The Politics of Pain: Supplementary Materials

Michael E. Shepherd*

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*Postdoctoral Fellow, Vanderbilt University, Nashville, TN. Email: michael.e.shepherd@vanderbilt.edu.

Contents

1 Appendix 1: Descriptive Statistics

In this section, I provide descriptive statistics and plots of the data used in the manuscript. In Table 1 I provide a list of each state's Medicaid expansion status as of 2015. States that are not included in the border sample GDD are listed in red. In Table 2, I provide the means, standard devisions, minimums, and maximums for all variables used in the GDD analyses for border sample. Table 3 reports the same quantities for the red-state sample. The red state sample includes: KY, TN, AR, IA, NM, WI, AZ, TX, OK, NE, WY, UT, MI, ND, SD, KS, LA, and MS.

Table 1: Expansion Status of each Status as of 2015

Expansion States (2015)	Non-expansion States (2015)
AK, AR, AZ, CA, CO, CT, DE, HI, IA, IL, IN, KY, MA, MD, MI, MN, NH, NJ, NM, NV, NY, OH, OR, PA, RI VT, WA, WV	AL, FL, GA, ID, KS, LA, ME, MO, MT, ND, NE, OK, SC, SD, TN, TX, UT, VA, WI, WY

Notes: States not included in the border sample study are in red.

Table 2: Descriptive Statistics for the GDD Border Sample

Statistic	N	Mean	St. Dev.	Min	Max
Democratic Vote Shift (2016-2012)	1,347	−7.197	5.102	−24.290	11.790
Opioid Prescription Rate (2016)	1,273	75.432	42.897	0.000	251.600
$\Delta OpioidRate(2016-2014)$	1,267	−9.518	17.187	−189.200	107.000
Medicaid Expansion	1,348	0.464	0.499	0	1
Distance to ME Border	1,348	−3.243	53.534	−98.700	99.500
Ln Median Income	1,348	10.625	0.253	9.845	11.626
Unemployment Rate	1,348	5.412	2.923	0.000	26.449
% Less than HS	1,348	13.326	6.431	1.615	46.095

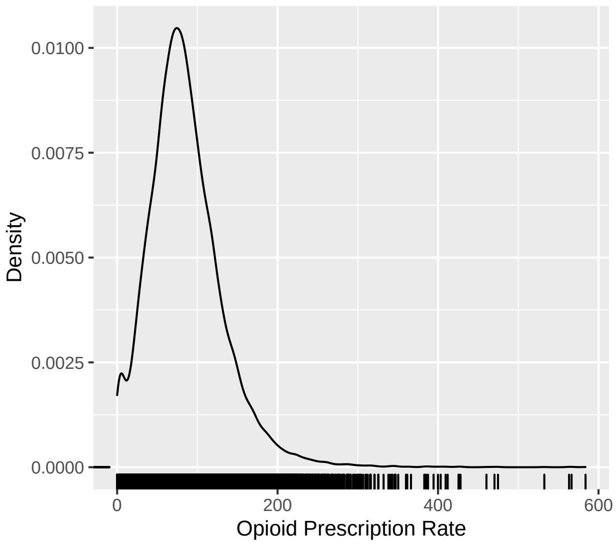


Figure 1: *Prescription Rates (2006-2016)*

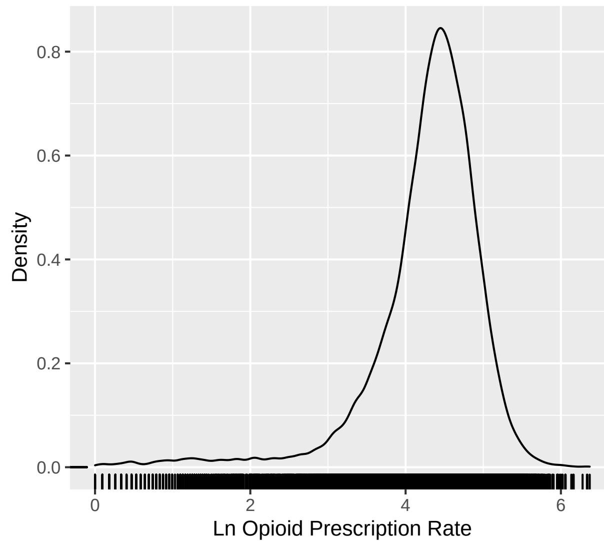


Figure 2: *log Prescription Rates (2006-2016)*

Table 3: Descriptive Statistics for GOP Expansion Border Sample

Statistic	N	Mean	St. Dev.	Min	Max
Democratic Vote Shift (2016-2012)	787	−6.971	4.877	−24.290	6.300
Opioid Prescription Rate (2016)	740	79.962	45.737	0.100	251.600
$\Delta OpioidRate(2016-2014)$	736	−8.671	16.534	−78.100	107.000
Medicaid Expansion	787	0.407	0.492	0	1
Distance to ME Border	787	−10.834	53.639	−98.700	99.300
Ln Median Income	787	10.568	0.229	9.845	11.389
Unemployment Rate	787	5.495	3.295	0.000	26.449
% Less than HS	787	14.434	7.069	2.924	46.095

Figures 1 and 2 provide density plots of the opioid prescription rate and the natural log of the opioid prescription rates from 2006-2016.

Figure 3 plots the relationship between the CDC opioid prescription rate data used in the manuscript analyses and the Washington Post's DEA Pills data for all counties in 2008 and 2012. To make the measures comparable, I transformed the WaPo Pills data to be the estimated yearly total in the county adjusted for the county's population. Thus, both the CDC prescription rate (prescriptions per 100) and WaPo pills data (pills per 1000) are population-adjusted rates. As we can see, the two variables are highly related to one another; the Pearson's correlation between the two is 0.8. Figure 4 provides a similar plot for the relationship between the CDC pills data and reports of rates drug-related deaths. These two variables are correlated at 0.5. I have opted to use the CDC data out of necessity, due to its greater available across the county and over time. The death and pills data are not available every year and not available at any point in 2015 or 2016. Given that the three variables are highly comparable, the use of one of the others is likely trivial. Figures 5 6, 7, and 8 plot the geographic dispersion of these variables.

To provide a substantive comparison between opioid prescription rates and drug/opioid-related death rates, I estimate a regression model prediction death rates as a function of opioid prescriptions. The results (presented in Table 4) of this correlational analysis imply that a two-standard deviation increase in opioid prescriptions is associated with an increase just over 5 drug-related deaths per 100,000 in the county, which is the equivalent of increasing from the minimum number of deaths per 100,000 (zero) to above the 25th percentile. The prediction of increasing opioid prescription rates from their min-to-max is 37 deaths per 100,000, above the 90th percentile in drug-related deaths.

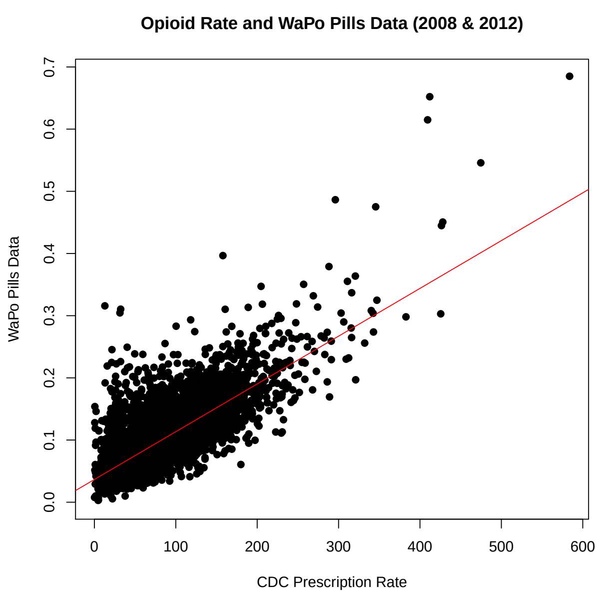


Figure 3: *CDC and Wapo Opioid Data*

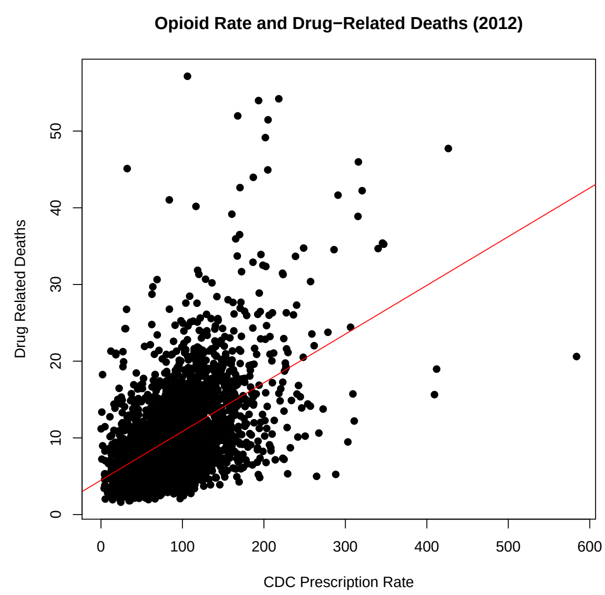
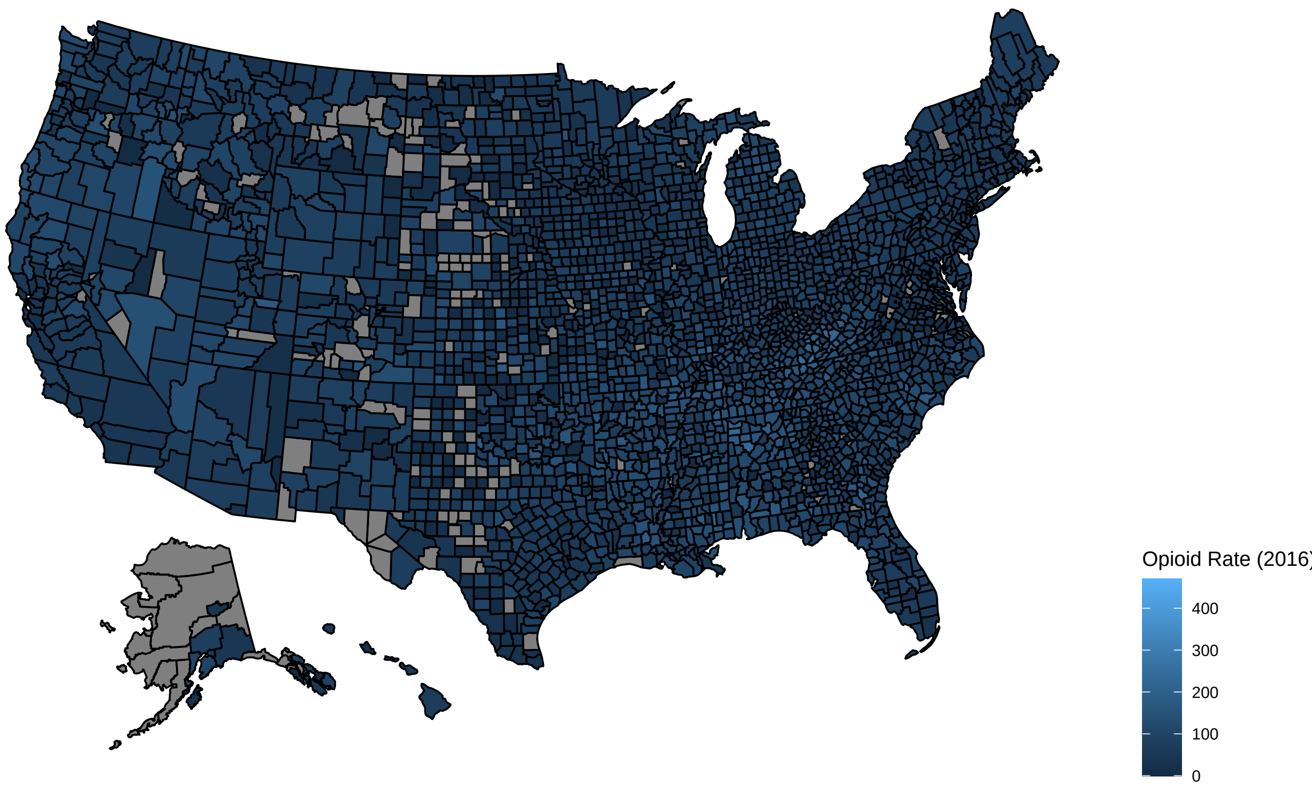


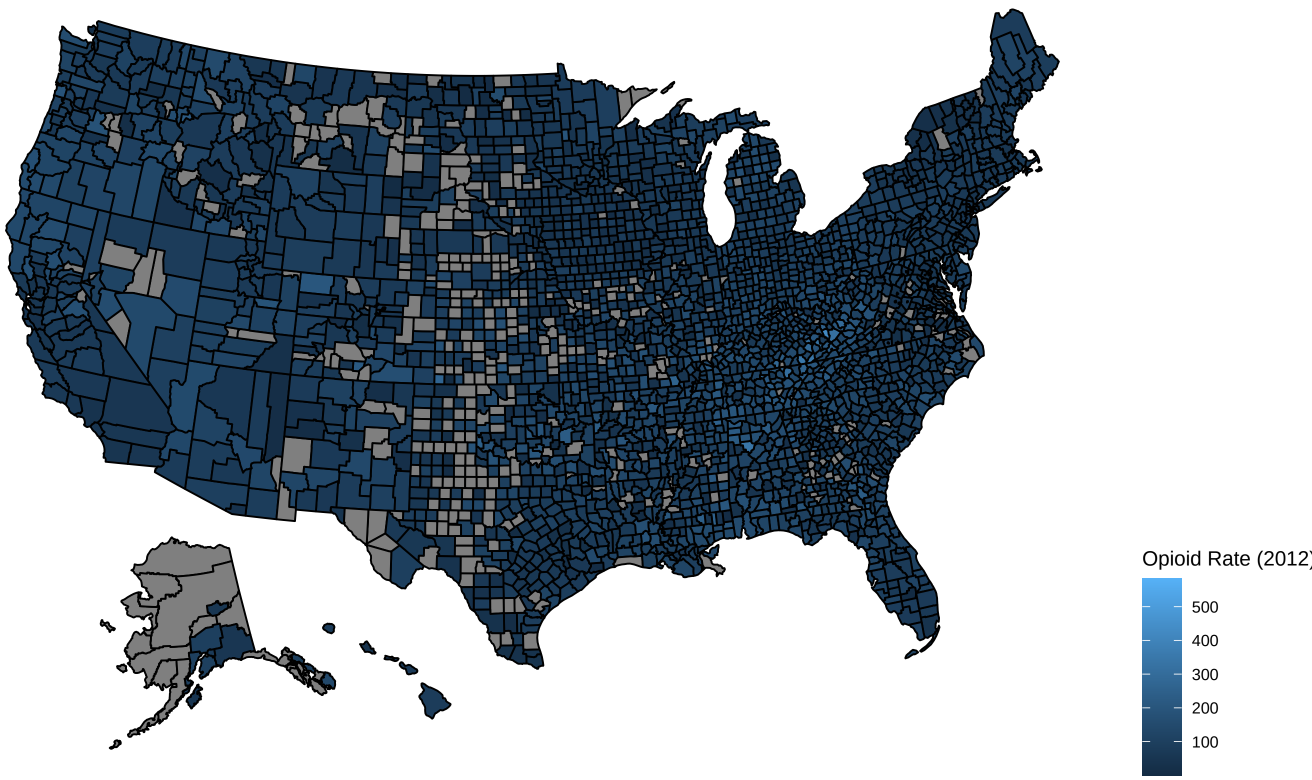
Figure 4: *CDC and Death Data*

Figure 5: County Level Opioid Prescription Rate (2016)



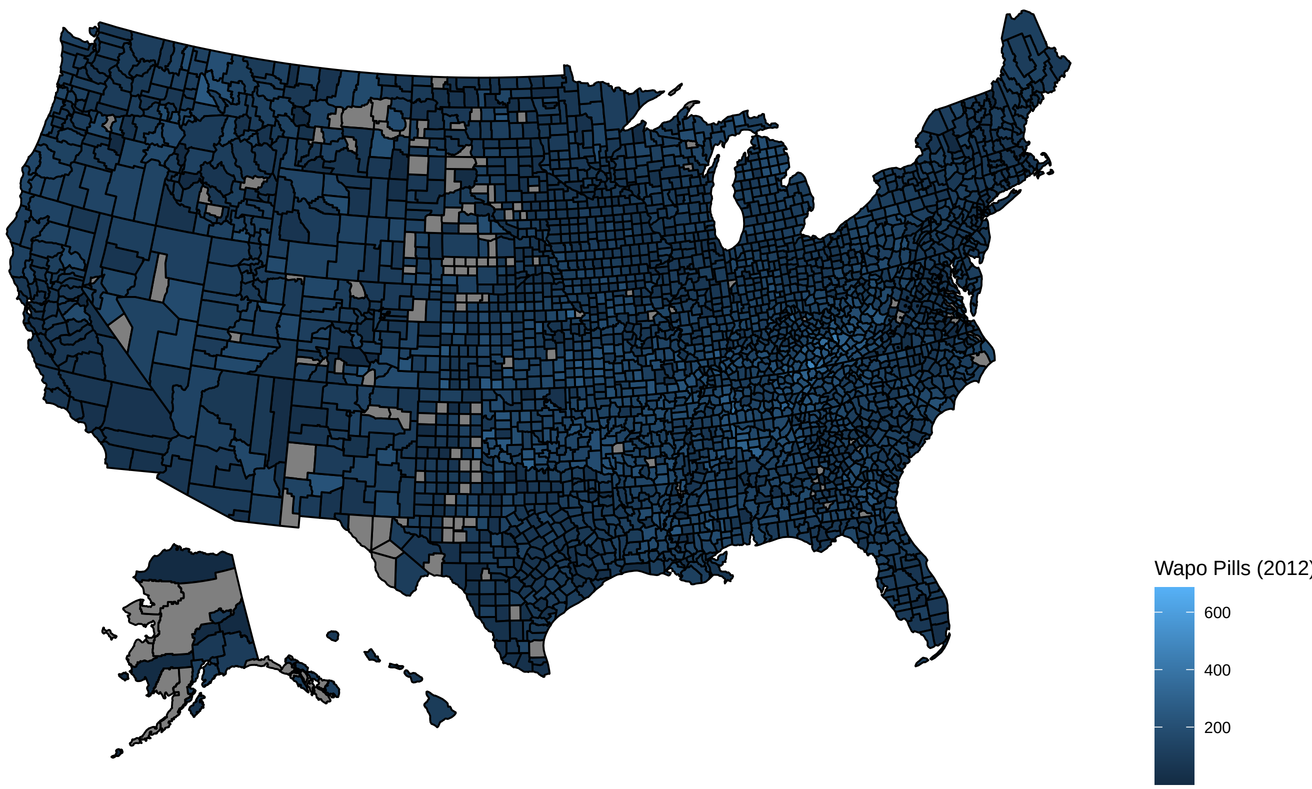
Source: Centers for Disease Control. The plot is the opioid prescription rate (prescriptions per 100) at the county level in 2016. Lighter colors indicate higher usage rates. Gray counties reflect missing data.

Figure 6: County Level Opioid Prescription Rate (2012)



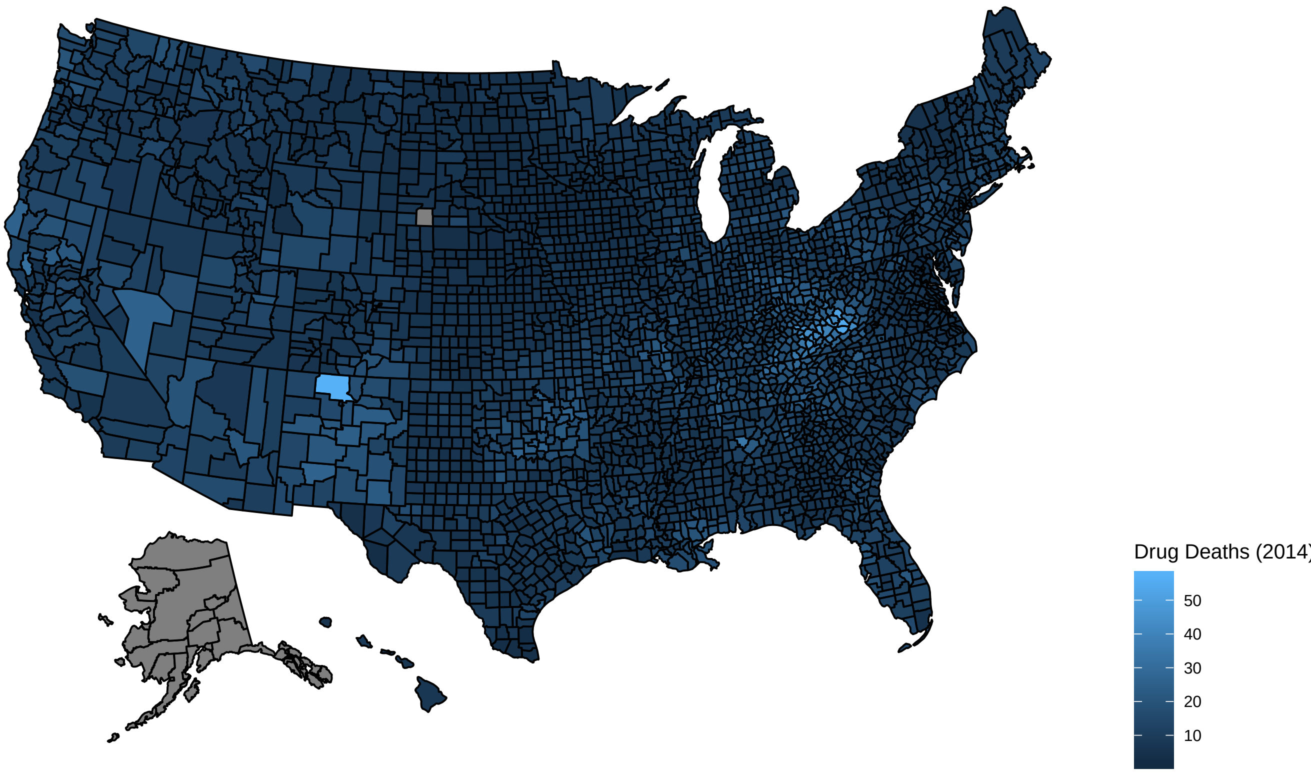
Source: Centers for Disease Control. The plot is the opioid prescription rate (prescriptions per 100) at the county level in 2012. Lighter colors indicate higher usage rates. Gray counties reflect missing data.

Figure 7: County Level WaPo Pills Rate (2012)



Source: Washington Post, DEA Pills Database. `https://www.washingtonpost.com/graphics/2019/investigations/dea-pain-pill-database/`*. The plot reflects the number of pills per 1000 at the county level in 2012. Lighter colors indicate higher usage rates. Gray counties reflect missing data.*

Figure 8: Drug Related Deaths (2014)



Source: Centers for Disease Control. The plot reflects the number of drug related deaths, population adjusted, at the county level in 2014. Lighter colors indicate higher usage rates. Gray counties reflect missing data.

Table 4: Implied Substantive Relationship between Prescriptions and Deaths

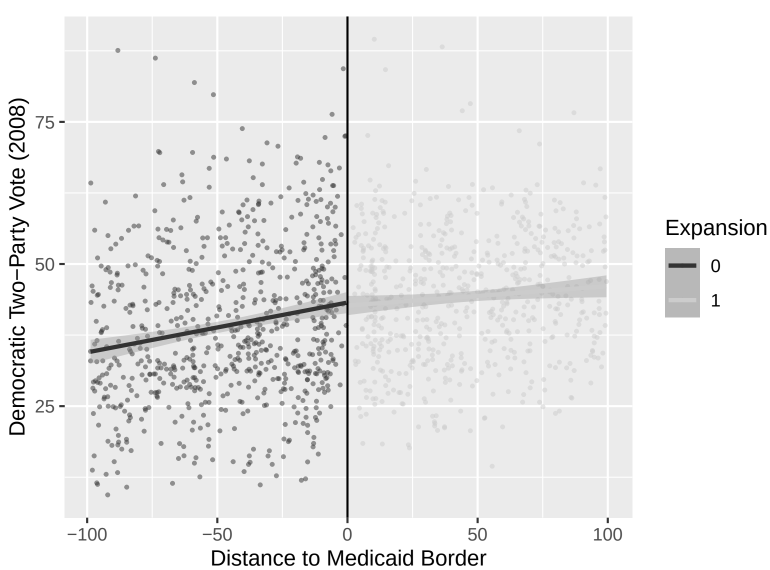
	Dependent variable:
	Drug-related Mortality Rate (2014)
Opioid Rate (2016)	0.064***
	(0.002)
Constant	4.479***
	(0.214)
Observations	2,735
R^2	0.262
Adjusted R^2	0.262
Note:	*p<0.1; **p<0.05; ***p<0.01

2 Appendix 2: Research Design Assumption Tests

Here, I provide graphical evidence in support of the major required identification strategies used within the main text. Figure 9 plots the Democratic Two Party vote share (2008) as a function of distance to the Medicaid expansion border. We should not observe a jump at the Medicaid expansion border in support for the Democratic party in 2008, prior to the Medicaid expansion onset. Indeed, we see that at the Medicaid border, the relationship was flat and there was no discontinuous jump. This placebo test reassures us that there were no differences in voting prior to the actual treatment.

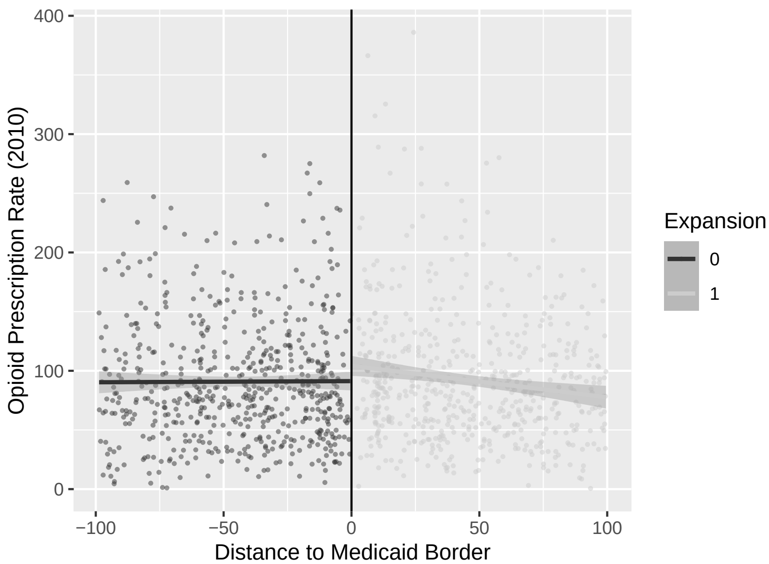
Figure 10 provides a similar plot for the opioid prescription rate in 2010, prior to the onset of Medicaid expansion and the ACA. Although there does appear to a slight jump at the border, this jump is not statistically significant and substantively negligible. Accordingly, the resulting differences we observe in opioid outcomes between the two groups of counties are likely due to Medicaid expansion.

Figure 9: Evidence of Pre-Treatment Discontinuity?



Note: This figure plots the relationship between 2008 Democratic two-party vote share and distance to the Medicaid expansion border. The plot shows that there was no pre-treatment difference between expansion and non-expansion units.

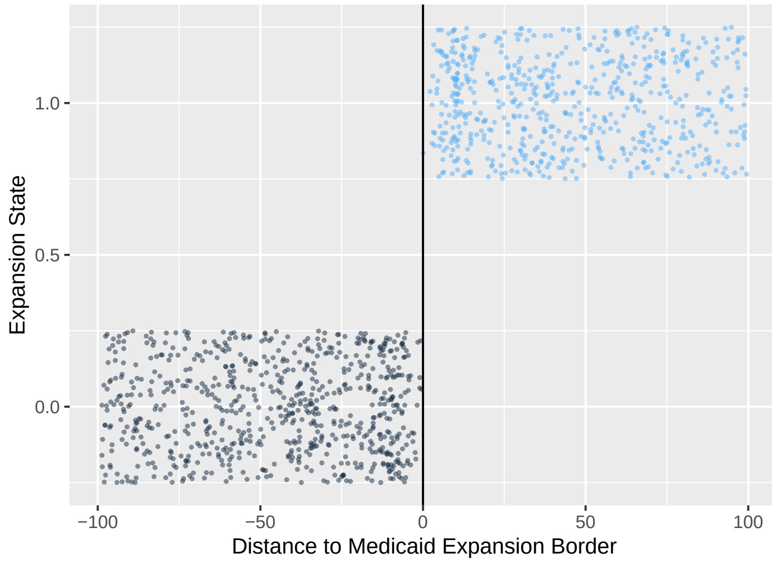
Figure 10: Evidence of Pre-Treatment Discontinuity?



Note: This figure plots the relationship between 2010 opioid prescription rates and distance to the Medicaid expansion border. The plot shows that there was no pre-treatment difference between expansion and non-expansion units.

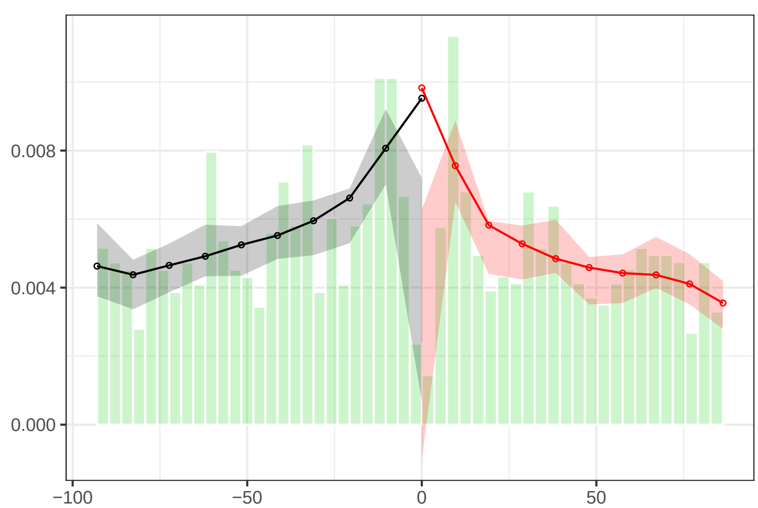
Figure 11 confirms that this GDD is indeed a sharp discontinuity. Obviously, counties cannot control whether or not they are exposed to Medicaid. This plot simply shows that the data conform to those expectations. Figure 12 plots the distribution of counties across the running variable (distance to the Medicaid expansion border). The number of counties is distributed normally across the range of the running variable, with fewer and fewer cases near the 100 mile points. The drop near the cutpoint is simply an artifact of using the county centroid to measure the distance. No county centroids are zero miles from a Medicaid expansion border.

Figure 11: Distance to Border as Sharp Discontinuity



Note: This figure plots evidence that the state borders provide a sharp discontinuity. All units in expansion states were treated and vice versa for the control units.

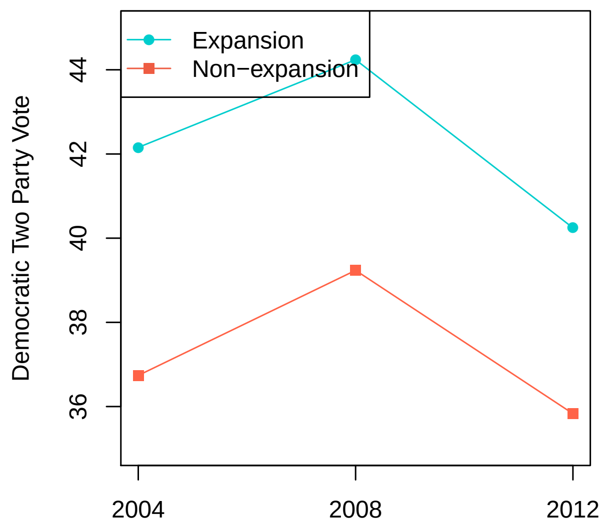
Figure 12: Distribution of Counties across Running Variable



Note: This figure plots the distribution of cases as a function of the running variable (distance to the border). The plot demonstrates that cases are normally distributes across distances to the border.

Figure 13 provides the parallel trends in Democratic two party vote share for treated and control units for the the GDD border sample. As we can see, the two groups trended together before the expansion of Medicaid. After, the non-expansion units become even less Democratic than their expansion peers.

Figure 13: Pre-treatment Parallel Trends in Democratic Vote Share



Note: This figure plots the parallel trends in the Democratic Party's share of the two party vote from 2004-2008. Expansion and non-expansion units trended similarly prior to treatment.

Table 5 provides balance statistics for Expansion and Non-expansion counties for the border sample, as well as their difference of means (with significance for t-test reported). Expansion counties were slightly more Democratic and white. However, both of these differences are no longer statistically significant once distance to the border is accounted for. This result indicates, as we may expect, that counties further from the border are less similar to each other than ones nearer to the border.

Table 5: Balance Between Expansion and Non-Expansion Counties

Statistic	Exp.	Exp SD	Non-Exp.	Non-Exp SD	Diff
Democratic Two Party Vote Share (2012)	40.24	12.294	35.83	14.457	4.41*
Opioid Prescription Rate (2012)	91.86	54.954	90.36	51.671	1.50
Percent Poverty	0.15	0.066	0.15	0.064	-0.00
Percent 65+	0.16	0.040	0.16	0.039	-0.00
Percent White	0.90	0.119	0.84	0.168	0.06*
Ln Median Income	10.62	0.264	10.62	0.243	0.01

Medicaid or Opioid Sorting?

Here, I probe the threat to inference posed by individuals moving or sorting into counties based on their Medicaid expansion status or opioid rate. As Clinton and Sances (2018) and Schwartz and Sommers (2014) suggest that this not likely an issue. Here, I further investigate whether opioid prescription rates or Medicaid expansion predict out migration. I use changes in a counties opioid prescription usage during the period (separately I also use the opioid prescription rate) and expansion status as the independent variables. The dependent variable is change in out-migration from 2013 to 2015. In Table 6 we see no relationship between the severity of the opioid rate or Medicaid expansion status and changes in out migration.

Table 6: Impact of Medicaid Expansion on Migration

	Dependent variable:	
	Δ Outmigration	
	(1)	(2)
$\Delta OpioidRate$	0.236	
	(0.158)	
Opioid Rate (2012)		0.080
		(0.052)
Medicaid Expansion	12.666	15.173
	(10.273)	(10.450)
Distance to Border	−11.313	-22.677^{***}
	(7.191)	(8.671)
Observations	1,267	1,179
R^2	0.011	0.011
Adjusted R^2	0.008	0.007
Note:	*p<0.1; **p<0.05; ***p<0.01	

3 Appendix 3: Voter Study Group and Opioid Severity

In this section, I examine the extent to which survey-based measures of individual knowledge of someone who is addicted to painkillers, alcohol, and drugs are related to objective measures of the opioid epidemic. Sides, Tesler and Vavreck (2018) use these items to assess the impact of the opioid epidemic, finding null results. Here, I show that these survey based measures do not reliably measure opioid epidemic severity.

Table 7: Personal Knowledge and Community Opioid Severity (VSG)

	Dependent variable:					
	Painkillers	Alcohol	Drugs	Painkillers	Alcohol	Drugs
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta OpioidRate$	-0.003^{***}	-0.002^{***}	-0.001^{**}			
	(0.001)	(0.001)	(0.001)			
Opioid Rate				0.002^{***}	0.0001	0.0003
				(0.0002)	(0.0002)	(0.0002)
Constant	0.263^{***}	0.513^{***}	0.362^{***}	0.174^{***}	0.524^{***}	0.353^{***}
	(0.007)	(0.008)	(0.008)	(0.013)	(0.015)	(0.014)
Observations	7,740	7,809	7,764	7,740	7,809	7,764
R^2	0.003	0.001	0.001	0.011	0.00004	0.0003
Adjusted R^2	0.003	0.001	0.0004	0.011	-0.0001	0.0002

Note: $^{**}p<0.05$; $^{***}p<0.01$

4 Appendix 4: Impact of ME on Opioids

In this section, I report regression estimates for the impact of Medicaid expansion on changes in opioid prescription rates from 2014 to 2016. I do this parametrically and non-parametrically. I report the full parametric regression results of the effects of Medicaid expansion on the opioid epidemic in Table 8. Specifically, I estimate a GDD model where Y_i, the change in the opioid prescription rate after Medicaid expansion (2016-2014), is regressed on an indicator for whether a county expanded Medicaid, the county's distance in miles to the nearest state border with a different expansion status (the running variable), and an interaction between the two. I estimate this model solely on counties within 100 miles of the nearest border. We see that Medicaid expansion reduced the severity of the opioid epidemic by an estimated 3.5 prescriptions per 100 people in the OLS model.

Table 8: GDD: Effect of Medicaid Expansion on Opioid Prescriptions

	Dependent variable:
	Δ Opioid Rate
Medicaid Expansion	-3.220^{*}
	(1.822)
Distance to Border	0.006
	(0.024)
Medicaid Expansion*Distance to Border	0.013
	(0.034)
Constant	-8.249^{***}
	(1.256)
Observations	1,267
R^2	0.004
Adjusted R^2	0.002
Note:	*p<0.1; **p<0.05; ***p<0.01

I gather non-parametric estimates of the effect of Medicaid expansion on the opioid epidemic using the "rdrobust" package in R. The package used a mserd bandwidth type and a triangular kernel. The optimal bandwidth selected by the package was 20.9 miles from the expansion border. These results are presented in Table 9. I present the conventional rdrobust estimate as well as the bias-corrected and robust estimates of the effects. All three non-parametric estimates correctly signed and statistically significant. Moreover, the nnon-parametric estimates are actually quite a bit larger, implying that Medicaid expansion reduced opioid usage by roughly 12 prescriptions per person.

Table 9: Non-Parametric RD Estimates of Effect of Medicaid Expansion on Opioid Usage

	Dependent variable:
	Δ Opioid Rate
Conventional	-11.569^{***}
	(5.238)
Bias-corrected	-12.167^{***}
	(5.238)
Robust	-12.167^{**}
	(6.339)
Note:	*p$<$0.1; **p$<$0.05; ***p$<$0.01

Nearly 20% of the sample experienced increases in opioid usage between 2014 and 2016. Arkansas, Colorado, Idaho, Illinois, Iowa, Kansas, Kentucky, Louisiana, Minnesota, Mississippi, Missouri, Montana, Nebraska, North Dakota, Oklahoma, Oregon, South Dakota, Tennessee, Texas, Utah, Virginia, West Virginia, and Wisconsin had counties that experienced increased in opioid usage. Most of these counties are in states that did not expand Medicaid.

5 Appendix 5: ME on Opioids Expansion Placebo Test

Here, I probe whether the Medicaid expansion effects on the opioid epidemic were driven by pre-treatment differences. Specifically, I conduct a placebo test to see if we observe similar expansion "effects" prior to the onset of Medicaid expansion, when logically we should observe no difference. In Table 10 I replicate the model from Table 8 in A4. However, this time I use change in the opioid rate from 2006 to 2008 (prior to Medicaid expansion) as the dependent variable. The results of the model show that there was no statistically significant relationship between a states future Medicaid expansion status and changes in its opioid rate from 2006 to 2008. If anything, unlike after expansion, Medicaid expansion counties experiences slightly greater increases in opioid usage, though estimate is not statistically significant.

Table 10: Placebo Test: Pre-treatment Changes in Opioid Rates in Expansion States?

	Dependent variable:
	Δ Opioid Rate (08-06)
Medicaid Expansion	2.453
	(2.221)
Distance to Border	0.014
	(0.030)
Medicaid Expansion*Distance to Border	−0.036
	(0.042)
Constant	7.729***
	(1.541)
Observations	1,170
R^2	0.003
Adjusted R^2	0.001
Note:	*p<0.1; **p<0.05; ***p<0.01

6 Appendix 6: Main Election Results

In this section, I provide full regression tables for the main regression results from the GDD in Table 11 and replicate these results dropping the polynomial terms (presented alongside the original models for ease of comparison) in Table 12. The original analyses are nearly identical when dropping the polynomial terms from the GDD regression.

Table 11: Effects of Opioid Epidemic and Medicaid Expansion on Voting Behavior

	Dependent variable:				
	Δ Democratic Two Party Vote (2016-2012)				
	(1)	(2)	(3)	(4)	(5)
Opioid Increase	−4.475***				
	(0.627)				
Opioid Rate (2016)		−0.049***	−0.028***		
		(0.009)	(0.009)		
log(Opioid Rate)				−1.035**	−0.589
				(0.492)	(0.397)
Medicaid Expansion	3.136*	6.684***	11.320***	10.555**	17.911***
	(1.719)	(2.306)	(2.284)	(4.752)	(4.208)
Opioid Increase*Expansion	−0.701				
	(1.242)				
Opioid Rate*Expansion		−0.009	−0.023*		
		(0.014)	(0.013)		
log(Opioid Rate)*Expansion				−1.549*	−2.171***
				(0.911)	(0.811)
Dem. Vote (2004)	0.151***	0.123***		0.138***	
	(0.025)	(0.025)		(0.025)	
log(Median Income)			12.178***		13.059***
			(1.261)		(1.238)
Unemployment Rate			0.685***		0.704***
			(0.146)		(0.150)
% Less than H.S.			−0.100*		−0.101*
			(0.057)		(0.058)
Constant	−10.392***	−6.416***	−138.083***	−5.675**	−147.088***
	(1.484)	(1.664)	(14.521)	(2.713)	(14.684)
State Fixed Effects	✓	✓	✓	✓	✓
Polynomial Terms	✓	✓		✓	
Population Weights	✓	✓	✓	✓	✓
Observations	1,266	1,272	1,272	1,272	1,272
R^2	0.379	0.406	0.521	0.370	0.510
Adjusted R^2	0.360	0.388	0.506	0.351	0.494
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 12: GDD Dropping Polynomial Terms

	Dependent variable:			
	(1)	(2)	(3)	(4)
Opioid Rate (2016)	−0.049***	−0.048***		
	(0.009)	(0.009)		
log(Opioid Rate)			−1.035**	−0.992**
			(0.492)	(0.504)
Medicaid Expansion	6.684***	6.205***	10.555**	10.321**
	(2.306)	(2.020)	(4.752)	(4.557)
Lagged Democratic Vote (2004)	0.123***	0.122***	0.138***	0.137***
	(0.025)	(0.025)	(0.025)	(0.025)
Opioid Rate*Expansion	−0.009	−0.010		
	(0.014)	(0.014)		
log(OpioidRate)*Expansion			−1.549*	−1.589*
			(0.911)	(0.912)
Constant	−6.416***	−6.038***	−5.675**	−5.558**
	(1.664)	(1.492)	(2.713)	(2.624)
State Fixed Effects	✓	✓	✓	✓
Polynomial Terms	✓		✓	
Population Weights	✓	✓	✓	✓
Note:			*p<0.1; **p<0.05; ***p<0.01	

7 Appendix 7: Election Robustness Tests

In this section, I subject the main regression analysis to a series of robustness checks. Specifically, I probe whether findings are robust to including other rival explanatory factors. Across the models, the results remain qualitatively similar, further suggesting that the main effects are not spurious.

For example, we may worry that the effects of the opioid epidemic are driven be other general health effects. In Table 13 I probe this by re-estimating the main GRD model from the main text, this time controlling for changes in a county's diabetes rates. As can be seen, controlling for the changes in a county's diabetes rates does not substantively alter the opioid findings.

Table 13: Effects of Opioid Epidemic Controlling for Other Health Effects

	Dependent variable:
	Δ Democratic Two Party Vote
Opioid Rate (2016)	-0.049^{***}
	(0.007)
Medicaid Expansion	6.680^{***}
	(2.586)
Democratic Vote (2004)	0.122^{***}
	(0.012)
Δ Diabetes Rate	0.062
	(0.067)
Opioid Rate*Medicaid Expansion	-0.009
	(0.010)
Constant	-6.316^{***}
	(2.375)
State Fixed Effects	✓
Polynomial Terms	✓
Observations	1,272
R^2	0.407
Adjusted R^2	0.388
Note:	*p<0.1; **p<0.05; ***p<0.01

In Table14 I assess the extent to which the uncovered opioid results are robust to accounting for the positive financial effects of the ACA/Medicaid expansion. Finkelstein et al. (2012)

found positive financial effects in addition to physical and mental health gains. Specifically, I control for the changes local health insurance rates. In Table 14 we see that controlling for these financial effects do not substantively alter the estimate effects of the opioid epidemic or Medicaid expansion on changes in Democratic voting. Changes in health insurance rates are positively related to Democratic support, though curiously somewhat less so in expansion states.

Table 14: Effects of Opioid Epidemic Controlling for Financial Effects of ACA

	Dependent variable:
	Δ Democratic Two Party Vote
Opioid Rate (2016)	-0.044^{***}
	(0.007)
Medicaid Expansion	7.070^{***}
	(3.228)
Democratic Vote (2004)	0.129^{***}
	(0.012)
Δ Pct. Insured	0.445^{***}
	(0.080))
Opioid Rate*Medicaid Expansion	-0.002
	(0.036)
Constant	-9.480^{***}
	(2.418)
State Fixed Effects	✓
Polynomial Terms	✓
Observations	1,272
R^2	0.419
Adjusted R^2	0.401
Note:	*p<0.1; **p<0.05; ***p<0.01

We may worry that some of what appears to be effects of the opioid epidemic is actually something related to opioid usage. Some have argued that areas with a lot of coal mining or coal workers are more likely to suffer negative fates via the opioid epidemic (Case and Deaton, 2020). To probe whether this affects my results, I drop West Virginia and Kentucky (the two highest coal producing states) from my analyses. I present the results from this analyses is Table 15. If anything, dropping these states strengthens the results.

Table 15: Effects of Opioids Dropping Coal States

	Dependent variable:
	Δ Democratic Two Party Vote
Opioid Rate (2016)	−0.049***
	(0.007)
Medicaid Expansion	8.824***
	(2.712)
Democratic Vote (2004)	0.117***
	(0.013)
Opioid Rate*Medicaid Expansion	−0.028**
	(0.011)
Constant	−6.127**
	(2.428)
State Fixed Effects	✓
Polynomial Terms	✓
Observations	1,125
R^2	0.407
Adjusted R^2	0.387
Note:	*p<0.1; **p<0.05; ***p<0.01

Next, I probe the robustness of the main results dropping all counties that rank in the bottom 10% of opioid epidemic severity (less than 24.6) and top 10% (greater than 129.9). Results for this analyses are presented in Table 16. As can be seen, the results are qualitatively similar.

Table 16: GDD Results Dropping Bottom and Top 10% of Opioid Observations

	Dependent variable:
	Δ Democratic Two Party Vote
Opioid Rate (2016)	-0.049^{***}
	(0.007)
Medicaid Expansion	6.684^{***}
	(2.586)
Democratic Vote (2004)	0.123^{***}
	(0.012)
Opioid Rate*Medicaid Expansion	-0.009
	(0.010)
Constant	-6.416^{***}
	(2.373)
State Fixed Effects	✓
Polynomial Terms	✓
Observations	1,272
R^2	0.406
Adjusted R^2	0.388
Note:	*p<0.1; **p<0.05; ***p<0.01

In Table 17 I explore whether the effects of Medicaid and the opioid epidemic varied based on the political control. of the states. To do so, I subset the original data into states that had Republican governors and Republican-controlled state legislatures during the 2016 election and compare the unconditional effects of Medicaid expansion and the opioid epidemic on changes in the Democratic Two Party share of the vote from 2012 to 2016. Specifically, I replicate the original models used in the main analyses, dropping the interaction between opioids and Medicaid expansion (results presented in column 2).[1] I provide the same estimates using the full GDD border sample in the first column for comparison.

First, the relationships between the opioid epidemic and Medicaid expansion on change in the Democratic vote are qualitative similarly between the models. The effect of Medicaid expansion on change in the Democratic vote is roughly 1 percentage point smaller in the GOP controlled states than in the full sample, perhaps suggesting that voters were more easily engage in this type of policy feedback when the partisan-alignment of the state government

[1]The main analyses showed essentially no-conditional relationship and the reduction in power from the drop sample size both suggest this is a wise decision.

matched the incumbent federal Democratic Party. Interestingly, the effects of the opioid epidemic, although still substantively and statistically significant, are about half as large in magnitude in the GOP-controlled sample as in the full sample.

Why aren't the differences larger? Part of this is no doubt driven by the construction of the original border sample. Recall, most of the heavily Democratic states in the Northeast and California are excluded from the analyses because they do not border states with different Medicaid expansion statuses. More theoretically, this is consistent with prior research that has shown that voters tend to blame the president for more local experiences.

Table 17: Heterogenous Effects of Medicaid and Opioid Effects, Full and GOP Samples

	Dependent variable:	
	Δ Dem Vote (Full)	Δ Dem Vote (GOP)
Opioid Rate (2016)	-0.053^{***}	-0.026^{***}
	(0.007)	(0.008)
Medicaid Expansion	5.891^{***}	4.995^{***}
	(1.650)	(1.909)
Democratic Two Party Vote (2004)	0.124^{***}	0.079^{***}
	(0.025)	(0.040)
Constant	-6.216^{***}	-7.248^{***}
	(1.635)	(2.125)
Observations	1,272	740
R^2	0.406	0.352
Adjusted R^2	0.388	0.332
Note: clustered errors reported	*p<0.1; **p<0.05; ***p<0.01	

8 Appendix 8: Individual Election Results

In this section, I extend the county-level election analyses to probe the extent to which the county level opioid measures reliably predict individual level behavior. We may be worried that the aggregate results are driven by an ecological fallacy. In Table 18 I use survey data from the Voter Study Group Study (Sides, Tesler and Vavreck, 2018) to assess the extent to which individual-level vote choice relates to the local opioid epidemic conditions. Specifically, I estimate a linear probability model of the probability of voting for Hillary Clinton over Donald Trump as a function of the respondents' local opioid rate, partisanship, educational level, race, income, gender, and state fixed effects. All observations are weighted according to provided survey weights and clustered standard errors are reported.

In Column 1 of Table 18, we see that as local opioid rates are worse, an individual's probability of voting for Hillary Clinton decreases. The model implies that a one standard-deviation increase in opioid usage (27 prescriptions per 100 people) in a respondents' community decreases their probability of voting for Hillary Clinton by 3 percentage points.

Table 18: Individual-Level Regression Results (Voter Study Group)

	Dependent variable:		
	Pr(Clinton)		
	(1)	(2)	(3)
Opioid Rate (2016)	-0.001^{**}	-0.001^{**}	-0.0003
	(0.0002)	(0.0002)	(0.0003)
Health Care Important Now		0.098	
		(0.091)	
Know Someone Addicted			0.063
			(0.040)
Republican	-0.341^{***}	-0.343^{***}	-0.343^{***}
	(0.033)	(0.033)	(0.034)
Democrat	0.502^{***}	0.510^{***}	0.499^{***}
	(0.034)	(0.035)	(0.035)
Education Level	0.021^{***}	0.020^{***}	0.020^{***}
	(0.005)	(0.005)	(0.005)
Non-white	0.064^{***}	0.053^{***}	0.065^{***}
	(0.019)	(0.018)	(0.019)
Family Income	-0.001	-0.0004	-0.001
	(0.002)	(0.002)	(0.002)
Female	0.059^{***}	0.049^{***}	0.058^{***}
	(0.015)	(0.015)	(0.015)
Opioid Rate*Health Important Now		-0.002^{**}	
		(0.001)	
Opioid Rate*Know Someone Addicted			-0.001^{*}
			(0.001)
Constant	0.321^{***}	0.319^{***}	0.307^{***}
	(0.087)	(0.088)	(0.091)
State Fixed Effects	✓	✓	✓
Note: clustered errors reported			*p<0.1; **p<0.05; ***p<0.01

In Column 2, I extend these analyses by probing a potential mechanism: health care importance. Specifically, I assess whether the effects of the opioid epidemic are larger for individuals who report health care as being important to them in 2016, but not in 2012. Again, drawing on Hopkins (2010), I have argued that these effects are likely to be observed in 2016 and not 2012 due to the new salience of the issue. As a result, we ought to expect larger effects for people who report new concern about health care. As the results of Column 2 Table 18 show, this is indeed the case. The results of the model imply that the effects of the opioid epidemic are nearly 400% larger for these individuals and suggest that a one standard deviation increase in the opioid epidemic decreases respondents' with newly found health care concerns probability of voting for Hillary Clinton by 8 percentage points.

In Column 3, I probe another potential mechanism: personal knowledge of someone addicted to opioids. Using the survey item from Sides, Tesler and Vavreck (2018) on personal knowledge of someone addicted to painkillers, I assess whether respondents with personal knowledge of a painkiller addict in areas where the opioid epidemic is more severe are less likely to vote for Hillary Clinton. Others have found that personal knowledge of an opioid overdose victim can affect political behavior (Kaufman and Hersh, 2020). The results imply that individuals in places with high opioid usage rates and personal knowledge of a painkiller addicted were much less likely to vote Hillary Clinton. A one standard deviation increase in the severity of the opioid epidemic is associated with a 3 percentage decrease in the probability of voting for Hillary Clinton.

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