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Choice Architecture and Incentives Increase COVID-19 Vaccine Intentions and Test Demand

Marta Serra-Garcia* and Nora Szech*

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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: choice architecture and monetary compensations. Some organizations, such as restaurants, supermarkets, fire departments or hospitals in some countries, use these measures. Yet there is the concern that compensations could erode intrinsic motivation and decrease vaccination intentions. We show that both approaches, compensations and choice architecture, can significantly increase COVID-19 test and vaccine demand. 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 choice architecture and avoidance of small compensations is 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: D01, D04, I12

Keywords: choice architecture, 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 choice architecture, on COVID-19 vaccination intentions and test demand. As vaccine and test scarcity decrease, the main decision of businesses and policy makers changes 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 a proposal to pay those getting the COVID-19 vaccine). Several employers have started compensating their employees for vaccinating themselves against COVID-19 (Dailey, 2021). Incentives offered by employers vary drastically, from smaller monetary amounts like $25, going up to $750 for those employees who get vaccinated. Employers using compensations include hospitals, telecommunications and train companies, restaurants, and supermarket chains (e.g., Dailey, 2021). Yet, an analysis of the causal influence of compensations is still missing.

An important concern is that low monetary incentives may commodify goods and behaviors of moral relevance (Gneezy and Rustichini, 2000). 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 consequences of COVID-19 vaccines are unknown, but may be severe for some

people (Sudre et al., 2021). Compensating individuals for taking the vaccine could lead to a loss in intrinsic motivation that could lower vaccination rates below those without compensation (Loewenstein and Cryder, 2020). A compensation may further be seen as a price tag by people. A low price may indicate the item is not of good quality.

We conduct an experiment to evaluate the impact of compensations and choice architecture on vaccination intentions and test demand. The data shows that, indeed, crowd-out can occur for COVID-19 vaccines: we find that low monetary compensations of $20 *reduce* vaccine demand compared to no compensation. Thus, employers must be cautious not to set too low incentives when it comes to vaccination in this pandemic. Only compensations of at least $100 significantly *increase* vaccine demand. If prevention of infection and outbreaks is a major goal, this investment can pay out for itself. Some US hospitals have offered compensations of $500 or more (Dailey, 2021). 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, also among patients. Moreover, for many other businesses, such as factories, it may be fundamental to avoid larger outbreaks, also to stay economically healthy.

Testing, by contrast, does not exhibit crowd-out. We study the uptake of 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 uptake 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 is an alternative type of intervention that has 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, 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., 2020). Encouragingly, our data show that choice architecture significantly increases COVID-19 vaccine and test demand. The increase in take-up is of 5 to 6 percentage points for the vaccine, where the baseline take-up is close to 70%, while it is of 11 to 12 percentage points for testing, where the baseline take-up of a free test is 50%.

Many scientists argue this pandemic will not be the last one within the next decades (Mahajan, 2020). Already the mutations in 2021 can be seen as a new Coronavirus pandemic compared to the original one from 2020 (Rourke, March 2021). It is thus of major importance that businesses and societies understand how to motivate people to take up preventative measures. Vaccination and testing are likely to play fundamental roles also 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 specifically low in 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 uptake 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 and examine which groups are predicted to exhibit stronger reactions to defaults. We

find that defaults more strongly affect vaccine uptake 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 inclination 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 inclination 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 decided 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. Participants were 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.

Taking the vaccine either involved no compensation (N=615) or 8 different compensation levels (from $0 to $500, N=929). Taking the test involved 8 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, participants could additionally receive an Amazon gift card and/or a PCR test. 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. The instructions presented in the study are shown in Online Appendix B, in addition to the pre-registrations.

After preregistration (on aspredicted.org, #55138 and #57775), data collection took place between December 2020 and February 2021 on Prolific Academic (Palan and Schitter, 2017). 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 6-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=0.4927).

In addition to vaccination and testing decisions, we also elicited demand for antibody tests under defaults and active choice (N=591) and air quality monitors (N=597). In Online Appendix C, we describe the results for these decisions and compare decisions regarding antibody testing in the Active Choice condition to a quota-representative sample of the US (N=1,984). We find that the results prove robust across samples (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. Previous research shows that Blacks are less interested in taking the COVID-19 vaccine (Funk and Tyson, 2020). As shown below, we document that this difference can be explained by their distrust of the vaccine. We targeted and achieved an overall share of Black participants of 34 to 36%.

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, Meier, Schneider, & Wengström, 2021). 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 use 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 take-up, 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 uptake in participants. 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. If taking the vaccine is seen as a morally relevant act as it also protects others, commodification (Sandel, 2013; Satz, 2012) could reduce uptake. For these two reasons, we extended our hypothesis (relative to the pre-registration) to acknowledge that vaccine uptake may be lower for small compensations compared to no compensations.

Hypothesis 1 (Vaccines and Compensations):

1a. Vaccine uptake increases in compensations.

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

It has been shown that pre-scheduled appointments increase the uptake of influenza vaccines (Chapman, Li, Colby, & Yoon, 2010; Lehmann, Chapman, Franssen, Kok, & Ruiter, 2016).[1] Yet a change in default may mostly affect people who are rather indifferent between taking a vaccine or not. With COVID-19 vaccines, people may have stronger preferences. COVID-19 appears to be a more dangerous disease than the regular influenza (Piroth et al., 2021; Xie, Bowe, Maddukuri, & Al-Aly, 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, it is not clear that an opt-out default in the form of a pre-scheduled appointment has a positive impact on COVID-19 vaccination.

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., 2019). 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.

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

Tests for COVID-19 can help detecting infections even if people are asymptomatic. So far, 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 risk in health providing a saliva sample, if people stick to the instructions. Hence, we expect that test demand increases if people must pay less for the test. We hypothesize it further increases with compensation.

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 Choice Architecture):

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 choice architecture on vaccine intentions and test demand, we also explore heterogeneity in levels of take-up as well as in the effect of these treatments. We expected Black participants to exhibit lower take-up of 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 demand for vaccines and testing 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).[2] Thus, small compensations can erode an intrinsic motivation to vaccinate or commodify the vaccine (Gneezy & Rustichini, 2000; Loewenstein & Cryder, 2020; Satz, 2012; Sandel, 2013; Falk & Szech, 2013; Ziegler et al.; Marx, 1904).

Result 1 (Vaccines and Compensations):

[2] This effect is robust to focusing only on the second wave of data collection.

1a. Vaccine uptake increases for compensations equal to or above $100.

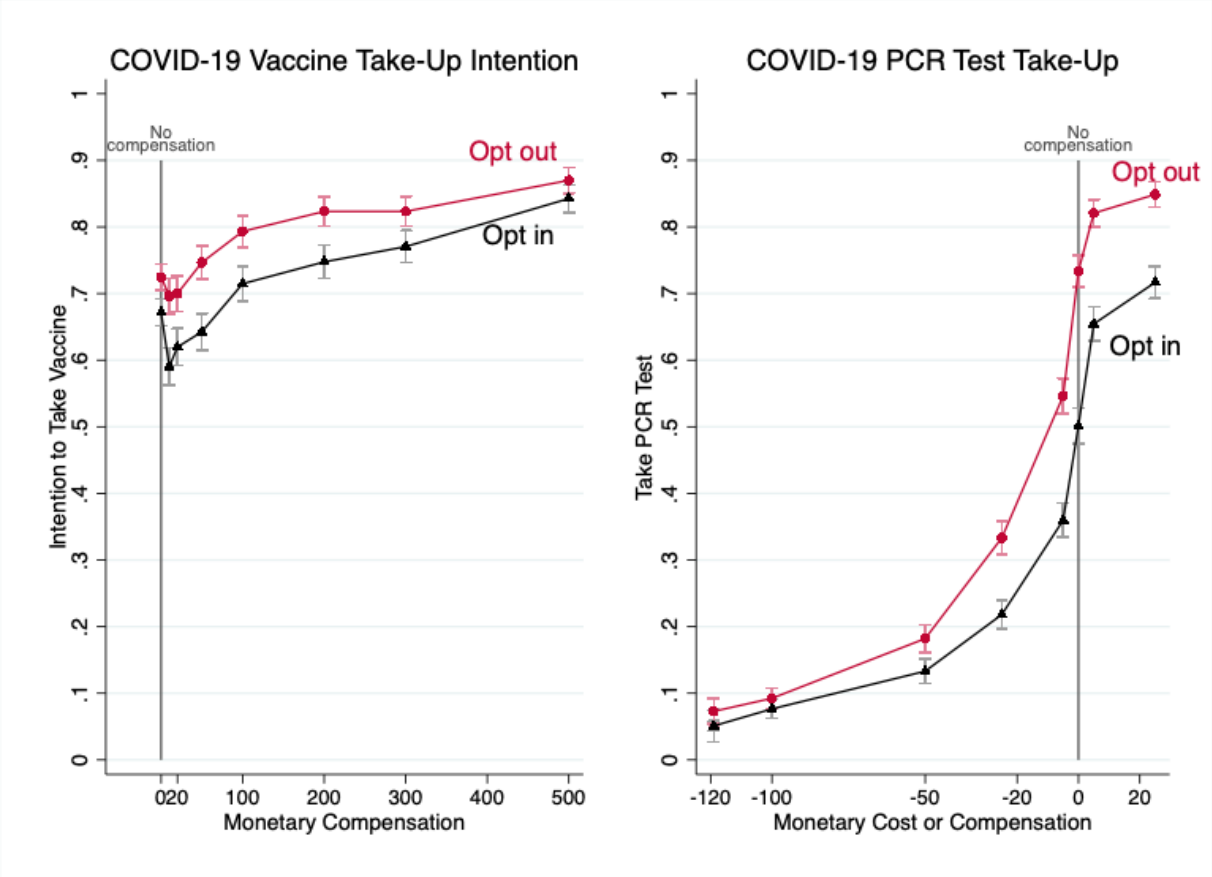
1b. For the smallest compensation of $20, uptake is lower than without compensation.

Larger incentives, of more than $100, significantly increase willingness 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 and test demand. We use linear probability models to estimate the effects on take-up 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. (2013), 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 (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 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.

As shown in column (1) of Table 1, compensations of more than $50 increase uptake 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 uptake grows above 80% and combined with an Opt-Out default it gets closer to 90%. This may make a big different for avoiding the spread and outbreaks 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.)

Figure 1. COVID-19 Vaccination Intention and PCR Test Uptake, by Default and Compensation



Notes: Percentage of participants who report an intention to take-up 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.

The analysis in Table 1 also shows that small compensations may not yield a positive effect, and even a negative one, on vaccine take-up. Overall, the results suggest that, if employers want to

increase vaccine intentions, incentives need to be large enough. Four qualifications to these results are in order. First, each company may face a different atmosphere and composition of employees. Second, we only study vaccination 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 uptake 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 "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 uptake, 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 is that PCR tests do not come with any larger health risk for participants. Testing is also more well-known to individuals since they became available significantly sooner during the pandemic.

Result 3 (Test Demand and Compensations):

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

3b. Test demand increases further with positive compensations.

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 uptake. 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 ($p>0.10$ in all cases).

Result 4 (Test Demand and Choice Architecture):

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.

Table 1. Vaccine and PCR Test Demand

	(1)	(2)	(3)	(4)	(5)	(6)
	COVID-19 Vaccine Uptake			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)
Controls for gender, ethnicity and income	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. (2013), 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

4.3. Heterogeneity in Vaccine and Testing Uptake

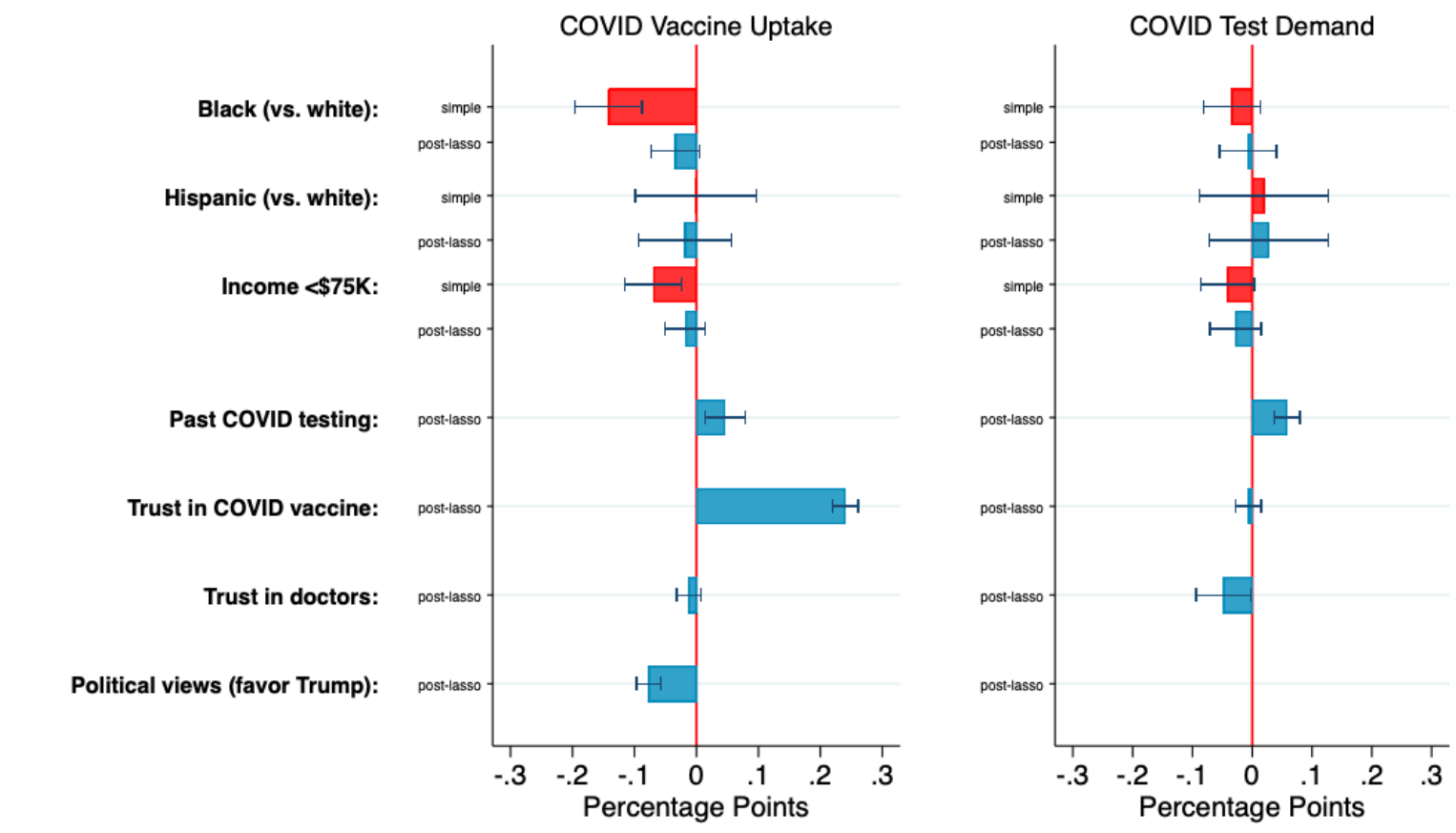
Existing studies have indicated that Blacks exhibit unequal access to immunization and have lower intentions to take the COVID-19 vaccine (Funk and Tyson, 2020). In this section, we examine whether there is a significant difference in vaccine and test uptake for Black participants, and also explore heterogeneity in uptake 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 and test uptake by age and gender. If the only controls included are demographic characteristics, vaccine, but not test, uptake is 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.

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 (but not test) uptake. Its inclusion reduces (and makes insignificant) the relationship between Black ethnicity and vaccine

uptake, as Blacks trust the vaccine significantly less than white (0.44 standard deviations, p-value<0.001).

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



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 (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.

In addition, Figure 2 shows that political views are important for vaccine uptake (though not selected or "relevant" for test demand). Individuals who favor Trump (and are less supportive of Dr. Fauci) are significantly less likely to intent 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 Uptake

An important question when designing interventions to increase uptake of testing and vaccine is whether they equally affect all groups in the population, or rather advantaged (or disadvantaged) ones. As pre-registered, we examined whether the effects defaults or compensations on vaccine and test uptake 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).[3]

Yet, the previous results raise two open questions regarding the effects of interventions on vaccine uptake. 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?

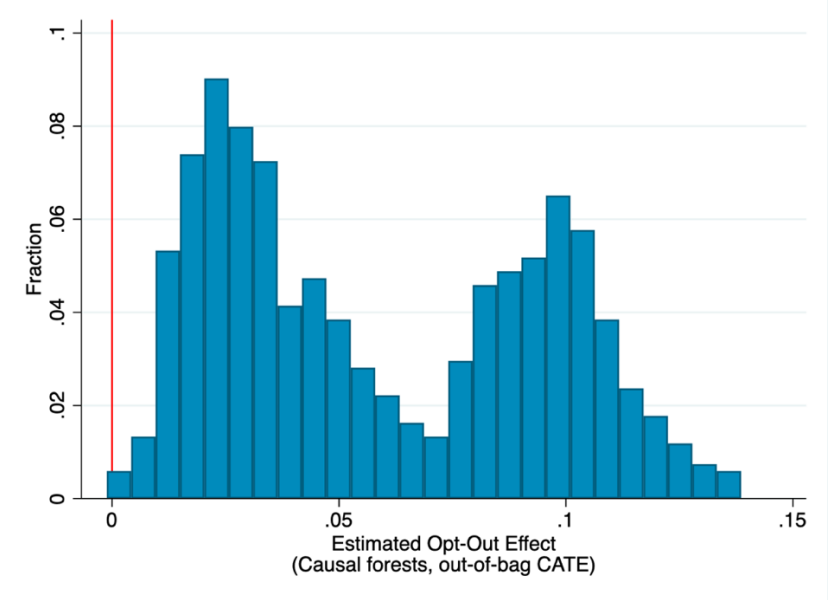
[3] When we examine heterogeneous treatment effects for COVID-19 testing, we observe that, when interaction effects are included for all treatments and compensation levels, Black participants demand testing significantly less often in the Opt-in condition without compensation (13 p.p.) relative to white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

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 the extent of heterogeneity in the response to the Opt-out treatment, for the case in which there is no compensation for taking the vaccine. We then explore whether individuals who are predicted to display stronger (above-median) differ from those who are predicted to display weaker (below-median) effects in their demographic characteristics.

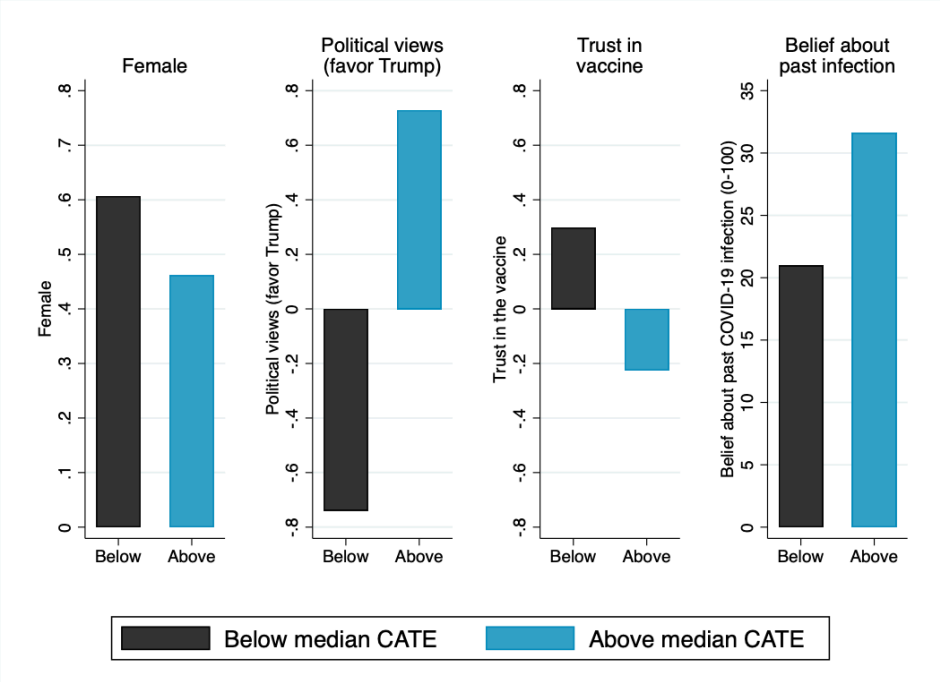
Following the methodology in Athey and Wager (2019) (and using the "grf" R package), we first split the dataset between the training sample, on which the forests are estimated, and the test sample, for prediction. The training sample is 66.7% of the dataset. This sample is then further separated into 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.

Figure 3. Heterogeneous Treatment Effects of Opt-out Treatment

Panel A. Distribution of CATE



Panel B. Above and Below Median CATE groups



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

To assess the extent of heterogeneity in the effect of the Opt-out treatment, we first present a histogram of the predicted treatment effects of the Opt-out treatment. The distribution of the out-of-bag conditional average treatment effect (CATE) for the Opt-out treatment is presented in Panel A of Figure 3. We observe the distribution 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.

To further assess the strength of the average treatment effects within subgroups, we divide the sample in two, 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 0.01 (s.e.=0.028), 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.

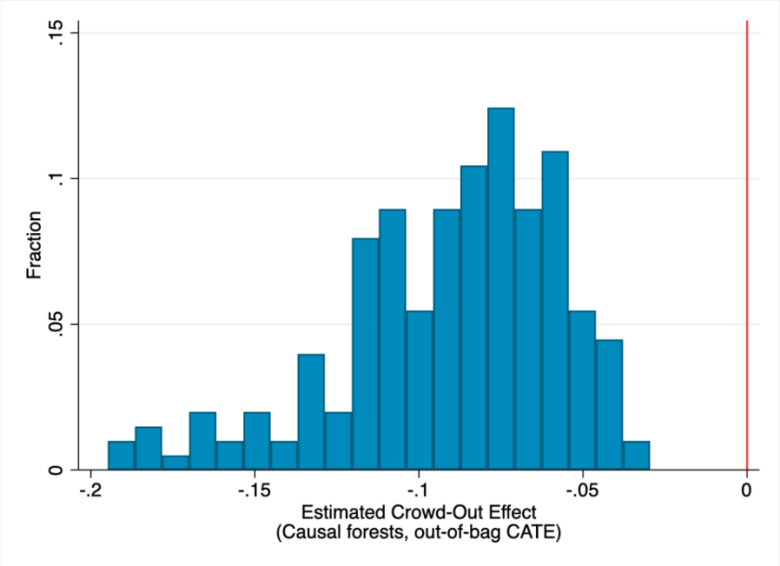
We next explore whether those who have above-median estimated conditional average treatment effects also have different covariate levels than those who have below-median estimated CATE. We observe strong heterogeneity according to gender, political views, belief about past infection and trust in the vaccine (detailed results for all covariates are shown in Online Appendix A). As shown in Panel B of 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 take-up, 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 are who believe they were infected in the past, vaccine demand was not significantly higher, but it could be more uncertain. These individuals may have doubted whether they "should" take the vaccine, since they may have antibodies.

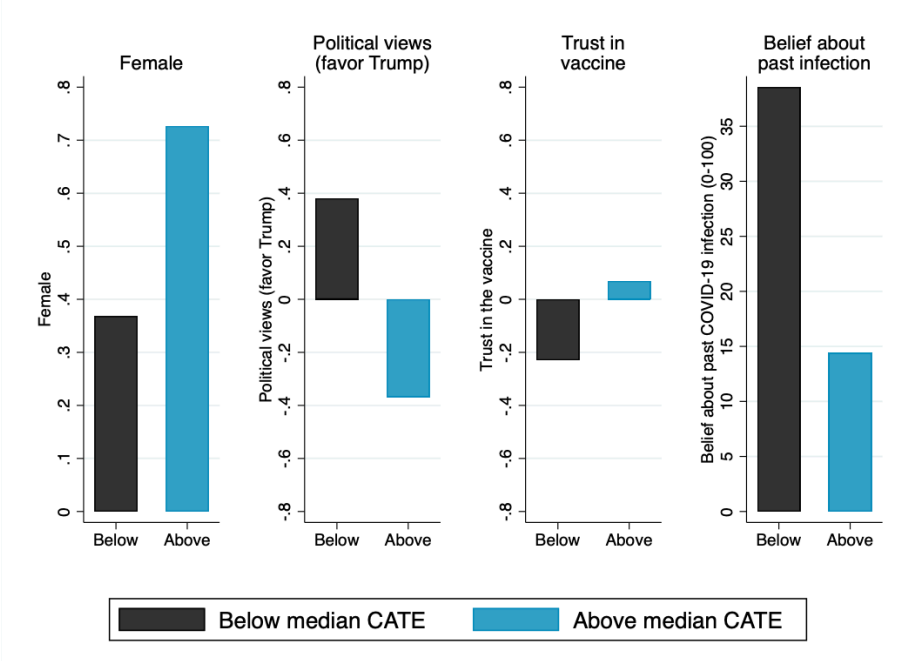
Next, we follow the same approach, but this time focusing on better understanding the potentially negative effects of small compensations on vaccine demand. For this reason, we focus on the effect of no compensation, compared to offering a $10 compensation for taking the vaccine in the Opt-in treatment, clustering observations at the individual level. The distribution of the out-of-bag conditional average treatment effect (CATE) for the small monetary compensation is presented in Panel A of Figure 4. The effects of the small compensation are generally negative, and between a 5 and a 20 percentage-point in take-up of the vaccine, and in this case the distribution has one mode. The estimated AIPW average treatment effect is -0.10 (s.e.=0.028), for those with below-median estimated CATE, while it is -0.07 (s.e.=0.035) 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.

Figure 4. Heterogeneous Treatment Effects of Small Monetary Incentives

Panel A. Distribution of CATE



Panel B. Above and Below Median CATE groups



Notes: Panel A shows the distribution of the estimated out-of-bag CATE for the $10 compensation, relative to no compensation, in the Opt-in treatment. Panel B 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 may have had a COVID-19 infection in the past. This heterogeneity suggests that, those who are less 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 choice architecture 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 choice architecture 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 also

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 also the beneficial potential of market design in this pandemic has been pointed out (Cramton et al., 2020). In our data, larger compensations prove successful at increasing vaccine uptake. 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 vaccine take-up, 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 they could free-ride on herd immunity once many

enough others are vaccinated. But we also see some costly aversion to the test (in line with Thunstrom et al., 2020), and small incentives around zero have pronounced impact on test demand.[4] This is qualitatively comparable to the demand function for moral information in Serra-Garcia and Szech (2021).[5] Indeed, taking a PCR test without having symptoms may be a mostly social and moral activity, in order to prevent spreading the virus to other people. Some people may not want to reduce social contacts should they test positive. Small monetary costs or incentives may transport a normative signal as well, thereby affecting demand around prices of zero a lot.

A limitation of our experiment is that, for vaccination, intentions were measured. For testing, we could measure real decisions. 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.

[4] 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, Schweizer, Wangenheim, Szech (2020) on test and information avoidance.

[5] 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

Choice Architecture and Incentives Increase COVID-19 Vaccine Intentions and Test Demand

Marta Serra-Garcia and Nora Szech

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 Uptake (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 Uptake (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 uptake, 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 variable across the three treatments.

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 Uptake	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 would take the COVID19 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 variable across the two waves treatments, from a 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 Uptake			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 Uptake Decisions

	(1)	(2)
	Vaccine Uptake	
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 decision 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

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

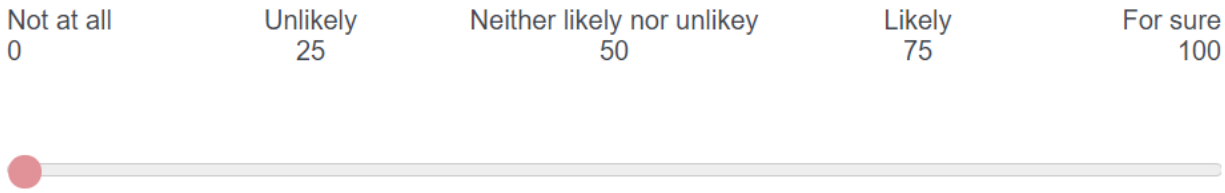
[Active treatment]

- 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 antibodies?

- 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)

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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 exactly 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)

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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 (*authors 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 *authors 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 1,930 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 $14.44 (SD=10.71) 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=0.2108). 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	14.44	10.71
75% chance of immunity for 3 months	15.87	11.02
95% chance of immunity for 3 months	16.36	11.26
99% chance of immunity for 3 months	17.14	10.91
50% chance of immunity for 6 months	18.39	10.85
75% chance of immunity for 6 months	19.51	10.92
95% chance of immunity for 6 months	18.64	11.02
99% chance of immunity for 6 months	20.06	10.87
50% chance of immunity for 12 months	21.54	10.83
75% chance of immunity for 12 months	19.67	11.03
95% chance of immunity for 12 months	21.29	10.88
99% chance of immunity for 12 months	22.02	10.88

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 Representative Sample	Active choice, opt-in, opt-out 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 Uptake	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 Uptake	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 variable across the three treatments.