ONLINE APPENDIX FOR

“Incentives and Defaults Can Increase

COVID-19 Vaccine Intentions and Test Demand”

By 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 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.

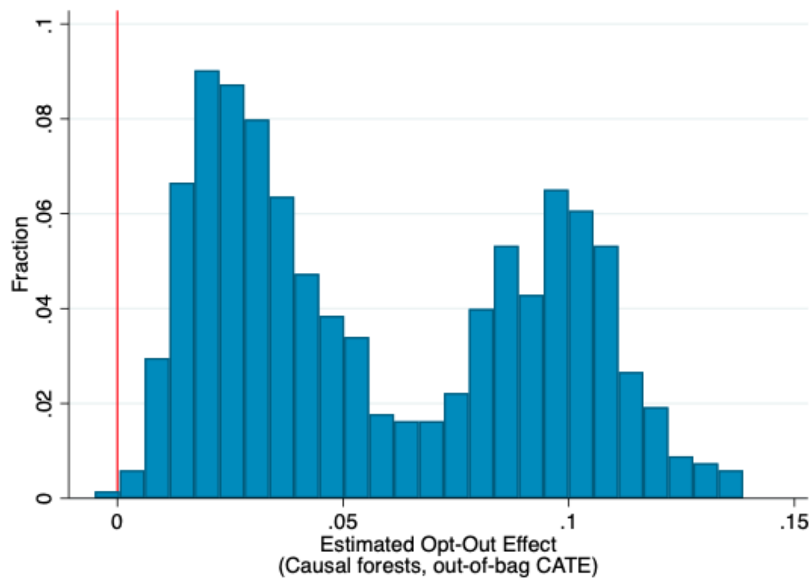
```
cf = causal_forest(as.matrix(df_train[covariate_names]),
            Y = df_train$Y,
            W = df_train$W,
            Y.hat = Y.hat , W.hat = W.hat,
            seed=1234,
            num.trees = 2500,
            min.node.size = 9,
            sample.fraction=0.50,
            alpha = 0.40,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

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 politicial 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

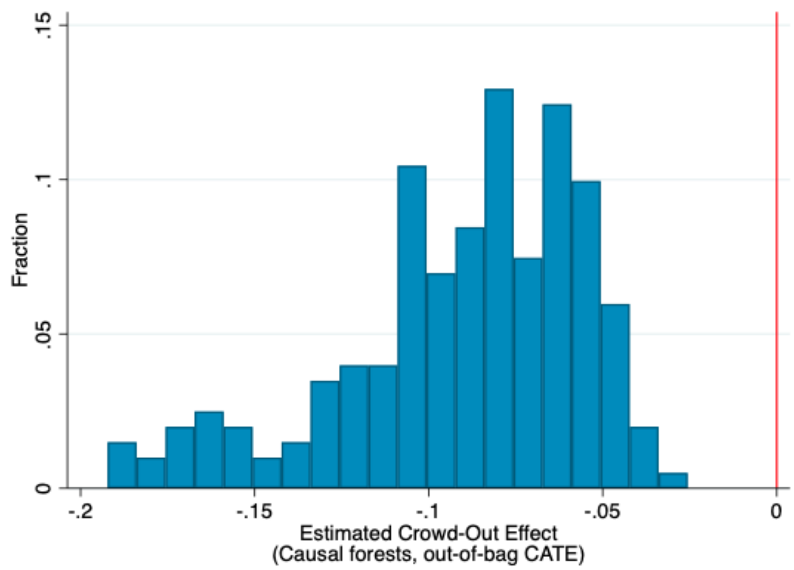
We follow the same approach to estimate heterogeneity in treatment effects for offering small compensations, relative to no compensations, to individuals who intend to take the vaccine, focusing on the Opt-in treatment. The code includes a cluster indicator for each individual.

```
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

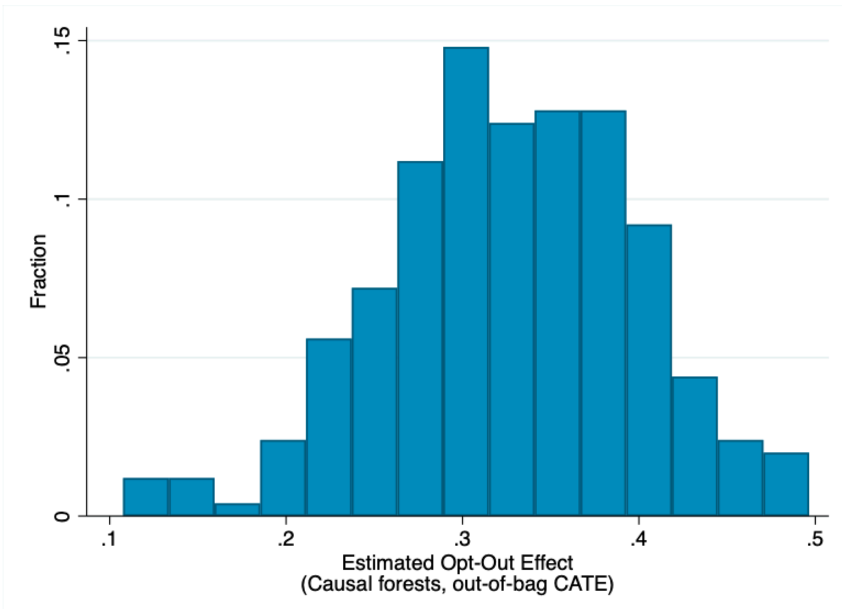
We follow the same approach to estimate heterogeneity in the treatment effect of the Opt-out treatment on COVID-19 PCR test demand. This analysis should be considered suggestive as the number of observations is limited (N=375). The main code command is as follows:

```
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

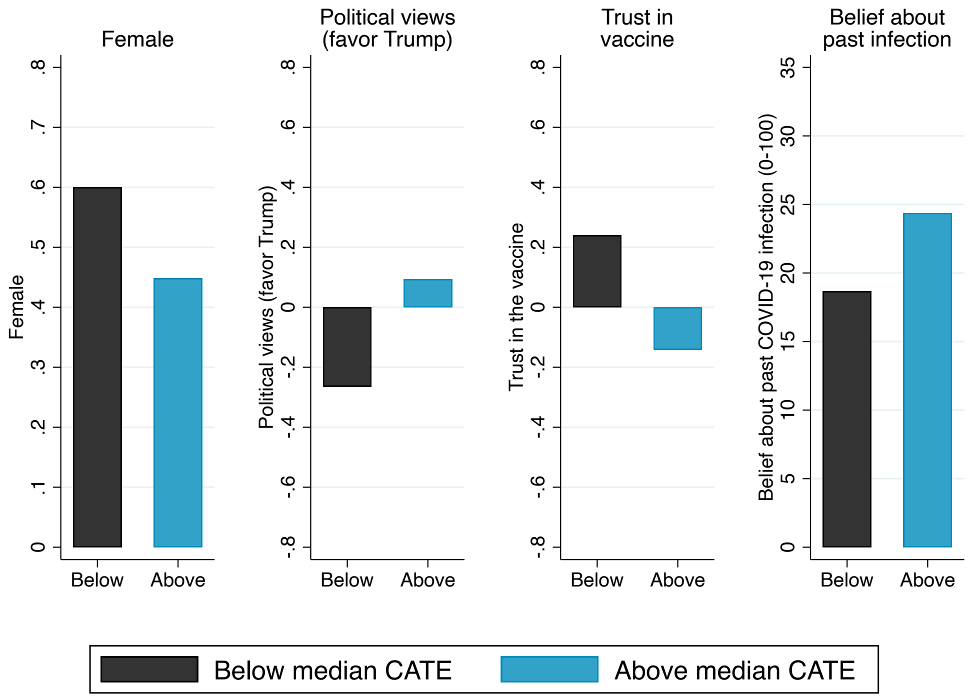


Notes: Figure A.3. shows the distribution of the estimated out-of-bag CATE for the Opt-out treatment, relative to Opt-in, in the absence of compensation for COVID-19 Test Decisions.

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) Above-median CATE	(2) Below-median CATE	(3) *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.

Not at all	Unlikely	Neither likely nor unlikey	Likely	For sure
0	25	50	75	100

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.