Appendix

Access to Healthcare and Voting: The Case of Hospital Closures in Rural America

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Abstract

We investigate how hardships affect rural politics, considering the case of hospital closures. In the last two decades, more than 200 rural hospitals have closed their doors or drastically reduced their services. Drawing from resource models of voting, our hypothesis is that personal- and community-level deprivations brought about by hospital closures should reduce election turnout. Empirical tests pair geographic information on the location of open and closed hospitals with data from state voter files to create a panel of over 10 million rural residents for the 2016, 2018, and 2020 national elections. Results show that individuals whose nearest hospital closed prior to the proximate election were less likely to vote than their unaffected counterparts. These effects are strongest for older and lower-income residents, but they decay over time so that voting likelihood resembles a pre-closure baseline within 12 months.

Keywords: Hospitals, Healthcare, Turnout, Rural Politics, Hardship

Supplemental Information

A Descriptive statistics & regression results

Table A1: Crosstabs and descriptive statistics.

	2016 (N)	2018 (N)	2020 (N)	Total (N)
Affected	33,687	66,530	133,993	234,210
Unaffected	10,484,512	10,401,731	10,326,111	31,212,354
Democrats	3,434,928	3,370,934	3,328,071	10,133,933
Republicans	4,512,734	4,683,123	4,883,812	14,079,669
65+	3,357,815	3,813,147	4,254,011	11,424,973
Low-income	1,658,557	1,837,162	1,711,593	5,207,312
65+ & low-income	715,846	870,475	953,425	2,539,746
	Mean	Min	Max	Total (N)
KM to nearest open hospital	15.43	0.0008	1,347.24	31,446,564

Table A2: Coefficients Characterizing the Effect of Hospital Closures on Voting by Demographic Subgroup.

	Baseline	Dem.	Rep.	65+	Low-income	65+ & Low-income
Affected	-0.002*	-0.005*	-0.002	-0.009**	-0.017**	-0.027**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.005)
2016	-	-	-	-	-	-
2018	-0.106**	-0.098**	-0.094**	-0.072**	-0.103**	-0.079**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2020	0.009**	-0.001**	-0.000**	-0.015**	-0.002**	-0.017**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.772**	0.758**	0.868**	0.842**	0.757	.834**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FEs Voter ID	✓	✓	✓	✓	✓	✓
N	31,211,401	9,472,722	13,341,719	10,803,104	3,439,282	1,700,587
Adjusted R^2	0.57	0.57	0.51	0.59	0.57	0.55

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

Standard errors are robust and clustered on voter ID.

Table A3: Coefficients Characterizing the Effect of Hospital Closures on Voting by Timing to the Election.

	Closes 9–11 months after election	Closes 6–8 months after election	Closes 3–5 months after election	Closes 0–2 months after election	Closes 1–3 months before election	Closes 4–6 months before election	Closes 7–9 months before election	Closes 10-12 months before election
Affected	-0.032	-0.026	0.033	0.020	-0.041**	-0.059**	-0.002	0.002
	(0.019)	(0.017)	(0.032)	(0.025)	(0.003)	(0.010)	(0.002)	(0.002)
2016	-	-	-	-	-	-	-	-
2018	-0.105**	-0.105**	-0.105**	-0.105**	-0.105**	-0.105**	-0.105**	-0.105**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2020	0.009**	0.009**	0.009**	0.009**	0.009**	0.009	0.009**	0.009*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.772**	0.772**	0.772**	0.772**	0.772**	0.772**	0.772**	0.772**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FEs Voter ID	✓	✓	✓	✓	✓	✓	✓	✓
N	30,919,522	30,920,049	30,919,182	30,919,246	31,087,077	31,072,018	31,095,778	31,088,667
Adjusted R^2	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57

$^{**}p < 0.01$ $^{*}p < 0.05$
Standard errors are clustered on voter ID.

Table A4: Coefficients Characterizing the Effect of Hospital Closures on Voting, Clustering SEs by Distance to Hospital.

	Model 1
Affected	-0.002* (0.001)
2016	-
2018	-0.106** (0.000)
2020	0.009** (0.000)
Constant	0.772** (0.000)
FEs Voter ID	✓
N	31,211,401
Adjusted R^2	0.57

$^{**}p < 0.01$ $^{*}p < 0.05$
Standard errors are clustered on distance to the nearest hospital in 2016.

B Hospital distance

The following table shows the estimated relationship between turnout and distance to the nearest open hospital for affected and unaffected individuals. Estimates are based on a regression interacting the affected variable with the logged distanced, measured in kilometers, to the nearest open hospital. As with other regressions, we include individual-level fixed effects and controls for the election year. By definition affected individuals had their nearest hospital close, so we might expect that the further away their nearest still-open hospital is the less likely they would be to vote. But this is not what we find. For the unaffected population, being further away from an open hospital decreases the likelihood of voting. This likely has to do with the types of communities and people that tend to live lengthy distances from hospitals. However, this negative relationship disappears and is no longer statistically significant for the affected population.

Table B5: Distance to the Nearest Open Hospital and Voting.

	Model 1
Affected	-0.005 (0.003)
KM to open hospital (logged)	-0.001** (0.000)
Interaction: affected x KM to open	0.000 (0.001)
2016	-
2018	-0.106** (0.000)
2020	0.009** (0.000)
Constant	0.775** (0.000)
FEs Voter ID	✓
N	31,211,401
Adjusted R^2	0.57

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

Standard errors are clustered on voter ID.

C Matching analysis

The table below shows the results of difference-of-means tests comparing the likelihood of voting for affected and unaffected individuals, separately for each election. These tests are run after using propensity score matching to pair affected and unaffected individuals. We matched individuals on the basis of their voting history, party registration, age, race, gender, household income, and levels of unemployment in their county of residence. The pool of potential matches included the entire affected population and a randomly drawn sample of 10% of the unaffected population. Using the full sample of unaffected individuals was too computationally intensive.

Table C6: Likelihood of voting for affected compared to unaffected populations.

	2016	2018	2020
Affected	-0.023* (0.011)	-0.033** (0.003)	-0.012** (0.001)
N	743,723	856,018	928,469

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

D Multinomial regression

For these models, we create a categorical variable coded 0 if an individual does not vote, 1 if they vote, and 2 if they exit the sample. We then predict this variable using a multinomial regression, separately estimating each outcome. We are unable to use individual-level fixed effects because doing so would automatically drop all the individuals who appear only once in the voter files and achieving convergence using a multinomial logit with fixed effects with such large data is computationally difficult. Results are shown in Table D7. Model 1 shows the baseline regression with only election-year indicators for controls and Model 2 adds individual-level demographic variables (age, voting history, party identification, gender, race, and income). Results from both models are supportive of findings with regard to voting: those that are affected by a closure are less likely to vote in the subsequent election. In Model 1, we find that being affected by a closure increases the likelihood of being missing in subsequent iterations of the voter file, but in Model 2 this effect changes direction (and loses its statistical significance).

Table D7: The Effect of Hospital Closures on Exiting the Sample and Voting, Multinomial Regression.

	Model 1	Model 2
Voted		
Affected	-0.206** (0.005)	-0.037** (0.006)
Constant	1.205** (0.000)	0.100** (0.002)
Exited sample		
Affected	-0.090**(0.007)	0.003 (0.007)
Constant	0.297** (0.000)	0.304** (0.003)
N	43,925,316	34,600,748
Pseudo R^2	0.0138	0.1722
Individual-level controls	✗	✓
Election year FEs	✓	✓
***p < 0.01 *p < 0.05*		
Standard errors are clustered on voter ID.		

E Geographic controls

To assuage concerns about time-varying unobserved heterogeneity beyond the individual level, we estimate two separate regressions (see Table E8). First, we regress voting on exposure to a hospital closure while including aggregated county-year means of all the individual covariates from the L2 files (distance to nearest hospital, party identification, gender, race, income, age, and voting history) and annual county-level educational attainment (high school graduation rate and college graduation rate), which we draw from the American Community Survey. In Model 2, we do the same thing at the zip code level. Results are highly consistent. In fact, we find even larger demobilizing effects in these specifications than those reported in the main analysis.

Table E8: The Effect of Hospital Closures on Voting including Geographic Controls.

	Model 1 (County Level)	Model 2 (Zip code Level)
Affected	-0.012** (0.001)	-0.023** (0.001)
2016	-	-
2018	-0.089** (0.001)	-0.088** (0.000)
2020	0.038** (0.001)	0.040** (0.001)
Age	0.017** (0.000)	0.017** (0.000)
Voting history	-0.067** (0.000)	-0.067** (0.000)
KM to nearest hospital	-0.001** (0.000)	-0.001** (0.000)
Political party	-0.025** (0.001)	-0.016** (0.001)
Gender	-0.569** (0.073)	-0.503** (0.061)
Race	-0.113** (0.009)	-0.066** (0.006)
Income	-0.015** (0.001)	-0.007** (0.001)
Percent HS degree	-0.000** (0.000)	-0.000** (0.000)
Percent college degree	0.000 (0.000)	-0.000** (0.000)
Constant	0.432*** (0.047)	0.333*** (0.040)
FEs Voter ID	✓	✓
N	30,717,923	30,446,191
R^2	0.723	0.724

***p < 0.01 *p < 0.05*
Standard errors are clustered on voter ID.

F Heterogeneous effects & interactions

In Figure 2 we show how exposure to a hospital closures affects voting for different demographic groups. This reveals that Democrats are especially less likely to vote, but it is possible that these effects are actually being driven by other traits that might correlate with being a Democrat – such as income, age, or race. To investigate, we further subset the data to condition on being a low-income Democrat, an elderly Democrat, or a white Democrat. Results from these regressions are shown in Table F9. For all three specifications, we find that the effect sizes of exposure to a hospital closure on voting are larger than when we look at all Democrats together. This suggests that being a Democrat is not simply a proxy for these other traits.

Table F9: The Effect of Hospital Closures on Voting for Different Types of Democrats.

	Democrat + low income	Democrat + elderly	Democrat + white
Affected	-0.032** (0.006)	-0.016** (0.003)	-0.010** (0.002)
2016	-	-	-
2018	-0.103** (0.000)	-0.076** (0.000)	-0.094** (0.000)
2020	-0.006** (0.000)	-0.020** (0.000)	-0.001** (0.000)
Constant	0.741** (0.000)	0.838** (0.000)	0.779** (0.000)
FEs Voter ID	✓	✓	✓
N	1,419,209	3,544,059	6,444,655
Adjusted R^2	0.563	0.573	0.576

$^{**}p < 0.01$ $^{*}p < 0.05$
Standard errors are clustered on voter ID.

Next, we consider heterogeneous effects along various voter characteristics using interaction terms and the full sample rather than subsetting the data (see Table F10). The interaction terms are statistically meaningful in ways that are consistent with the findings shown in Figure 2 and indicate differences from the baseline result across demographic groups.

Table F10: The Effect of Hospital Closures on Voting using Demographic Interactions.

	Political party	Income	Age
Affected	-0.007** (0.001)	-0.009** (0.002)	0.065** (0.004)
Democrat	-	-	-
Republican	0.026** (0.000)	-	-
Other	-0.010** (0.000)	-	-
Affected x Democrat	-	-	-
Affected x Republican	0.001 (0.002)	-	-
Affected x Other	0.023** (0.003)	-	-
Low income	-	-	-
Middle-low income	-	0.000 (0.000)	-
Middle-high income	-	0.001** (0.003)	-
High income	-	0.019** (0.006)	-
Affected x Low income	-	-	-
Affected x Middle-low income	-	0.008** (0.002)	-
Affected x Middle-high income	-	0.014** (0.003)	-
Affected x High income	-	0.019** (0.006)	-
Age	-	-	-0.001** (0.000)
Affected x Age	-	-	-0.001** (0.000)
2016	-	-	-
2018	-0.106** (0.000)	-0.106** (0.000)	-0.108** (0.000)
2020	0.008** (0.000)	0.011** (0.000)	0.004** (0.000)
Constant	0.763** (0.000)	0.783** (0.000)	0.686** (0.004)
FEs Voter ID	✓	✓	✓
N	31,211,401	28,350,060	30,463,367
Adjusted R^2	0.578	0.571	0.572

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

Standard errors are clustered on voter ID.

G Electoral competitiveness

Our empirical focus has been on rural areas because these are the only places that had a hospital close between 2016 and 2020. Rural America tends to be relatively homogeneous both demographically and politically. How might our findings change if we could include a wider range of geographies? One possibility is that in places with more robust inter-party competition demobilization would be less pronounced. Without local party competition or other activist activity, the necessary learning in regards to the public goods loss and thus policy-related election mobilization is less likely to occur (Soss and Schram, 2007). Moreover, rural residents tend to have weaker social networks on average (Shea and Jacobs, 2023; Gimpel et al., 2020), which scholars have identified as being important for mobilization generally and especially for mobilization in the case of retrenchment (Nuamah and Ogorzalek, 2021). A recent study of health care services highlights the importance of "health care parties" as a viable alternative for voters suffering through health-related service withdrawals (Lindbom, 2014). The Democratic Party is the closest US voters get to a health-care party (Petrocik, 1996), but, in many rural areas, Democratic candidates struggle to compete electorally.

However, we lack enough variance for a meaningful test of this idea. To illustrate, we calculate the two-party vote share in House congressional races for every district in our data for the 2016, 2018, and 2020 elections. On average, across districts and elections, the Republican candidate received 57% of the vote. If we define a seat as electorally competitive if the two-party vote share is between 45% and 55%, then only 16% of individuals in the data resided in a competitive district and only 7,174 individuals affected by a hospital closure. Future research on the subject might be able to leverage other types of socioeconomic hardship that are more evenly distributed geographically to test how electoral competitiveness factors into voting turnout.

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