Part IIA Paper 3 Project

Anonymous

May 17, 2022

Q1. Vaccination take-up rates: Inter-State differences in the USA in 2021.

At the end of 2021 the share of the population fully vaccinated against Covid-19 differed widely across US States.

a) Identify and evaluate the main economic and social factors giving rise to this outcome.

b) On the basis of your answer to a), suggest how high vaccination rates might be achieved across the entire United States.

2182 words

1 Introduction

Hello world hi hi hello d

By the end of 2021, only 2% of people wanted a vaccine and had not yet got it, from survey

2 Data and Methods

2.1 Data

Regressions were generally done on the county level. Data on vaccination rates across time by county (and by state) were all sourced from the CDC (CITE). A dataset of time-invariant characteristics of each county was also compiled from many sources for

3075 counties in the United States; remaining counties were excluded due to some or all information not being available for them. This includes all US territories (such as Puerto Rico), which do not have presidential voting records, and all counties in Alaska and Hawaii. Utah's counties were also excluded due to spotty COVID-19 case data. Outside of these states, the following counties also had missing records: Bedford and Clifton Forge City, Dukes, Nantucket, Barnstable, and Ogala Lakota County, and Yellowstone National Park (which has no population).

2020 election results by county were obtained from the MIT Election Data and Science Lab's Election Returns Dataverse (CITE). Religious breakdowns by county were obtained from the Public Religion Research Institute (PRRI) 2020 census of American Religion (CITE). Education attainment by county, averaged over 2015-2019, was obtained from the US Census Bureau ('the Census'), via the 2015-2019 American Community Survey (CITE). Poverty rates by county in 2019 were obtained from the Census' Small Area Income and Poverty Estimates, which also contained the 2013 Rural-Urban Continuum Code assigned to each county, which classifies counties based on their level of urbanization and proximity to metropolitan areas (CITE explanation). Racial breakdowns by county were obtained from the 2020 Decennial Redestricting Dataset, maintained by the Census (CITE). Age breakdowns by county were obtained from the County Characteristics Resident Population Estimates maintained by the Census (CITE). Median family incomes and costs of living for a family of four were obtained from the Economic Policy Institute's (EPI) Family Budget Calculatior (CITE). COVID-19 Cases recorded in each county, as of 1 December 2020, were obtained from the CSSE COVID-19 Data Repository maintained by John Hopkins (CITE). Finally, data mapping each county to every county it borders was obtained (the 'county adjacency dataset') from a dataset maintained by the National Bureau of Economic Research (CITE), originating from a dataset maintained by the Census.

All datasets tagged each county with their Federal Information Processing Standard Publication (FIPS) codes, which was used to merge them together.

2.2 Methods

As mentioned, vaccine access seems to not have been a substantial problem by the end of 2021. Instead, vaccination status reflects the willingness of individuals to get vaccinated.

The decision on vaccination can reasonably be broken down into its costs and benefits, and beliefs that agents have about them. We would expect, hence that in areas of lower population density, or where COVID would generally spread less quickly, the benefit of vaccination would be lower. Furthermore, as COVID-19 has a much higher fatality rate among older persons (CITE), they would find a greater benefit to vaccination, and we would expect more vaccination, in counties with more elderly people. As beliefs on vaccination's benefits and supposed harms seem to be affected by, or at least correlated with, religious status, race, and political identity, we also expect these variables.

We begin hence by first running the following cross-sectional regression on the national dataset of 3075 counties:

$$\begin{aligned}\text{vaccuptake}_i =&\beta_0 + \beta_1\text{repvotes}_i + \beta_2\text{whiteevangelical}_i + \beta_3\text{catholic}_i \\ &+ \beta_4\text{black}_i + \beta_5\text{poverty}_i + \beta_6 ln(\text{medincome}_i) + \beta_7 ln(\text{col}_i) \\ &+ \beta_8\text{pop60to79}_i + \beta_9\text{above80}_i + \beta_{10}\text{fullcollege}_i + \beta_{11}\text{casespc}_i \\ &+ \boldsymbol{\delta}\cdot\textbf{rural}_i + \boldsymbol{\gamma}\cdot\textbf{state}_i + u_i\end{aligned} \tag{1}$$

Where vaccuptake_i is a measure of vaccine uptake for a county i. Definitions for each covariate are listed in Table 1. The model was estimated for a cross-section of vaccine uptake by county as of 31 December 2021, and also for vaccine uptake as of 1 June 2021, to see if the effects of the covariates on uptake had changed over time. We measured vaccine uptake as the percentage of county residents who had taken at least two doses of the vaccine, and also an alternatively looked at the percentage of county residents who had taken at least one dose of the vaccine, in case effects were substantially different between the two.

As the various covariates having different units and standard deviations, interpreting their relative effect sizes (ie, which variables are "more important" in explaining variation in vaccine up take) can be difficult. I hence also estimated the *beta coefficients* of the model - these are calculated by using the z-score of every variable (defined for a covariate x_j, with a sample standard deviation $\hat{\sigma}_j$, as $z_j := \frac{x_{ij}-\bar{x}_j}{\hat{\sigma}_j}$)) and noticing then that, if Model

Table 1: Variable Definitions

	Definition	Justification
repvotes	Percentage (0-100) of county vote that Donald Trump received in the 2020 election	Aim to measure effect of political affiliation, which affects news consumption and beliefs on the costs and benefits of vaccination
whiteevangelical	Percentage (0-100) of county identifying as White Evangelical Protestants as of 2020	Aim to measure effect of religion - White Evangelicals are a heavily conservative and Republican-supporting religious group. (CITE)
catholic	Percentage (0-100) of county identifying as Catholics as of 202	Aim to measure the effect of religion - the Pope has actively extolled the benefits of vaccination (CITE), check effect.
black	Percentage (0-100) of county who are African-American as of 2020	Due to historical grievances and mistrust of government, African-Americans are known to be less likely to choose to vaccinate. (CITE)
poverty	Percentage (0-100) of county under the poverty line as of 2019(as defined by the Census)	Those in poverty may have difficulty finding access to vaccines, or more broadly, access to good-quality information on their costs and benefits.
medincome	Nominal median family income for a family of four, as of 2020	Same reason as above. Poverty variable lets us see if effect is stronger at the low end of the income distribution.
col	Cost of living as of 2020, as measured by the EPI.	Allows coefficient on medincome to be interpreted as the effect of changes in real median income (holding prices/cost of living fixed)
pop60to79	Percentage (0-100) of county aged between 60 and 79 in 2019.	Elderly are at greater risk of death and serious illness from COVID-19
above80	Percentage (0-100) of county aged 80 and above in 2019	See above
fullcollege	Percentage (0-100) of county who completed at least 4 years of college, averaged 2015-2019	Those with college degrees may be less susceptible to misinformation on the supposed harms of vaccination
casespc	Total recorded COVID-19 cases as of 1 December 2020, before the start of the vaccination program.	A proxy for how amenable the area is to COVID-19 spread, which would increase the benefit of vaccination against COVID-19
rural	Vector of dummy variables for each possible score on the 2013 Rural-Urban Continuum Code	More rural areas typically have lower population density and hence less risk of catching COVID-19, and so there are lower benefits to vaccination.
state	Vector of state fixed effects	Allows for variation in state policy responses that affected COVID-19 vaccination rates

(1) holds, then it is also true that

$$z_y = \frac{y_i - \bar{y}}{\hat{\sigma}_y} = \sum_{j=1}^{k} \frac{\hat{\sigma}_j}{\hat{\sigma}_y} \beta_j z_{ij} \tag{2}$$

Hence, we can calculate, for each covariate x_j, a beta coefficient $\hat{b}_j := \frac{\hat{\sigma}_j}{\hat{\sigma}_y}\beta_j$, interpreted as the standard deviation change in in $y_i = \text{vaccuptake}_i$ (in this context) frome a one standard deviation change in covariate x_j. This in a sense standardizes the units across the covariates and makes their corresponding effect sizes more directly comparable (although, not perfectly so, as some covariates are drawn from more-spread-out distributions).

We also more explicitly estimate any trends in the covariates over time, by estimating the model

$$\text{vaccuptake}_{it} = \beta_0 + \boldsymbol{\alpha} \cdot \mathbf{x}_i + \boldsymbol{\beta} \cdot \mathbf{x}_i \cdot t + \boldsymbol{\gamma} \cdot \mathbf{x}_i \cdot t^2 + u_i \tag{3}$$

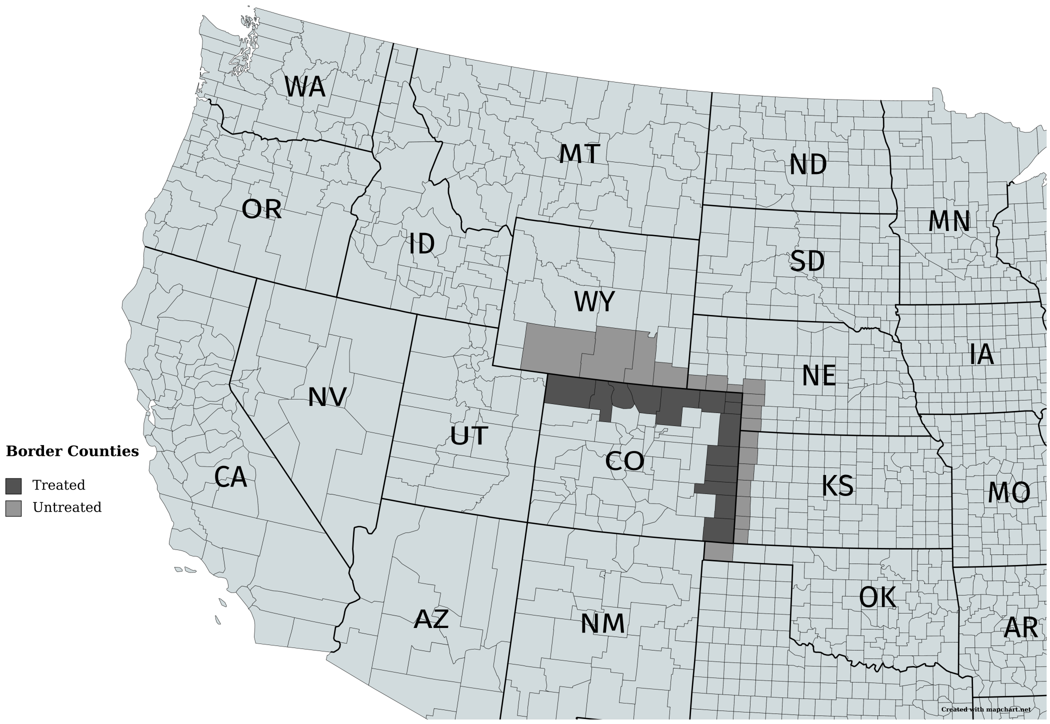
on a panel dataset of observations of vaccine uptake at the start of every month (from May 2021 to March 2021), where $\mathbf{x}_i$ is a vector of covariates (including the state fixed effects), using clustered standard errors by county, so as to correct for serial correlation across time in each county. For any covariate x_j, we have that

$$\frac{\partial \text{vaccineuptake}_{it}}{\partial x_{ij}} = \alpha_j + \beta_j t + \gamma_j t^2 \tag{4}$$

Hence, β_j and γ_j measure a quadratic trend in the effect size of the covariate on the vaccination rate over time.

It is important to note that we cannot interpret any of the coefficients estimated in Model (1) and Model (4) as estimates of the *causal impact* of the respective covariate on vaccine uptake. That would require an assumption of exogeneity (and strict exogeneity in the panel Model (4)), which is unlikely to be satisfied; for example, we cannot conclude, if the coefficient on $ln(\text{medincome})$ is positive, that increasing incomes would increase vaccine uptake. Higher incomes may simply correlate with being more informed, an unobserved variable, and so being less likely to believe myths about vaccination harms. This would lead to omitted variable bias, biasing the coefficient on $ln(\text{medincome})$ upwards. Instead these coefficients simply reflect correlations in the data, which are at best suggestive.

To answer part (b), however, we need to find out what *causes* vaccine uptake to increase.



Oklahoma, Kansas, Nebraska and Wyoming did not have vaccine lotteries over this period (CITE). New Mexico did, and hence counties bordering New Mexico are excluded from this regression. Utah is excluded from the dataset due to missing data on some covariates. Each county-pair in the pair design dataset consists of one county in Colorado (in dark grey), and one county in an untreated state (in light grey). County-pairs were matched using the NBER county adjacency dataset.

Figure 1: Counties in Pair Design

We hence turn our attention to a policy many states attempted in 2021: vaccine lotteries. We will focus in particular on Colorado's "Colorado Comeback Cash" program, where all those who had received at least one dose of the vaccine were eligible for a weekly \$1 million dollar lottery (CITE). The program began on May 25, and ran to June 30 (CITE).

To evaluate the effect of the vaccine lottery, we use a design inspired by Dube (2010) (CITE). We pick counties in Colorado which border counties in states which did not have vaccine lotteries across this period (see Figure 1). We reason that these counties are reasonably similar to counties they share a border with (and hence, form a 'county-pair') - most things which affect one county in any period t will probably also affect a paired county across the state border. Table 2 compares the selected border counties on some selected covariates; within each county-pair, differences in covariate values are generally within one standard deviation of the covariate.

However, only one member of each pair (the county within Colorado) is affected by the lottery. We can hence use the paired non-treated county as a control to estimate

Table 2: Summary Statistics

	(1) Treated	(2) Untreated	(3) Pair Differences	(4) Nationwide SD
repvotes	72.87	80.46	8.65	16.03
black	0.82	0.72	0.67	14.79
fullcollege	24.75	24.51	7.12	9.54
casespc	0.04	0.06	0.03	0.02
whiteevangelical	31.79	32.67	6.65	12.64
catholic	13.79	15.89	4.45	10.03
poverty	12.81	11.74	3.13	5.78
medinc	68923.79	69379.73	11087.17	16720.16
pop60to79	21.72	21.87	3.61	4.58
above80	5.37	5.98	1.75	1.50
N	14	18	62	3075

Columns 1 and 2 report the average value of the predictive covariates in the treated and untreated groups, corresponding to the Colorado border counties and their neighbors respectively (see Figure 1). Column 3 contains the average absolute difference in covariates between two counties along the Colorado border which are connected. Column 4 is the standard deviation of the covariates across the entire nationwide dataset. Selected covariates are those with the largest standardized effect sizes with respect to vaccine uptake from estimating Model 2, with results in Table 3.

the causal impact of the vaccine lottery. We construct, as in Dube (2010), a panel of consisting of every cross-border county-pair, from 10 days before the start of the lottery, to 10 days after. We then estimate the model:

$$\text{vaccuptake}_{ipt} = \alpha + \beta\text{treated}_{it} + \phi_i + \tau_{pt} + u_{ipt} \tag{5}$$

i is a specific county, p is a county-pair it belongs to, and t is the day in the panel. τ_{pt} is a pair-specific time fixed effect (shocks beside the lottery happen to both members of a pair) , and ϕ_i is a county fixed account (accounting for initial differences). $\text{treated}_{it} = 1$ if the county i is in Colorado, and t is after 25 May. β, the effect of the vaccine lottery on vaccine uptake, is consistently estimated if $Cov(\text{treated}_{it}, u_{itp}) = 0$ - ie, if some other shocks occurred to Colorado counties without affecting the paired counties, after 25 May.

Finally, to further check the robustness of this causal estimate, we utilize a Synthetic Control design, as detailed in (CITE) and used in prior studies on Ohio's vaccine lottery (CITE, CITE, CITE). We collapse our 3075 county level dataset into a state-level dataset, and exclude the 23 other states who had vaccine lotteries in this period (CITE).

We construct a synthetic Colorado by taking a weighted average of other states to closely match Colorado on some predictive covariates (see CITE for exact details on the estimation method). We use these weights to see how vaccine uptake would have evolved in the synthetic Colorado (made of untreated states), and take the difference between the synthetic Colorado and the real Colorado's vaccine uptake on day t as the causal impact of the vaccine lottery on day t, and test its significance.

3 Results and Discussion

Results from the estimation of Model (1) are presented in Table 3. Our estimates (not to be interpreted causally, but reflecting correlations within the data) match prior work and have the expected sign - Republicans and black individuals are less likely to get vaccinated, and this is reflected on the county level. Counties with older people, or more college graduates, are more likely to get vaccinated. Poverty and income have the expected signs, and are jointly significant (see caption), although individually insignificant likely due to multicollinearity. Places which had more cases per person in 2020 had higher vaccination rates in 2021, as hypothesized that the benefits of vaccination would be higher and more clear when this was true.

By comparing beta coefficients, we can identify that by far the factor associated with the biggest effect size on vaccine uptake is the republican vote share in the 2020 election, followed by the number of blacks. These effect sizes seem to grow over time, possibly suggesting an increasing hardening of attitudes towards the vaccine.

Catholicism was not associated with higher vaccination rates in June, but was by December. The estimation of Model (4), presented in Table 4 affirms this, as in either specification there is an increase in the effect size of Catholicism over time. While we do not have an adequate design to demonstrate this, this may suggest that the Pope's messaging on vaccination (see CITE) has successfully changed attitudes over time. This suggests one way to achieve high vaccination rates across the Untied States: engaging local religious leaders to get them to urge their worshippers to get vaccinated, and to educate them against COVID-19 vaccine related misinformation.

Table 4 also affirms that the Republican and black aversion to vaccination is only getting

Table 3: Cross-Section Regression

	December 31 Sample			June 1 Sample	
	(1)	(2)	(3)	(4)	(5)
	Two Doses	Two Doses Standardized	One Dose	Two Doses	Two Doses Standardized
repvotes	-0.52***	-0.65	-0.60***	-0.31***	-0.35
	(0.03)		(0.04)	(0.03)	
whiteevangelical	-0.03	-0.03	-0.05	-0.04	-0.03
	(0.06)		(0.07)	(0.05)	
catholic	0.11*	0.09	0.14**	-0.02	-0.02
	(0.04)		(0.05)	(0.04)	
black	-0.25***	-0.29	-0.27***	-0.16***	-0.17
	(0.03)		(0.04)	(0.03)	
poverty	-0.15	-0.07	-0.14	-0.13*	-0.05
	(0.08)		(0.10)	(0.06)	
lmedincome	2.22	0.04	1.33	4.01	0.07
	(2.96)		(3.46)	(2.28)	
lcol	4.19	0.04	6.37	0.41	0.00
	(3.41)		(4.19)	(3.01)	
pop60to79	0.18*	0.06	0.20*	0.31***	0.10
	(0.08)		(0.10)	(0.06)	
above80	0.73***	0.08	0.43	0.53**	0.06
	(0.21)		(0.26)	(0.17)	
fullcollege	0.10*	0.07	0.11*	0.11***	0.08
	(0.04)		(0.05)	(0.03)	
casespc	57.27***	0.11	55.28**	52.05**	0.09
	(15.05)		(16.87)	(16.25)	
Constant	2.87		4.21	-11.61	
	(41.54)		(50.46)	(33.07)	
rural Wald Statistic	0.72		1.59	1.08	
N	3075	3075	3075	3075	3075
White Test F-Stat	1.274		52.24***	5.16**	

Notes: The dependent variable in Columns 1 and 4 was the percentage of people in each county who had received at least two doses of the vaccine. The dependent variable in Column 3 was the percentage of people who had received at least one dose of the vaccine. Columns 1-3 consider vaccine up take as of 31 December 2021, whilst columns 4-5 consider vaccine uptake as of 1 June 2021. The one-dose regression is not repeated for 1 June for brevity, as its results are shown to be very similar to the two-dose regression in the 31 December sample. Beta coefficients for the two dose regressions are presented in Columns 2 and 5 without standard errors (their significance is the same as in Columns 1 and 4 respectively). The F statistic of the special variant of the White test for heteroskedasticity, ie regressing $\hat{u}_i^2 = \beta_0 + \beta_1 \hat{y}_i + \hat{y}_i^2$ and testing for overall significance, is reported at the bottom. As there is evidence of heteroskedasticity in 2 out of 3 regressions, heteroskedasticity-robust standard errors are reported inparantheses for **all** coefficients for convenience (robust standard errors are still consistent in the absense of heteroskedasticity). State fixed effects are excluded for brevity, and the effect of the rural dummies are excluded as they are jointly insignificant, and their F-statistics are reported instead. The regressors poverty, lmedincome and lcol are jointly significant, with Wald statisitics of 6.46 (p=0.00), 3.80 (p=0.01), and 12.34 (p=0.0) in Columns 1,3 and 4 respectively.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Coefficient Change Over Time

	(1) Linear Trends	(2) Quadratic Trend
t · repvotes	-0.0323***	-0.0489***
	(0.00321)	(0.00558)
t · whiteevangelical	0.00238	0.0148
	(0.00515)	(0.00792)
t · catholic	0.0198***	0.0131*
	(0.00415)	(0.00651)
t · black	-0.0112***	-0.00437
	(0.00266)	(0.00460)
t · poverty	-0.00860	-0.0691***
	(0.00704)	(0.0118)
t · lmedincome	-0.223	-1.213**
	(0.277)	(0.401)
t · lcol	1.087***	2.204***
	(0.238)	(0.466)
t · pop60to79	-0.0158*	-0.0426***
	(0.00664)	(0.0115)
t · above80	0.0135	-0.00855
	(0.0190)	(0.0300)
t · fullcollege	-0.00415	0.0173**
	(0.00414)	(0.00643)
t · casespc	0.417	3.850*
	(1.271)	(1.787)
t^2 · repvotes		0.00139**
		(0.000496)
t^2 · whiteevangelical		-0.00104
		(0.000745)
t^2 · catholic		0.000559
		(0.000658)
t^2 · black		-0.000566
		(0.000459)
t^2 · poverty		0.00504***
		(0.00108)
t^2 · lmedincome		0.0825*
		(0.0413)
t^2 · lcol		-0.0931*
		(0.0398)
t^2 · pop60to79		0.00224*
		(0.000975)
t^2 · above80		0.00183
		(0.00274)
t^2 · fullcollege		-0.00179**
		(0.000605)
t^2 · casespc		-0.286
		(0.156)
N	33825	33825

Notes: Standard errors, clustered by county, in brackets. Dependent variable was percentage of people with at least two doses of the COVID-19 vaccine. **rural** omitted as it was insignificant in Table 1, state fixed effects and non-interactions ommitted for brevity. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Effect of Colorado Vaccine Lottery

	(1) Two Doses	(2) One Dose	(3) ΔTwo Doses	(4) ΔOne Dose
treated	0.0315	1.696	0.00712	0.0332
	(0.116)	(1.814)	(0.0239)	(0.0187)
N	1178	1178	1178	1065

Notes: Standard errors in parentheses, clustered by state and county-pair. Column 1 shows the estimated treatment effect on the percentage of people who received two doses of the vaccine, within seven days of the start of the treatment. Column 2 shows the estimated treatment effect on the percentage of people who received at least one dose of the vaccine. Columns 3 and 4 measure the effect of the treatment on the daily change in the percentage of people who received both doses and one dose of the vaccine respectively. County fixed effects and pair-time fixed effects are not reported, for brevity. It is worth noting that, as would be expected, the effect of the lottery on the uptake of first doses is substantially higher the effect on the uptake of second doses, given that only the former enters you into the lottery and we consider only the first 10 days after the lottery began, before those who just got their first doses for the lottery would get a second dose. However, the effects are still not statistically different from 0.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

stronger with time (although, at a declining rate for Republicans, by the coefficient on $t^2 \cdot \text{repvotes}$). This is again suggestive of polarization, and further highlights the need to break into the Republican and black social networks with pro-vaccine messaging.

The focus on social messaging and religious factors is then highlighted by our results on the effects of the Colorado vaccine lottery. Regardless of dependent variable chosen, there is no statistically significant effect of the Colorado vaccine lottery on vaccination rates. This is conclusion is supported by our alternative method using a Synthetic Control. Across all days the vaccine lottery was in effect, the gap between Colorado's actual vaccine uptake and the vaccine uptake in the synthetic control was not statistically different from 0, regardless of what measure of vaccine uptake was used.

Our results here are consistent with the broader literature - though the pair design is novel for this topic - which generally finds that such lotteries had either no effect or very small or positive (and negative!) effects on vaccination. If non-vaccination is largely driven by false beliefs on supposed extreme health dangers of the vaccine, or a simple mistrust of the government, offering financial rewards may not overcome these perceived costs of vaccination.

Table 6: Synthetic Control Results

		(1) Two Doses	(2) One Dose	(3) ΔTwo Doses	(4) ΔOne Dose
Gap between real and synthetic Colorado by day					
18 May (pre-treatment)		2.41	2.35	0.00506	.000720
25 May		2.28	2.58	-0.00004367	.000292
		(0.462)	(0.423)	(0.999)	(0.269)
1 June		2.17	2.94	-0.0000253	0.000432
		(0.500)	0.346	(0.923)	(0.115)
8 June		2.35	3.01	0.000737	.0000947
		(0.500)	(0.308)	(0.653)	(0.231)
15 June		2.56	3.02	0.000330	0.000111
		(0.500)	(0.269)	(0.538)	(0.269)
22 June		2.76	3.11	0.000501	0.000151
		(0.462)	(0.269)	(0.538)	(0.269)
29 June		2.93	3.20	0.000199	0.000133
		(0.462)	(0.307)	(0.538)	(.346)
Covariates	Real Colorado				
repvotes	42.1	43.1	42.4	42.1	42.53
black	4.64	14.5	16.2	16.9	16.6
fullcollege	41.0	37.3	38.4	37.9	38.1
casespc	0.0402	0.0329	0.0359	0.0354	0.0358
whiteevangelical	16.4	13.5	13.3	13.7	13.6
catholic	18.2	22.2	20.01	20.5	19.9
poverty	9.43	11.2	11.4	11.5	11.4
medincome	93200	92300	93600	92300	92700
pop0to4	5.75	5.95	6.03	6.04	6.03
pop5to9	6.01	6.05	6.03	6.07	6.05
pop10to14	6.31	6.07	5.95	6.02	5.99
pop15to19	6.35	6.37	6.22	6.30	6.25
pop60to64	6.05	6.19	6.12	6.05	6.10
pop65to69	5.16	5.10	5.09	5.01	5.06
pop70to74	3.93	3.98	3.94	3.90	3.93
pop75to79	2.47	2.64	2.61	2.49	2.60
pop80to84	1.54	1.67	1.66	1.64	1.65
above85	1.57	1.79	1.79	1.76	1.78
State Weight					
Washington, DC		0.172	0.246	0.218	0.232
Georgia				0.035	0.029
New Hampshire		0.341	0.254	0.264	0.251
Texas		0.403	0.304	0.358	0.311
Virginia		0.007			
Wyoming		0.078	0.196	0.124	0.176

Notes: **p-values**, not standard errors, in parantheses. Estimates for the gap between Synthetic (untreated) Colorado and real Colorado were available everyday from 15 April to 30 June, but only select few were reported for brevity. All post-treatment gaps are statistically insignificant from 0. Covariates of real and each synthetic Colorado (constructed for each possible dependent variable) in the second section of the table. Covariates were selected based on what Table 1 revealed to be most predictive - with finer controls for age group; a version of Model 1 was estimated with finer age controls and found the number of children and elderly to be highly significant, although this was omitted for brevity. Synthetic Colorado was constructed, ultimately, using only a few states as weights, in all designs, and their weights are listed in the third section of the table.

4 Conclusion

In conclusion