Data Task for the Pre-Doctoral Research Fellowship

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Part 1. Comparison of treatments

Please refer to Table 1 for comparing the effects of the two treatments using probit models. The 500 individuals who took part in the baseline survey but not the final one, as well as 1009 people vaccinated at the beginning of the survey, are excluded from the analysis. If attrition from the survey is non-random and the covariates correlated with attrition affect vaccine take-up, then a simple regression comparing the groups is biased. However, controlling for the observables that explain differences in attrition[1] can help eliminate the bias.[2]

In specification I, we detect a significant positive effect of the "emotions" treatment and an insignificant positive effect of the "reason" treatment. These findings are corroborated by specification II: the detected effect of "emotions" is even higher while the effect of "reason" is closer to zero. Please note that since attrition is non-random, the control group and the treatment groups might differ in terms of covariates. The coefficients at controls, therefore, capture a mix of (1) differential vaccine take-up even in absence of treatment; (2) group differences due to attrition; (3) effect heterogeneity.

[1] Ideally, one should verify if the observable variables predict attrition well enough.

[2] Alternatively, one could have modelled the missing values of vaccination take-up using observables.

Table 1: Effects on full sample

	vaccinated_end I	vaccinated_end II
intercept	-1.1336***	-1.0429**
	(0.0451)	(0.4699)
treatment_reason	0.0643	0.0019
	(0.0642)	(0.0671)
treatment_emotion	0.2544***	0.3658***
	(0.0624)	(0.0646)
covid_cases_start		0.2236***
		(0.0535)
female		0.1634***
		(0.0557)
educ_middle_sch		0.1677
		(0.1293)
educ_high_sch		0.1364
		(0.1230)
educ_some_college		0.0147
		(0.1517)
educ_college		0.0755
		(0.1380)
black		0.1641
		(0.1412)
hispanic		0.2515*
		(0.1463)
native_am		0.1988
		(0.1791)
white		0.2244
		(0.1429)
age		-0.0659***
		(0.0169)
age2		0.0005***
		(0.0002)
employed		0.0291
		(0.0751)
unemployed		0.3352
		(0.2090)
log_income		0.1015***
		(0.0250)

Table 2: Emotions treatment vs control group

	vaccinated_end
intercept	-0.7624
	(0.6385)
treatment_emotion	-3.6714**
	(1.4628)
covid_cases_start	0.2707***
	(0.0895)
female	0.1689*
	(0.0958)
age	-0.0110
	(0.0258)
age2	0.0001
	(0.0003)
log_income	-0.0365
	(0.0297)
treatment_x_covid_cases_start	0.0991
	(0.1401)
treatment_x_female	0.1389
	(0.1486)
treatment_x_age	-0.0678
	(0.0704)
treatment_x_age2	-0.0006
	(0.0009)
treatment_x_log_income	0.6688***
	(0.0676)

Part 2. Emotions treatment

Let us focus on the successful "emotions" treatment and take a closer look at effect heterogeneity. In Table 2, you can find the comparison of vaccine take-up rates between the control group and the "emotions" treatment, without another treatment group. The negative coefficient at the treatment dummy suggests that the treatment effect is negative for a man of age 0, who had no COVID-19 cases before the beginning of the experiment and has zero income.

A person who had experienced COVID before the baseline survey is significantly more likely to get vaccinated, which is unaffected by the treatment. The same applies to women, though the differences in control group are insignificant on 5 % level. Age seems unrelated to the treatment effect.

Most interestingly, income is unrelated to vaccine take-up in the control group, but has a significant and economically large effect on it in the treatment group. This suggests that the treatment effect is highly heterogeneous: while people of low income are diverted from vaccination when it is advertised using emotions, higher-income individuals respond to the advertisement by vaccinating more often.