

Between Withdrawal and Engagement: Disentangling the Effects of Covid-19 on Turnout

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This project marks the first test of the household-level turnout effects of living with someone who died from Covid-19. Drawing on policy feedback and threat literatures, I argue that the theoretical effects of close Covid contact are unclear. I link death records with the registered voter file to identify Americans who lived with a decedent, leveraging a triple-differences design to distinguish the effect household Covid deaths on turnout from non-Covid ones in Minnesota, North Carolina, and Washington State. The results are ambiguous, pointing to a distinctly demobilizing effect from a Covid death in Washington, but no distinct effect from other household deaths in Minnesota or North Carolina. I thus conclude that while Covid deaths clearly lowered household turnout, they operated largely through the opportunity costs associated with household deaths more generally.

Key Words: Covid-19; Administrative Data; Voter Turnout

The abstract is 131 words. The paper is 2,933 words, which includes references, tables, and figure captions, but excludes the title page and supplemental materials.

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On January 21, 2020, the first case of SARS-CoV-2 (“Covid”) was confirmed in the state of Washington (McNerthney, 2020). By early March, the Evergreen State was being called the center of the outbreak in the United States, although New York City would soon claim that dubious honor. By the time of the 2020 presidential election, the *New York Times* reported that more than 8.3 million Americans had tested positive for the novel coronavirus, with more than 220,000 dead. Reporting from a few months earlier, however, indicates that the official reports may be undercounts (Lu, 2020). There was also a widespread public narrative that the government—and, especially, the federal government—was culpable for many deaths thanks to a lackluster response (Choli and Kuss, 2021).

Despite the highly politicized rhetoric surrounding the pandemic in 2020 in the US, this project indicates that close contact—defined as living with someone who died from the virus—was not an especially politicizing experience. Using administrative records from Minnesota, North Carolina, and Washington, entropy balancing, and triple-differences models, I demonstrate that 2020 turnout for those with close contact with Covid did not differ meaningfully from that of individuals who lived with someone who died from a *non-Covid* cause. Thus, while Covid deaths reduced household turnout, the impact on turnout operated primarily through the channels by which all household deaths reduce turnout (Hobbs, Christakis and Fowler, 2014). Given how widespread these deaths were, their racial disparities (see Tables A1–A3 in the Supplemental Information (SI)), and the competitive nature of the 2020 election, understanding how these deaths might have distorted the electorate that year is of signal importance.

Theory and Expectations

I start from the expectation that household deaths reduce turnout generally by increasing the opportunity cost of participation. In particular I draw on Hobbs, Christakis and Fowler (2014), who link records from the Social Security Master Death File to the California registered voter file to identify voters whose spouses had died in the months before and after

statewide elections. Unsurprisingly, they find that voters whose spouses die immediately before or after an election are substantially less likely to vote than their controls, whose spouses did not die. I expect the same forces were at play in 2020, perhaps exacerbated by pandemic-era changes to voting policy (Sweren-Becker, 2020); household deaths, combined with new ways of casting ballots, might have imposed more opportunity costs than in an ordinary year. This would be less likely in Washington, however, which has a long history of the sort of mail voting widespread in 2020.

The theoretical impact of household Covid deaths on turnout—relative to other household deaths—however, is not clear. A political response seems likely given the widespread attribution of blame for the pandemic to the Trump administration (e.g. Choli and Kuss, 2021). But as Marsh (2023) makes clear, the turnout effects of traumatic events can vary based on social circumstances and identities. On the one hand, contact with a government failure of this magnitude might undermine external efficacy via the policy feedback mechanism (e.g., Béland and Schlager, 2019). When citizens receive messages that their problems are unimportant to policymakers, they can disengage from politics altogether. Soss and Jacobs (2009, 110) describe how policies can “foster atomized publics with little sense of what they have in common and at stake in politics and government.” The (lack of) response to Covid at the federal level might send messages to citizens that the lives of their loved ones were not important, thus leading to a withdrawal from the political process. This could make Covid-related deaths *more* demobilizing than other household deaths.

On the other hand, policy threat literature indicates that voters might turn out at higher rates when they feel targeted by the government (e.g., Tam Cho, Gimpel and Wu, 2006). When “narrative frames” (Benford and Snow, 2000) allow voters to understand their particular experiences in larger, political terms, it can increase political engagement (e.g., Piven and Cloward, 1979; Morris and Shoub, 2023). If voters internalized the widespread frames about the Trump administration’s culpability, Covid deaths might have been *less* demobilizing than other household deaths. It also seems possible that these effects vary by

party, with Republicans particularly demobilized by a policy failure attributable to their own party's leader (e.g., Hirschman, 1970).

Research Design and Data

I begin by identifying all individuals who died in 2020 in the study states using individual death records. These records include a variety of data about the deceased individual, including residential address and cause of death. In the case of Washington and North Carolina, the death records were obtained through research agreements with the states' Departments of Health. Records from Minnesota come from researchers at the University of Minnesota (Wrigley-Field et al., 2020). Deaths are considered attributable to Covid when the International Classification of Diseases (ICD) code on a record was U07.1.¹

Voter data come from snapshots of the registered voter file collected shortly following the election by L2, a vendor that collects voter files and sells them to campaigns and academic institutions. The files include characteristics such as age, gender, and turnout history. I use Bayesian Improved Surname Geocoding (BISG) to estimate each voter's race / ethnicity by incorporating information about both their surname and the racial characteristics of the Census tract in which they live (Imai and Khanna, 2016). In North Carolina, where most voters self-identify their race when they register to vote, I use BISG only for the individuals marked as "other" or "unknown."

I merge the death records to the registered voter file using recorded address following the procedures laid out in Morris (2021): using Appendix C of the USPS Postal Addressing Standards I standardize common address abbreviations such that (for example) "ROAD" becomes "RD." About 74% of decedents in Washington in 2020 lived with a registered voter; the comparable figures for North Carolina and Minnesota were 69% and 70%, respectively. Exact matching between the death data and the voter file is required, and I remove deceased individuals who had not yet been removed at the time the voter file snapshot was collected.

¹See <https://www.cdc.gov/nchs/data/nvss/coronavirus/Alert-6-ICD-10-code-COVID-19-U071.pdf>.

In the SI, I show that my results do not differ meaningfully when I allow the cumulative string distance between the street name and municipality to be a distance of 1 or 2; in all cases, I require exact matching on the house number.

I compare the over-time turnout of voters whose housemates had died from Covid to voters whose housemates died from other causes, and also to the turnout of individuals who did not live with anyone who died—a difference-in-difference-in-differences, or triple-differences, approach. To account for potential violations of the parallel trends assumption, I use entropy balancing (Hainmueller, 2012) prior to estimating the difference-in-differences model to ensure consistency along covariates between the treatment and control groups. Entropy balancing assigns every control unit a weight such that the weighted average of controls mirrors the treated group. Individual level characteristics come from the registered voter file or BISG; characteristics about the decedent come from the states’ death records; and all other neighborhood-level characteristics come from the 2020 5-year ACS estimates.

To account for potential *unobservable* differences, my control group—that is, the group with no 2020 household deaths—is drawn from the population who lived with someone who died between May 3 and December 31, 2021. I assume that a household death that occurred 6 months after the election did not impact household turnout in 2020. Insofar as these deaths might have impacted turnout 6 months before (it is possible someone who died in June of 2021 might have required extensive care in November of 2020, dampening household turnout among caregivers), I collapse the distinction between treated and control voters, making my estimates conservative.

I balance twice to facilitate the triple-differences specification (Morris and Miller, 2023). I begin by weighting individuals who experienced a non-Covid household death so that they mirror those who lived with someone who died from Covid. Any difference between these two groups of voters represents the *unique* effect of living with someone who died of Covid; because voters in each group experienced a household death in 2020, that “treatment” is held constant. I drop individuals who lived with more than 2 people who died during 2020;

I assume these individuals lived in congregant settings where treatment effects might have been very different, along with the theoretical mechanisms at play.

I repeat the process for those voters without a household death, once again weighting them so they mirror the voters with a household Covid death. Any difference in the 2020 turnout of those who lived with no one who died, and those who lived with someone who died from a non-Covid cause, will capture the baseline effect of a household death on turnout. After constructing the weights, I estimate a triple-differences model at the individual-level, incorporating each individual’s turnout history, with year and individual fixed effects.

These models allow me to test my hypotheses (H2a and H2b mutually exclusive):

H1: Household deaths resulted in lower 2020 turnout.

H2a: If the “policy threat” theory is operable, and narratives linking individual experiences with Covid to larger social processes predominated, Covid deaths were *less* demobilizing than non-Covid household deaths.

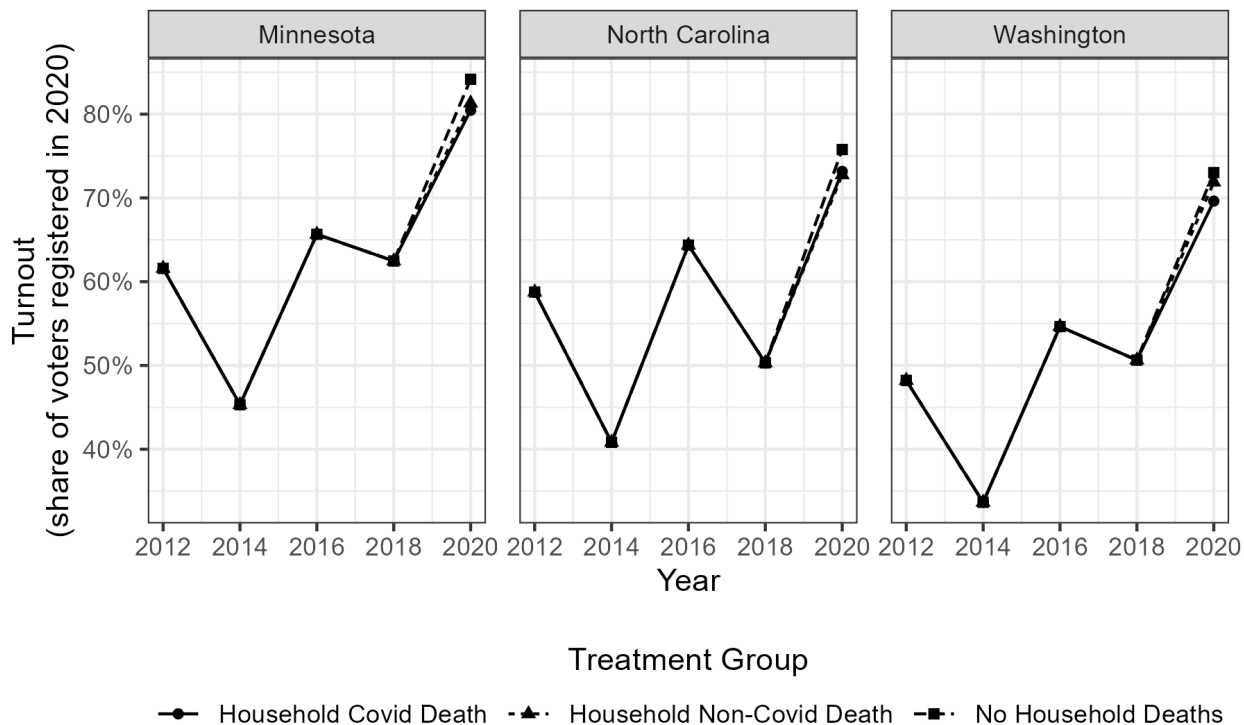
H2b: If, on the other hand, “policy feedback” factors predominate, Covid deaths were just as or more demobilizing than other household deaths.

Results

In Figure 1, I plot entropy balance-weighted turnout rates for each of the three groups, in each of the three states. As the figure makes clear, the entropy balancing process was successful at removing differences in historical turnout rates. Figure 1 provides preliminary visual support for Hypothesis 1: in all 3 states, 2020 turnout was slightly higher for the control voters who lived with no one who died during 2020. The figure also indicates that Covid may not have impacted turnout in distinct ways relative to other household deaths.

I present the results of the regression models testing these relationships in Table 1. Here, the coefficient on *Housemate Died* \times *2020* tests whether individuals who lived with someone who died from a non-Covid cause turned out at lower rates than those with no household deaths (**H1**); that on *Housemate Died from Covid* \times *2020*, meanwhile, tests

Figure 1: Turnout by Household Death Status



'No Household Deaths' and weighted to mirror 'Household Covid Death' using entropy balancing. Balancing covariates include decedent's age, number of household deaths, historical turnout, latitude, longitude, party affiliation, voter's age, registration date, voter's race / race predictions, gender, party (in WA and NC), block group median income, block group education, and block group population density. 'Household Non-Covid Death' are weighted using the preceding covariates, along with decedent's date of death.

whether the effects of a Covid death differed from other household deaths (**H2a** and **H2b**). Model 1 tests the overall effects; Model 2 asks whether these effects were different for Republicans (relative to independents and Democrats, for whom supporting Biden may have been easier than abstaining).

Table 1 provides corroboration for Figure 1: household non-Covid deaths depressed turnout by approximately 3 percentage points in Minnesota and North Carolina, and 1.1 points in Washington ($p < 0.01$ in all states). The impact of Covid deaths relative to non-Covid deaths, however, is less clear. In Minnesota ($p = 0.24$) and North Carolina ($p = 0.31$) Covid deaths did not have an impact on turnout distinguishable from non-Covid ones. In Washington State, however, Covid related deaths appear to have decreased turnout by considerably more (2.3 points) than non-Covid ones. I do not uncover evidence that these

Table 1: Household Deaths and Voter Turnout

	Minnesota	North Carolina		Washington	
	(1)	(2)	(3)	(4)	(5)
Household Covid Death \times 2020	-0.008 (0.006)	0.004 (0.003)	0.007 (0.004)	-0.023* (0.005)	-0.024* (0.007)
Household Death \times 2020	-0.029** (0.004)	-0.030*** (0.002)	-0.029*** (0.002)	-0.011** (0.002)	-0.010* (0.003)
2020 \times Republican			0.045** (0.008)		-0.058*** (0.003)
Household Covid Death \times 2020 \times Republican			-0.009 (0.009)		0.006 (0.017)
Household Death \times 2020 \times Republican			-0.004 (0.004)		-0.005 (0.007)
Year Fixed Effects	✓	✓	✓	✓	✓
Voter Fixed Effects	✓	✓	✓	✓	✓
Num.Obs.	258195	811435	811435	475980	475980
R2	0.579	0.607	0.607	0.636	0.637
R2 Adj.	0.474	0.508	0.509	0.545	0.546

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors clustered by voter and year.

treatment effects differ meaningfully for Republicans (in Minnesota, where voters do not register with a party, this moderation model is not possible).

Conclusion

At the time of writing, more than 1.1 million Americans had perished from Covid related causes; more than 104 million cases had been recorded.² It is difficult to overstate the impact of the coronavirus pandemic on social life over the past 4 years. While the political ramifications of the pandemic will continue to be studied for years to come, this project provides the first insight into how Covid impacted household-level turnout in the 2020 presidential election, across 3 states with very different geographies and social circumstances.

Covid presents one type of a new class of policy threats. Unlike past examples of threat, Covid took shape largely as *inaction* on the government's behalf; put differently, voters were made worse off not through action taken by the state, but because the government

²<https://covid.cdc.gov/covid-data-tracker/#datatracker-home>.

failed to adequately protect citizens from a detrimental environment. For this reason, the expected effect of a household Covid death was not *a priori* clear; as Mettler and Soss (2004, 64) explain, the participatory consequences of any policy “depend ultimately on how public policies fit into the lives of individuals and social groups. Citizens must therefore be treated as active agents [by scholars] in the processes that give rise to policy-feedback effects.” By decomposing general death-related effects from the (potentially) specific effects of a Covid death, I made space for the mobilizing and demobilizing processes present in the Covid pandemic, attempting to decompose them using administrative data.

The results indicate a certain level of ambiguity with respect to the aggregate turnout effects of living with someone who died from Covid: while Covid deaths were *more* demobilizing than other household deaths in Washington State, they were indistinguishable from non-Covid deaths in Minnesota and North Carolina. Similarly, the administrative records uncover no meaningful differences in treatment effects for Republican voters. Unfortunately, it is difficult to know whether the null results here reflect no distinct politicizing effect in either direction or, rather, mask heterogeneous treatment effects pushing in opposite directions. Survey-based work exploring psychological dispositions of voters (and their turnout) could be fruitful for further addressing this question. It also is possible that political forces influenced which deaths were considered due to Covid, muddying the distinction between voters who lived with someone who died *from* Covid versus *with* Covid (Eutsler et al., 2023).

Covid ravaged the United States in ways unlike any crises in at least a century. It took the lives of more Americans than any war ever has, and it continues to smolder in our communities. But for Covid’s novelty, the federal response to the coronavirus pandemic also presents a new sort of threat that may come to typify threat in the 21st century: one of government inaction, rather than targeted action. From climate change to income inequality, from Covid to air pollution: in the years to come the inactive state might threaten more in what it does *not* do than what it *does*. Finding ways to engage voters around these issues should be of paramount concern for scholars and activists alike.

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Supplementary Information

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1 Entropy Balancing Tables, Minnesota and Washington

The central identification strategy in the manuscript relies on a combination of entropy balancing and difference-in-differences. In Table A1 I present the results of the entropy balancing procedure for the state of North Carolina (Tables A2 and A3 present the tables for Minnesota and Washington, respectively). The first 3 numeric columns show the unweighted averages; the following 3 present the weighted averages. In all cases, household Covid death voters receive a weight of 1. With the exception of latitude, longitude, and past turnout, Table A1 includes all the variables used in the weighting procedure (in Minnesota, where voters do not register with parties, partisan affiliation is not used). The final 3 columns of the table indicate that the entropy balancing procedure was highly successful at removing differences between the three groups.

Table A1 details interesting differences between voters whose household members died from Covid and the rest of the study population (as a reminder, all voters included in the analysis lived with someone who died in 2020 *or* the second-half of 2021). Of particular note are the differences between voters with a household Covid death and those with a non-Covid death. Covid deaths were clearly associated with a different population than deaths more generally: household members were more likely to be Democrats; lived in somewhat lower-income neighborhoods; and were substantially more likely to be nonwhite. These general patterns hold across the three states, though of course in Minnesota we do not know partisan affiliation.

Table A1: Balance Table for Entropy Balancing, North Carolina

	Means: Unweighted Data			Means: Weighted Data		
	Household Covid Death	Household Non-Covid Death	No Household Death	Household Covid Death	Household Non-Covid Death	No Household Death
Age	55.7	55.1	56.9	55.7	55.7	55.7
Share Democrat	45.4%	40.4%	39.0%	45.4%	45.4%	45.4%
Share Republican	28.9%	30.5%	32.1%	28.9%	28.9%	28.9%
Registration Date	June 18, 2004	July 30, 2005	April 16, 2005	June 18, 2004	June 18, 2004	June 18, 2004
Share Male	42.9%	43.8%	45.2%	42.9%	42.9%	42.9%
Share White	56.7%	65.7%	68.0%	56.7%	56.7%	56.7%
Share Black	34.0%	28.9%	26.7%	34.0%	34.0%	34.0%
Share Latinx	5.5%	2.4%	2.3%	5.5%	5.5%	5.5%
Share Asian	2.0%	1.2%	1.2%	2.0%	2.0%	2.0%
Neighborhood Income	57,685	60,751	61,483	57,685	57,685	57,685
Neighborhood Share with Some College	57.7%	60.6%	60.3%	57.7%	57.7%	57.7%
Neighborhood Population Density	1,279.3	1,380.8	1,278.5	1,279.3	1,279.3	1,279.3
Number of Deaths	1.1	1.0	1.0	1.1	1.1	1.1
Death Date	September 25, 2020	July 01, 2020		September 25, 2020	September 25, 2020	
Decedent's Age	74.6	69.2	68.7	74.6	74.6	74.6

Table A2: Balance Table for Entropy Balancing, Minnesota

	Means: Unweighted Data			Means: Weighted Data		
	Household Covid Death	Household Non-Covid Death	No Household Death	Household Covid Death	Household Non-Covid Death	No Household Death
Age	55.9	58.3	61.3	55.9	55.9	55.9
Registration Date	October 27, 2012	June 14, 2011	August 19, 2009	October 27, 2012	October 27, 2012	October 27, 2012
Share Male	41.7%	43.0%	45.0%	41.7%	41.7%	41.7%
Share White	71.7%	81.7%	80.7%	71.7%	71.7%	71.7%
Share Black	9.1%	6.7%	7.1%	9.1%	9.1%	9.1%
Share Latinx	3.3%	2.3%	2.2%	3.3%	3.3%	3.3%
Share Asian	11.0%	4.2%	4.9%	11.0%	11.0%	11.0%
Neighborhood Income	77,492	80,090	79,951	77,492	77,492	77,492
Neighborhood Share with Some College	67.3%	68.5%	68.0%	67.3%	67.3%	67.3%
Neighborhood Population Density	3,502.3	2,877.4	3,001.2	3,502.3	3,502.3	3,502.3
Number of Deaths	1.0	1.0	1.0	1.0	1.0	1.0
Death Date	September 25, 2020	June 27, 2020		September 25, 2020	September 25, 2020	
Decedent's Age	76.2	70.9	69.7	76.2	76.2	76.2

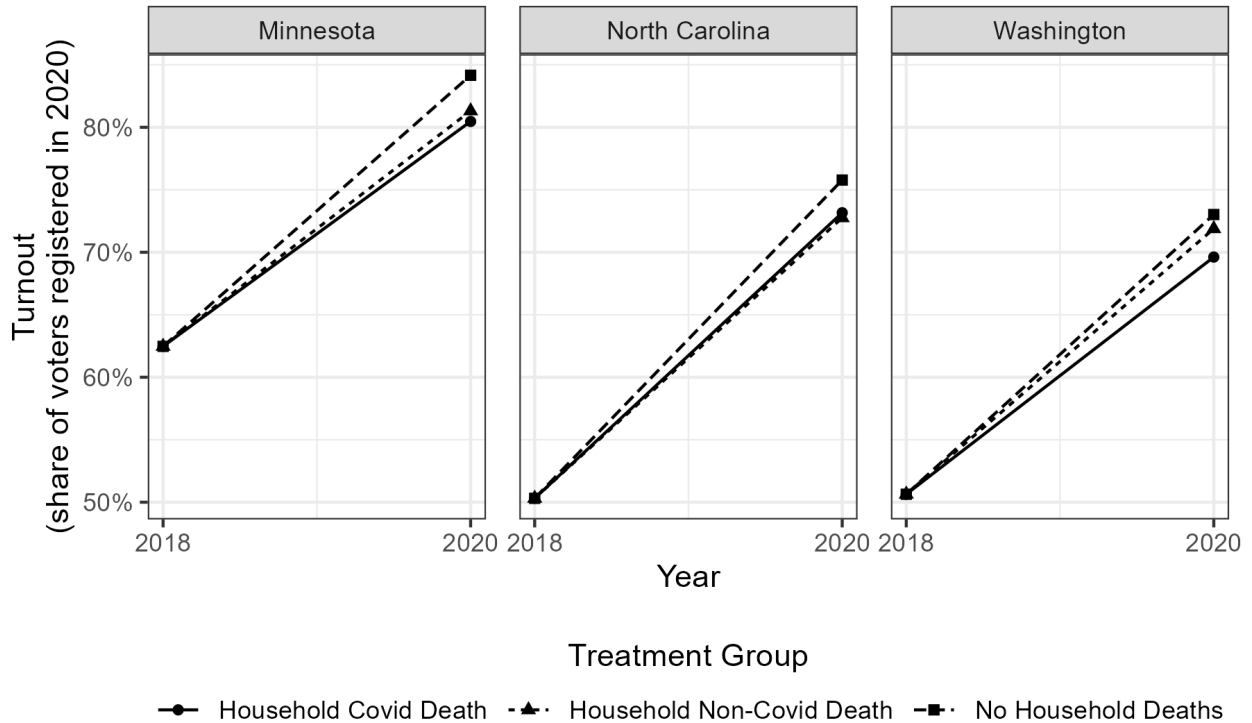
Table A3: Balance Table for Entropy Balancing, Washington

	Means: Unweighted Data			Means: Weighted Data		
	Household Covid Death	Household Non-Covid Death	No Household Death	Household Covid Death	Household Non-Covid Death	No Household Death
Age	52.1	54.1	53.9	52.1	52.1	52.1
Share Democrat	53.9%	49.3%	48.3%	53.9%	53.9%	53.9%
Share Republican	28.5%	30.6%	34.1%	28.5%	28.5%	28.5%
Registration Date	August 29, 2006	August 19, 2005	July 01, 2005	August 29, 2006	August 29, 2006	August 29, 2006
Share Male	44.8%	45.3%	45.4%	44.8%	44.8%	44.8%
Share White	57.4%	72.7%	72.5%	57.4%	57.4%	57.4%
Share Black	4.8%	4.4%	4.6%	4.8%	4.8%	4.8%
Share Latinx	16.7%	7.0%	7.2%	16.7%	16.7%	16.7%
Share Asian	11.2%	6.5%	6.3%	11.2%	11.2%	11.2%
Neighborhood Income	82,654	83,558	83,019	82,654	82,654	82,654
Neighborhood Share with Some College	64.4%	67.8%	67.3%	64.4%	64.4%	64.4%
Neighborhood Population Density	4,286.4	3,602.8	3,446.2	4,286.4	4,286.4	4,286.4
Number of Deaths	1.1	1.0	1.0	1.1	1.1	1.1
Death Date	August 18, 2020	June 28, 2020		August 18, 2020	August 18, 2020	
Decedent's Age	75.4	71.2	70.5	75.4	75.4	75.4

2 Entropy Balancing Tables, Minnesota and Washington

In the body of the manuscript I include the full time series used for the triple-differences model. This makes some of the variation between 2018 and 2020 less visually obvious. Here, I plot the three groups for the three states but only in 2018 and 2020. Note that the balancing process is identical here as in the body and includes all years; this is only a visual transformation of Figure 1 in the body.

Figure A1: Turnout by Household Death Status, Showing Only 2018 and 2020

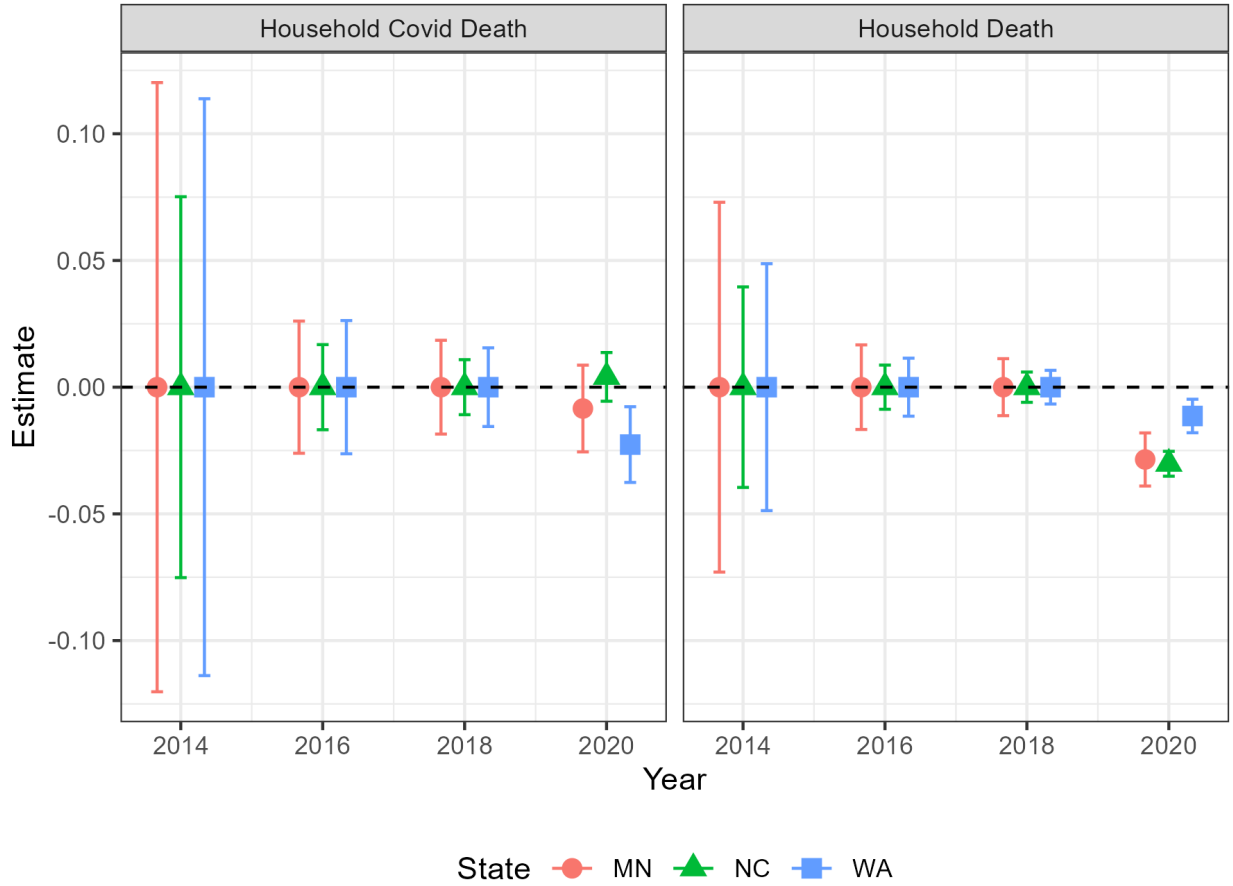


'No Household Deaths' and weighted to mirror 'Household Covid Death' using entropy balancing. Balancing covariates include decedent's age, number of household deaths, historical turnout, latitude, longitude, party affiliation, voter's age, registration date, voter's race / race predictions, gender, party (in WA and NC), block group median income, block group education, and block group population density. 'Household Non-Covid Death' are weighted using the preceding covariates, along with decedent's date of death.

3 Robustness Check: Event Study

Here, I show that there is no significant difference between treated and control voters in the years prior to 2020—that is, in the years prior to treatment. This is meant to bolster the parallel trends assumption: these three groups of voters moved in tandem prior to the Covid pandemic. Of course, past turnout is included in the entropy balancing procedure. Nevertheless, Figure A2 provides evidence that there were not divergent pre-treatment trends in any of the states. As in the regression tables, “Household Covid Death” captures the unique effect of a Covid household death relative to other household deaths, while “Household Death” captures the effect of a household non-Covid death relative to those with no household deaths in 2020.

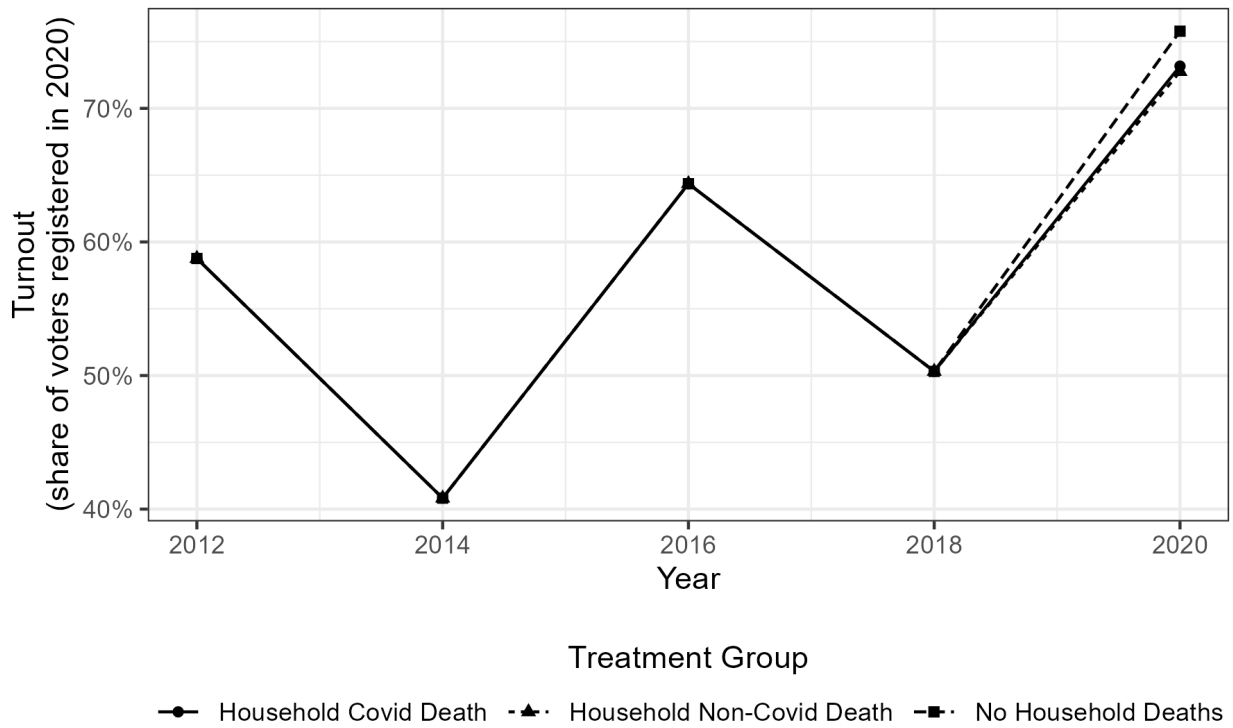
Figure A2: Turnout by Household Death Status



4 Robustness Check: Fuzzy Matching

In the body of the manuscript, addresses in the death record data sets are required to exactly match the records in the voter files, conditional on the cleaning processes explained in the manuscript. Here, I present the results when I allow for a maximum Levenshtein distance of 2 between the data sets. As Figure A3 and Table A4 make clear, the results are not meaningfully different when this “fuzzy matching” is allowed. In no case does a coefficient become statistically (non)significant at the 0.05-level as a result of the fuzzy matching.

Figure A3: Turnout by Household Death Status



'No Household Deaths' and weighted to mirror 'Household Covid Death' using entropy balancing. Balancing covariates include decedent's age, number of household deaths, historical turnout, latitude, longitude, party affiliation, voter's age, registration date, voter's race / race predictions, gender, party (in WA and NC), block group median income, block group education, and block group population density. 'Household Non-Covid Death' are weighted using the preceding covariates, along with decedent's date of death.

Table A4: Household Deaths and Voter Turnout

	Minnesota	North Carolina		Washington	
	(1)	(2)	(3)	(4)	(5)
Household Covid Death \times 2020	-0.010 (0.006)	0.003 (0.003)	0.006 (0.004)	-0.020* (0.005)	-0.020 (0.007)
Household Death \times 2020	-0.036*** (0.004)	-0.029*** (0.002)	-0.027*** (0.002)	-0.012** (0.002)	-0.010* (0.003)
2020 \times Republican			0.044** (0.008)		-0.062*** (0.003)
Household Covid Death \times 2020 \times Republican			-0.011 (0.009)		0.002 (0.017)
Household Death \times 2020 \times Republican			-0.007 (0.004)		-0.006 (0.006)
Year Fixed Effects	✓	✓	✓	✓	✓
Voter Fixed Effects	✓	✓	✓	✓	✓
Num.Obs.	283395	886800	886800	523655	523655
R2	0.576	0.606	0.606	0.633	0.633
R2 Adj.	0.470	0.507	0.507	0.541	0.542

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors clustered by voter and year.