politician's management of the crises are related to their WTP. We will also examine individuals' willingness to receive the vaccine relative to others and their trust in the vaccine and doctors.

As Predicted:"*Intentions to vaccinate against COVID-19: the role of choice architecture*" (#57775)

Created: 02/08/2021 11:21 AM (PT)

Author(s)

1) Have any data been collected for this study already?
No, no data have been collected for this study yet.

2) What's the main question being asked or hypothesis being tested in this study?
We study individuals' stated willingness to get vaccinated against COVID-19. We investigate the impact of choice architecture and of being compensated for taking the vaccine. We hypothesize that
a) Willingness to take the vaccine may depend on choice architecture.
b) Compensations render the vaccine more attractive.
c) For larger compensations, the influence of choice architecture may be non-significant.

3) Describe the key dependent variable(s) specifying how they will be measured.
People state if they would take the vaccine (hypothetical). They decide without compensation and for various compensations in form of gift-cards.

4) How many and which conditions will participants be assigned to?
Depending on the treatment, subjects face an active choice, opt-in or opt-out choice architecture. For monetary compensations, we will use the strategy method.

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
We plan to analyze the impact of choice architecture and of incentives on taking the vaccine (hypothetical). We plan to test whether there are heterogeneous treatment effects by ethnicity and use causal forests to explore heterogeneity more broadly. If the impacts of the choice architecture conditions are not significant, we plan to merge the data across conditions for the analysis.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
We will exclude subjects who fail to provide consistent answers.

7) How many observations will be collected or what will determine sample size?
No need to justify decision, but be precise about exactly how the number will be determined.
We plan to collect approximately 1000 observations. As we saw differences according to ethnicity in a previous study, we will try to oversample non-Hispanic black participants.

8) Anything else you would like to pre-register?
(e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)
We aim to examine whether intentions to vaccinate depends on age, individuals' income, own beliefs about whether they have had Coronavirus, trust in the vaccine, cases of Coronavirus among friends or family, higher degree of being scared of Corona, gender, and ethnicity. We also plan to test whether intentions depend on the individual's degree of prosociality, political position and evaluation of politician's management of the pandemic.
We will compare the results from this study to those in study #55138. If comparable, we will merge the results of vaccine intentions in that study with those in this study in the data analysis.

C. Description of Additional Decisions Elicited

In our main study, some participants (n=591) were also randomized into making decisions about air quality monitors or about antibody tests (n=597). Regarding the air quality monitor, we offered one from Amazon that was rated above 4 stars, the Hydrofarm APCEM2. Participants could get the monitor or an Amazon gift card. The value of the gift card went from $10 to the listed market price of the monitor at the time of the study $107.08, in the following steps: $10, $20, $30, $40, $50, $75, $90, $107.08. Depending on treatment, one of the options was the default, or neither was and participants made an active choice. In the opt-out treatment, participants were randomly assigned to receive the monitor but could change it for a gift card. In the opt-in treatment, they were randomly assigned the gift card but they could change it for the air quality monitor. In the Active choice treatment, participants had to make an active decision regarding what they preferred. For the air quality monitor, participants knew that about 1 in 25 of them would see their decision materialize. For the antibody test, everything was similar except that we employed an antibody test to be performed at home, and only measured hypothetical decisions. The value of the gift card went from $0.50 to $30.

Regarding antibody testing, we also refer to an additional, quota-representative study we ran in May 2020, at a point when antibody tests for at home were not FDA-approved yet. That study was based on 1,984 participants, selected to represent the US population. The study was anonymous. Details can be found in (Serra-Garcia and Szech, 2020). In that study, participants took an active choice whether they wanted an antibody test that could be carried out at home, once it became FDA approved and available on the market. Alternatively, participants could decide to get money in the form of an Amazon gift card. We expected the market price of such tests could come close to $30 based on prices in other countries where such tests were already approved and available. Therefore, each individual decided whether they preferred an antibody at-home testing kit or a gift card (Amazon), with the value of the latter varying from $0.50 to $30. Subjects decided in different testing scenarios, as it was unclear at that time how much protection a positive test result could offer. Across scenarios, the protective immunity of a positive test result varied as follows. A positive test result could lead to a likelihood of protection from a new COVID-19 infection with 50%, 70%, 90%, or 99% probability. We stressed that this could be caused by the test making a mistake, and/or by antibodies not giving perfect protection. The expected length of protection also varied. It was either 3, 6, or 12 months. Eight out of these in total 12 possible testing scenarios were randomly chosen and presented to each individual in random order. Individuals knew that about 1 in 25 of them would be drawn randomly and one of their decisions would be implemented if tests became available soon. They knew we would implement according to the scenario that was scientifically most plausible when tests got approved and available. We also informed them that if tests would not become approved, they would get $15 as a thank you payment (in the form of an Amazon gift card) instead. Unfortunately, by the end of 2020, no at-home antibody tests had been approved yet in the US and we had to give out the thank you voucher. The experiment was pre-registered on Aspredicted.org (details in Serra-Garcia and Szech, 2020).

For all products, defaults and incentives significantly increase take-up of antibody testing and air quality monitors. In the quota-representative sample all decisions were under the active choice treatment. In quota-representative sample 51% of participants were women (52% in the Prolific Academic sample), the average age of participants was 47 (older than those in Prolific Academic who were 35 years old on average), and 61% of participants were white while 13% of participants were Black. In the quota-representative study, we measure willingness to pay (WTP) for the test in each scenario as the first value for which subjects choose the gift card over the antibody test. We focus on 1,925 participants who made choices consistent with the law of demand (switched at most once between choosing the test and the gift card). Average WTP for an at-home antibody test was \$14.39 (SD=10.72) when the likelihood of protective immunity was 50% and protection lasted 3 months. This value is not significantly different from the WTP in the Active choice treatment in our main study, \$13.42 (SD=11.06, *t*-test *p*-value=0.2344). Consistent with our findings throughout, in all scenarios, monetary incentives had a strong impact.

We also report below participant characteristics and average decisions for participants who made decisions about antibody testing and air quality monitors in two additional studies.

Table C.1. Antibody Testing Demand Across Samples

	Willingness to Pay for Antibody Test	
	Mean (in \$)	SD
Prolific		
Active choice	13.42	11.06
Representative sample		
50% chance of immunity for 3 months	14.39	10.72
75% chance of immunity for 3 months	15.82	11.03
95% chance of immunity for 3 months	16.32	11.27
99% chance of immunity for 3 months	17.14	10.91
50% chance of immunity for 6 months	18.41	10.86
75% chance of immunity for 6 months	19.53	10.93
95% chance of immunity for 6 months	18.62	11.03
99% chance of immunity for 6 months	20.03	10.89
50% chance of immunity for 12 months	21.50	10.87
75% chance of immunity for 12 months	19.61	11.06
95% chance of immunity for 12 months	21.24	10.90
99% chance of immunity for 12 months	21.94	10.94

Notes: This table presents the mean (and SD) of willingness to pay for an at-home antibody test. At the individual level, willingness to pay is calculated as the price at which the individual chooses to take the Amazon gift card (of \$0.50, \$2, \$5, \$10, \$15, \$20, \$25 and \$30) over the antibody test. For the representative sample N=1930, and for Prolific N=191, including only subjects who make decisions consistent with the law of demand.

Table C.2. Antibody Testing: Comparison of Sample Characteristics

	(1)	(2)
	Antibody Testing	
	Active choice only	Active choice, opt-in, opt-out
	Representative Sample	Prolific Academic
Female	0.509	0.519
Age	47.326	34.844
White	0.615	0.472
Black	0.126	0.369
Hispanic	0.179	0.055
Other	0.080	0.104
Income <$25K	0.167	0.188
Income $25-50K	0.230	0.253
Income $50-75K	0.186	0.209
Income $75-100K	0.141	0.149
Income $100-150K	0.152	0.129
Income >150K	0.124	0.072
N	1965	597

Notes: This table shows the fraction of female participants, participants who are white, Black, Hispanic or other ethnicities, their average age, and their household income group, among participants in the quota-representative sample (only active choice), and Prolific Academic (active choice, opt-in and opt-out).

Table C.3. Effects of Defaults on Antibody Testing and Air Quality Monitor Demand

	(1)	(2)	(3)
		Treatment	
Panel A. Antibody Test	Opt-in	Opt-out	Active Choice
Cost $0.50	0.763	0.825	0.756
Cost $2.00	0.732	0.804	0.717
Cost $5.00	0.621	0.732	0.610
Cost $10.00	0.439	0.546	0.478
Cost $15.00	0.359	0.459	0.390
Cost $20.00	0.227	0.330	0.239
Cost $25.00	0.177	0.268	0.215
Cost $30.00	0.121	0.196	0.171
		Treatment	
Panel B. Air Quality Monitor	Opt-in	Opt-out	Active Choice
Cost $10.00	0.635	0.788	0.693
Cost $20.00	0.577	0.768	0.633
Cost $30.00	0.513	0.675	0.573
Cost $40.00	0.429	0.581	0.508
Cost $50.00	0.280	0.399	0.337
Cost $75.00	0.164	0.222	0.241
Cost $90.00	0.132	0.167	0.211
Cost $107.08	0.111	0.108	0.146

Notes: This table shows the frequency with which the antibody test (Panel A) or the air quality monitor (Panel B) were chosen over each gift card value.

Table C.4. Balance Check for Sample Characteristics in Antibody and Air Quality Decisions

	(1)	(2)	(3)	(4)	(5)
		Treatment			
	Active Choice	Opt-in	Opt-out	*p*-value	Sample
Panel A: Antibody Test					
Female	0.517	0.500	0.541	0.715	597
Age	34.380	35.333	34.835	0.738	597
White	0.454	0.510	0.454	0.431	597
Black	0.405	0.298	0.402	0.036	597
Hispanic	0.054	0.056	0.057	0.991	597
Other	0.088	0.136	0.088	0.228	597
Panel B: Air Quality Monitor					
Female	0.472	0.487	0.537	0.398	591
Age	34.809	35.968	36.020	0.570	591
White	0.487	0.429	0.522	0.173	591
Black	0.347	0.397	0.310	0.202	591
Hispanic	0.055	0.074	0.049	0.588	591
Other	0.111	0.101	0.118	0.853	591

Notes: This table shows the fraction of female participants, participants who are white, Black, Hispanic or other ethnicities, for each treatment, as well as their average age. Column (4) indicates the *p*-value for a *t*-test of the difference in each individual characteristic across the three treatments, from a linear regression on each individual characteristic.