The Immigration Issue and the 2010 House Elections: A Research Design*

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Abstract

This paper proposes a research design for evaluating the effect of Republican candidates' immigration stances on House election outcomes. It develops a measure of immigration stance which is based on the text of each candidate's issue statement. With this as the treatment, propensities to support a harsh line on immigration are calculated for each candidate based on a variety of covariates that also may influence election outcomes. In this way, a research design is developed before election outcomes are observed. Thus, this project clearly reflects the advice of Rubin, who argues that the research design ought to be set before the outcome is even observed.

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With Arizona's adoption of strong anti-immigrant legislation by a unified Republican state government, immigration became a highly salient issue of 2010. The law, which was Senate bill 1070, requires police officers to investigate the legal status of detainees they reasonably suspect are in the country without authorization and makes it a misdemeanor to not carry immigration papers (Archibold 2010). While highly controversial, the policy has proven politically popular, with 73% of Americans feeling the law is "about right" or "doesn't go far enough" in handling illegal immigration.[1] Republicans, then, eager to regain control of the House of Representatives following consecutive terms as the minority party, perhaps feel an incentive to exploit the popularity of anti-immigrant legislation.

Yet, not all Republicans feel harsh immigration stances are the best strategy. George W. Bush, John McCain, and Lindsey Graham have all at some point pushed for comprehensive immigration reforms that, while strengthening border security, would also allow undocumented residents to stay. (Though the latter two have hardened their position somewhat.) Further, in 1994 when California Governor Pete Wilson sought to win re-election on the back of Proposition 187, several prominent Republicans, such as Bill Bennett, Ralph Reed, and Jack Kemp, opposed the campaign on the grounds that Latinos might be recruited to the Republican party in the future. All of this demonstrates that there is a lot of variation within the Republican party on how best to deal with immigration.

Given that much of the variation in immigration position-taking will be on the Republican side, this paper focuses on how posturing on this issue influences Republican electoral prospects in the 2010 House elections. Are there actually short-term electoral rewards for taking harsh stances on the issue? Overall, how did Republican candidates'

[1] Accessed from http://www.pollingreport.com/immigration.htm on October 2, 2010. CBS News Poll of 1,082 adults, August 20-24, 2010. Question wording: "As you may know, the state of Arizona recently passed a law that gives the police the power to question someone they have already stopped, detained, or arrested about their legal status in the country. The law requires people to produce documents verifying their status if asked. Do you think this law goes too far in dealing with the issue of ILLEGAL immigration, doesn't go far enough, or is about right?"

tone on the immigration issue influence their vote share in the 2010 House elections?

At present, the purpose of this version of this paper is to publicly release a research design before election outcomes are observed. Rubin (2006) makes the case that the design phase of research should be completed with no reference to the outcome variable. The advantage of completing this design before the election is it forces a commitment to estimating a causal effect through principled techniques. Doing so means the design efforts cannot "inappropriately slant estimation of the treatment effects on outcomes" (Rubin 2006: 369).[2] Therefore, the public release of this research design prior to the 2010 election implies that the analysis of actual vote shares in House races should provide the most honest and accurate possible assessment of the effect of the immigration issue in the election.

The paper proceeds first by laying-out a theory of how a stand on immigration can influence electoral outcomes. Second, it describes the data and measurement strategies for the outcome, treatment, and covariates. Third, the research design for capturing the causal effect of immigration position on election outcomes is described. Fourth, the estimates of propensity scores are presented, along with the implications they have for a study of election otucomes, once vote counts are released.

1 Theory

The notion that immigration could have a substantial impact on electoral outcomes is clearly grounded in the literature on the politics of racial threat. The primary notion in this literature is that politicans can use fear among whites that a minority group threatens them economically and socially. By taking political stances to limit the opportunities and influence of the out-group, whites may be more likely to vote for the candidate they feel will protect their lifestyles. Key (1949) describes how racial politics of this variety

[2] Alternatively, see Rubin (2001).

frequently were used to electoral success among Southern Democrats in the pre-Civil Rights Era. On the topic of immigration, Diamond (1996) argues that Pete Wilson in 1994 used the politics of racial threat by campaigining on Proposition 187. This behavior was instrumental in his re-election, yet cost the Republicans in the long term, as it alienated the party from a growing Latino constituency. Thus, campaigning on policies that are hostile to minorities has been known to help politicians win elections, both in general and with regards to immigration.

Raising the issue of immigration should elicit a reaction from voters. Given that the recovery from the recession of 2008 has been slow, many voters are nervous about job prospects and their financial futures. Thus, attempting to discourage the arrival of immigrants—who potentially create added competition in the labor market—could prove electorally popular among the many voters concerned with the economy. Thus, the sour economy ought to make 2010 a prime year for campaigning on immigration in general, and the effect of the issue ought to be greatest in districts where unemployment has been particularly high.

Further, the relatively high levels of immigration in recent years could lead voters to be easily influenced by the issue. In fact, Hopkins shows that localities are much more likely to adopt hostile ordinances on immigration if the area has seen an inflow of migrants (2010: 55). Given that the number of foreign-born residents in the United States increased 22% from 2000 to 2008, a large number of voters is likely to have the growing migrant population in mind.[3] Overall, then, this serves as another reason voters may respond to immigration-based campaigns. Further, those districts with larger foreign born populations ought to show larger treatment effects in electoral outcomes.

In testing for a causal effect of immigration position on election outcome in a House race, it is essential to account for the other factors known to influence vote shares for

[3]Data from Terrazas & Batalova's table on percent change in foreign born by state. Available at the MPI Data hub, http://migrationinformation.org/DataHub/, accessed June 22, 2010.

congressional candidates. These are: district ideology, relative campaign funding, and incumbency status (Abramowitz 2004; Abramowitz and Segal 1992). Further, the unemployment rate of each district and the percentage of the population that is foreign born should also be measured, as the effect of the treatment of immigration position may vary across the values of these covariates. By accounting for these factors in the design stage of this research, I should be in a better position to evaluate the causal effect of the immigration issue.

2 Data and Measurement

Having considered the reasons immigration politics ought to shape election results, I turn now to the measurement of the key variables. The outcome of interest is the Republican candidate's share of the two-party vote in his or her district. After the election, voting results should be available from each state's Secretary of State, as well as the major news outlets. (The final version of this paper will focus on official counts.)

2.1 Measuring the Treatment: Text Analysis

To assess how the immigration issue influences outcomes in this election, I define the treatment variable as the tone of the Republican candidate's public stance on immigration. The treatment in this case is administred at the end of the primary season, which concluded on October 2, 2010. I make this assumption about the time frame because the identity of the party nominees in each district has to be set before the electorate can assess their respective issue positions. Thus, the treatment is best defined as how the Republican candidate presents him or herself regarding immigration during the general election campaign, so the measurement of the variable is defined accordingly. Given that the treatment is the Republican's public stance, I measure this variable using the text of

the immigration issue statement posted on each candidate's website.[4]

With the text of each Republican's immigration issue statement, I conducted automated content analysis using Yoshikoder.[5] This software employs a user-defined dictionary of how words and word stems should be classified, and it counts the number of words from each dictionary category in a given document. In this case, I used the dictionary from Kopacz (2008), which divides immigration-related content into six frames: ethics, Latinos, law enforcement, law making, material resources, and national security.

Figure 1 offers the distribution of immigration vocabulary in 2010, as well as the distribution from 2006 presented in Kopacz (2008) for comparison. The figure reports the average percentage of words from Republican immigration statements that fell into each of the five listed categories. As the figure shows, the overall emphases in 2010 are similar to the distribution Kopacz found in 2006, with law enforcement gaining a little more relative emphasis.

Finally, I collapsed these six categories into a single treatment measure of the Republican candidate's overall immigration stance. I classified law enforcement and national security as frames that are harsh towards immigrants. Material resources, ethics, and Latinos were classified as frames that are friendly towards immigrants.[6] Lastly, words related to law making did not have a consistent tone, so this category was ignored for the final measure. The overall measure of public immigration stance then, is the proportion of a candidate's statement that uses harsh vocabulary among all words that put either a welcoming or hostile frame on immigration. It can also be represented by Equation 1:

$$T_i^A = \frac{\text{law enforce}_i + \text{national sec}_i + 1}{\text{law enforce}_i + \text{national sec}_i + \text{ethics}_i + \text{Latinos}_i + \text{material resources}_i + 2} \quad (1)$$

[4]These websites are listed at http://congress.org/election/home, and the text used in the analysis was gathered from each site on October 4-15, 2010. When statements were embedded in an image, Free OCR was used to extract the text, http://www.free-ocr.com.

[5]Yoshikoder is available for free download at http://yoshikoder.org and was developed as part of the Identity Project at Harvard's Weatherhead Center for International Affairs.

[6]The terms placed under "material resources" focus on the pro-business advantages of migrant labor. Hence, this is considered as a welcoming frame.

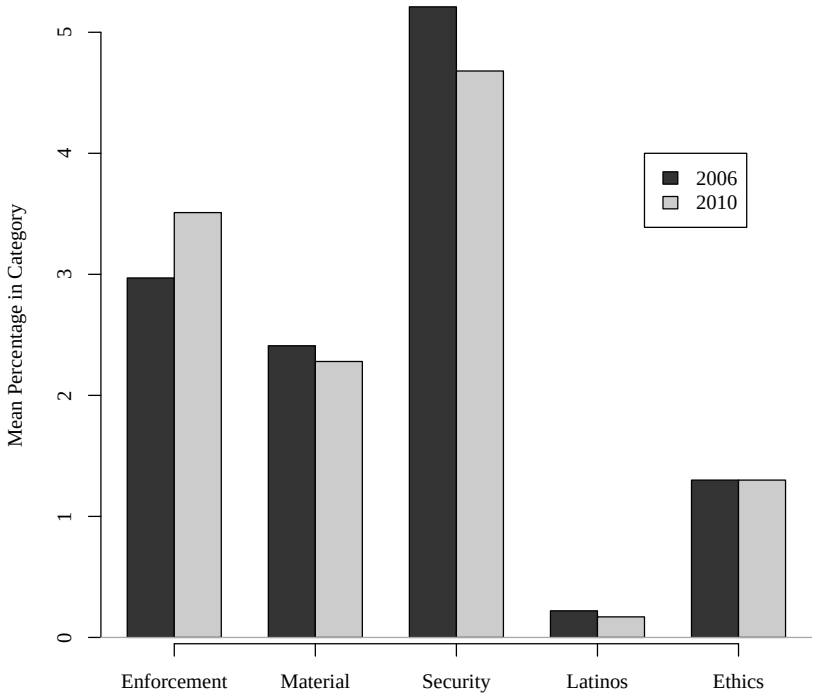

Figure 1: Mean percentage of words in immigration statements falling into five categories for Republicans in 2006 and 2010 House races.

In the above equation, each right-hand side variable is the number of words classified into each respective dictionary category. Thus, a candidate who only discusses immigraton in hostile way receives a score approaching 1, while a candidate only discussing the issue using welcoming terms receives a score approaching 0. The equation also adds one welcoming and one hostile word to each candidate's score, seen as the addition of 1 in the numerator and 2 in the denominator. This adds several features to this measure: First, it prevents any undefined proportions. Second, it places all candidates who said nothing on immigration at the neutral point of 0.5, the same score that would go to a candidate who used an equal number of friendly and harsh terms on immigration. Third, it prevents any candidate from scoring exactly 0 or 1 on the measure, which is useful for modeling purposes. Finally, it moderates scores, but to a lesser degree for candidates who said more about the issue.

2.2 Covariates

Regarding the covariates that need to be considered in the design stage: Whether the seat is open or the Democratic or Republican candidate is an incumbent is recorded in the House election profiles of CQ Press. CQ Press also compiled the presidential vote shares by congressional district, which was used to capture the ideological disposition of each district's electorate. The 2009 American Community Survey by the U.S. Census Bureau reports estimates by congressional district of the percent foreign born and the unemployment rate. Finally, a candidate's campaign finances are considered only through the first three quarters of 2010, as reported by the Federal Election Commission. Because the treatment is how the Republican candidate projects him or herself after primary season ends, considering money raised later than this could induce post-treatment bias. Since the third quarter ended before primary season, though, I consider pre-treatment money raised to account for a key source of variance in election outcomes.

3 Research Design

To isolate the causal effect of immigration stance on election outcome, I follow the methdology laid-out in Imai and van Dyk (2004). Their technique extends the propensity score model of Rosenbaum and Rubin (1983) to nonbinary treatments such as categorical or continuous variables. To illustrate, in the case of a continuous treatment, T_i^A, Imai and van Dyk's method would start with fitting a linear model:

$$T_i^A|\mathbf{X}_i \sim \mathcal{N}(\mathbf{X}_i^T\boldsymbol{\beta}, \sigma^2) \tag{2}$$

From this, a researcher could use the predicted values, $\hat{\theta}_{\boldsymbol{\psi}}(\mathbf{X}_i) = \mathbf{X}_i^T\hat{\boldsymbol{\beta}}$, to match or subclassify on the propensity function (Imai and van Dyk 2004: 856).

In this study, I extend their logic into a case where the treatment is a proportion (specifically, proportion of hostile words). Hence, to handle the bounded nature of this treatment, I fit a general linear model where I take the probit of the proportion of hostile words.[7] More formally, suppose for congressional district i, T_i^A is the treatment of Republican tone on immigration, and $\mathbf{X}_i$ is a vector of the other covariates for the district. In this case, I can determine $\hat{\theta}_{\boldsymbol{\psi}}(\mathbf{X}_i) = \Phi(\mathbf{X}_i^T\hat{\boldsymbol{\beta}})$ by fitting the general linear model:

$$\Phi^{-1}(T_i^A|\mathbf{X}_i) \sim \mathcal{N}(\mathbf{X}_i^T\boldsymbol{\beta}, \sigma^2) \tag{3}$$

The outcome is transformed to account for the bounded nature of proportions. Note that the probit of the outcome is itself normally distributed because there is still uncertainty in the prediction of an observed proportion. Once the model of Equation 3 has been fit, $\hat{\theta}_i$ can be calculated for each district.

With predicted values of immigration position for each Republican, I can better measure the effect immigration position has on electoral outcome. I will estimate a smoothed

[7] The probit is defined for all values because $0 < T_i^A < 1$ based on the definition in Equation 1.

coefficient model across all data. This model will include an intercept and coefficient for the treatment variable that are each smoothed over the propensities, as well as the covariates used on the right hand side of the model in Equation 3. This model is expressed as:

$$\Phi^{-1}(Y_i|T_i^A, \mathbf{X}_i) \sim \mathcal{N}(\alpha_0(\hat{\theta}_i) + \alpha_1(\hat{\theta}_i)T_i^A + \mathbf{X}_i^T\mathbf{\Gamma}, \nu^2) \tag{4}$$

In this case, Y_i is the outcome variable, the proportion of the vote share for the Republican candidate, and T_i^A and $\mathbf{X}_i$ are respectively the observed treatment and covariates for a district. Equation 4 takes the probit of the vote share outcome to account for its bounded nature, and again the probit of the vote share itself is normally distributed to account for uncertainty. $\alpha_1(\hat{\theta}_i)$ is the coefficient for the treatment of immigration stance, smoothed over propensities of immigration stance (which are predicted values from Equation 3). Estimating $\alpha_1(\hat{\theta}_i)$ offers an estimate of the causal effect of position-taking for Republican candidates at similar propensities based on the covariates. The smoothed coefficient aspect of this model allows the causal effect to vary at different propensity levels. Further, by having a sense of how the moderator variables of percent foreign born, change in foreign born, and unemployment shape the propensity, I can evaluate how the estimated treatment effect varies over the domain of these variables.

4 Results

With this research design in mind, I present the model of the propensity to adopt harsh rhetoric on immigration. A model of how this treatment influences electoral outcomes will come after the election. Table 1 presents the results from estimating the model of the treatment specified in Equation 3. To maximize the treatment's balance on the covariates, all interaction terms are included in the model as well.

In accordance with the design, the propensity score for each district is calculated by

Table 1: General Linear Model of 2010 Republican House Candidates' Rhetoric on Immigration

	Estimate	Std. Error	t value	Pr(>|t|)
Republican incumbent	0.4038	0.5156	0.78	0.4340
Democratic incumbent	0.3495	0.4287	0.82	0.4154
Presidential vote 2008	-0.2928	1.2327	-0.24	0.8124
Unemployment 2009	-0.0253	0.0721	-0.35	0.7259
% foreign born	0.0061	0.0159	0.38	0.7019
Relative funding	0.0000	0.0000	1.00	0.3158
Republican incumbent×Presidential vote 2008	-0.5761	1.0665	-0.54	0.5894
Democratic incumbent×Presidential vote 2008	-0.8019	0.9284	-0.86	0.3883
Republican incumbent×Unemployment 2009	0.0070	0.0517	0.13	0.8931
Democratic incumbent×Unemployment 2009	0.0344	0.0456	0.75	0.4515
Republican incumbent×% foreign born	-0.0138	0.0107	-1.29	0.1982
Democratic incumbent×% foreign born	-0.0078	0.0097	-0.81	0.4191
Republican incumbent×Relative funding	-0.0000	0.0000	-1.31	0.1900
Democratic incumbent×Relative funding	-0.0000	0.0000	-1.09	0.2752
Presidential vote 2008×Unemployment 2009	0.0194	0.1049	0.19	0.8530
Presidential vote 2008×% foreign born	0.0118	0.0177	0.66	0.5067
Presidential vote 2008×Relative funding	-0.0000	0.0000	-0.70	0.4841
Unemployment 2009 ×% foreign born	-0.0012	0.0015	-0.79	0.4302
Unemployment 2009 ×Relative funding	0.0000	0.0000	0.31	0.7552
% foreign born×Relative funding	0.0000	0.0000	0.33	0.7414
Intercept	0.4456	0.6029	0.74	0.4603

Notes: $N = 406$, AIC$= -309.61$, $R^2 = 0.0705$, probit link function used due to bounded nature of outcome.

predicting treatment values according to the estimated model in Table 1. The propensity score for each district is listed in Table 3 in the appendix, and these values will be used to estimate the model in Equation 4 after the election.

Table 2: Assessing Balance of Covariates with and without Controlling for the Estimated Propensity Function

Covariate	Without Propensity	With Propensity
Republican incumbent	-1.213	-0.010
Democratic incumbent	-1.410	0.004
Presidential vote 2008	-4.370	0.024
Unemployment 2009	-1.457	0.011
% foreign born	-3.439	0.032
Relative funding	1.153	0.012

Notes: $N = 406$, cell entries are t-statistics on the coefficient of treatment (immigration rhetoric) from linear models of each covariate. (For incumbency, a probit models were run, and z-statistics are reported.) Lower absolute values suggest better balance on the covariate.

To assess this research design, Table 2 studies how balanced the treatment is for each of the covariates. Following the advice of Imai and van Dyk (2004: 858-859), the table reports the t-ratios of linear models where the treatment variable is the input and the covariate is the outcome. In the left column, the treatment is the only input. In the right column, the propensity scores (or fitted treatment values) are also included in the model. Smaller t values indicate better balance. As the table shows, the balance in the covariates becomes substantially better once the propensity function is controlled for. All of this suggests that this research design should serve well in estimating the causal effect of Republican immigration positions on election outcomes.

A Data Sources and Propensity Function

Covariates were gathered from the following data sources:

- Incumbency status: Congress.org Election Guide. Accessed from http://congress.org/election/home on October 4-15, 2010.
- Campaign funding: FEC 2009-2010 Candidate Summary File, http://www.fec.gov/data/CandidateSummary.do?format=html. Accessed from http://data.gov on October 26, 2010. Missing data supplemented by a *New York Times* report, accessed from http://elections.nytimes.com/2010/house/ on October 30, 2010.
- 2008 presidential vote by congressional district: Calculated and prepared by Greg Giroux. Accessed from http://CQPolitics.com on October 26, 2010.
- Percent foreign born by congressional district: U.S. Census Bureau, American FactFinder, 2009 American Community Survey 1-Year Estimates. Accessed from http://factfinder.census.gov on October 28, 2010.
- Unemployment by congressional district in 2009: U.S. Census Bureau, American FactFinder, 2009 American Community Survey 1-Year Estimates. Accessed from http://factfinder.census.gov on 28 October 2010.

Table 3: Fitted Values of 2010 Republican House Candidates' Immigration Rhetoric, by District

State	District	Propensity	State	District	Propensity	State	District	Propensity	State	District	Propensity
AL	2	0.6884651	GA	1	0.6635567	MN	6	0.5966692	OK	3	0.7052571
AL	3	0.6464527	GA	2	0.6267719	MN	7	0.6421284	OK	5	0.6660945
AL	5	0.6018261	GA	3	0.6604723	MN	8	0.6326921	OR	1	0.5955615
AL	7	0.5048325	GA	4	0.5397956	MS	1	0.6718545	OR	2	0.6291257
AK	1	0.6438306	GA	5	0.5611011	MS	2	0.6043853	OR	3	0.5757333
AZ	1	0.6482271	GA	7	0.6137114	MS	3	0.6630273	OR	4	0.6310313
AZ	2	0.6373895	GA	8	0.6574647	MS	4	0.6954110	OR	5	0.6183600
AZ	3	0.6470643	GA	10	0.6585084	MO	1	0.5464682	PA	2	0.5159934
AZ	4	0.5791213	GA	12	0.6272648	MO	2	0.6270282	PA	3	0.6413711
AZ	5	0.6306794	GA	13	0.5711987	MO	3	0.5984898	PA	4	0.6486814
AZ	6	0.6377510	HI	1	0.5574616	MO	4	0.6661736	PA	5	0.6456303
AZ	7	0.6008825	HI	2	0.5676436	MO	5	0.6072277	PA	6	0.5888369
AZ	8	0.6316614	ID	1	0.6603614	MO	6	0.6419705	PA	7	0.6619151
AR	1	0.5573041	ID	2	0.6468160	MO	7	0.6599818	PA	8	0.6212357
AR	2	0.6368211	IL	1	0.5232444	MO	8	0.6786360	PA	9	0.6787756
AR	3	0.6287126	IL	2	0.5313405	MT	1	0.6362854	PA	10	0.6493913
AR	4	0.6649621	IL	3	0.5774724	NE	1	0.6407394	PA	11	0.6123309
CA	1	0.5897856	IL	4	0.5352867	NE	2	0.6079083	PA	12	0.6378343
CA	3	0.5689480	IL	5	0.5670623	NE	3	0.6877866	PA	13	0.6050752
CA	4	0.6206269	IL	6	0.5224301	NV	1	0.5797420	PA	14	0.5765666
CA	5	0.5464850	IL	7	0.5197858	NV	2	0.5995311	PA	15	0.5985120
CA	6	0.5918475	IL	8	0.5990999	NV	3	0.6026373	PA	16	0.6237513
CA	6	0.5535330	IL	9	0.5545829	NH	1	0.6435996	PA	17	0.6389497
CA	7	0.5535760	IL	10	0.6333862	NH	2	0.5398743	PA	18	0.6407488
CA	8	0.5233025	IL	11	0.6314982	NJ	1	0.5940244	PA	19	0.6515800
CA	9	0.5325604	IL	12	0.6210955	NJ	2	0.5760406	RI	1	0.5554685
CA	10	0.5826559	IL	13	0.5833148	NJ	3	0.6233712	RI	2	0.5950910
CA	11	0.6039571	IL	14	0.6116629	NJ	4	0.6028457	SC	1	0.6511775
CA	12	0.5556715	IL	15	0.6213749	NJ	5	0.5963060	SC	2	0.6255671
CA	13	0.5362429	IL	16	0.5883899	NJ	6	0.5954149	SC	3	0.6284605
CA	14	0.5657539	IL	17	0.6354124	NJ	7	0.5807729	SC	4	0.6471960
CA	15	0.5553549	IL	18	0.6190935	NJ	8	0.5891801	SC	5	0.6569658
CA	16	0.5381640	IL	19	0.6413599	NJ	9	0.5817238	SC	6	0.6268225
CA	17	0.5523468	IN	1	0.6079907	NJ	10	0.5278877	SD	1	0.6423679
CA	18	0.5670041	IN	2	0.6422611	NJ	11	0.5772287	TN	1	0.6880537
CA	19	0.6692385	IN	3	0.5928882	NJ	12	0.5946536	TN	2	0.6761032
CA	20	0.5607762	IN	4	0.6429314	NJ	13	0.5567887	TN	3	0.6715883
CA	23	0.5743878	IN	5	0.6589178	NM	1	0.6020562	TN	4	0.6882638
CA	24	0.5759841	IN	6	0.6265219	NM	2	0.6331527	TN	5	0.6127770
CA	25	0.5598298	IN	7	0.5660638	NM	3	0.6059656	TN	6	0.6972093
CA	26	0.5532398	IN	8	0.6138318	NY	1	0.6419555	TN	7	0.6726707
CA	27	0.5521337	IN	9	0.6318411	NY	2	0.5899864	TN	8	0.5763987
CA	28	0.5128358	IA	1	0.6213404	NY	3	0.6001926	TN	9	0.5784311
CA	29	0.5517248	IA	2	0.5988429	NY	4	0.5943605	TX	3	0.5876245
CA	30	0.5702383	IA	3	0.6397790	NY	5	0.5780092	TX	4	0.6752037
CA	31	0.5128957	IA	4	0.5925094	NY	6	0.5466473	TX	5	0.6497224
CA	32	0.5427307	IA	5	0.6350928	NY	7	0.5631963	TX	6	0.6200812
CA	33	0.6030946	KS	1	0.6939546	NY	8	0.5689594	TX	8	0.6919686
CA	34	0.5404025	KS	2	0.6466429	NY	9	0.5801802	TX	9	0.5402279
CA	35	0.5202881	KS	3	0.6475825	NY	10	0.5545853	TX	10	0.6020604
CA	36	0.5735721	KS	4	0.6194592	NY	11	0.5364836	TX	11	0.6998184
CA	37	0.5139100	KY	1	0.6695668	NY	13	0.6007051	TX	12	0.6273414
CA	38	0.5504118	KY	2	0.6626928	NY	14	0.5710451	TX	14	0.6596196
CA	39	0.5605065	KY	3	0.6199578	NY	15	0.5789482	TX	15	0.5914522
CA	40	0.5367625	KY	4	0.6652111	NY	16	0.4951251	TX	16	0.5839785

State	District	Propensity	State	District	Propensity	State	District	Propensity	State	District	Propensity
CA	41	0.5924504	KY	5	0.6950867	NY	17	0.5522682	TX	17	0.6761779
CA	42	0.5612088	KY	6	0.6583326	NY	18	0.5874718	TX	18	0.5491076
CA	43	0.5388635	LA	1	0.6988764	NY	19	0.6227683	TX	19	0.6948628
CA	44	0.5309726	LA	2	0.5163677	NY	20	0.6317228	TX	20	0.5860224
CA	45	0.5304456	LA	3	0.6231647	NY	21	0.6125453	TX	21	0.6433277
CA	46	0.5602409	LA	4	0.6599826	NY	22	0.6029884	TX	22	0.6137955
CA	47	0.5372135	LA	6	0.6532370	NY	23	0.6424869	TX	23	0.6215487
CA	48	0.5685448	ME	1	0.6043050	NY	24	0.6402499	TX	25	0.5986844
CA	49	0.5640180	ME	2	0.6205821	NY	25	0.6231455	TX	26	0.6173492
CA	50	0.5736976	MD	1	0.6673873	NY	26	0.6236313	TX	27	0.6138462
CA	51	0.5604815	MD	2	0.6046785	NY	27	0.6346383	TX	28	0.5996621
CA	52	0.6015565	MD	3	0.6032731	NY	28	0.5837174	TX	29	0.5642839
CA	53	0.5691363	MD	4	0.5316710	NY	29	0.6554519	TX	30	0.5253956
CO	1	0.5597678	MD	5	0.6214033	NC	1	0.5911414	TX	32	0.5511132
CO	2	0.5899385	MD	6	0.6529506	NC	2	0.6234422	UT	1	0.6633477
CO	3	0.6376530	MD	7	0.5466671	NC	3	0.6731101	UT	2	0.6527293
CO	4	0.6305363	MD	8	0.5469595	NC	4	0.5977738	UT	3	0.6649989
CO	5	0.6487759	MA	1	0.5875536	NC	5	0.6471755	VT	1	0.5790026
CO	6	0.6273476	MA	2	0.6126313	NC	6	0.6486193	VA	1	0.6285034
CO	7	0.5983936	MA	3	0.6049385	NC	7	0.6428868	VA	2	0.6279304
CT	1	0.5907526	MA	4	0.5958991	NC	8	0.6242413	VA	3	0.5408180
CT	2	0.6129853	MA	5	0.6011704	NC	9	0.6085536	VA	4	0.6154757
CT	3	0.5966748	MA	6	0.6115242	NC	10	0.6540944	VA	5	0.6385440
CT	4	0.5888865	MA	7	0.5849657	NC	11	0.6475294	VA	7	0.5855378
CT	5	0.6081156	MA	9	0.5954462	NC	12	0.5674064	VA	8	0.5762416
DE	1	0.5507470	MA	10	0.5996875	NC	13	0.6017298	VA	9	0.6581501
FL	2	0.6470740	MI	1	0.5946616	ND	1	0.6557938	VA	10	0.5715465
FL	3	0.5840301	MI	2	0.5992245	OH	1	0.6234168	VA	11	0.6020912
FL	5	0.6068659	MI	3	0.5818380	OH	2	0.6523628	WA	1	0.5924367
FL	7	0.6142720	MI	4	0.6039933	OH	3	0.6279628	WA	2	0.6142528
FL	8	0.5942190	MI	5	0.6127449	OH	4	0.6650218	WA	3	0.5540591
FL	9	0.6064661	MI	6	0.5857955	OH	5	0.6376862	WA	4	0.6140115
FL	10	0.5976165	MI	7	0.6404658	OH	6	0.6474836	WA	5	0.6243635
FL	11	0.5797198	MI	8	0.5914691	OH	7	0.6397971	WA	6	0.6137229
FL	12	0.6235915	MI	9	0.6040376	OH	8	0.6690725	WA	8	0.5885203
FL	13	0.5914136	MI	10	0.5975559	OH	9	0.6142863	WA	9	0.6004337
FL	14	0.5959571	MI	11	0.5819141	OH	10	0.6136116	WV	1	0.6075429
FL	15	0.5868667	MI	12	0.6013276	OH	11	0.5520513	WV	2	0.6447309
FL	16	0.5836526	MI	13	0.5037992	OH	12	0.5873487	WV	3	0.6644563
FL	18	0.4939320	MI	14	0.5656899	OH	13	0.6055970	WI	1	0.5795107
FL	19	0.5775022	MI	15	0.5974604	OH	14	0.6192606	WI	2	0.5779064
FL	20	0.5621260	MN	1	0.6275360	OH	15	0.6164894	WI	3	0.6013979
FL	22	0.6269937	MN	2	0.6128914	OH	16	0.6492268	WI	4	0.5569108
FL	23	0.5137683	MN	3	0.5836624	OH	17	0.6149746	WI	5	0.6532378
FL	24	0.6269274	MN	4	0.5890948	OH	18	0.6543048	WI	6	0.6282857
FL	25	0.6710092	MN	5	0.5683202	OK	2	0.6727446	WI	7	0.6022689
						WY	1	0.6864673	WI	8	0.6219903

References

Abramowitz, Alan I. 2004. *Voice of the People: Elections and Voting in the United States*. New York: McGraw-Hill.

Abramowitz, Alan I. and Jeffrey A. Segal. 1992. *Senate Elections*. Ann Arbor, MI: University of Michigan Press.

Archibold, Randal C. 2010. "Arizona Enacts Stringent Law on Immigration." *New York Times*, 8 April 2010. 8 August 2010, nytimes.com.

Diamond, Sara. 1996. "Right-Wing Politics and the Anti-Immigration Cause." *Social Justice* 23(3):154–168.

Hopkins, Daniel J. 2010. "Politicized Places: Explaining Where and When Immigrants Provoke Local Opposition." *American Political Science Review* 104:40–60.

Imai, Kosuke and David A. van Dyk. 2004. "Causal Inference with General Treatment Regimes: Generalizing the Propensity Score." *Journal of the American Statistical Association* 99(467):854–866.

Key, V.O. Jr. 1949. *Southern Politics in State and Nation*. New York: A. Knopf.

Kopacz, Maria A. 2008. "Framing Immigration Online: Online Position Statements of 2006 Candidates for Congress." *Electronic Journal of Communication* 18(1).

Rosenbaum, Paul R. and Donald B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70:41–55.

Rubin, Donald B. 2001. "Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation." *Health Services & Outcomes Research Methodology* 2:169–188.

Rubin, Donald B. 2006. *Matched Sampling for Causal Effects*. New York: Cambridge University Press.