# The Politics of Need[*]

*Examining Governors' Decisions to Oppose the "Obamacare" Medicaid Expansion*

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**Abstract**

This paper explains governors' decisions to support or oppose Medicaid expansions offered under the 2010 Patient Protection and Affordable Care Act (PPACA). Though the two are often in tension, we theorize that governors' decisions to oppose the funding should depend on both the demands of the political context and the level of need in the state. We find that the governor's partisanship and the composition of the legislature have substantively meaningful effects on governor's decisions, but we find that the level of need in the state exerts a much smaller, if any, effect on governors' decisions. This suggests that for high-profile, highly-politicized issues such as the Affordable Care Act, the political context outweighs the needs of citizens in gubernatorial decision making.

"I cannot in good conscience deny Floridians access to healthcare," Gov. Rick Scott (R, FL) on deciding to accept Medicaid expansion following long-time opposition to Obamacare, February 20, 2013 (Reeve, 2013).

"I'm trying to determine how the Medicaid expansion is going to pay for the surgery to remove the knife planted in my back," Henry Kelley, Florida Tea Party blogger, March 5, 2013 (Alvarez, 2013)

[*] All data and code necessary to replicate these results are available at github.com/carlislerainey/need. We thank participants at

## Introduction

Health care reform is the central accomplishment of the Obama administration and has been a source of conflict between the parties since its passage in February, 2010. The Patient Protection and Affordable Care Act (PPACA, or "Obamacare") is a complex bill that was designed to improve U.S. citizens' health care coverage. One important piece of the policy's design was a Medicaid expansion in which the national government would assume initially all and eventually 90 percent of the cost of Medicaid for a previously non Medicaid-eligible portion of the population, the group that is most at risk for being uninsured. In June 2012, the Supreme Court ruled that portion of Obamacare to be in violation of U.S. law, but the Court also provided states a way to retain their existing Medicaid programs while rejecting the expansion (Rosenbaum and Westmoreland 2012).

The Court's Medicaid ruling was a surprise. The U.S. District and Appellate court decisions that preceded the June ruling did not address the Medicaid expansion issue, focusing instead on whether the national government could legitimately require persons to purchase health insurance. The Court upheld that portion of the PPACA. The Court's Medicaid ruling gave U.S. governors the unexpected power to oppose expanding their Medicaid programs as required under the original law.[1]

This was an easy decision for Democratic governors, but the statements from Florida Governor Rick Scott and Florida Tea Party activist Henry Kelley illustrate the difficulty that Republican governors faced. Scott entered Florida politics in 2009 by establishing an anti-health reform political action committee. He opposed reform throughout his closely fought successful gubernatorial campaign in 2010, in which received substantial Tea Party support. To the dismay

[1] Kaiser Family Foundation (2012) provides a succinct discussion of the 2012 Court decision.

of key Tea Party supporters, though, Governor Scott dropped this key policy position by 2013, noting that the Supreme Court upheld the law and that to turn away federal money is negligent. Other governors face similar decisions. This paper seeks to explain why some governors opposed the PPACA Medicaid expansions and other governors did not.

## The Politics of Medicaid Expansion under Obamacare

The PPACA was passed under a unified Democratic administration with no Republican support, a circumstance that has fueled conflict between the parties. Republican criticism of the law contributed to their winning the U.S. House in 2010 (Balz and Branigan 2010; Brady, et al. 2011; Campbell 2010). Complaints and warnings about Obamacare also figured prominently in the GOP platform in 2012 (Thompson 2012), and the number of U.S. House votes for its repeal, defunding, or prohibition topped 40 in September 2013. The attorneys general of 26 states mounted legal challenges to the law, which culminated in *National Federation of Independent Business v. Sebelius* (132 S. Ct. 603, 2011) being argued before the U.S. Supreme Court. Some states refused to establish health exchanges, which are the marketplaces through which citizens are to shop for and purchase their mandated health insurance (Rigby 2012). The federally established "health navigators" who were intended to help provide information about state insurance exchanges were a point of contention in some states. Insurance lobbyists in several states convinced legislators to pass laws to limit navigators' abilities to perform outreach (Kuznetz 2013). In short, national and state-level groups spent enormous time and efforts to defeat or block Obamacare.

The Court's 7-2 vote determined that states could not be forced to expand their Medicaid programs, despite a generous federal subsidy. (The Court upheld the legality of PPACA with a 5-4 vote). The Court's 2012 decision was an overall victory for supporters of PPACA, bit its

Medicaid decision introduced an unexpected barrier to the policy's implementation and shifted the opposition's strategy.

As of October 22, 2013, the governors of 29 states supported the expansion (though fewer saw it passed into law by their legislatures), 16 opposed it, and five were weighing their options. All Democratic governors supported the expansion, but not all Republican governors opposed the proposal. Ten Republicans supported the expansion, five were undecided, and 16 Republicans opposed it.

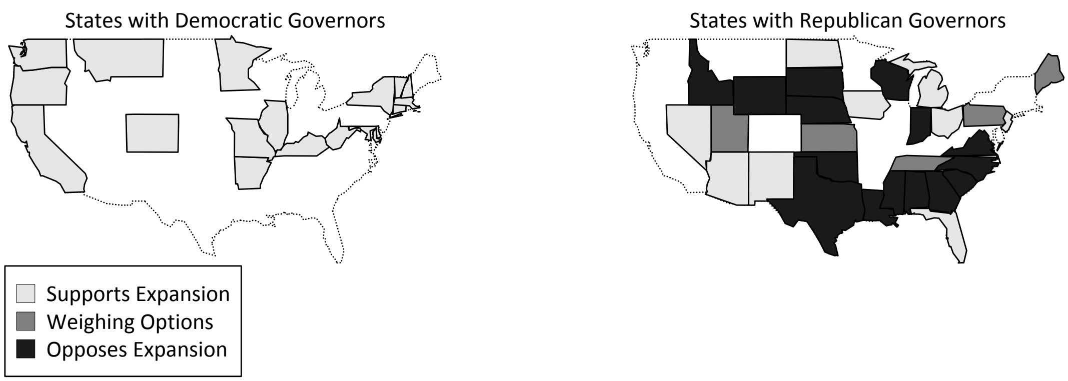


Figure 1: States whose governors support and oppose the expansion of Medicaid coverage. Dark grey indicates states whose governor opposes the expansion. Light grey indicates states whose governor supports the expansion. Notice that all Democratic governors support the expansion while some Republican governors support the expansion and others oppose it. The Democratic governor of Hawaii and the Republican governor of Alaska are not shown, who support and oppose expansion, respectively.

### *States' Preferences for Federal Money Differ*

State governments depend on the national government for funds but vary in their tastes for federal spending. States received about 32 percent of their total revenue from national sources in 2005 (Donovan, et al. 2009). In 2012, Mississippi ranked first on the list of states relying on the national government for revenues, with nearly half of its funding (49.01%) coming from Washington. Mississippi's Republican governor opposes the Medicaid expansion. Alaska was the lowest recipient of federal support, garnering only 24 percent (Tax Foundation 2012) and its Republican governor also rejects the Medicaid expansion. The refusal of Medicaid expansion under the PPACA does not indicate a general disavowal of federal funds going to state or a stand against the federal deficit, but appears to represent a partisan rejection of Obamacare. In the past, governors typically accepted Medicaid expansions as a form of "free" federal money, and U.S. House and Senate members claimed credit for those expansions as a benefit to the states that was a bargain due to the steep subsidy (Brown and Sparer 2003).

Both liberal-leaning and conservative-leaning states have refused federal funds at times in the past fifty years, for both practical and ideological reasons (Nicholson-Crotty 2012). Some states refused abstinence-only funding during the George W. Bush administration and some refused to compete for Race to the Top money under the Obama administration (Nicholson-Crotty 2012). In 2010, a number of conservative states refused to accept federal stimulus money that would have extended unemployment coverage. Others refused to accept previously granted funds for high-speed rail and funds for creating a health exchange (Nicholson-Crotty 2012 449-450). Some states take cues from the federal government on health care spending, others are not as welcoming (Weissert and Scheller 2008). The division over Medicaid expansion is consistent with other recent partisan divisions, but differs in part because of Medicaid's prominence in state health coverage and its crucial role in the PPACA plan.

The 1994 Contract with America was a precursor to the recent refusal by some Republican governors to expand Medicaid. Although Medicaid was not considered in the Contract, some Republican governors pushed for an end to the Medicaid entitlement in favor of a more limited block grant program. Their success was stymied by the Clinton administration's reaction to the 1994-1995 budget shutdown, in which the administration successfully created fears among the elderly of the effects of the block grant on nursing home care and on care for special needs children. By 1996, despite early signs that the block grant initiative might succeed, the

Republican push for Medicaid block grants was defeated (Thompson 2012).

The GOP governors' failure to secure a block grant for Medicaid in the mid-1990s led Republicans not to seek large Medicaid changes until fairly recently. Block grants and other proposals to cut Medicaid did not re-emerge until 2011, with the rise of the Tea Party bloc in Congress (Thompson 2012). It is reasonable to expect that this antipathy toward Medicaid expansion among Tea Party legislators may inform gubernatorial actions on program expansion as governors weigh the political costs and benefits of accepting the funds.

Despite the early refusal to accept Recovery Act funds, and despite early disavowal of PPACA and the legal challenge to the law, some governors have softened on their prior rejection of the Medicaid expansion. Republican governors who once opposed the expansion have shifted to supporting it, albeit grudgingly. Ohio Governor John Kasich said of the uninsured "What are we going to do, leave them out in the street, walk away from them when we have a chance to help them?" (Klein 2013). His support of the Medicaid expansion was met with strong criticism from conservative groups and failed to receive support from the Ohio legislature, leading Kasich to circumvent the legislature and use a state board to bring about the expansion. Gov. Jan Brewer (R, AZ), who initially opposed the PPACA, signed the expansion into law in June, 2013 after a protracted fight with conservatives in the Arizona House and Senate, with whom she was once joined in opposition to Obamacare. Florida's Scott shifted to support the Medicaid expansions after being assured that Florida would be allowed to continue with its managed-care style Medicaid program. It was not supported in the legislature and he did not call a special session to address Medicaid.

*Governors May be Wary of Medicaid Expansion*

Governors are often held responsible for state economic performance and spending regardless of whether they are able to affect either (Brace 1993). Medicaid has been described as the budget PacMan that consumes them without concern for other state spending needs (Altman and Beatrice 1990; Weissert 1992). Medicaid payments consumed nearly 24 percent of state budgets in 2011-2012. They ranged from a low of 9.3 percent in Wyoming and 30.1 percent in Florida in fiscal 2012 (NASBO 2013). Medicaid is a state-federal program designed to provide the indigent or medically indigent access to mainstream medical care. The national government pays at least 50 percent of states' program costs, but can pay as high in 83 percent in states with lower median family incomes. It is not organized on a health delivery model, but is simply a payment system that relies on private providers as a source of care. Medicaid was first implemented in 1966 and has constantly been more expensive than expected. The strain between the desire to provide access through generous eligibility and service coverage and the need to control Medicaid are longstanding problems faced by states and Medicaid program administrators (Holahan and Cohen 1986).

The PPACA Medicaid expansion promises 100 percent of state Medicaid costs for people with incomes as high as 138 percent of the federal poverty level through 2017, after which reimbursements decline slowly and are fixed at 90 percent beginning in 2020. It is a generous offer from the national government and would do much to reduce the portions of state population who have no health insurance that is most difficult to reach, the working poor. Fiscally strapped state governments recognize that the money is not free in the long run since states will have to pay ten percent of the bill for persons who are at or below 138 percent of the federal poverty level in 2020. Some partisan critics warn that the federal government may simply remove support for Medicaid with a change of party control of Congress, leaving the states responsible for the program's entire price (Coburn and Jindal 2013; Singer 2013).

The national government has not reneged on Medicaid spending commitments in the past, although the amounts states receive through the Federal Medical Assistance Percentages (FMAPs) have changed as states' wealth has changed.[2] Income increases in the South and Southwest have resulted in those states receiving lower FMAPs and higher state Medicaid shares. Income declines relative to national income per capita in parts of the East and the Midwest have produced increases in FMAPs (and lower state Medicaid shares) in those areas (Miller 2011). Thus there is some evidence of change in FMAP among the states, but no evidence of the US government refusing to pay for Medicaid benefits.

Another state concern with the expansion is the fear that public knowledge will produce a Medicaid enrollment explosion. There is concern that states will experience a "woodwork" or "Medicaid surge" effect upon implementation of PPACA in which new Medicaid enrollees and latent enrollees--those who were previously eligible but did not enroll--who come to the program in response to new knowledge about their eligibility and produce more-costly-to-the-states payment increases (Lewin Group 2013). Existing research shows increased knowledge of Medicaid eligibility to increase program enrollment and service use (Stuber and Bradley 2005). Thus there may be some reason to believe that Obamacare, with its health navigators and other outreach efforts to increase public knowledge, may produce higher Medicaid enrollments and spending for states.

## Why Might Governors Refuse the Obamacare Medicaid Expansion?

Governors face a constant tension over their ties to their party, public opinion, the state legislature, and the public good. We theorize the each of these factors weighs on governors'

[2] The FMAP is calculated: FMAP = 1 - .45 x [(State PCI)2 / (U.S. PCI)2] . A state with average income receives an FMAP of 55%, and no state may receive less than 50% FMAP, where the national government matches state spending dollar for dollar, and no state may receive more than 83% FMAP (Miller, 2011).

decisions and we use this framework to model their decisions empirically. The first three factors relate specifically to the political context of reform and the fourth relates directly to need for health insurance.

*Politics*

Political beliefs and ideology affect Medicaid decisions, and partisan conflict has defined much of the debate over health reform (see, e.g., Grogan and Rigby 2009). Governors often oppose an opposite-party president's position, but opposition is tempered by concern for the state budget. For example, several Republican governors willingly accepted Obama administration Recovery Act funds in 2009 (Pear and Goodman 2009), and governors typically accepted Medicaid expansions mandated by the national government regardless of party (Brown and Sharer 2003). However, in the case of the Medicaid expansion under the PPACA, when the issue relates to key component of the Democratic president's signature legislative achievement, we expect the probability that a Republican governor opposes the president to be large. Similarly, Democratic governors should be substantially less likely to oppose the president on this highly salient, partisan issue. Elizabeth Rigby (2012) notes that partisan politics are the main influence on state government behavior on the choice to create state health exchanges, and the same may be true of the Medicaid expansion, even with such a large amount of aid available. This leads to the first hypothesis.

> GUBERNATORIAL PARTISANSHIP HYPOTHESIS: Republican governors are more likely to oppose the Medicaid expansion funds than Democratic governors.

Second, governors are accountable to a constituency, so they pay attention to voter preferences and opinion. Indeed, if governors cannot appeal to the majority of the voters in their state, then their future political prospects seem bare. Republican governors are more likely than

GOP legislators to support redistributive policy spending because it benefits that statewide constituency from which they must seek support (Barrilleaux and Berkman 2003; Lewis, et al. 2013). Therefore, if the people of a state have a generally favorable view of the Affordable Care Act, then we expect that governors will be less likely to oppose the expansion..

> PUBLIC OPINION HYPOTHESIS: Governors are less likely to oppose the Medicaid expansion funds as the proportion of the state with a favorable view of the Affordable Care Act increases.

Third, any decision to accept Medicaid funds must pass through the legislature. Governors should be more likely to oppose the funds when they can expect their decision to oppose expansion to be supported by the state legislature. In particular, governors can expect fellow-opposition if their legislature is controlled by Republicans. This leads to the final hypothesis concerning politics.

> LEGISLATIVE PARTISANSHIP HYPOTHESIS: Governors are more likely to oppose the federal Medicaid expansion if the state legislature is controlled by Republicans.

*Citizen Needs*

Regardless of party or public opinion, we expect governors to be responsive to the needs of the public. The proposed expansion is the most generous Medicaid reimbursement in the program's history, and most observers expected states committed to reducing uninsurance would adopt that portion of the PPACA willingly. Given the effectiveness of past Medicaid expansions on insurance coverage (see, e.g., Kail, Quadagno and Dixon 2009), the decision to refuse a federal subsidy that would provide insurance to large uninsured populations is an extreme political choice. However, states vary in their need for a Medicaid expansion. While some states would benefit a great deal from the expansion, other states would benefit less. The states that would benefit most in terms of expanding coverage are those with the most limited Medicaid programs, several with governors who oppose the expansion.

In 2011, about 48.6 million non-institutionalized adults between the ages of 18-64 were uninsured, about 15.7 percent of the non-institutionalized adult population (Todd and Summers 2012). The bloc of persons who are most likely to take advantage of the Medicaid expansions are those who will gain services as a result of the expansion, people whose incomes equal 138 percent of federal poverty level or less. Demand for expanded insurance should increase where there is more unrealized demand, those in which states provide coverage at levels below the 138% mark. Two specific groups stand to benefit from expansion: the uninsured and healthcare providers.

The size of the uninsured population among the states may affect states' choices to expand Medicaid. Medicaid expansions were the sole effective tool used by states to increase health insurance coverage in the aftermath of the Clinton health reforms (Barrilleaux and Brace 2007; Bernick and Myers 2008; Kail, Quadagno and Dixon 2009), but only a handful of states with the most generous prior Medicaid policies used that approach to reducing uninsurance. Thus Medicaid expansion is a policy tool that's proved to work well in reducing the numbers of uninsured in the states.

Healthcare providers also stand to gain from the expansion, especially in states with large numbers of uninsured. Expanding health coverage reduces the uncompensated care burden for providers, so that healthcare suppliers, hospitals, clinics, participating physicians, managed care organizations, pharmacies, and other providers also stand to benefit from broader Medicaid coverage, which makes it more likely that they will get paid for the services they provide. Thus providers, especially not-for-profit and public hospitals, support Medicaid expansions.

Thus, the benefit that each state received from the expansion seems to increase with the size of the uninsured population. This leads to the hypothesis relating to needs.

> NEEDS HYPOTHESIS: Governors are less likely to oppose the federal Medicaid expansion funds as the percent of uninsured in their state increases.

To review, we expect governors' decisions to be affected by some mixture of political and citizen needs considerations, and we test four hypotheses that fall within those heading. In the section below we discuss measurement and estimation.

## Empirical Analysis

Our outcome of interest is public opposition to the Medicare expansion, so our outcome variable equals one if the governor opposes Medicaid expansion and zero otherwise.[3] We model the outcome using logistic regression as a simple linear function of the (standardized) explanatory variables along with several (standardized) control variables.[4] Our explanatory variables of interest are an indictor for whether the governor is a Republican, an estimate of the percentage of a state's citizens with favorable view of the Affordable Care Act, an indicator for whether the legislature is controlled by Republicans, and the percentage of the state's population that is uninsured.[5] We use four other explanatory variables as controls. First, we include a

[3] We maximize our statistical leverage by combining governors who publicly support expansion and those who have remained quiet into a single "does not oppose" category.We combine the "Supports Expansion" and the "Weighing Options" categories for two reasons. First, the two are conceptually similar. We are interested in why governors would publicly oppose such a generous offer from the federal government and particularly how politics and need affect this decision. Given our question, the decision to support the expansion or remain quiet on the issue are similar. Second, our data do not offer sufficient information to parse out the different effects that our explanatory variables have across these different outcomes.

[4] See Section 1 of the Technical Appendix for the details.

[5] The state-level estimates of the percent with favorable views toward the ACA are computed using multilevel regression with post-stratification, combining the May though September 2013 Kaiser Health tracking polls with 2000 Census data. See Section 2 of the Technical Appendix for the details. We also consider several alternative measures of our key concepts. Instead of state-level favorability toward the ACA as a measure of public opinion, we consider a generic ideology measure, Obama's vote share in 2012, and whether Obama won the state in 2012. We also consider alternative models for the impact of the composition of the legislature by including indicators for GOP control of the House, GOP control of the Senate, and both. Finally, as an alternative measure of need, we use a states share of DSH payments per capita. Since these payments disappear under the ACA, states with higher shares per capita might be viewed as in greater need of the expansion funds.

measure of fiscal health, using the states' year-end reserves as a percentage of total spending and intended to capture states' ability to pay [Charles: Perhaps we should add a cite here?].[6] We also include the states' current Medicaid multiplier to captures the "deal" that states' are getting on the new Medicaid money relative to their current rate. For example, it could be that the national government's offer to pay 90% of the new Medicaid expenses in not attractive to Mississippi, for whom the national government already pays 74% of Medicaid expenses. Lastly, African-Americans and those living in cities are more likely to enroll in Medicaid, so we include controls for the percent of the state that is non-white and the percent of the state living in metropolitan areas. We scale each explanatory variable to have mean zero and standard deviation 0.5, with the exception of binary explanatory variables, which we simply center by subtracting the mean. This allows us to place a common prior distribution on all coefficients (Gelman et al. 2008) and more directly compare the magnitude of the coefficients (Gelman 2008).

| | Supports Expansion | Opposes Expansion |
|---|---|---|
| Democratic Governor | 19 | 0 |
| Republican Governor | 15 | 16 |

Table 1: A table showing the distribution of opposition of expansion by governors' partisanship. Notice that the data are quasi-separated in that no Democratic governor opposes expansion.

The usual likelihood estimation fails in two important ways with our data. First, and most importantly, the data are quasi-separated (Zorn 2005). Data reported in Table 1 show that being a Democratic governor predicts non-opposition perfectly. In this situation, maximum likelihood does not provide reasonable estimates.[7] As a solution, we follow Gelman et al.'s (2008)

[6] Note the Alaska is a outlier on this measures, with 2012 year-end reserves of 260% of their total 2012 spending. The next largest is North Dakota at 75% and the smallest is California at -2%. Excluding Alaska from the analysis does lead to a substantively meaningful change in the effect of fiscal health, but it does not change the effects of our key variables. See Section 3.4 of the Technical Appendix for the details.

[7] Quasi-separation leads to estimated coefficients and standard errors of infinity. In practice, though, the estimates and standard error will be unexpectedly large. How large the estimates will be depends on the numerical precision of the optimization routine.

suggestion to build in a small amount of prior information into the estimation through a (scaled) Cauchy prior distribution. The prior for the model coefficients takes the form of a Cauchy distribution centered at zero with scale 2.5 (with a scale of 10 for the intercept).[8] The Cauchy distribution has very heavy tails, which does not rule out very large coefficients, but places higher prior weight on coefficients that are between -5 and 5. Because all variables are rescaled to have mean zero and standard deviation one-half, a logistic regression coefficient of five means that a two standard deviation increase in continuous measures or change from zero to one in a dichotomous measures increases the probability of an event from 0.01 to 0.99. Our prior simply suggests that effects larger than this are unlikely, but not impossible.[9]

Secondly, the sample of 50 states is too small to rely on asymptotic variance estimators. While maximum likelihood estimators are normally distributed about the true mean with the smallest possible variance for large sample sizes, these properties might not hold for small samples (Train 2009, Casella and Berger 2002).[10] Thus, instead of relying on the analytical (asymptotic) standard errors and assuming normality to conduct hypothesis tests and calculate confidence intervals, we use MCMC to directly sample from the posterior distributions of the

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For example, using R's default convergence criteria for the `glm()` function, the estimated coefficient for the GOP governor indicator is 19.5 with a standard error of 2,146.4. When we increase the convergence tolerance standards as much as possible, we obtain an estimate of 33.4 with a standard error of 15,395,829.3. Of course, neither estimate is statistically significant, despite the pattern being extremely unlikely under the null hypothesis of no effect. See Zorn (2005) for a detailed explanation of this pattern.

[8] We intentionally include less prior information than we actually have as suggested by Gelman et al. (2008). However, our results are robust to a range of prior specifications including increasing and decreasing the scale within the Cauchy family and considering alternative families such as the normal and scaled *t* families. We also considered non-Bayesian approaches, including various combinations of Firth's penalty (Zorn 2005), asymptotic approximations (Gelman et al. 2008), and bootstrapping (1979). See Sections 3 and 4 of the Technical Appendix for the details.

[9] Zorn (2005) suggests using Firth's penalty when facing separation (see Firth 1993 and Bell and Miller 2013). This approach is similar conceptually to our own, but relies on Jeffrey's invariant prior distribution, which is not directly interpretable in the context of regression models. Instead, we prefer the Cauchy prior, since it allows us to directly interpret the prior as actual prior information (Gelman et al. 2008). However, the results are substantively similar if we rely on Zorn's (2005) suggested approach of combining Firth's penalty with likelihood profiling. See Section 3.3 of the Technical Appendix for the details.

[10] For the details see Casella and Berger (2002), especially Theorem 10.1.6 (asymptotically distributed about the mean) and Theorem 10.1.12 (with the smallest possible variance). Train (2009, pp. 200-202) discusses the asymptotic properties of MLE estimators and discusses using bootstrapped samples to obtain variance estimators. Another potential concern with small samples is that a single case drives the conclusions. Dropping any single state from the analysis does not change the substantive conclusions. See Section 3.4 of the Technical Appendix for the details.

model coefficients and transform these simulations to obtain substantively meaningful quantities of interest (King, Tomz, Wittenberg 2000). We use the median of the posterior simulations as our point estimates and the 5th and 95th percentiles to construct a 90% (equal-tailed) credible interval. To assess the evidence for our hypotheses, we simply calculate the proportion of the simulations that are inconsistent with the research hypothesis, which we denote as $Pr(H_r|\text{data})$. The quantity $1 - Pr(H_r|\text{data})$ can be interpreted as the probability of the null hypothesis given the data and is approximately comparable to a classical *p*-value for the directional hypotheses we examine.[11] Thus, $Pr(H_r|\text{data}) = 0.95$ is evidence comparable to *p = 0.05*. Because we have a small sample of 50 states, we interpret $Pr(H_r|\text{data}) > 0.95$ as strong evidence, $0.90 < Pr(H_r|\text{data}) < 0.95$, as moderate evidence, and $0.85 < Pr(H_r|\text{data}) < 0.90$ as weak evidence and $Pr(H_r|\text{data}) < 0.85$ as ambiguous evidence.

## Estimates

Figure 2 shows the coefficient estimates and Table 2 summarizes the evidence for each hypothesis. Notice first that the data strongly support the Gubernatorial Partisanship Hypothesis ($Pr(H_r|\text{data}) > 0.99$), which suggests that Republican governors are more likely to oppose the expansion than their Democratic counterparts. In particular, in otherwise "Republican" states (GOP-controlled legislatures, 38% view ACA favorably, and all other variables set at their sample medians), having a Republican governor (as opposed to a Democratic governor) increases the chance of gubernatorial opposition by about 49 [23, 74] percentage points.[12] In

[11] This comparability does not extend to situations in which the null or research hypothesis suggests that the effect lies in a non-contiguous region (e.g., Rainey 2014).

[12] The intervals given in parentheses are 90% confidence intervals. We define "Republican" states (in part) to be those in which 38% view the ACA favorably because 38% favorability is the 25th percentile of the favorability measure. States such as Texas, Louisiana, South Dakota, and Tennessee have favorability measures near 38%. Similarly, we define "Democratic" states (in part) to be those in which 51% view the ACA favorably because 51% favorability is the 75th percentile of the favorability measure. States such as New Mexico, Oregon, Washington, and Maine have favorability measures near 51%. Utah has the lowest favorability at 27% and Hawaii has the highest at 63%.

otherwise "Democratic" states (legislatures not controlled by GOP, about 51% view ACA favorably, and all other variables set at their sample medians), having a Republican governor increases the chance of gubernatorial opposition by about 9 [0.01, 0.38] percentage points.[13]

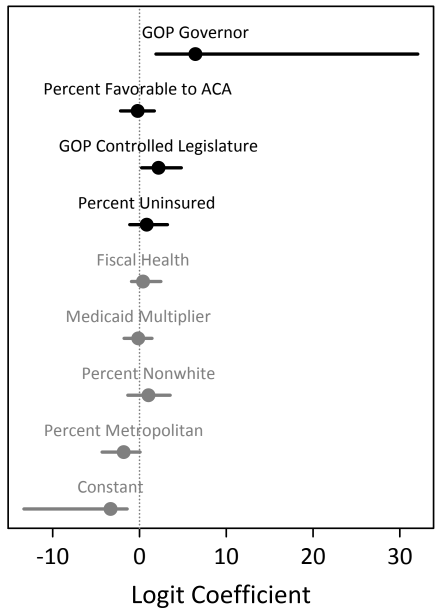


Figure 2: This figure shows the posterior medians and (equal-tailed) 90% credible intervals from the model. Notice that the results are generally consistent with the hypotheses, except the percent uninsured does not have the expected large effect.

[13] While we discuss the difference in the effects across "Democratic" and "Republican" states, it is important to avoid drawing strong conclusions about the difference in these effects, since they are assumed by the structure of the model (Berry, DeMeritt, and Esarey 2014; Rainey 2014; though see Berry, DeMeritt, and Esarey 2010). We present the effects in different contexts to give a sense of the magnitude of the estimates implied by the model, not to draw strong conclusions about the differences in the effects across contexts.

| Hypothesis | $Pr(H_r\|\text{data})$ | Evidence |
|---|---|---|
| Gubernatorial Partisanship | 0.99 | Strong Evidence in Favor |
| Public Opinion | 0.89 | Weak Evidence in Favor |
| Legislative Partisanship | 0.94 | Moderate Evidence in Favor |
| Need | 0.49 | Ambiguous Evidence |

Table 2: A table summarizing the evidence for each research hypothesis. Notice that we have at least weak evidence for each of the political hypotheses, but the evidence for the Needs Hypothesis remains ambiguous. The probability of the research hypothesis given the data are calculated by simply computing the proportion of the MCMC draws that have the correct sign (i.e., consistent with the research hypothesis). Because our sample is quite small, we interpret probabilities near 0.9 (comparable to the frequentist $\alpha = 0.1$) as offering some evidence for our hypothesis.

We have little support for our Public Opinion Hypothesis ($Pr(H_r|\text{data}) = 0.57$). However, it is important to avoid drawing the conclusion that governors are unresponsive to public opinion. Because we consider this evidence ambiguous at best. First, in otherwise Republican states, increasing the favorability of the ACA from 38% to 51% leads to a 4 [-28, 35] percentage point *decrease* in the chance of gubernatorial opposition. Thus, the effect is in the hypothesized direction and effects as large as 35 percentage points are plausible based on the data (Rainey, forthcoming). Second, the the estimate is not robust to alternative measures. We discuss this in more detail below, but an Obama victory in the state in 2012, for example, seems to make governors much less like to oppose the expansion.

We also have strong evidence for our Legislative Partisanship Hypothesis ($Pr(H_r|\text{data})$ = 0.97), which suggests that governors of states with a Republican-controlled state legislature are more likely to oppose the expansion. According to our statistical model, having a Republican legislature in an otherwise Republican states increase the chance of opposition by about 36 [-0.05, 0.64] percentage points.[14] The model suggests that he composition of the legislatures has

[14] Unfortunately, we do not have sufficient data to parse out the separate effects of Republican-controlled, Democratic-controlled,

essentially no effect in otherwise Democratic states because Democratic governors are highly unlikely to oppose the expansion.

We have no evidence for our Needs Hypothesis ($Pr(H_r|\text{data})$ = 0.25) and the effect actually goes in the *wrong direction* so that the probability of opposing expansion *increases* with need. Again though, it is important to avoid drawing the conclusion that a variable has "no effect" based only on a lack of statistical significance (Rainey, forthcoming). Instead, we should consider all effects contained in the 90% confidence interval plausible. In Democratic states (states in with a Democratic governor and legislature that Obama won in 2012), the model suggests that increasing the percentage uninsured from a low value (the 25$^{th}$ percentile, or 10.7% uninsured) to a high value (the 75$^{th}$ percentile, or 17% uninsured) has almost no effect, since the probability that these governors oppose the expansion is nearly zero, regardless of the magnitude of the need. The confidence interval suggests that the effect of increasing the percent uninsured from 10% (25$^{th}$ percentile; North Dakota, Pennsylvania, and Maryland) to 17% (75$^{th}$ percentile; Arkansas, Arizona, Louisiana, Mississippi) is probably smaller than a one percentage point has almost no effect. This is simply because the probability that these governors oppose the expansion is nearly zero, regardless of the magnitude of the need.

The story is much different in Republican states, however (states with ACA favorability of 38%, and with Republican governors and legislatures). Regardless of the level of need, governors in Republican states are quite likely to oppose expansion. When the percent uninsured is only 10%, the model suggests that these governors have about a 47 [19, 76] percent chance of opposing the expansion. Increasing the percent uninsured to 17% *increases* the chance of opposition to about 60 [31, 84] percentage points. Thus, although we cannot be confidence about

and divided state legislatures. However, there are only four divided legislatures in the data (IA, KY, NH, and NY). In this situation, we draw heavily on prior literature to specify the model correctly. However, this conclusion is reasonably robust to alternative specifications, including a model that includes separate indicators for GOP control of the House and Senate .

the sign of the difference, the model estimates that an increase in the level of uninsurance from 10% to 17% leads to an 11 [-15, 42] percentage point *increase* in the likelihood of opposition. Notice that the model suggests that a 15 percentage point decrease is plausible, so that we cannot rule out a small to moderate effect of need, but these effect pale in comparison to the estimates from the political variable, especially the partisan control of the governorship and legislature. But these hypotheses—that the political variables have a larger effect than the need variables—are directly testable in the context of the model.

Since the change in probability of opposition depends on the values of other explanatory variables, the fairest test is to compare the logit coefficients directly.[15] Table 3 shows the evidence from each of these tests. While the evidence for opinion is somewhat weak, we have strong evidence that gubernatorial partisanship and legislative control has a larger effect on the decision to oppose the expansion of Medicaid than the level of need in the state. It is worth noting, though, that the evidence that public opinion has a larger effect than need depends on the measure. We discuss this in more detail below.

| Hypothesis | $Pr(H_r \mid \text{data})$ | Evidence |
|---|---|---|
| The effect of gubernatorial partisanship is larger than the effect of need. | > 0.99 | Strong Evidence in Favor |
| The effect of public opinion is larger than the effect of need. | 0.75 | Weak Evidence in Favor |
| The effect of legislative partisanship is larger than the effect of need. | 0.96 | Weak Evidence in Favor |

Table 3: This table summarizes the evidence for each hypothesis that the political variable has a larger effect than the level of need. The evidence only weakly supports the claim that public opinion and legislative partisanship matter more than need, but the data offer strong support for the claim that gubernatorial partisanship has a larger impact on the decision to oppose expansion than the level of need.

[15] Recall that the coefficients are comparable because we standardize all numeric explanatory variables to have mean zero and standard deviation 0.5 and simply center binary explanatory variables. This makes the magnitude of the coefficients comparable (Gelman 2008).

Just to get a sense of how much more politics matters than need, consider the relative effects of the governor's partisanship and the level of need. Shifting from a Democrat to a Republican governor in an otherwise Republican state (38% favorable to the ACA and a GOP-controlled legislature) increases the chance of gubernatorial opposition by about 49 [23, 74] percentage points. Shifting a from low-need to a high-need Republican state (38% favorable to ACA and a Republican governor and legislature) *increases* the chance of opposition by about 11 [-15, 42] percentage points. This suggests that moving to a Republican governor has a 61 [25, 96] percentage point larger effect than increasing the percent without insurance from 10% to 17%.

*Robustness Check #1: Alternative Measures of the Key Concepts*

To evaluate the robustness of our conclusion that politics matters and need matters less if at all, we evaluate the robustness of the conclusions drawn from the model to plausible alternative measures. In place of the state-level estimates of ACA favorability, we consider Obama's share of the two-party vote in 2012, whether Obama won the state in 2012, a generic measure of state ideology (Tausanovitch and Warshaw 2013), the percent of the state that support the Medicaid expansion, and the percent that support the Tea Party. We also consider alternative strategies for modeling the composition of the legislature by including an indicatory for GOP-controlled House, an indicator for GOP-controlled Senate, or both indicators. As an alternative measure of need, we consider states' shares of DSH payments per capita, the percent below 138% poverty, the rate of low birth weights, the heart disease death rate, and the life expectation. Table 5 shows the results.

| Hypothesis | Variable | Expectation | Estimate | $Pr(H_r \| data$ | Evidence |
|---|---|---|---|---|---|
| Public Opinion | *Percent Favorable to ACA* | - | -0.21 | 0.57 | Ambiguous Evidence |
| | Obama's 2012 Vote Share | - | -0.82 | 0.76 | Ambiguous Evidence |
| | Obama Victory in 2012 | - | -1.85 | 0.94 | Moderate Evidence in Favor |
| | State Ideology | + | 2.33 | 0.92 | Moderate Evidence in Favor |
| | Percent Supporting Medicaid Expansion | - | 1.01 | 0.17 | Ambiguous Evidence |
| | Percent Supporting Tea Party | + | 1.09 | 0.82 | Ambiguous Evidence |
| Legislative Composition | *GOP Controls Both House and Senate* | + | 2.31 | 0.97 | Strong Evidence |
| | GOP House | + | 6.48 | 1.00 | Strong Evidence in Favor |
| | GOP Senate | + | 2.17 | 0.97 | Strong Evidence in Favor |
| | GOP House<br>GOP Senate<br>(as separate variables in the model) | +<br>+ | 6.44<br>0.21 | 0.98<br>0.55 | Strong Evidence in Favor<br>Ambiguous Evidence |
| Need | *Percent Without Health Insurance* | - | 0.91 | 0.25 | Ambiguous Evidence |
| | DSH Payments per Capita | - | 1.21 | 0.10 | Moderate Evidence Against |
| | Percent Below 138% Poverty | - | 0.53 | 0.35 | Ambiguous Evidence |
| | Low Birth Weight | - | 2.76 | 0.02 | Strong Evidence Against |
| | Heart Disease Death Rate | - | 1.23 | 0.09 | Moderate Evidence Against |
| | Life Expectancy | + | -1.50 | 0.09 | Moderate Evidence Against |

Table 4: This table summarizes the evidence for (or against) our research hypotheses using alternative measures of the key concepts. The original measures appear in italics. Notice that the evidence for the Public Opinion Hypothesis is generally weak, though correctly signed except for the percent supporting the Medicaid expansion. The evidence for the Legislative Composition Hypothesis remains consistent with the estimates, though it seems that the state house matters more than the state senate. Finally, and more importantly, notice that all the measures of need are incorrectly signed and, in most some cases, we have moderate to strong evidence *against* the hypothesis. Thus, it seems that governors of states in greater need are more likely to oppose the expansion.

Notice that although the amount of evidence for the hypotheses might increase or decrease at the margin, the results are quite similar to those from the main model, and in some cases, are much stronger. The alternative measures of public opinion all have the correct sign, except for the percent supporting the Medicaid expansion. While the evidence for the hypothesis ranges from moderate to ambiguous, notice that the results are generally consistent with the smaller effect of public opinion that we find the in main text. Further, notice that the most obvious cue that governors face, whether Obama won their state in 2012, has a large effect, while much more subtle cues (such as the percent supporting the Medicaid expansion) have much smaller effects.

Regardless of how we model with composition of the legislature, the model suggests that the legislature matters. However, it seems that the composition of the lower house has the largest effect. [Charles: I seem to recall you saying that the lower house tends to be more important, perhaps you can add something about that here.].

Perhaps the most interesting result from these additional analyses come from the alternative measures of need. All but one of the alternative measures suggest evidence against the hypothesis that governors of states with greater levels are *more* likely to oppose the expansion. Indeed, the coefficient for low birth weight rate is among the largest for the variables we consider and is in the wrong direction. These alternative measures suggest more strongly than the level of uninsurance that the level of need in a state has little to no effect on governors' decisions to support or oppose expansion.

But in addition to the absolute impact of need, we care about the effect of need compared to the effect of politics. Table 5 provides a summary of the evidence for the hypothesis that politics matters more than need for the three political variables and five alternative measures of need. Notice that, with the possible exception of life expectancy, the evidence is generally stronger for the alternative measures.

| Hypothesis | DSH Payments Per Capita | Percent Below 138% Poverty | Low Birth Weight Rate | Heart Disease Death Rate | Life Expectancy |
|---|---|---|---|---|---|
| The effect of gubernatorial partisanship is larger than the effect of need. | 1.00 | 0.99 | 1.00 | 1.00 | 0.96 |
| The effect of public opinion is larger than the effect of need. | 0.88 | 0.71 | 0.95 | 0.88 | 0.27 |
| The effect of legislative partisanship is larger than the effect of need. | 0.99 | 0.95 | 1.00 | 0.99 | 0.55 |

Table 5: This table provides the evidence for the hypothesis that each political variable has a large effect than the alternative measures of need. Notice that the evidence for the hypothesis that politics matter more than need is supported more strongly by the alternative measures than the percent uninsured, with the possible exception of the life expectancy. In general, though, the evidence presented in this table strongly supports the hypothesis that politics matters more than need.

*Robustness Check #2: Random Forests and Variable Importance*

As an alternative to the parametric (and linear) approach above, we evaluate the robustness of our claim that politics is more important than need using random forests (Breiman 2001, Hill and Jones forthcoming), which are a large collection of decision trees used to predict gubernatorial opposition to the Medicaid expansion. This approach allows a variety of interactions and nonlinearities to enter the model (Biau, Devroye, and Lugosi 2008) and provides a robust tool for assessing variable importance (Strobl et al. 2007). Thus, this approach serves as a useful robustness check on our claim that politics is more important than need in influencing governors' decision to support or oppose the Medicaid expansion.

Intuitively, random forests are a collection of decision trees that classify (with error) governors' decisions to support or oppose the expansion. Each tree in the forest is built as follows:

1. Select 32 cases (63%) without replacement to train the model. Set the remaining 18 test cases aside. Use training cases to build a decision tree to classify governors as opposing the expansion or not.
2. Select three predictors at random from a larger set of predictors. We consider eight variables measuring the political context and six variables measuring the level of need. The political predictors are the governor's partisanship, the percent favorable to the ACA, Obama's vote share in 2012, the general ideology of the state, the percent supporting the Medicaid expansion, the percent supporting the Tea Party, whether the state house is controlled by Republicans, and whether the state senate is controlled by Republicans. The need predictors are the percent without insurance, the percent below 138% of poverty, DSH payments per capita, the low birthweight rate, the heart disease death rate, and life expectancy. From these three, choose the variable and, if continuous, the split that best classifies the observations in the training data. Continue drawing three predictors at random and optimally partitioning the data using these predictors until the splits are not longer statistically significant.
3. Use this tree to predict the 18 test cases. Compute the proportion of cases correctly

predicted as a measure of model accuracy.

4. Now randomly permute each variable (one-by-one) and re-compute the proportion of cases correctly predicted. If the variable is an "important" predictor of opposition, then the accuracy of the tree should decrease substantially. However, if the variable is "unimportant," then the accuracy should decrease only slightly or not at all.

To grow a forest, as opposed to a single tree, we simply repeat this procedure 1,000 times (i.e., grow 1,000 trees). This collection of trees serves as a forest and we assess variable importance by averaging the difference in accuracy before and after permuting each variable across the entire forest. This difference serves as our point estimate of variable importance. Larger values (positive and away from zero) indicate that a variable is more important and smaller values (closer to zero or negative) indicate that a variable is less important. To assess the uncertainty around these point estimates of variable importance, we follow Hill and Jones (forthcoming) and grow 100 forests on bootstrap re-samples of the data (that is, we grow 100 forests by resampling 50 states with replacement and growing a forest of 1,000 trees 100 times). We use the collection of variable importance measures from these forests to obtain a 90% confidence interval around the estimates of variable importance. The estimates and 90% confidence intervals for each variable are shown in Figure 3.

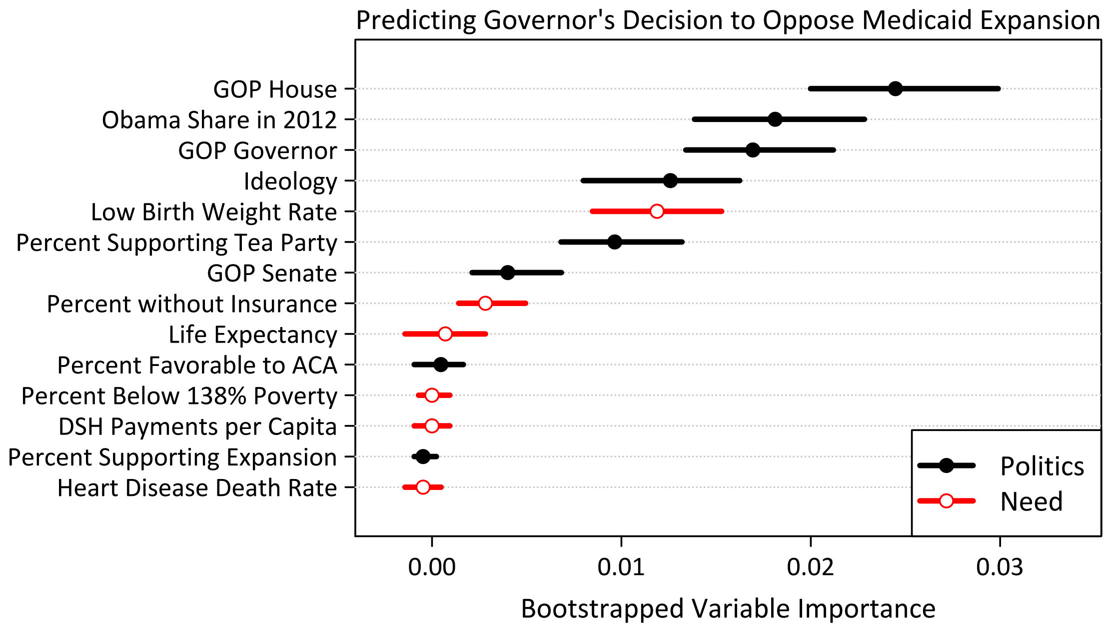


Figure 3: This figures shows the estimates of variable importance and 90% bootstrapped confidence intervals for a range measures of the political context and the level of need. First, notice that most of the political predictors are more important than the need predictors. Second, the only need predictor that seems to perform well is the low birth weight rate. However, this variable work in the wrong direction, so that states with more need are more likely to oppose the expansion.

The results offer stark support for our claim that politics matters more than need. Even without a close examination of the results, almost all of the political variables are important predictors and almost all of the need variables are *un*important. These results suggest that if one wanted to predict which governors oppose the expansion, on probably wanted to know whether the lower house is controlled by Republicans, Obama's margin of victory in 2012, the governor's partisanship, and perhaps the ideology of the state. All of these variables focus on the immediate political context.

However, a close examination only strengthens the evidence for the claim that politics is more important than need. The least important political variable is the percent of a state supporting the Medicaid expansion. This measure is based on a July 2012 Kaiser Family Foundation survey immediately following the Supreme Court decision. Since the political implications of the expansion were not yet well known, this measure might not be the best indicator of the electoral cost that Republican governors might pay for “supporting Obamacare.”

The most important need variable, the low birth weight rate, seems somewhat important, but works in the wrong direction—governors facing more low birth weights are more likely to *oppose* the expansion. Although the model suggests it is less important, the random forests suggest that life expectancy might have some predictive power, but again, it has an effect in the wrong direction.

The only real surprise from this analysis is the relative unimportance of the favorability of the Affordable Care Act. However, it has the smallest effect of the political variables in the main model, and the random forests suggest it plays a relatively unimportant role as well. In short, the random forest offer solid evidence in favor of our claim that politics matters more than need.

## Conclusion

The Supreme Court shifted the terms of the PPACA debate in June 2012 when they affirmed the constitutionality of the individual mandate but gave state governments the choice to accept or not accept Medicaid expansions to cover 138% of the federal poverty population.  Evaluations of the 1990s-era state health reforms revealed Medicaid expansion to be the single most effective way to expand insurance coverage, so state decisions to refuse those benefits may prove to have substantial effects on access to care for the poor or working poor.  In addition, citizens of states that do not expand Medicaid under the federal plan are ineligible for the subsidies for low-income persons that are available under PPACA.

A possible silver lining in the Medicaid expansion dispute is that it provides an opportunity for evaluation of the decision's effects on health access and spending.  State welfare reforms in the 1990s allowed states considerable discretion in program design, which has made possible evaluations of specific program features (see, e.g., Soss, et al. 2001). The Medicaid expansions may result in similar variation in programs under the PPACA and afford similar program analysis possibilities. Baiker, et al. (2013, 1722) report that the persons who received Medicaid coverage under the 2008 Oregon randomized Medicaid enrollment had "...increased access to and utilization of health care, substantial improvements in mental health, and reductions in financial strain" but the investigators report no marked improvement in health status among enrollees. The 2013 Medicaid expansion decisions may enable analysts to develop similar models using a nationwide panel in a natural experiment.

State governments rely on federal money for large portions of their budgets (Cho and Wright 2007) and the Medicaid expansion is certainly a large infusion of federal money. Refusal to expand the program means states are giving up billions of dollars that would flow into their health systems, boost their economies, and reduce uninsurance. On the other hand, states that refuse the money may be staking out a strong states-rights position, one that has received substantial support in the courts over the past thirty-odd years (Hanson 2008, pp. 24-36). The debate within states' about whether to expand Medicaid is ongoing and often reflects tension between politics and need. It is unclear how citizens will respond to their states' refusing benefits that leave large numbers of citizens without health insurance. But for now, in the tug-of-war between politics and need, politics seems to be winning.

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# Technical Appendix

## 1. Mathematical Representation of the Statistical Model

Let $y\_i$ be an indicator that equals one if the governor of state $i$ opposes the Medicaid expansion and zero otherwise. Then we model the probability of opposition as $\Pr(y_i = 1) = \text{logit}^{-1}(X_i\beta)$, where

$$\begin{aligned} X_i\beta = {} & \beta_{cons} + \beta_{GOP\ gov.}\text{GOP Governor}_i + \beta_{opinion}\text{Opinion}_i + \beta_{GOP\ leg.}\text{GOP Legislature}_i \\ & + \beta_{uninsured}\text{Percent Uninsured}_i + \beta_{income}\text{Income}_i + \beta_{nonwhite}\text{Percent Nonwhite}_i \\ & + \beta_{metro}\text{Percent Metropolitan}_i \end{aligned}$$

and Cauchy(2.5) priors are placed on the coefficients and a Cauchy(10) prior is placed on the intercept.

The variables are defined as follows: *GOP Governor* is an indicator that equals one if the governor is a Republican and zero if the governor is a Democrat; *Opinion* is an estimate of the proportion of a state's population that has a favorable opinion of the Affordable Care act (see Section 2 of this Appendix for the details); *GOP Legislature* is an indicator variable that equals one if Republicans control both branches of the state legislature and zero otherwise; *Income* is the total personal income in the state per capita; *Percent Nonwhite* is the fraction of the state's population that identify as non-white Hispanic or African-American; *Percent Metropolitan* is the percent of the state that resides in a metropolitan area. Prior to estimation, the continuous variables are standardized by subtracting the mean and dividing by two standard deviations and binary variables are centered by subtracting the mean (Gelman 2008).

We place weakly informative Cauchy(2.5) prior distributions on the coefficients for the (standardized) explanatory variables and a more diffuse Cauchy(10) prior on the intercept. We use JAGS called through R to perform a 50,000 iteration burn-in and 50,000 additional posterior simulations for three MCMC chains. We combined these simulations to perform the inferences.

## 2. State-Level Estimates of ACA Favorability

In the main text, we rely on a state-level estimate of the favorability of the 2010 Affordable Care Act as our measure of public opinion. As robustness checks, we also use state-level estimates of support for the Medicaid expansion and support for the Tea Party. The estimate state-level public opinion on the Affordable Care Act, we use multilevel regression with post-stratification (MRP; Lax and Phillips 2009) to combine the Kaiser Family Foundation Health Tracking Polls from January to November of 2013 with census data from 2000 (with 2008 weights).[16] Where $y\_i$ is an indicator for whether the respondent views the ACA favorably, supports the Medicaid expansion, or supports the Tea Party,

[16] Data for the support for the Medicaid expansion are available only fro the July 2012 Tracking Poll.

$$\Pr(y_i = 1) = \text{logit}^{-1}(\alpha^{cons} + \alpha^{race}_{j[i]} + \alpha^{gender}_{k[i]} + \alpha^{race \times gender}_{l[i]} + \alpha^{age}_{m[i]} + \alpha^{income}_{p[i]} + \alpha^{education}_{q[i]} + + \alpha^{state}_{s[i]})$$

In our model, $\alpha^{cons}$ is a fixed intercept; $\alpha^{race}_j$, $\alpha^{gender}_j$, $\alpha^{race \times gnder}_j$, $\alpha^{age}_j$, $\alpha^{income}_j$, and $\alpha^{education}_j$ are unmodeled random intercepts by the (categorical) variables indicated by the superscripts and shown in Table 4; and $\alpha^{state}_s$ is a random intercept modeled as $\alpha^{state}_s \sim N(\alpha^{region}_{r[s]} + \alpha^{Obama}\text{Obama Vote Share in } 2012_s)$, where $\alpha^{region}_{r[s]}$ is an unmodeled random effect and $\alpha^{Obama}$ is a fixed effect. We fit the model and performed the poststratification in R using the MRP package available at https://github.com/malecki/mrp. Our state-level estimates are given below in Figure 4 and available for download at https://github.com/carlislerainey/ACA_Opinion.

| Variable | Categories |
|---|---|
| Race | • White<br>• Black<br>• Hispanic<br>• Other |
| Gender | • Male<br>• Female |
| Race and Gender Interaction | • White male<br>• White female<br>• Black male<br>• Black female<br>• Hispanic male<br>• Hispanic female<br>• Other male<br>• Other female |
| Age | • 18-29<br>• 30-44<br>• 45-64<br>• 65+ |
| Income | • Less than $20,000<br>• $20,000 to $40,000<br>• $40,000 to $75,000<br>• $75,000+ |
| Education | • Less than high school<br>• High school graduate<br>• Some college<br>• College graduate<br>• Postgraduate |
| State | 50 states plus the District of Columbia, though the latter is not included in our model of gubernatorial opposition. |
| Region | • South<br>• Northeast<br>• Midwest<br>• West |

Table 6: This table provides individual-level categorical variables used in the MRP process to estimate ACA favorability in the states.

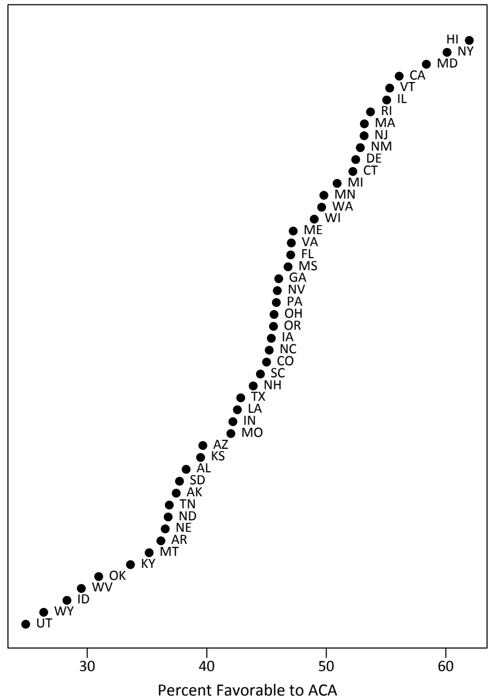


Figure 4: This figures shows the estimates of ACA favorability by state used in the main analysis.

## 3. Robustness Checks

We examine a variety of robustness checks, including the choice of prior scale for the Cauchy family, the choice of prior family, the choice of estimation technique, model specification, and case selection.

### *3.1. Prior Scale*

First, we demonstrate that the substantive conclusions are similar regardless of the prior scale. We re-estimated the main model with an alternative prior specifications to the default Cauchy(2.5) prior specification suggested by Gelman et al. (2008). Figure 5 shows the posterior medians and 90% credible intervals. Notice that the substantively conclusions do not change as the prior scale varies. Notice, though, that the prior scale mainly affects the upper bound of the 90% credible interval for the constant term and the coefficient for *GOP Governor*. This makes sense, as the likelihood is highly informative that the coefficient for *GOP Governor* is "not negative" but the prior is required to provide the information that the coefficient is "not positive infinity."

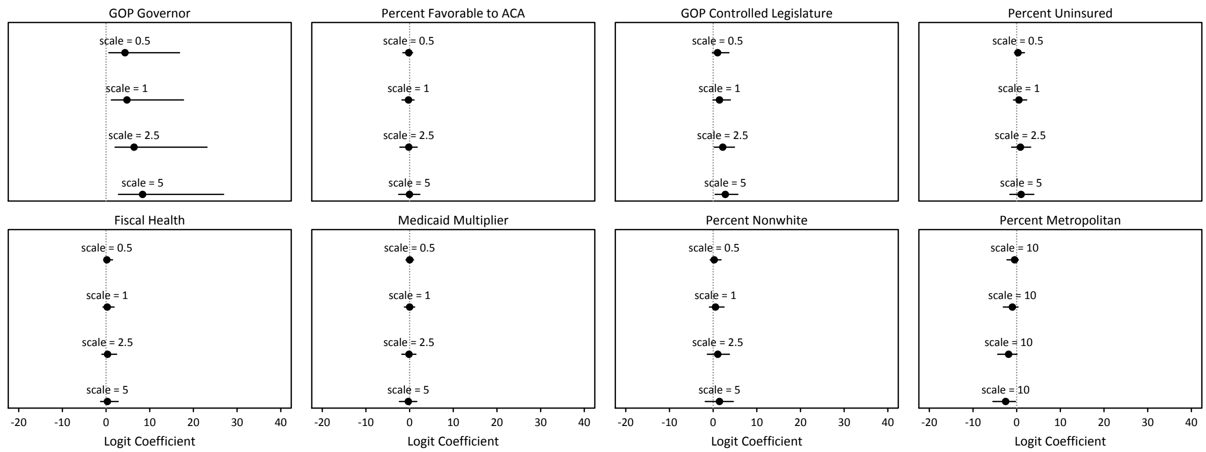


Figure 5: This figure shows how the inferences change as the scale on the Cauchy family of prior distributions changes. Notice that while the uncertainty around the estimate increases (mainly the upper bound), the substantive conclusions remain relatively unaffected.

### *3.2. Prior Family*

In addition to the results being robust to the prior *scale*, they are also robust to the prior *family*. To demonstrate this, we considered two alternative prior families, the normal and the $t_{10}$. We use the normal family because of its familiarity and the $t_{10}$ because the $t_{10}$ with scale 2.5 made the most sense to us as an informative prior based on a simple heuristic analysis.[17] Figure 6 shows the estimated using the normal prior with various scales (standard deviations). Notice that the normal family pools the coefficients much more strongly toward zero, but the results are otherwise similar.

[17] We arrived at the $t_{10}$ with scale 2.5 by simulating from the prior predictive distribution, computing quantities of interest, and choosing the simulations that seem to best reflect the prior uncertainty in the quantity of interest. The Cauchy(2.5) treats first differences of nearly one (or nearly negative one) as overly probable. On the other hand, the Normal priors do not give these possibilities enough weight. The $t_{10}$ prior with scale 2.5 allows these large shifts without placing undue prior weight on them. However, this is not to suggest that the $t_{10}$ with scale 2.5 is the best informative prior distribution, but simply useful as a robustness check.

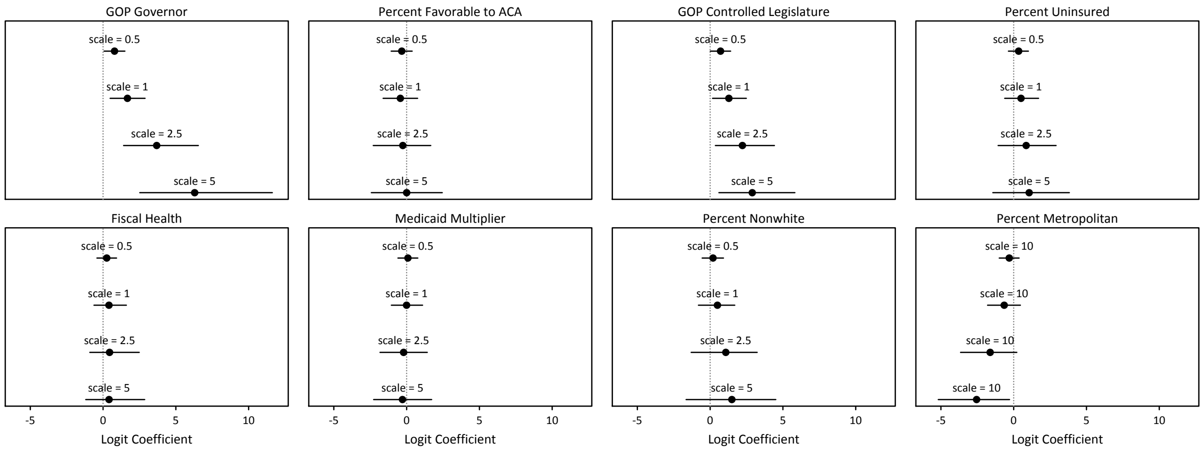


Figure 6: This figure shows how the inferences change as the scale (standard deviation) on the normal family of prior distributions changes. Notice that while the uncertainty around the estimate increases (mainly the upper bound), the substantive conclusions remain relatively unaffected. Compare to Figure 5 to see that while the normal family pools the coefficients more strongly toward zero, the substantive conclusions do not change.

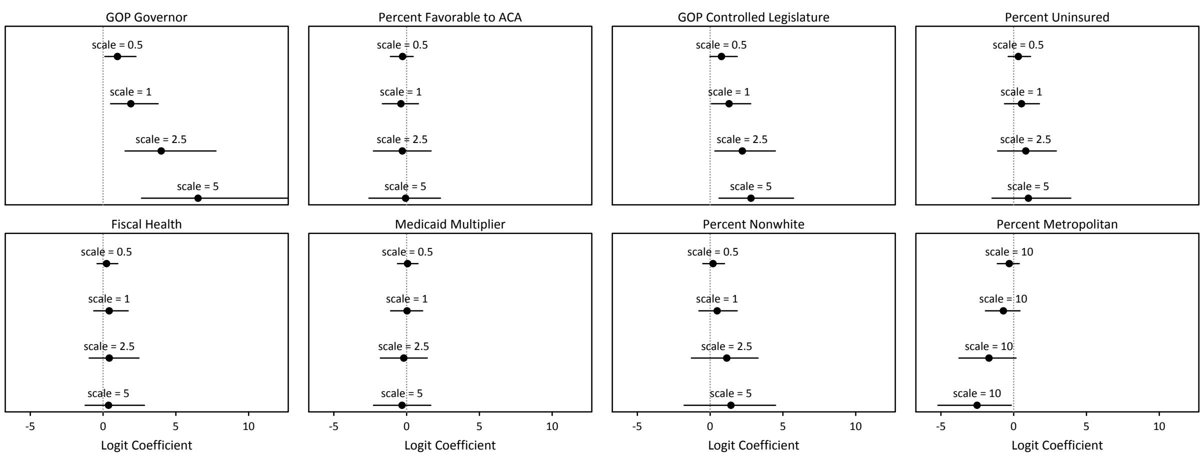


Figure 7: This figure shows how the inferences change as the scale (standard deviation) on the $t_{10}$ family of prior distributions changes. Notice that while the uncertainty around the estimate increases (mainly the upper bound) compared to the Cauchy family in Figure 5 and decreases compared to the normal family shown in Figure 6, the substantive conclusions remain relatively unaffected.

## *3.3. Choice of Estimation Technique*

In addition to the key substantive conclusions being robust to a range of prior specifications, they are also robust to several alternative estimation techniques. We consider several here. First, we compute the MLE estimates in spite of the separation. Second, we use Firth's penalty (Zorn 2005) and compute standard errors using both asymptotic approximations, likelihood profiling, and bootstrapping. We also use Gelman et al.'s (2008) approximation to the posterior mode and asymptotical approximate confidence intervals and bootstrapping. Finally, we compare each of these to our preferred approach of MCMC with a Cauchy(2.5) prior and include the results from the Normal(1) prior as a basis of comparison. The key point to take away from these results is the consistency in the estimated coefficients and uncertainty across the various estimation strategies.

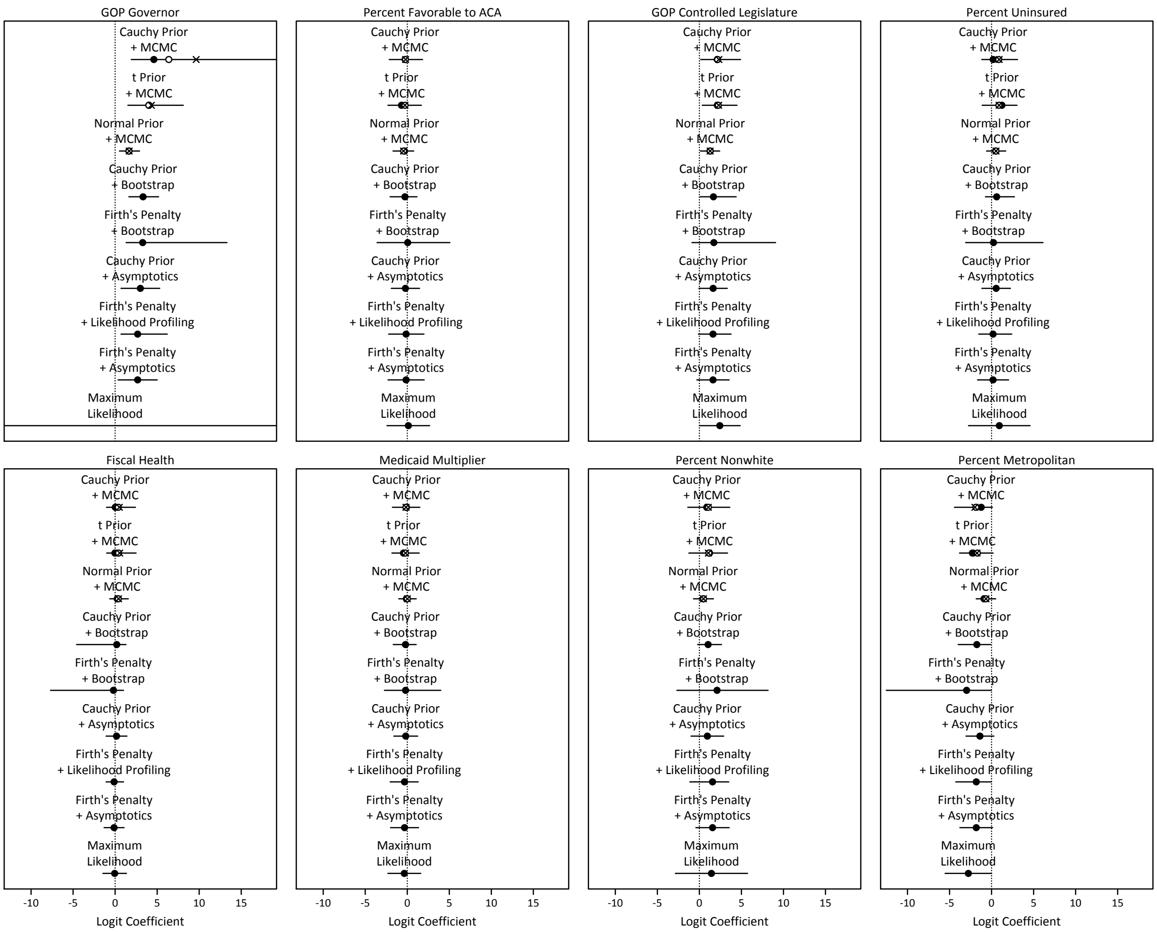


Figure 8: This figure shows how the inferences change across various estimation procedures for numeric explanatory variables transformed to have mean zero and standard deviation 0.5 and binary explanatory variables simply centered at their mean. The intercept is omitted to save space. For the models estimated with MCMC, the “x” represents the posterior mean, the circle represents the posterior median, and the dot represents the posterior mode. This distinction is consequential only for highly skewed posterior distributions. The substantive effects reported in the main text rely on MCMC approach with Cauchy priors, but the results do not change if we rely on the analytical standard errors or Firth’s penalty. Maximum likelihood clearly fails in this case. Though the maximum likelihood estimates depend on the convergence criteria, the default criteria in R suggests that the intercept is about -7.7 with a 90% confidence interval from 1,345 to 1,360. For the coefficient for GOP Governor, the defaults lead to a coefficient estimate of 18.3 and a 90% confidence interval from 1,334 to 1,371. Notice that the Cauchy prior and Firth's penalty regularizes these quantities, providing more reasonable estimates.

### *3.4. Case Selection*

With such a small number of cases included in the analysis, we leave open the possibility that a particular case drives the results. To address these concerns, we refit the models dropping one state at a time.[18] Figure 9 shows the results. Notice that although some states are more influential than others, the results are similar regardless of which state is dropped from the analysis.

[18] For the sake of computational tractability, we compute these estimates and standard errors using Gelman et al.’s (2008) EM approximation to the posterior mode and asymptotic confidence intervals.

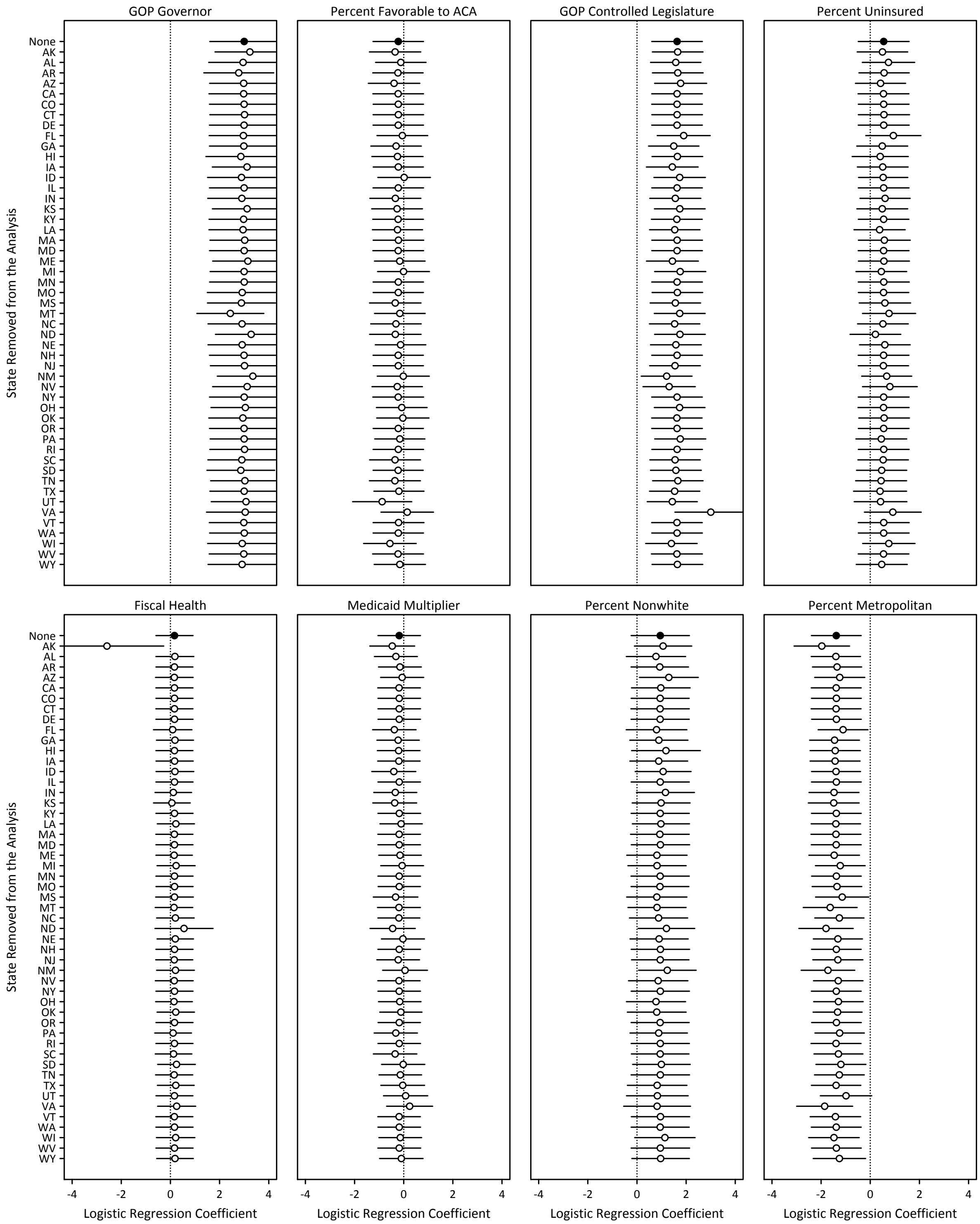


Figure 9: This figure shows how the estimates change when each state is removed from the analysis. The top estimate in each panel presents the estimate using the full data set. Though sometimes dropping a state causes the confidence interval to overlap zero, notice how little the estimates change when each state is dropped. The exception to this pattern is that dropping Alaska, which has a unusual amount of reserves given their spending, dramatically and substantively changes the estimated coefficient of fiscal health. However, this change does not affect the inference about the key variables in our analysis.

## 4. Evaluating the Possibility of Overfitting and an Overly Informative Prior

Related to the robustness checks above, we now demonstrate that (1) the Cauchy(2.5) prior is not overly informative and (2) the model does not overfit the data. We do this by showing the more informative priors predict out-of-sample observations slightly better than the prior that we rely on. To do this, we computed Brier scores using leave-one-out cross validation for a range of prior families and scales. The procedure works as follows:

1. Start by dropping a single observation (say, Alabama).

2. Use the rest of the data (all states except Alabama) to estimate the model and the probability that the governor of the left-out state opposes the expansion. Save the estimated probability.

3. Do this for all 50 states.

4. Calculate the Brier score B using the equation $B = \sum_{i=1}^{50}(y_i - p_i)^2$ where $y_i$ equals one if the governor of state $i$ opposes expansion and $p_i$ represents the out-of-sample estimated probability that $y_i$ equals one.

We repeat the procedure above for a variety of different prior families, including the Cauchy, normal, and t, and vary the scale parameter across each of the distributions. Figure 3 shows how the Brier scores change as the prior family and scale vary.

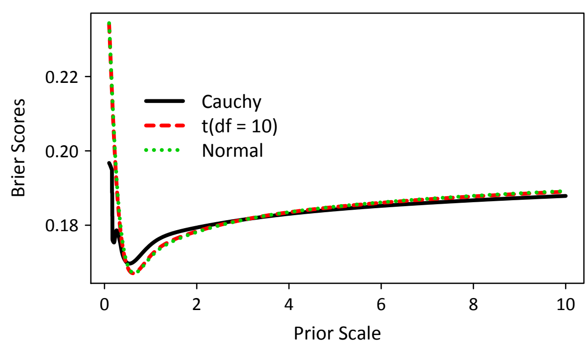


Figure 10: This figure shows the out-of-sample performance of three prior distributions as the scales vary. Lower Brier scores indicate improved out-of-sample predictions. Notice that informative priors (e.g. Normal(1) and Cauchy(2.5)) only slightly outperform weaker prior distributions. Because the more and less informative priors perform similarly, we are not as worried about overfitting the data. Because we would rather supply too little prior information than too much, we choose use the less informative Cauchy(2.5) prior distribution in the main analysis.

Notice that the Brier scores are lower (i.e. the out-of-sample prediction is better) when the prior is more informative that the prior we rely on. However, the improvement is not dramatic, so we prefer to use too little prior information rather than too much. To err on the side of caution, we use the default Cauchy(2.5) prior suggested by Gelman et al. (2008).

Another potential concern with the small sample is that we are over-fitting the data. (The problem of separation that we identify in the main text is just one example of over-fitting.) However, the Brier scores shown in Figure 10should alleviate any concerns about over-fitting. Notice that the Brier score for our preferred Cauchy(2.5) is about 0.17. The lowest Brier score among the parameterizations shown is about 0.15 for the much-more-informative

Normal(0.8) prior distribution. Slightly better performance from a more informative prior is expected. Indeed, Gelman et al. (2008) find a very similar pattern across their large corpus of data sets (see especially the right panel of their Figure 6). If a more informative prior fit the data substantially better, then over-fitting would be a concern. However, the pattern shown in Figure 10 suggests that over-fitting is not a concern.