

The Ideological and Electoral Determinants of Laws Targeting Undocumented Migrants in the U.S. States

Online Appendix

In this additional methodological appendix I present some alternative model specifications that are designed to serve as robustness checks of the models that are included in the main text of the article. These models are designed to address four questions:

- 1.) Does the logic of my argument work in reverse? Are liberal Democratic legislatures more likely to pass laws expanding immigrants' access to social welfare programs and protect immigrants from investigation from law enforcement when the electoral costs are low and the benefits are high?
- 2.) How does operationalizing the dependent variable as a count opposed to a binary affect the substantive findings?
- 3.) How does the inclusion of several additional right-hand side variables affect the substantive findings?
- 4.) What are the consequences of clustering within the data? What is the best way to deal with the potential bias that this type of clustering introduces?

1. The Relationship Between Party Control, Latino CVAP and the Passage of Bills Benefitting Immigrants

In this paper I examined the relationship between the passage of laws targeting undocumented migrants and party ideology, party control of the state legislature, the size of the Latino CVAP and recent immigrant inflows. The key finding of this analysis is that Republican legislatures tend to pursue tough immigration laws where the electoral costs are low and the electoral benefits are high. However, enforcement is just one of several immigration related policy dimensions, others include immigrant access to social welfare programs, human trafficking, and professional licensure. There is no reason why the logic of my argument should not apply to the passage of laws pertaining to other facets of immigration policy. In this appendix I present analysis that examines the determinants of the passage of a different dimension of immigration policy, the eligibility of immigrants for social welfare programs.

Restricting immigrants' access to social welfare programs has been one component of most of the high profile omnibus immigration bills that have recently been passed by Republican controlled legislatures. Yet, there are numerous instances where states passed legislation that

expands immigrants' eligibility for various types of social welfare programs. These bills granted immigrants eligibility for in-state tuition, Medicare other various types of government assistance—often without consideration of citizenship status. As I show in *Table 1A*, there were 27 of these bills passed between 2005-2011. The majority of these bills were passed by Democratic controlled legislatures.

(Table 1A Here)

The key question here is whether the same factors explain the adoption of enforcement provisions will explain the likelihood that a state legislature will adopt legislation expanding immigrants' access to social programs? Conservative Republican controlled legislatures were most likely to pass enforcement provisions when the electoral costs were low and the potential benefits were high. These instances were in states with small populations of Latino citizens that were experiencing a rapid relative increase in the size of the foreign born population—meaning voters were likely paying attention to immigration and the electoral costs of targeting immigrants is low because there is a small pool of co-ethnic voters to present an electoral threat. Do Democratic controlled legislatures pass liberal immigration policies when the electoral costs are low and the potential benefits are high?

I address this question by analyzing the determinants of laws that benefit immigrant groups. The dependent variable in this analysis is whether or not a state passed a law expanding immigrants' access to social welfare benefits or in a given year. All of the independent variables are the same as in the models in the main text, except I include an interaction between Democratic control of the legislature and Democratic ideology opposed to Republican control and ideology. This interaction will test whether liberal Democratic legislatures are more likely to pass legislation expanding immigrants' access to social welfare benefits, compared to moderate Democratic or Republican controlled legislatures.

(Table A2 Here)

The results of this model largely confirm the pattern of adoption of legislation that was established in models that analyzed the passage of restrictive legislation. The interaction term between Democratic control and Democratic ideology is negative and significant. This finding demonstrates that Democratic controlled legislatures are more likely to pass legislation expanding immigrant benefits as they become more ideologically liberal (when values for state party ideology take on increasingly negative values). Additionally, these legislatures are also

likely to pass these laws in states with large Latino CVAPs—places where the electoral benefits are high. One difference between the adoption of legislation targeting enforcement and the adoption of legislation expanding immigrant’s access to benefits is the effect of recent inflows of immigrants. States experiencing recent inflows of immigrants are more likely to pass legislation targeting enforcement, while recent immigrant inflows have no effect on the likelihood will pass legislation expanding immigrants’ access to social welfare programs. This finding suggests that recent immigrant inflows do not affect a Democratic legislatures’ willingness to pass legislation expanding immigrants’ access to social welfare programs, which implies these recent inflows do not present a serious electoral cost. Instead, the likelihood that a legislature will pass one of these laws is determined by the legislature’s ideology and the size of the Latino CVAP.

2. A Zero Inflated Poisson Model of Immigration Enforcement Bills

I start by assessing how modeling the dependent variable as a count affects the overall findings. The first model that I present is a zero inflated Poisson model.¹ The dependent variable is a count of the total number of bills that a state passed in a given year. A zero inflated Poisson (ZIP) model corrects for the under prediction of zeros that occurs when an ordinary count model is run on data with an excessive amount of zeros (as is the case here, 302 out of 350 state years are zeros). A ZIP model accounts for the under prediction of zeros by estimating two equations: a logit model that predicts the excess zeros and a Poisson count model. The assumption that underlies a ZIP model is that the data is divided into two latent groups, cases that are always zero and cases that are not always zero (Long and Freese 2006, 394).

I have the expectation that Democratic controlled legislatures will fall into the “always zero” group because Democrats oppose strict immigration enforcement legislation on ideological grounds. Secondly, I expect the presence of large Latino CVAPs to cause state legislatures to avoid passing enforcement legislation, which should also inflate the number of zeros in the sample. I include Republican control of the state legislature and the governorship in the binary inflation equation, along with the Latino percentage of the state’s citizen voting age population.

¹ I initially estimated this equation as a negative binomial model, which makes the least restrictive assumptions about the distribution of the data. When I ran the model as a negative binomial model, alpha was not significant, meaning that we cannot reject the null hypothesis that the distribution is equally dispersed. Therefore I moved to a Poisson model in order to improve efficiency. The Poisson is a special case of the negative binomial where the mean and variance are equally dispersed (Cameron and Trivedi 1998, 59). I then adopted a zero inflated Poisson model to deal with the under-prediction of zeros.

I expect these three variables to potentially have an effect on the likelihood that a state's count is always zero. I include the full equation (as in *Model 2* from *Table 3* of the main document) in the count portion of the model. The only difference between the base probit model and the count portion of the ZIP model is that I omit the Republican control*Republican ideology interaction term in the count equation because the inflation portion of the model will account for the possibility that Republican control of the state legislature is a necessary condition required to observe a non-zero outcome.

(Table A3 Here)

The results of the ZIP model largely confirm the findings of the probit models from *Table 3* in the main text of the article. The likelihood of an observation falling into the “always zero” category significantly declines when the Republican Party controls the state legislature. Likewise, the size of the Latino CVAP has a statistically significant positive effect on the odds that an observation will always be zero. The partisanship of a state's governor has no effect on the likelihood of falling into the always zero category. Drawing comparisons between the count portion of the ZIP model in the base models from *Table 3* is less straightforward, since I do not have a distinct set of theoretical expectations about what factors lead a state to pass 1 bill opposed to 2 or 3 in any given year (i.e. why a state would choose to pass numerous separate bills opposed to a single omnibus bill). While most of the variables in the count portion of the model are not statistically significant, Republican ideology has a statistically significant positive effect on the expected count. The substantive conclusions that can be drawn from the ZIP model are largely the same as the conclusions that can be drawn from the probit models; Republican controlled legislatures are more likely to pass immigration enforcement bills than their Democratic counterparts. The likelihood of observing a state's legislature pass an enforcement bill increases as a function of the state Republican Party's level of ideological conservatism. However, the likelihood that a state will pass enforcement legislation declines as a function of the size of the Latino CVAP.

3. Alternative Models with Additional Explanatory Variables

I explore the effect of including some additional independent variables in this portion of the appendix. In the baseline set of models I include a dummy variable for the partisanship of the governor—the variable is coded as a 1 if a state's governor is a Republican. The results of the model in *Table 3* demonstrate that the governor's partisanship does not have a significant effect

on the likelihood that a state will pass an immigration enforcement law in a given year. However, this finding might be a result of the fact that measuring gubernatorial control as a binary variable might not adequately capture the complexity of the governor's role in the policy making process and the between state differences in the power of the governors to veto legislation. I include several additional variables in an effort to determine whether a certain subset of governors significantly effects the policy making process. I introduce Thad Beyle's measure of gubernatorial power rankings as an independent variable in an effort to determine whether institutionally powerful governors shape the policy making process.² In addition, I include an interaction term between gubernatorial power and gubernatorial partisanship in an effort to assess whether the presence of institutionally powerful Republican governors make the adoption of immigration enforcement laws more likely. I test this possibility in *Model A3*. Additionally, I also test whether the combination of a Republican governor and Republican controlled legislature increase the likelihood of enforcement legislation being passed with an interaction term between the two variables.

Another possible factor that can affect the policy making process is the availability of legislative referendum. Some state legislatures (mainly those west of the Mississippi) have the option of sending a piece of legislation to the voters for approval (opposed to passing a law in the legislature and sending it to the governor).³ It is possible that state legislatures utilize the referenda process in order to circumvent the electoral consequences of passing controversial immigration enforcement laws. California's Proposition 187, one of the most infamous and consequential state level immigration laws, was passed via popular referendum (Nicholson 2005). It is certainly possible that legislatures with the ability to propose legislative initiatives are less likely to directly pass enforcement legislation and more likely to simply place these laws on the ballot. I include a variable for states that have a legislative referendum in *Model A6* in an effort to test this possibility.

(Table A4 Here)

The results of the models in *Table A4* suggest that a governor's partisanship does not appear play a significant role in the adoption of immigration enforcement legislation, however,

² The Gubernatorial Power Dataset was obtained from Thad Beyle's website:
<http://www.unc.edu/~beyle/gubnewpwr.html>

³ Information about states with legislative referenda comes from the National Council of State Legislatures: <http://www.ncsl.org/legislatures-elections/elections/chart-of-the-initiative-states.aspx>

states with institutionally powerful governors are more likely to pass restrictive immigration legislation. The coefficients for gubernatorial partisanship fails to reach traditional levels of statistical significance by a wide margin, as do the interaction terms between gubernatorial power and gubernatorial partisanship and Republican control and gubernatorial partisanship. Additionally, the availability of a popular referendum does not appear to affect the likelihood that a state will pass restrictive immigration legislation. The coefficient for the referendum variable fails to reach traditional levels of statistical significance, as does the interaction between Republican control and popular referendum.

4: Approaches for Dealing with the Clustering of Observations Within States

The clustering of observations within larger constituent units presents a set of methodological issues that must be addressed in order to draw valid statistical inferences. This set of potential issues stem from the possibility that the clustering of observations within larger units (states, counties, countries etc) introduces unmodeled correlations among observations within a cluster. The fundamental problem is that clustering potentially leads to correlation among the residuals. The correlation of the errors violates the independence assumption. This type of clustering is especially prevalent in the study of state politics, where observations are often grouped within states in some way. In my case, the data are organized as a cross-sectional panel time series that spans seven years with a unique observation for each state in each year. The potential source of unmodeled correlation is the clustering of observations within each state across multiple years. Scholars often include cluster level fixed effects as a way of accounting for any unmodeled correlation within each cluster. However, I am unable to include fixed effects in my models because the inclusion of fixed effects would drive out all of the variation on numerous substantively important variables. Therefore, I must adopt a different approach for dealing with clustering.

The concern with this type of clustering is that it can potentially lead to downward bias in the standard errors of regression coefficients and the possibility of improperly rejecting the null hypothesis when it is actually true (Harden 2011, 224). This downward bias is caused by the fact that “effective sample size” is not the total number of observations; rather it is closer to the total number of clusters (Arceneaux and Nickerson 2009). There are several methods that scholars have developed in an effort to account for the potential bias that clustered data can introduce into

an analysis. These methods include the use of robust clustered standard errors (RCSE) and obtaining bootstrapped clustered standard errors (BCSE) via Monte Carlo simulation. Harden, (2011; 2012) has demonstrated via simulation that the use of BCSEs can produce less biased standard errors when compared to RCSE under a number of different potential scenarios. I estimate my base equation from Table 3 from the main text with traditional, robust, robust clustered and bootstrapped clustered standard errors and present the results in the table below.

(Table A5 Here)

The main and most dramatic difference between the approaches is that clustered bootstrapped standard errors are typically twice as large the three other standard errors. This finding is consistent with Harden's replication of several studies, where the biggest difference in SEs was between variables on the group opposed to individual level (2011, pg 232-236). The fact that the use of the CBSEs substantially increases the standard errors compared to every other model specification is not necessarily an issue; the fact that these variables are significant using other SE specifications might simply be a Type 1 error that was produced as a result of unmodeled correlation among the errors. The key question here is what factors are contributing to the difference between CBSE and all other methods of estimating the standard errors

The key distinction that must be made is what type of variance is driving the results of the models—variance between the states (panels) or variance within each state over time. The interclass correlation coefficient is .79, which demonstrates that the majority of the variance is between states rather than within each state. This finding is reasonable because most of the variables included in the analysis (such as a state's foreign born population and Latino populations, partisan control of the legislature and party ideology) vary considerably from state to state but change only slowly within a state. Thus, the results of my analysis are likely being driven by inter-cluster, as opposed to intra-cluster variations. To demonstrate this fact, I adopt an approach that varies from the normal cross sectional panel time series design, which includes state fixed effects in order to explicitly account for any unmodeled correlation within each cluster. I take the opposite approach and look to directly model the determinants of these between cluster differences. Green and Vavreck (2008) demonstrate that one way to evaluate between cluster differences is to aggregate each cluster up to the cluster mean and conduct a cluster level analysis. According to Green and Vavreck (pg 140-141), aggregate level between cluster analyses can to produce less biased standard errors than individual level analyses. In the

event that two approaches produce conflicting results, aggregate level analyses produce the more reliable results.

I evaluate the consequences of any potential clustering by removing clustering from the data. I do this by collapsing each state cluster down to a single 7-year average for each variable. Collapsing each variable to its cluster mean leaves me with one observation per state—effectively removing any clustering from the data. By using this approach, I can directly evaluate whether my findings as reported in the main text are the result of unaccounted between-cluster correlation. If the findings are still significant in this model, the results in the original model were likely not a product of Type-1 error. I present two alternative model specifications, one where the dependent variable is the average number of bills passed in each state per year (OLS) and a second where the dependent variable is the total number of bills each state has passed in the entire seven-year period (Poisson). The models are specified as an OLS and a Poisson respectively. The results of these models are displayed in the *Table A6*.

(Table A6 Here)

The results of the aggregate level cluster analysis largely conform to the results of the models presented in the main body of the paper. The interaction between Republican ideology and Republican control of the legislature is positive and significant in both models. The percent of the state's population that is foreign born and the percent change in the foreign born percentage since 2000 are significant in the OLS model but not the Poisson. The size of each state's Latino CVAP is negative but is not significant in either model. These aggregate level findings are further corroborated when I adopt another approach to dealing with the potential ramifications of clustering. I present separate regressions for each panel in the time series. This year-by-year analysis removes clustering because I am only looking at one panel at a time—there are no repeated observations within each yearly subsample. The results of these year-by-year analyses are displayed below in *Table A7*.⁴

(Table A7 Here)

The results of the year-by-year analysis are similar to the results presented in the main body of the text. The interaction between Republican ideology and Republican control of the legislature is always positive and significant in two of the four models presented. The percent of

⁴ Note: several independent variables must be dropped in these year-by-year analyses do to the fact that they perfectly predict success or failure within a particular yearly sample.

the state's population that is foreign born and the percent change in the foreign born percentage since 2000 are positive in all of the models and generally significant. Each state's Latino CVAP is negative and significant in three out of the four models. Overall, the findings of the individual panels and collapsed panel closely resemble models in the main text. The fact that the results largely hold when all clustering is removed suggests that the standard errors are not being underestimated, at least not substantially, as a result of having repeated observations in the analysis. Rather, the discrepancies between the models specifications stem from how the estimators deal with the between-cluster variance. The results of this supplemental analysis suggest that how one models the between-cluster variance is important element in determining the substantive implications of an analysis.

Works Cited

- Arceneaux K. and Nickerson, D.W. 2009. Modeling Certainty with Clustered Data: A Comparison of Methods. *Political Analysis* 17: 177-190.
- Cameron, C.A. & Trivedi, P.K. (1998). *Regression Analysis of Count Data*. New York, NY: Cambridge University Press.
- Green, D.P. & Vavreck, L. 2008. Analysis of Cluster-Randomized Experiments: A Comparison of Alternative Estimation Techniques. *Political Analysis*, 16: 138-152.
- Harden, J.J. (2011). A Bootstrap Method for Conducting Statistical Inference with Clustered Data. *State Politics and Policy Quarterly*, 11(2): 223-246.
- Harden, J.J. (2012). Improving Statistical Inference with Clustered Data. *Statistics, Politics and Policy*, 3(1): 1-27.
- Long, J.S. & Freese, J. (2006). *Regression Models for Categorical Dependent Variables Using Stata (2nd ed)*. College Station, TX: Stata Press.
- Nicholson, S.P. (2005). *Voting the Agenda: Candidates, Elections and Ballot Propositions*. Princeton, NJ: Princeton University Press.

Table A1: Party Control of the State Legislature and Bills Passed

<i>Number of Bills Expanding Protection of Immigrant Groups</i>	<i>Unified Democratic Control</i>	<i>Divided Control</i>	<i>Unified Republican Control</i>	<i>Total</i>
0	133	73	124	325
1	16	1	5	22
2	2	0	0	2
3	0	0	0	0
4	1	0	0	1
Total Number of Bills Passed	21	1	5	27
N	129	74	152	350

Table A2: Probit Model Regressing Legislative Output on Democratic Control and Ideology

<i>VARIABLES</i>	<i>Model A1</i>
Democratic Control	-1.082 (0.689)
Republican Ideology	-0.330 (0.413)
Democratic Ideology* Democratic Control	-2.761*** (0.953)
Democratic Ideology	0.765 (0.563)
Latino CVAP	0.0772*** (0.0285)
Term Limits	0.520 (0.321)
Professionalization	-0.0186 (0.148)
Republican Governor	-0.160 (0.295)
Border State	-1.873** (0.870)
The South	0.433 (0.359)
Foreign-born%	0.00451 (0.0339)
Foreign-born% since 2000	0.000163 (0.0312)
Unemployment %	-0.0958 (0.0585)
Citizen Ideology	-0.0119 (0.0116)
Constant	-0.799 (1.435)
Observations	350

Robust clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A3: Zero Inflated Poisson Model
 (Note: yearly fixed effects included but not shown)

<i>VARIABLES</i>	<i>Count Equation</i>	<i>Binary Equation</i> <i>(Modeling the Excess Zeros)</i>
Republican Control	-1.39* (0.84)	-4.34*** (1.28)
Republican Ideology	1.85* (1.1)	
Democratic Ideology	0.08 (0.72)	
Latino CVAP	-0.06 (0.08)	0.21*** (0.06)
Term Limits	0.27 (0.44)	
Professionalization	0.13 (0.21)	
Republican Governor	0.11 (0.32)	0.63 (0.9)
Border State	0.94 (0.83)	
The South	0.70* (0.42)	
Foreign-born%	0.17** (0.07)	
Foreign-born% since 2000	0.05 (0.04)	
Unemployment %	-0.07 (0.09)	
Citizen Ideology	-0.02 (0.01)	
Constant	-5.92*** (1.91)	0.45 (.72)
Observations	350	

Robust clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A4: Probit Model Regressing Legislative Output on Gubernatorial Power and Partisanship
(Note: yearly fixed effects included but not shown)

<i>VARIABLES</i>	<i>Model A3</i>	<i>Model A4</i>	<i>Model A5</i>	<i>Model A6</i>	<i>Model A7</i>
Republican Control	-0.62 (0.77)	-0.73 (0.81)	-0.66 (0.75)	-0.57 (0.75)	-0.61 (0.77)
Republican Ideology	-0.40 (0.67)	-0.40 (0.67)	-0.41 (0.66)	-0.32 (0.64)	-0.22 (0.73)
Republican Control*Republican Ideology	1.70** (0.86)	1.78** (0.88)	1.77** (0.87)	1.63* (0.88)	1.55* (0.92)
Democratic Ideology	-0.020 (0.41)	-0.061 (0.45)	-0.024 (0.47)	-0.067 (0.46)	-0.038 (0.48)
Latino CVAP	-0.13* (0.078)	-0.13 (0.079)	-0.11 (0.081)	-0.11 (0.078)	-0.11 (0.078)
Term Limits	0.29 (0.25)	0.27 (0.25)	0.24 (0.26)	0.45 (0.33)	0.41 (0.39)
Professionalization	-0.050 (0.14)	-0.041 (0.14)	0.0097 (0.14)	-0.027 (0.14)	-0.023 (0.14)
Republican Governor	-0.10 (0.21)	-1.61 (1.83)	-0.12 (0.41)	-0.13 (0.20)	-0.14 (0.21)
Border State	1.29 (1.13)	1.26 (1.15)	0.86 (1.23)	0.75 (1.17)	0.73 (1.17)
The South	0.93*** (0.25)	0.95*** (0.27)	0.72** (0.28)	0.61** (0.30)	0.63** (0.30)
Foreign-born%	0.092** (0.041)	0.087** (0.041)	0.089** (0.041)	0.092** (0.041)	0.093** (0.041)
Foreign-born% since 2000	0.041* (0.023)	0.043* (0.025)	0.038* (0.022)	0.042* (0.023)	0.040 (0.025)
Unemployment %	-0.024 (0.083)	-0.020 (0.082)	-0.050 (0.077)	-0.039 (0.079)	-0.032 (0.080)
Citizen Ideology	-0.016* (0.0094)	-0.015 (0.0094)	-0.015 (0.0099)	-0.016* (0.0092)	-0.016* (0.0090)
Gubernatorial Power	0.74** (0.31)	0.51 (0.43)			
Gubernatorial Power*Republican Governor		0.44 (0.55)			
Republican Governor*Republican Legislature			-0.039 (0.54)		
Initiative				-0.31 (0.26)	-0.42 (0.35)
Initiative*Republican Control					0.21 (0.62)
Constant	-6.03*** (1.61)	-5.41*** (1.68)	-3.33*** (1.12)	-3.40*** (1.08)	-3.41*** (1.06)
Observations	350	350	350	350	350

Robust clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A5: Base Equation with Four Different Methods of Estimating the Standard Error

<i>Variables</i>	<i>Normal</i>	<i>Robust</i>	<i>Robust Clustered</i>	<i>Clustered Bootstrapped</i>
Republican Control	-0.752 (0.658)	-0.752 (0.702)	-0.752 (0.678)	-0.752 (1.224)
Republican Ideology	-0.386 (0.586)	-0.386 (0.585)	-0.386 (0.578)	-0.386 (1.128)
Republican Control*Republican Ideology	1.751** (0.774)	1.751** (0.802)	1.751** (0.788)	1.751 (1.399)
Democratic Ideology	0.146 (0.416)	0.146 (0.459)	0.146 (0.444)	0.146 (1.006)
Latino CVAP	-0.106** (0.0528)	-0.106 (0.0667)	-0.106 (0.0651)	-0.106 (0.124)
Term Limits	0.150 (0.267)	0.150 (0.259)	0.150 (0.230)	0.150 (0.519)
Professionalization	0.0375 (0.123)	0.0375 (0.118)	0.0375 (0.127)	0.0375 (0.213)
Republican Governor	-0.191 (0.216)	-0.191 (0.203)	-0.191 (0.197)	-0.191 (0.263)
Border State	0.765 (0.707)	0.765 (0.889)	0.765 (0.848)	0.765 (1.377)
The South	0.506** (0.228)	0.506** (0.234)	0.506* (0.266)	0.506 (0.455)
Foreign-born%	0.0905** (0.0406)	0.0905** (0.0401)	0.0905** (0.0400)	0.0905 (0.0790)
Foreign-born% since 2000	0.0347 (0.0257)	0.0347 (0.0215)	0.0347 (0.0238)	0.0347 (0.0464)
Unemployment %	0.0113 (0.0409)	0.0113 (0.0369)	0.0113 (0.0350)	0.0113 (0.0433)
Citizen Ideology	-0.0177* (0.00968)	-0.0177* (0.0100)	-0.0177* (0.00990)	-0.0177 (0.0249)
Constant	-2.046* (1.177)	-2.046* (1.102)	-2.046* (1.104)	-2.046 (2.045)
Observations	350	350	350	350

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A6: OLS and Poisson Models Regressing Average Number/Total Bills Passed 2005-2011 on State Party Ideology and Latino CVAP (all IVs 2005-2011 Averages)

<i>VARIABLES</i>	<i>OLS</i>	<i>Poisson</i>
Republican Control	-2.465 (1.815)	-0.286 (0.241)
Republican Ideology	-0.308 (1.178)	0.00378 (0.179)
Republican Control*Republican Ideology	3.601* (1.899)	0.537* (0.292)
Democratic Ideology	-1.006 (0.930)	-0.0304 (0.107)
Latino CVAP	-0.0499 (0.116)	-0.00242 (0.0127)
Term Limits	0.927* (0.514)	0.0530 (0.101)
Professionalization	-0.151 (0.267)	-0.00949 (0.0390)
Republican Governor	-0.510 (0.383)	-0.112 (0.0917)
Border State	-0.937 (2.092)	-0.0835 (0.396)
The South	1.500*** (0.542)	0.234** (0.112)
Foreign-born%	0.129** (0.0646)	0.0142 (0.00889)
Foreign-born% since 2000	0.109** (0.0541)	0.00860 (0.00671)
Unemployment %	-0.340** (0.164)	-0.0360 (0.0272)
Citizen Ideology	-0.0262 (0.0187)	-0.000939 (0.00230)
Constant	-2.090 (2.489)	-0.0301 (0.346)
Observations	50	50

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A7: Probit Models Regressing Legislation Output on State Party Ideology and Latino CVAP by Year⁵

	2006	2007	2008	2009	2010	2011
Republican Control	1.802 (2.958)	-8.145** (4.024)	-1.204 (1.523)	5.071* (2.676)	0.943 (1.358)	0.878 (1.621)
Republican Ideology	2.190 (2.392)	-1.02 (1.029)	0.967 (1.434)	-4.624** (2.281)	-0.290 (0.684)	-1.039 (1.496)
Republican Control* Republican Ideology	-2.655 (3.527)	8.327** (3.977)	4.866*** (1.841)	6.184** (2.564)	0.754 (1.482)	1.090 (1.619)
Latino CVAP%	-0.008 (0.0268)	0.03 (0.03)	-0.36*** (0.126)	-2.11*** (0.622)	-0.123 (0.0948)	-0.676** (0.331)
Foreign Born%	-0.09** (0.04)	-0.09 (0.06)	0.502*** (0.152)	1.545*** (0.496)	0.184 (0.113)	0.334** (0.150)
Foreign-born% since 2000	-0.02 (0.04)	0.03 (0.0418)	0.249** (0.0992)	0.147 (0.188)	0.0676* (0.0361)	0.0660 (0.0601)
Citizen Ideology	-0.004 (0.02)	-0.02 (0.02)	-0.0446 (0.0272)	-0.0887* (0.0465)	-0.00934 (0.0171)	-0.0510* (0.0289)
Constant	-1.253 (3.825)	0.392 (2.105)	-13.12** (5.163)	-11.11 (8.651)	-4.417* (2.333)	-1.637 (4.911)
Observations	50	50	50	50	50	50

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

⁵ Note: a separate regression for 2005 is not shown because Republican control perfectly predicts the passage of an immigration bill.