Differential effects of advertisement strategies on vaccine uptake: data analysis

Aspen Han

Following the simulation of the field experiment, I turn to analyze its data. Foremost, I check whether attrition has eroded the internal validity of the study, before proceeding to check for average and differential effects of Facebook ad campaigns on Covid-19 vaccine uptake.

Covariate balance post-attrition

Using covariates[1] as a proxy for potential outcomes, I first check whether they are balanced between treatment groups in the endline sample, as presented in Table 1. This checks whether we can recover causal ATE estimates among the respondents, and indeed the table shows no significant differences in any of the covariates between treatment groups. Note if there were significant differences found at the individual covariate level, one would still have to correct for multiple hypotheses testing, or just a joint test of covariates to ascertain actual differences.

I also check for covariate balance between the baseline and endline sample, which helps to inform whether we can recover ATE for the whole sample. Table 2 shows that there is a sole significant

[1] States have been omitted from this and subsequent analysis and it introduces too much dimensionality and restrictions on degrees of freedom.

difference in initial willingness to take the updated 2024-2025 Covid-19 vaccine (p-value = 0.043) although this will likely not hold after correcting for multiple hypotheses testing or using a joint test.

Hence, it is likely that causal treatment effects can be consistently estimated, though this was somewhat by construction since I simulated the attrition to be random. In reality, treatment receipt may affect attrition if for some reason people exposed to the ad campaigns were more or less likely to return for the endline survey (e.g. they are more likely as they felt more engaged by the increased ad exposure) which would reintroduce selection bias effects. Running the above tests are important to establish continued internal validity of longitudinal studies like this which are susceptible to attrition.

Average treatment effects from ad exposure

I regress the new willingness to take the updated vaccine on a treatment dummy for whether the subject was exposed to an ad campaign at all (and other covariates), measuring an intention to treat (ITT) effect. I also use treatment as an instrument for ad awareness, to measure the local average treatment effect (LATE) of the ad campaign on vaccine uptake among those who were actually engaged with it.

Table 4 shows the results. Both ITT and LATE (coefficients on `ad_exposed` and `ad_aware` respectively) are significant and quite similar, with LATE being stronger as expected since people who engage more with the ads are likely to be more influenced by them. Controlling for covariates does not affect the ITT estimate much though it reduces the standard error considerably. Overall, ad campaigns are associated with around a 0.4 increase in willingness to take the updated vaccine, which corresponds

Table 1: Covariate balance across treatment groups in the endline sample

Characteristic	**pathos** N = 1,473[1]	**logos** N = 1,524[1]	**control** N = 1,503[1]	**p-value**[2]
gender				0.6
female	760 (52%)	761 (50%)	775 (52%)	
male	713 (48%)	763 (50%)	728 (48%)	
race				0.7
asian	87 (5.9%)	91 (6.0%)	92 (6.1%)	
black	196 (13%)	212 (14%)	235 (16%)	
hispanic	305 (21%)	314 (21%)	284 (19%)	
other	25 (1.7%)	30 (2.0%)	32 (2.1%)	
white	860 (58%)	877 (58%)	860 (57%)	
age_group				0.7
<30	275 (19%)	299 (20%)	316 (21%)	
30-44	347 (24%)	367 (24%)	353 (23%)	
45-64	491 (33%)	495 (32%)	464 (31%)	
65+	360 (24%)	363 (24%)	370 (25%)	
edu				>0.9
below high school	157 (11%)	175 (11%)	162 (11%)	
high school	435 (30%)	442 (29%)	449 (30%)	
some college	357 (24%)	384 (25%)	364 (24%)	
bachelor's or above	524 (36%)	523 (34%)	528 (35%)	
income_bracket				0.9
<25k	107 (7.3%)	114 (7.5%)	120 (8.0%)	
25k-<50k	470 (32%)	476 (31%)	480 (32%)	
50k-<75k	362 (25%)	394 (26%)	358 (24%)	
75k-<120k	355 (24%)	353 (23%)	344 (23%)	
120k-<200k	166 (11%)	169 (11%)	179 (12%)	
>=200k	13 (0.9%)	18 (1.2%)	22 (1.5%)	
fb_usage				0.4
1	393 (27%)	412 (27%)	412 (27%)	
2	99 (6.7%)	87 (5.7%)	86 (5.7%)	
3	138 (9.4%)	183 (12%)	162 (11%)	
4	260 (18%)	260 (17%)	241 (16%)	
5	583 (40%)	582 (38%)	602 (40%)	
vax_percpt				0.3
1	515 (35%)	480 (31%)	504 (34%)	
2	253 (17%)	266 (17%)	260 (17%)	
3	205 (14%)	230 (15%)	197 (13%)	
4	194 (13%)	217 (14%)	187 (12%)	
5	306 (21%)	331 (22%)	355 (24%)	

[1] n (%)

[2] Pearson's Chi-squared test

Table 2: Covariate balance across baseline and endline

Characteristic	**0** N = 500[1]	**1** N = 4,500[1]	**p-value**[2]
gender			0.3
female	242 (48%)	2,296 (51%)	
male	258 (52%)	2,204 (49%)	
race			0.5
asian	30 (6.0%)	270 (6.0%)	
black	67 (13%)	643 (14%)	
hispanic	88 (18%)	903 (20%)	
other	7 (1.4%)	87 (1.9%)	
white	308 (62%)	2,597 (58%)	
age_group			0.8
<30	90 (18%)	890 (20%)	
30-44	120 (24%)	1,067 (24%)	
45-64	170 (34%)	1,450 (32%)	
65+	120 (24%)	1,093 (24%)	
edu			0.4
below high school	63 (13%)	494 (11%)	
high school	152 (30%)	1,326 (29%)	
some college	127 (25%)	1,105 (25%)	
bachelor's or above	158 (32%)	1,575 (35%)	
income_bracket			0.8
<25k	31 (6.2%)	341 (7.6%)	
25k-<50k	165 (33%)	1,426 (32%)	
50k-<75k	131 (26%)	1,114 (25%)	
75k-<120k	117 (23%)	1,052 (23%)	
120k-<200k	50 (10%)	514 (11%)	
>=200k	6 (1.2%)	53 (1.2%)	
fb_usage			0.2
1	127 (25%)	1,217 (27%)	
2	23 (4.6%)	272 (6.0%)	
3	67 (13%)	483 (11%)	
4	75 (15%)	761 (17%)	
5	208 (42%)	1,767 (39%)	
vax_percpt			**0.043**
1	185 (37%)	1,499 (33%)	
2	104 (21%)	779 (17%)	
3	62 (12%)	632 (14%)	
4	58 (12%)	598 (13%)	
5	91 (18%)	992 (22%)	

[1]n (%)

[2]Pearson's Chi-squared test

to a jump up of almost half a category, which is quite substantial given the campaign only lasted one month, though it is difficult to say how effects would scale with time.

In terms of covariate effects, one notable finding is that initial vaccine perceptions show a significantly high and positive correlation with later vaccine perceptions, suggesting people who already viewed the vaccines more favourably to begin are more amenable to them in the future. Given its huge standalone effect, I considered its interplay with ad campaign exposure effects, which found a significantly negative interaction effect (coefficient of -0.22, p-value < 0.01). This means ad campaigns are not only less effective on those who already were willing to get the updated effect but may reverse their perceptions, perhaps due to annoyance or crowding out effects, so there are perhaps unintended consequences on top of limited scope of gains we have to bear in mind when deciding who to target such ads to.

Differential effects of ad campaign strategies

Finally, I am interested in how logos and pathos used in ads differ in their efficacy of increasing willingness for vaccine uptake. This time, I regress the same outcome variable but on the treatment groups, with pathos as the baseline (omitted regressor). Table 4 shows that ad campaigns appealing to reason are more effective at encouraging vaccine uptake than those appealing to emotions, being a third more likely to induce people to move up a category in their likelihood of getting an updated vaccine shot. It would be interesting to understand what features of the context can contribute to these differences.

Table 3: Average effects of Facebook ad campaigns on vaccine uptake

	New willingness for vaccine uptake		
	ITT: No controls	ITT: With controls	LATE
(Intercept)	2.75^{***}	0.34^{***}	0.41^{***}
	(0.04)	(0.04)	(0.05)
ad_exposed	0.37^{***}	0.40^{***}	
	(0.05)	(0.01)	
gendermale		0.04^{***}	0.03^{**}
		(0.01)	(0.01)
raceblack		0.02	0.01
		(0.03)	(0.03)
racehispanic		−0.01	−0.00
		(0.03)	(0.03)
raceother		−0.05	−0.05
		(0.05)	(0.06)
racewhite		−0.01	−0.01
		(0.03)	(0.03)
age_group30-44		−0.03	−0.02
		(0.02)	(0.02)
age_group45-64		−0.01	−0.00
		(0.02)	(0.02)
age_group65+		-0.05^{***}	-0.05^{**}
		(0.02)	(0.02)
eduhigh school		−0.03	−0.03
		(0.03)	(0.03)
edusome college		0.00	0.01
		(0.03)	(0.03)
edubachelor’s or above		−0.04	−0.03
		(0.03)	(0.04)
income_bracket25k-<50k		0.03	0.04
		(0.03)	(0.03)
income_bracket50k-<75k		0.04	0.05
		(0.03)	(0.03)
income_bracket75k-<120k		0.03	0.04
		(0.04)	(0.04)
income_bracket120k-<200k		0.04	0.06
		(0.04)	(0.05)
income_bracket>=200k		0.09	0.09
		(0.07)	(0.08)
fb_usage		0.01^{***}	-0.01^{**}
		(0.00)	(0.00)
vax_percpt		0.86^{***}	0.86^{***}
		(0.00)	(0.00)
ad_aware			0.43^{***}
			(0.02)
Adj. R^2	0.02	0.90	0.90
Num. obs.	4500	4500	4500

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 4: Differential effects of Facebook ad campaigns on vaccine uptake

	New willingness for vaccine uptake	
	No controls	With controls
(Intercept)	2.90^{***}	0.56^{***}
	(0.04)	(0.04)
treatmentlogos	0.45^{***}	0.36^{***}
	(0.05)	(0.02)
treatmentcontrol	-0.15^{***}	-0.21^{***}
	(0.06)	(0.01)
gendermale		0.04^{***}
		(0.01)
raceblack		0.02
		(0.03)
racehispanic		−0.01
		(0.03)
raceother		−0.06
		(0.05)
racewhite		−0.01
		(0.03)
age_group30-44		−0.02
		(0.02)
age_group45-64		−0.01
		(0.02)
age_group65+		-0.05^{**}
		(0.02)
eduhigh school		−0.02
		(0.03)
edusome college		0.01
		(0.03)
edubachelor's or above		−0.03
		(0.03)
income_bracket25k-<50k		0.03
		(0.03)
income_bracket50k-<75k		0.03
		(0.03)
income_bracket75k-<120k		0.03
		(0.04)
income_bracket120k-<200k		0.03
		(0.04)
income_bracket>=200k		0.06
		(0.07)
fb_usage		0.01^{***}
		(0.00)
vax_percpt		0.86^{***}
		(0.00)
Adj. R^2	0.03	0.91
Num. obs.	4500	4500

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 5