

# Replication of Green & Vasudevan

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# Overview

- Theory
- Design
- Replication of main results
- Robustness to other coding of vote buying
- Heterogeneous effects

# Theory

brief discussion of theory

# Design

Intervention:

Does this really test the theory that you've laid out?

# Suggestions for replication package

- Code written in Matlab + Stata
  - Randomization - Stata
  - Data Building - Stata
  - Regressions - Matlab
  - Standard Errors - Matlab
  - Randomization Inference Simulations - Stata
  - p-values - Matlab
- Possible to do everything in R
- Include a roadmap (master R file, markdown, etc)

# Main results from the paper

**Table 6: Average Treatment Effect (ATE) of receiving radio ads on vote-share of vote-buying parties and on the voter turnout rate**

	Vote-share of vote-buying parties (%)						Turnout rate (%)	
	Specification 1 <sup>5</sup>		Specification 2		Specification 3			
	IPW	FE	IPW	FE	IPW	FE	IPW	FE
ATE <sup>1</sup>	-5.86	-6.04	-7.68	-7.73	-3.68	-3.41	-0.49	-0.61
SE <sup>2</sup>	3.97	4.08	3.92	4.18	1.92	2.04	0.96	0.99
p-value <sup>3</sup>	0.08	0.08	0.00	0.00	0.02	0.03	0.64	0.57
R-squared	0.44	0.43	0.38	0.28	0.51	0.33	0.80	0.76
Mean <sup>4</sup> (Control)	67.23		90.85		91.73		68.45	
N	628		665		665		665	
Control	315		324		324		324	
Treatment	313		341		341		341	

All specifications have the lagged outcome variable as covariate.

<sup>1</sup>IPW are inverse probability weighted and FE are fixed effects regression estimates respectively.

<sup>2</sup>Standard errors are robust to heteroskedasticity and known cross-sectional dependence of the error term.

<sup>3</sup>p-values obtained from randomization inference with 10,000 iterations.

<sup>4</sup>Control Means are inverse probability weighted.

<sup>5</sup>Responses identifying vote-buying parties for 37 ACs are missing.

# Correcting standard errors

Imagine a scenario of 3 clusters with 2 units each.

Table : Constant error variance

	$e_{11}$	$e_{12}$	$e_{21}$	$e_{22}$	$e_{31}$	$e_{32}$
$e_{11}$	$\sigma^2$	0	0	0	0	0
$e_{12}$	0	$\sigma^2$	0	0	0	0
$e_{21}$	0	0	$\sigma^2$	0	0	0
$e_{22}$	0	0	0	$\sigma^2$	0	0
$e_{31}$	0	0	0	0	$\sigma^2$	0
$e_{32}$	0	0	0	0	0	$\sigma^2$

Table : Not-constant error  $\Sigma$

	$e_{11}$	$e_{12}$	$e_{21}$	$e_{22}$	$e_{31}$	$e_{32}$
$e_{11}$	$\sigma_{11}^2$	0	0	0	0	0
$e_{12}$	0	$\sigma_{12}^2$	0	0	0	0
$e_{21}$	0	0	$\sigma_{21}^2$	0	0	0
$e_{22}$	0	0	0	$\sigma_{22}^2$	0	0
$e_{31}$	0	0	0	0	$\sigma_{31}^2$	0
$e_{32}$	0	0	0	0	0	$\sigma_{32}^2$

$$\text{Var}(\hat{\beta}) = (X'X)^{-1}(X'\Sigma X)(X'X)^{-1}$$

Huber-White “Robust” SEs estimate  $\hat{\Sigma}$  where  $\sigma_i^2$  is  $\hat{u}_i^2$

But, still assumes no clustered or spatial correlation

# Correcting standard errors

Imagine a scenario of 3 clusters with 2 units each.

Cluster-robust “block diagonal”

Table : Cluster robust

	$e_{11}$	$e_{12}$	$e_{21}$	$e_{22}$	$e_{31}$	$e_{32}$
$e_{11}$	$\sigma_{11}^2$	$\sigma_{11}\sigma_{12}$	0	0	0	0
$e_{12}$	$\sigma_{12}\sigma_{11}$	$\sigma_{12}^2$	0	0	0	0
$e_{21}$	0	0	$\sigma_{21}^2$	$\sigma_{21}\sigma_{22}$	0	0
$e_{22}$	0	0	$\sigma_{22}\sigma_{21}$	$\sigma_{22}^2$	0	0
$e_{31}$	0	0	0	0	$\sigma_{31}^2$	$\sigma_{31}\sigma_{32}$
$e_{32}$	0	0	0	0	$\sigma_{32}\sigma_{31}$	$\sigma_{32}^2$



## Correcting standard errors

Imagine a scenario of 3 clusters with 2 units each,  
but Station 1 covers 11, 12, 21; Station 2 covers cluster 2;  
Station 3 covers cluster 3.

Table : Barrios Dependency Matrix

	$e_{11}$	$e_{12}$	$e_{21}$	$e_{22}$	$e_{31}$	$e_{32}$
$e_{11}$	1	1	1	0	0	0
$e_{12}$	1	1	1	0	0	0
$e_{21}$	1	1	1	1	0	0
$e_{22}$	0	0	1	1	0	0
$e_{31}$	0	0	0	0	1	1
$e_{32}$	0	0	0	0	1	1

Multiply this matrix element-by-element with  $\hat{u}\hat{u}'$

## Correcting standard errors

Imagine a scenario of 3 clusters with 2 units each,  
but Station 1 covers 11, 12, 21; Station 2 covers cluster 2;  
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Table : Barrios  $\hat{\Sigma}$

	$e_{11}$	$e_{12}$	$e_{21}$	$e_{22}$	$e_{31}$	$e_{32}$
$e_{11}$	$\sigma_{11}^2$	$\sigma_{11}\sigma_{12}$	$\sigma_{11}\sigma_{21}$	0	0	0
$e_{12}$	$\sigma_{12}\sigma_{11}$	$\sigma_{12}^2$	$\sigma_{12}\sigma_{21}$	0	0	0
$e_{21}$	$\sigma_{21}\sigma_{11}$	$\sigma_{21}\sigma_{12}$	$\sigma_{21}^2$	$\sigma_{21}\sigma_{22}$	0	0
$e_{22}$	0	0	$\sigma_{22}\sigma_{21}$	$\sigma_{22}^2$	0	0
$e_{31}$	0	0	0	0	$\sigma_{31}^2$	$\sigma_{31}\sigma_{32}$
$e_{32}$	0	0	0	0	$\sigma_{32}\sigma_{31}$	$\sigma_{32}^2$

$$\text{Var}(\hat{\beta}) = (X'X)^{-1}(X'\hat{\Sigma}X)(X'X)^{-1}$$

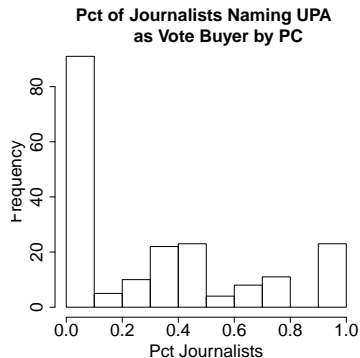
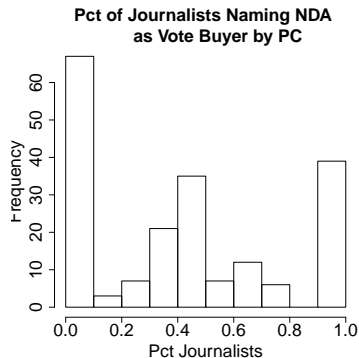
## Main results from the paper

	Spec 1		Spec 2		Spec 3	
	IPW	FE	IPW	FE	IPW	FE
ATE	-5.86	-6.04	-7.68	-7.73	-3.68	-3.41
SE	3.97	4.08	3.92	4.18	1.92	2.04
p-value (Barrios)	0.07	0.07	0.03	0.03	0.03	0.05
p-value (RI)	0.08	0.08	0.00	0.00	0.02	0.03
R <sup>2</sup>	0.44	0.43	0.38	0.28	0.51	0.33

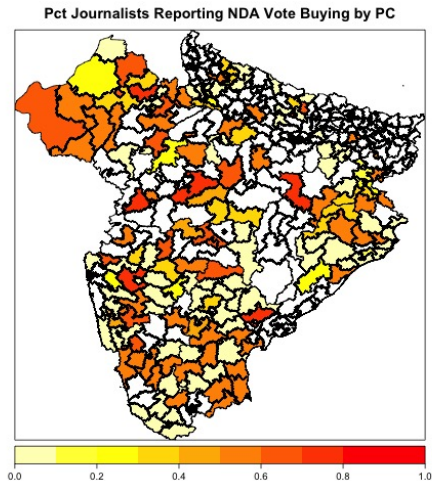
# What does it mean to be a vote buying party?

- Very innovative measure of illicit electoral technique
  - Cost-effective
  - Draws on local expertise
  - Covers comprehensive area
- What is the data generating process?
  - Journalistic ethics to tell the truth
  - Journalists have ideological biases?
  - Journalists pay more attention to major parties?
- How to think about uncertainty with journalist data?
  - Levels of informedness
  - Under-identification
  - Over-identification
  - Random noise

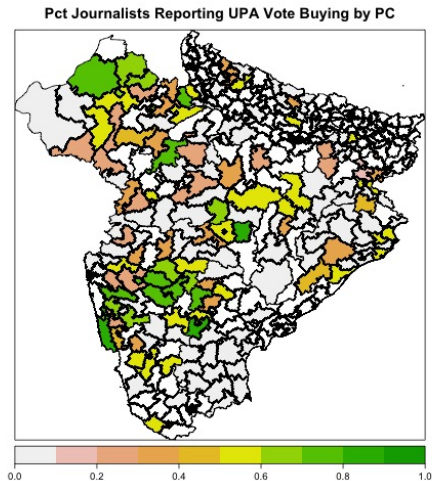
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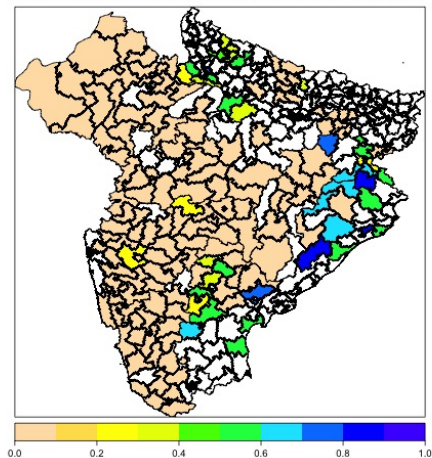


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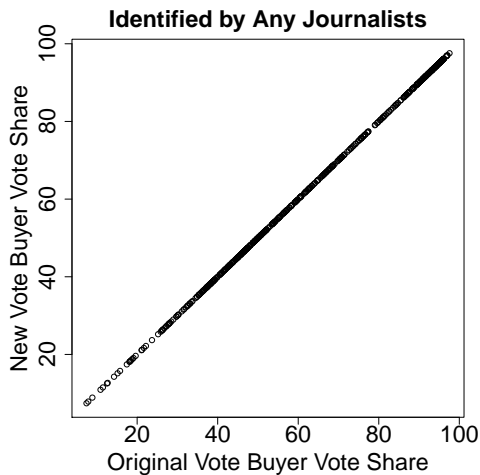
# What does it mean to be a vote buying party?

Pct Journalists Reporting Other Parties Vote Buying by PC

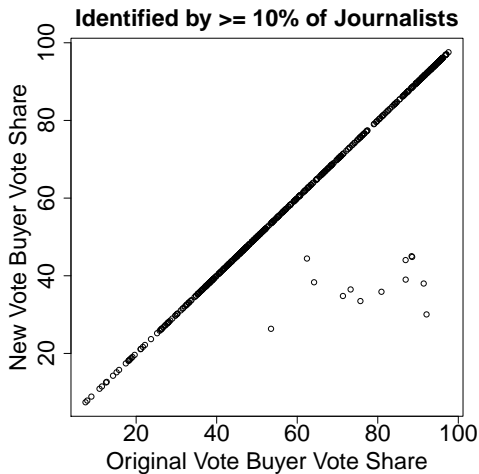




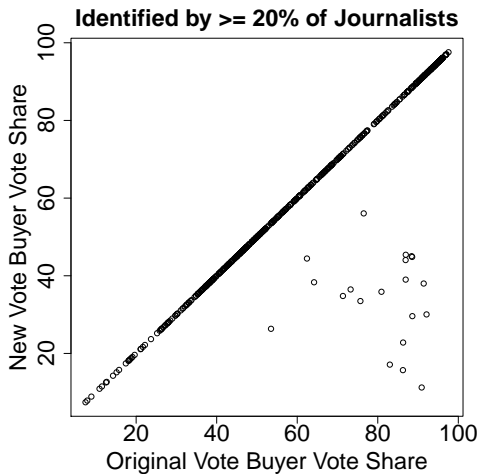
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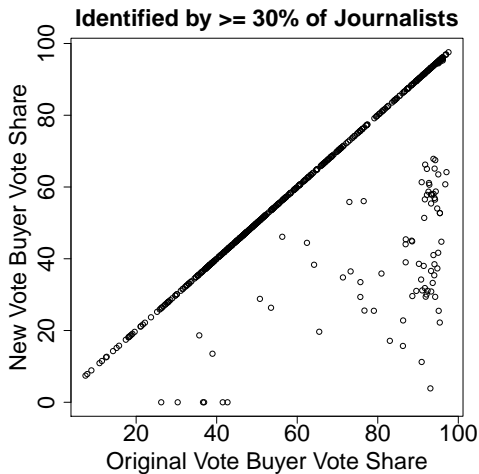
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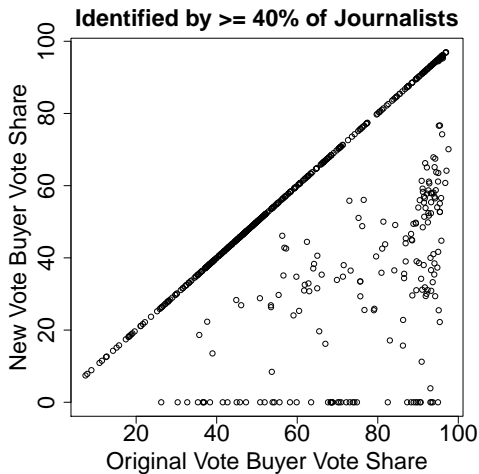
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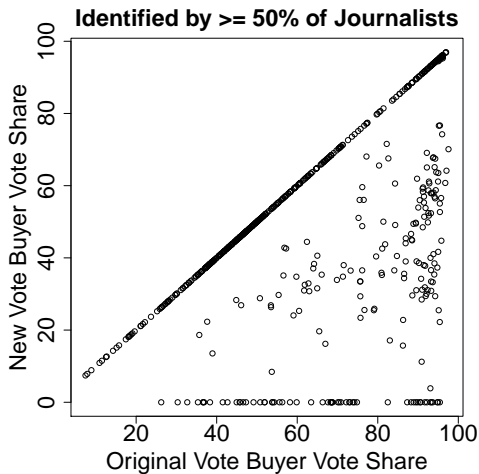
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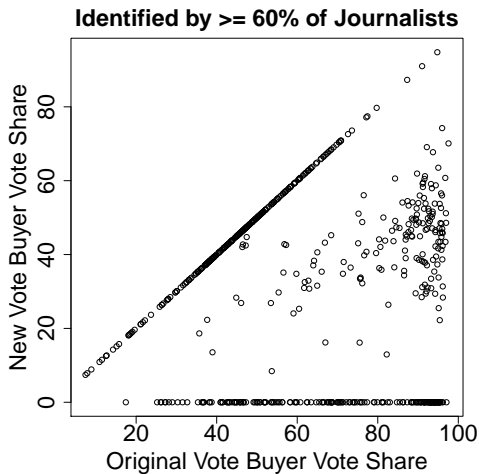
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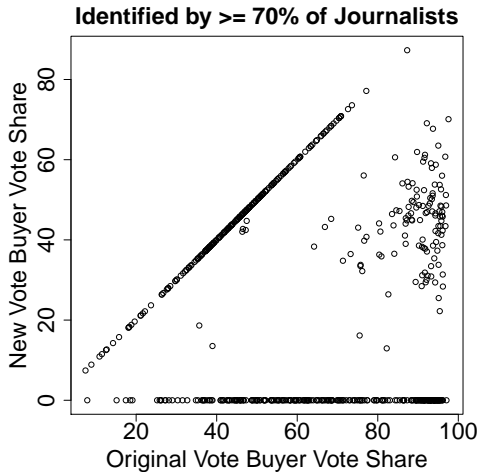
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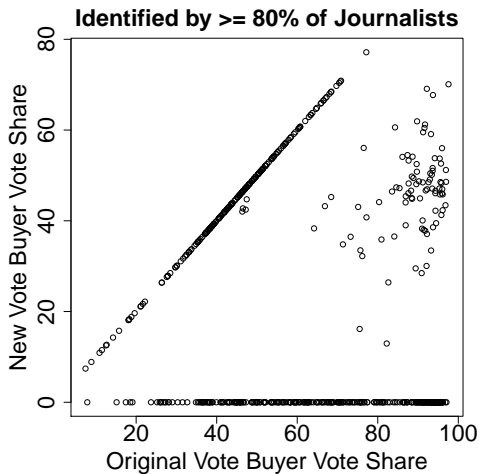


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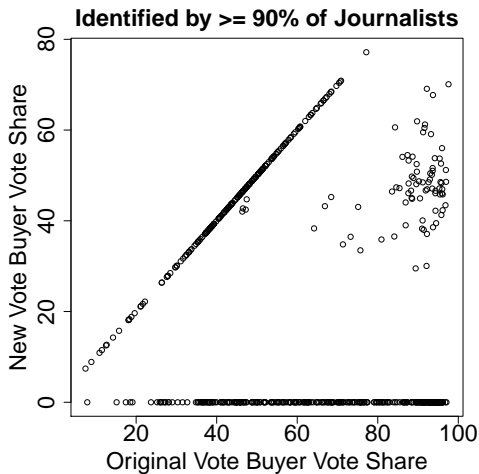




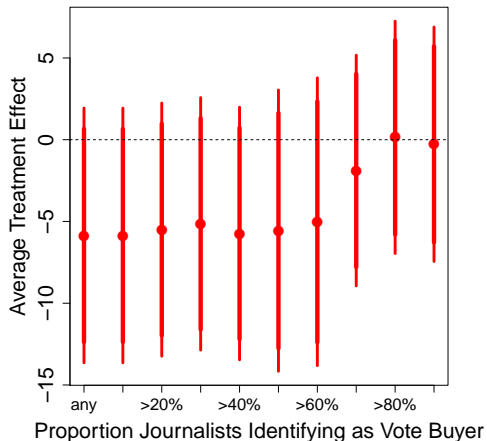
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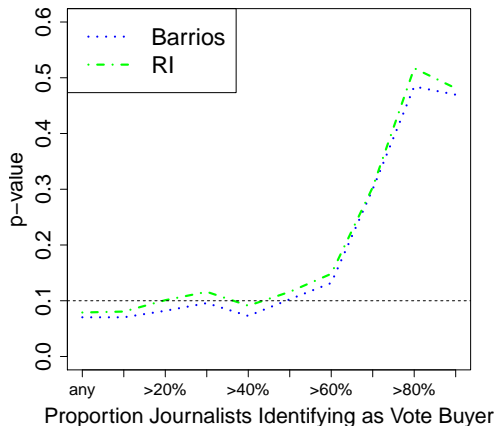
# What does it mean to be a vote buying party?



# Robustness to the definition of vote buying party



# Robustness to the definition of vote buying party



# Interpretation of the results

are people just fleeing from the major parties and voting for minor parties?

does this change the results?

can het effects tell us more about how this works?

## Interpretation: Implications for who wins

In how many PCs do these results change the results? calc het effects by state and then do projections of which party would have won if the intervention hadn't happened

# Heterogeneous effects: Urban

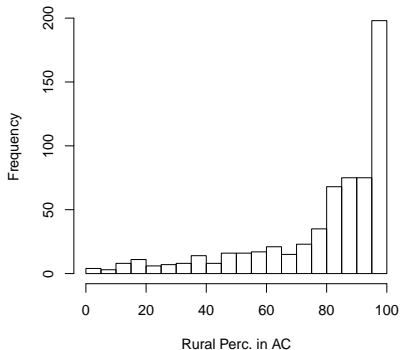
Dummy: More than 90% Rural

	Coef.	SE	p
Treat	-4.68	3.6	0.1
Rural >90 pc	1.69	2.55	0.25
Treat:Rural90	-3.16	3.83	0.2
R squared	0.44		

Continuous Rural

	Coef.	SE	p
Treat	1.79	6.79	0.4
Rural pc	-0.01	0.05	0.45
Treat:Rural pc	-0.1	0.06	0.06
R squared	0.44		

Histogram of Percent Rural in AC



# Heterogeneous effects: Minority voters

Dummy: More than 50%

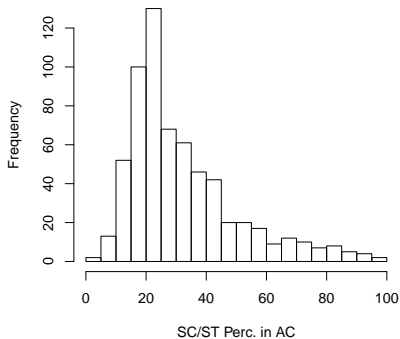
SC/ST

	Coef.	SE	p
Treat	-6	4.4	0.09
SC/ST >50 pc	-4.88	3.66	0.09
Treat:SC/ST50	1.87	5.06	0.36
R squared	0.44		

Continuous SC/ST

	Coef.	SE	p
Treat	-6.03	6.36	0.17
ST/SC pc	-0.06	0.09	0.26
Treat:SC/ST pc	0.01	0.11	0.48
R squared	0.44		

Histogram of Percent SC/ST in AC





## Heterogeneous effects: Competitiveness of election

## Heterogeneous effects: State

Table : Treatment Status of ACs by State

	Control AC	Treated AC
Andhra Pradesh	82	31
Bihar	0	14
Chattisgarh	15	27
Jharkhand	15	17
Karnataka	50	25
Madhya Pradesh	27	18
Maharashtra	60	38
Orissa	23	26
Rajasthan	42	54
Uttar Pradesh	1	63

# Heterogeneous effects: State

Table

	<i>Dependent variable:</i>
	2014 Vote Share
	Vote Buying Parties
State Bihar	-26.287*** (5.571)
State Chattisgarh	-5.774 (4.893)
State Jharkhand	-3.946 (4.916)
State Karnataka	-8.440*** (3.115)
State Madhya Pradesh	-2.123 (3.875)
State Maharashtra	-4.945* (2.909)
State Orissa	-4.407 (4.084)
State Rajasthan	1.235 (3.420)
State Uttar Pradesh	-61.526*** (17.276)
Vote Share 2009	0.588*** (0.030)
Num Radio 1	2.224 (17.458)
Num Radio 2	1.392 (17.560)
Constant	35.029** (17.569)

Table

Treat	4.353 (3.702)
Treat:Bihar	
Treat:Chattisgarh	-9.903 (6.618)
Treat:Jharkhand	0.761 (7.062)
Treat:Karnataka	-3.484 (5.559)
Treat:Madhya Pradesh	-11.592* (6.357)
Treat:Maharashtra	-8.632* (5.113)
Treat:Orissa	-8.085 (6.116)
Treat:Rajasthan	-14.242*** (5.046)
Treat:Uttar Pradesh	43.523** (17.650)
Constant	35.029** (17.569)
Observations	628
R <sup>2</sup>	0.485
Adjusted R <sup>2</sup>	0.467
Residual Std. Error	17.111 (df = 606)
F Statistic	27.158*** (df = 21; 606)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

# Heterogeneous effects: State

Map het effects by state