The Political Economy of Vermont's Anti-Fracking Movement

Alexandre R. Scarcioffolo*
Shishir Shakya †
Joshua C. Hall ‡

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Abstract

In 2012, Vermont became the first state in the United States to ban hydraulic fracturing for natural gas and oil production despite having zero known natural gas reserves. We evaluate the role of legislator and median voter characteristics on Vermont General Assembly voting outcomes on Act 152, which essentially bans fracking in the state. Using a double-selection post-LASSO approach, we find evidence that campaign donations and being a member of the Democratic party positively are related to voting to ban fracking. Median voter characteristics appear not to play an essential role in shaping legislator voting behavior, corroborating the theory of expressive voting on the decision to ban fracking in Vermont.

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*Alexandre R. Scarcioffolo, Department of Resource Economics and Management & Regional Research Institute (RRI), West Virginia University, Morgantown WV 26506, Morgantown WV 26506 E-mail: ar0044@mix.wvu.edu

†Shishir Shakya, College of Business and Economics & Regional Research Institute (RRI), West Virginia University, Morgantown WV 26506 E-mail: shishir.shakya@mail.wvu.edu.

‡Joshua C. Hall, College of Business and Economics & Regional Research Institute (RRI), West Virginia University, Morgantown WV 26506 E-mail: joshua.hall@mail.wvu.edu.

1 Introduction

Federal regulations are an essential determinant of energy sector output in the United States (Hall and Shakya, 2019). The recent technological advancement in horizontal drilling and hydraulic fracturing (fracking) technologies has boosted natural gas and oil production from shale and other lower-permeability formations. As a result, many US regions, which were net importers of natural gas, have become net exporters (Culver and Hong, 2016). The rise of fracking has led to an increase in calls to regulate or ban shale development due to possible negative externalities. A growing literature examines fracking regulations and bans from a political economy perspective (Rahm, 2011; Rabe and Borick, 2013; Boudet et al., 2014; Ritchie, 2014; Clarke et al., 2015, 2016; Hall et al., 2018). These studies look at locations that have known natural gas and oil reserves and thus reflect both political and economic factors at play. In this paper, we look at House and Senate voting on the Vermont General Assembly bill that became Act 152. This Act made Vermont the first state in the United States to ban fracking. As Vermont has no known natural gas and oil reserves, the vote to ban fracking was mostly symbolic. This event, therefore, provides a unique opportunity to examine whether voters' views or legislator views drive legislators' expressive voting. The polycentric nature of U.S. governance encourages expressive voting (Murtazashvili and Piano, 2019a), and thus it is important to better understand its determinants. Especially since there are spillover consequences of having a fractured federation when it comes to fracking (Wiseman, 2009).

It is crucial to understand expressive voting on fracking, given that fracking has both positives and negatives for citizens. From a narrow economic perspective, shale development positively impacts regional economies. Shale development has lowered electricity bills (Hausman and Kellogg, 2015), created jobs (Maniloff and Mastromonaco, 2017), and reduced natural gas prices (Scarcioffolo and Etienne, 2019). Additionally, the shale boom has positively affected housing values, school funding, and led to decreased property tax rates (Weber et al., 2016). Overall, the increase in shale development due to fracking appears to have substantial and positive net welfare effects for many citizens and local communities (Bartik et al., 2018). However, some citizens and regions are negatively affected by shale development (Muehlenbachs et al., 2015).

Purportedly in response to possible environmental and health concerns, Vermont became the first state in the U.S. to ban fracking (Maur, 2015). On May 12, 2012, then Vermont Governor Peter Shumlin signed the bill that banned hydraulic fracturing wells from producing natural gas and oil. If a new fracking technique is feasible and can produce without jeopardizing Vermont's environment, the Vermont General Assembly has the power to revoke the moratorium on hydraulic fracturing (Department of Environmental Conservation, 2015). More interesting, however, is that the state of Vermont does not have commercial production of natural gas or oil or known reserves.[1] The state's only natural gas utility receives its inputs from a small-capacity pipeline from Canada (US Energy Information Administration, 2018).

Unlike Vermont, southwestern New York is located at the confluence of two of the shale gas basins in the United States – the Marcellus and Utica formation (Wegener, 2014). In 2010 some of New York's regions applied local zoning laws to ban fracking, followed by the state-level ban in December of 2014 (Podolny, 2013; Hall et al., 2018). New York's ban also reflects the possible adverse effects of drilling natural gas and oil, i.e., environmental and health deterioration. Since Vermont does not have proven shale reserves nor commercial production of fossil fuels, an interesting question arises. What were the main determinants in banning fracking activity in a state that does not possess proven reserves of oil and natural gas? The vote seems to be purely expressive and not directly related to economic benefits or costs. This allows us to isolate whether legislator voting in a purely expressive context is driven by the characteristics of the legislator, the characteristics of the median voter in her district, or some combination of the two. In doing so, we follow the general approach of Hall et al. (2018), who utilizes the median voter to understand the factors leading to local fracking bans in New York State.

In answering the question of what drives expressive voting by legislators, we contribute to the literature using the median voter model by being the first paper to show how a double-selection post-Least Absolute Shrinkage and Selection Operator (LASSO) approach can be used to take advantage of the fact that high dimensional data is now often readily available in a public choice context. Typically, median voter papers employ *a priori* theory to choose a variable of interest and include a small set of control in their reduced-form median voter models (see, for example, Hall and Karadas (2018)). They then typically report the sensitivity of their estimates across

[1] Existence of natural gas or oil resources in the state cannot be ruled out in Vermont (Department of Environmental Conservation, 2015).

different specifications. While this approach has merit, especially in a limited data environment, in many current situations scholars can obtain hundreds of possible explanatory variables. We employ a double-selection post-LASSO approach in our data-rich environment to examining the importance of median voter versus legislator characteristics.

We examine two channels that could shape Vermont's fracking ban expressive voting. First is the channel of legislator's characteristics like birthplace, party affiliation, incumbent status, education, and political donations. The second channel is the characteristics of the median voter in the legislator's district, like the poverty rate, unemployment rate, income, and education. These channels are not randomized over voting, therefore explaining the relationship of these channels to voting outcome can be tenuous. If the common causes (confounders) between the channel and voting outcomes are appropriately conditioned, then the relationship between the channel and voting outcome is identified. By utilizing high-dimension data and a double-selection post-LASSO method, we reduce the chances of omitting relevant confounding variables.

Our results suggest that Democratic legislators and those with higher levels of campaign contributions were more likely to support the fracking ban bill. With respect to characteristics of the median voter, districts with a higher poverty rate were less likely to have their legislator support the ban, on the margin. This result fades in the robustness checks, however, highlighting a benefit of the double-selection post-LASSO approach when researchers have high dimensional data. Our results indicate that, at least in the case of fracking in Vermont, legislator characteristics are what seem to drive voting on the margin, not median voter characteristics. Our findings contributes to the Expressive NIMBYism 'Not In My Back Yard" (Fischel, 2001) literature as well as to public choice, public finance and energy policy literature.

We proceed as follows. Section 2 explores the state policy rationale for banning fracking. Section 3 describes the data. Section 4 presents our empirical results, and Section 5 concludes.

2 Policy rationale for banning fracking

A large literature focuses on understanding the determinants of energy policy, in particular policies related to fracking. More specifically, studies investigate the economic benefits (Rabe and Borick, 2013) and costs (James and Smith, 2017) associated with fracking. This literature informs policymakers and the general public on the economic benefits that fracking activity brings and potential negative externalities. Regions that have shale development often perceive regulation as a mechanism to protect the environment from the possibility of negative externalities (Ritchie, 2014). However, what are the justifications for banning fracking in regions that do not produce oil nor natural gas? Possible explanations for why a state like Vermont banned fracking might be related but not limited to public perception, geographic distance, and expressive voting.

From the viewpoint of the public choice literature, the framing of the extraction of unconventional natural gas and oil can impact public perceptions. As shown in Clarke et al. (2015), regions where the terminology "fracking" is more relevant than "shale gas development" are more likely to support the ban since the term "fracking" has negative connotations. Moreover, Gottlieb et al. (2018) highlight the importance of the Narrative Policy Framework (NPF) in shaping public perception to influence policy outcomes. For example, narratives played an important role in New York on both sides of the debate. Mayer (2016) highlights that public perception of the risks and benefits of hydraulic fracking depends on how much individual's trust the oil and gas industry.

Using telephone surveys, Kriesky et al. (2013) find evidence that residents of Pennsylvania that live in areas under shale development perceive shale development as an economic opportunity and therefore are more supportive of fracking than residents of non-shale development areas. Ferrar et al. (2013) investigate the mental and physical health stressors perceived to result from Marcellus Shale development, and find that perceptions of health may be influenced by fracking, regardless of direct exposure. Muehlenbachs et al. (2015) argue that the perception of nearby shale wells play a role in decreasing the value of groundwater-dependent homes. For example, national mortgage lenders and insurance providers are refusing to provide services to houses within the proximity of nearby shale wells.

Geographic distance to areas under shale development might exert influence as well according to construal level theory (Clarke et al., 2016). Under construal level theory, areas geographically closer to shale gas development, i.e., southwestern Vermont, would be more likely to favor a ban on fracking since they can "experience" and "see" the impacts of the fracking activities on their neighbors (Clarke et al., 2016). Arnold and Holahan (2014) and Arnold and Neupane (2017) note that two neighboring regions might have different views toward hydraulic fracking not only because of "experience", but also because of government structure. Arnold and Holahan (2014) highlight how New York's southern counties possesses more civic engagement towards fracking than in neighboring Pennsylvania border areas due to the vital role of town halls in New York compared to the centralized decision-making in the Pennsylvania state capitol. Furthermore, Arnold and Neupane (2017) shows that poor southern areas with fewer Democratic partisans in New York are more likely to support fracking.

A majority of the literature focuses on explaining the political economy of shale development with respect to geographic distance or a rational response to the economic benefits and costs. Murtazashvili and Piano (2019b) argue that continued fracking regulation reflects political considerations beyond economic cost-benefit considerations. One way that politics might matter is if voters want to their politicians to do something, even if the action is merely symbolic. Citizens might want to be seen as an area that is doing something for the environment. Similarly, legislators might want to be seen as doing something good for their citizens, even if there is no pressure from their citizens to do so and there is no public interest in doing so. Given the lack of known natural gas reserves in Vermont, it would seem to be an ideal case to test whether legislator activity reflects expressive voting by legislators, median voters, or some combination of both.

3 Theoretical Model

This section provides a theoretical model of how a utility maximizing individual legislator votes based upon her characteristics and the voter's characteristics which she represents. The researcher can access or collect data of the individual characteristics of the legislator, the voter's characteristics and the voting outcome (either for or against) hence, these are observable to a researcher. However, a researcher cannot access data on how the legislator weighs her costs and benefits of voting, thus these variables are unobservable. Based upon a few statistical assumptions, we provide a theoretical argument to link the unobservable – the net-benefit of the legislator or the latent regression – on how to estimate the probability of voting in favor for fracking bans with the observable variables of legislator's characteristics and the voter's characteristics which she represents.

Our model of legislative voting begins with an individual legislator. The conditional indirect utility function for a legislator g who has selected a voting option $y = \{0, 1\}$ can be written as:

$$U_{g,y} = V_{g,y}\left(x_{g,y}, \phi_{g,y}\right) + \varepsilon_{g,y} \tag{1}$$

where, $x_{g,y}$ are the observable characteristics of a legislator who selected a voting option $y = \{0, 1\}$ and $\phi_{g,y}$ are the median voter's observable characteristics in that legislator's district. This conditional indirect utility function consists of two part: deterministic $(V_{g,y}(\cdot))$ and random error part $(\varepsilon_{g,y})$. Although, the utility that a legislature receive voting 0 or 1 is unobserved. For simplicity sake, we drop the index g. We can define the unobserved utility as y_h^*. The unobserved utility that a given legislator derives from voting "Nay" can be represented as:

$$y_0^* = \mathbf{x'}_0\beta_0 + \varepsilon_0 \tag{2}$$

where, x'_0 includes two components. First, the observable characteristics of the legislator such as party affiliation, incumbent status, education, and political donations (Hall and Shultz, 2016). Second, the median voter's observable characteristics that the legislature represents like poverty rate, unemployment rate, working aged population, education, income. Similarly, the utility for voting "Yea" can be expressed as:

$$y_1^* = \mathbf{x'}_1\beta_1 + \varepsilon_1 \tag{3}$$

Voting also entails costs that may be related to the individual legislator. The real cost is also unobserved and can be defined as:

$$C^* = \mathbf{z'}\alpha + u \tag{4}$$

Any legislature will weigh his option to vote either "Nay" or "Yea" if the benefit of voting, i.e $y_1^* - y_0^*$ is greater than the cost C^*. The net benefit of voting is:

$$y^* = y_1^* - y_0^* - C^* = \mathbf{x'}_1\beta_1 - \mathbf{x'}_0\beta_0 - \mathbf{z'}\alpha + (\varepsilon_1 - \varepsilon_0 - u) = \mathbf{x'}\beta + \varepsilon \tag{5}$$

The net-benefit of the legislator is also not observable but the legislator's vote itself is observable. Following the approach of Greene (2003), the $y^* = \mathbf{x'}\beta + \varepsilon$ is the latent regression. We observe that $y = 1$ for a legislator when she votes "Yea" and $y = 0$ when a legislator votes "Nay".

Therefore, our observation will be:

$$y = \begin{cases} 1 \quad if \quad y^* > 0 \quad or \quad 0 \quad if \quad y^* \leq 0 \end{cases} \tag{6}$$

Let a be a nonzero threshold[2] and α be an unknown constant term. $\mathbf{x}$ and β contain the rest of the index not including the constant term. Then, the probability that a legislator vote "Yea" $(y = 1)$ is:

$$P\left(y^* > a|\mathbf{x}\right) = P\left(\alpha + \mathbf{x}'\beta + \varepsilon > a|\mathbf{x}\right) = P\left((\alpha - a) + \mathbf{x}'\beta + \varepsilon > 0|\mathbf{x}\right) \tag{7}$$

Since, the $(\alpha - a)$ is an unknown parameter, the model has a constant term which remains for any choice of threshold α. If we normalize the constant to zero, then

$$P\left(y^* > 0|\mathbf{x}\right) = P\left(\varepsilon > -\mathbf{x}'\beta|\mathbf{x}\right) = P\left(\varepsilon < \mathbf{x}'\beta|\mathbf{x}\right) \tag{8}$$

The only assumption to be made is for the choice of distribution of ε. For any symmetrical cumulative distribution F, the probability of a legislator voting "Yea" is $P\left(y^* > 0|\mathbf{x}\right) = P\left(\varepsilon < \mathbf{x}'\beta|\mathbf{x}\right) = F\left(\mathbf{x}', \beta\right)$ and the probability of legislator voting "Nay" is:

$$P\left(y = 1|\mathbf{x}\right) = P\left(y^* > 0|\mathbf{x}\right) = P\left(\varepsilon < \mathbf{x}'\beta|\mathbf{x}\right) = 1 - F\left(\mathbf{x}', \beta\right) \tag{9}$$

The assumption of cumulative distribution largely depends upon assumption imposed in the ε. If the error terms are assumed to be *i.i.d.* with the extreme value distribution, then it assumed to be a logit model. Suppose the legislatures make the same assumptions subjectively, the voting to "Yea" probability would be in logit form as:

$$P\left(Y = 1|\mathbf{x}\right) = \frac{\exp\left(\mathbf{x}'\beta\right)}{1 + \exp\left(\mathbf{x}'\beta\right)} = \Lambda\left(\mathbf{x}'\beta\right) \tag{10}$$

[2]The $\mathbf{x}'\beta$ is the index function and ε demands an assumption of its variance. Say, ε is scaled by an unrestricted parameter σ^2 then the latent regression is $y^* = \mathbf{x}'\beta + \sigma\varepsilon$ and $y^*/\sigma = \mathbf{x}'\left(\beta/\sigma\right) + \varepsilon$ represents the same model. Hence, the assumption of variance is an innocent normalization. The observed data remains unchanged; y is still 0 or 1, depending only on the sign of y^*not on its scale. This means that there is no information about σ in the sample data so σ cannot be estimated. The parameter vector β in this model is only "identified up to scale." The assumption of zero for the threshold is likewise innocent if the model contains a constant term (and not if it does not) (Greene, 2003).

4 Data

We web scraped the Vermont General Assembly's website to acquire the vote of each legislator on the House bill (H. 464) that became Act 152.[3] If the legislator voted "Yea", the variable VOTE assumes the value one and zero otherwise. From the total of 180 legislators in Vermont, 150 belong to the House while the other 30 belong to the Senate. We have vote data for 167 legislators who voted.[4]

The median voter literature typically categories variables into legislator, median voter, and special interest factors (Congleton and Bennett, 1995). Here we assume that special interests are either weak (due to their being no known natural gas reserves in the state) or affecting legislators directly. This leaves us with two mechanisms: legislator or median voters preferences. For legislator characteristics we use variables that are standard in the median voter literature, such as birthplace, party affiliation, incumbent status, and political donations (Hall and Shultz, 2016). We retrieve this data from the votesmart.org website. We also include the educational background of legislators, following O'Roark and Wood (2011), who find that members of Congress with undergraduate degrees in economics were less likely to vote for minimum wage legislation.

If the legislator majored in the economics subjects in their higher education program, i.e., Bachelor of Arts (BA), Bachelor of Science (BS), Master or Ph.D. in economics, the variable ECONOMICS assumes the value of one and zero otherwise. Similarly, we consider another dummy variable to represent whether the legislator majored in any natural resource field in higher education programs or not, which the variable ENVIRONMENT takes the value of one when it is true. To account for the possible effect of being a native Vermont resident, the variable BIRTHPLACE assumes the value one when the legislator was born in Vermont, zero otherwise. This dummy variable shed light on the intrinsic aspect of the local populations that are associated with a longer-term commitment to the state. As presented in Hall and Shultz (2016), campaign donations might influence voting behavior. Hence, we retrieved the total amount of donation that the legislator received (DONATION) from the followthemoney.org website. We also collect data on the incumbency status (INCUMBENT) of each legislator. To

[3] Interested readers can find our full data set online at figshare (Shakya et al., 2020).

[4] Six legislators filled vacancy positions during the 2010-2012 term. All six legislators were elected in the 2012 election. Due to the lack of data from these legislators for the 2010 election, we considered their 2012 election data instead.

differentiate legislator variables from median voter variables in our tables, we append LEG to each of the legislator variables.

The second mechanism is related to the characteristics of the median voter in each House or Senate district. Typically we would use theory to motivate variables like the poverty rate, unemployment rate, income, and education. However there are several dozen variables available at the House and Senate district level in the American Community Survey 5-year estimates. Other variables could be important, or at very least, confounders for the poverty rate, unemployment rate, income, and education. Therefore, to accurately estimate which median voter characteristics affect the electoral outcomes, we retrieved social, economic, housing, and demographic data for lower chamber and upper chamber district level from the 2010 5-year American Community Survey estimates.[5] In total, we have 80 potential variables as controls. Later in our analysis, we include their square term and a set of full interaction terms, which lead to additional 81 + 81 * 80/2 = 3240 variables.

5 Econometric model and results

Our goal is to estimate how legislator's and median voter characteristics influence voting outcomes. We could study how specific legislator characteristics like education and party affiliation affect voting on fracking, controlling for some median voter covariates. Similarly, we could focus on some median voter characteristics like the unemployment rate and income levels, controlling for some legislator characteristics. However, several other variables are likely to confound with the variables selected *a priori*.

For correct inference, adequately dealing with confounding and control variables is necessary. As researchers, however, we do not observe the data generating process. Failure to adequately control for important covariates can lead to omitted variable bias. Over-controlling, however, leads to a loss in efficiency. A standard empirical strategy is to use theory in selecting controls and variables of interest and then report the estimates implementing different sets of controls. This standard strategy, while lacking a principled method for variable selection, makes sense

[5]The full list of 80 potential confounders is too long to list here but includes households type, relationship, marital status, fertility, grandparents, school enrollment, educational attainment, veteran status, residence one year ago, place of birth, language spoken at home, ancestry, employment status, commuting to work pattern, occupation, industry, class of worker, income and benefits, various poverty levels, housing occupancy, sex and age, race, mortgage status, gross rent as a percentage of household income, housing values, etc. A full list is available upon request.

in a world with limited data at the unit of analysis. Today, however, the 5-year estimates of the American Community Survey have given researchers a large number of potential variables observed for all different sized political districts at regular intervals.

For example, we have 80 different potential variables as controls in our analysis. Including square terms and a set of full interactions leads to an additional 3240 variables (81 + 81 * 80/2). Note that we have only 167 legislators, so traditional Ordinary Least Square (OLS) methods are infeasible as the numbers of variables are more abundant than numbers of observations. Therefore, in this setting, we implement a double-selection post-LASSO methodology as suggested by Belloni et al. (2014a,b) to adequately select the confounder and covariate controls. The double-selection post-LASSO methodology utilizes the strengths and innovation of the least absolute shrinkage selection operator (LASSO[6]) − a predictive machine learning algorithm − and re-engineers it for causal inferences.

Belloni et al. (2014a) describes the double-selection post-LASSO method, which is comprised of three steps. First, run LASSO of the dependent variable (VOTE) on the list of potential control variables to select a set of predictors for the dependent variable. Second, run LASSO of the variable of interest on the list of possible control variables to pick a set of predictors for each of the variables of interest. In our study, the legislator's observable characteristics and the median voter's characteristics are variable of interest. The second step is essential, because the exclusion of a covariate that is a modest predictor of the dependent variable, but a strong predictor of the channel variable can create an important omitted variable bias problem. In experimental data, the second step also serves as a test of randomization. If the channel variable is effectively randomized, no covariates should be selected in this step. Third, run OLS (in our case a Limited Probability Model (LPM) since our dependent variable is binary) regression of the outcome variable on the variables of interest and the union of the sets of regressors chosen in the two LASSO runs. Then, after correcting the standard errors for heteroscedasticity, the

[6]The Least Absolute Shrinkage and Selection Operator (LASSO) is an appealing method to estimate the sparse parameter from a high-dimensional linear model is introduce by Frank and Friedman (1993) and Tibshirani (1996). LASSO simultaneously performs model selection and coefficient estimation by minimizing the sum of squared residuals plus a penalty term. The penalty term penalizes the size of the model through the sum of absolute values of coefficients. Consider a following linear model $\tilde{y}_i = \Theta_i \beta_1 + \varepsilon_i$, where Θ is high-dimensional covariates, the LASSO estimator is defined as the solution to $\min_{\beta_1 \in R^p} E_n \left[(\tilde{y}_i - {}_i\Theta\beta_1)^2 \right] + \frac{\lambda}{n} \|\beta_1\|_1$, the penalty level λ is a tuning parameter to regularize/controls the degree of penalization and to guard against overfitting. The cross-validation technique chooses the best λ in prediction models and $\|\beta\|_1 = \sum_{j=1}^{p} |\beta_j|$. The kinked nature of penalty function induces $\hat{\beta}$ to have many zeros; thus LASSO solution feasible for model selection.

estimates yield can yield a causal interpretation in the proper setting (Belloni et al., 2014b).

5.1 Model Estimation

First, we estimate the impacts of the legislator's observable characteristics on the H.464 (Act 152). We estimate a unique regression for each of the legislator's characteristics; i.e., party affiliation, incumbent status, contributions to the campaign, birthplace, degree in Economics, and degree in Environmental studies. This captures the mechanism effect of those variables on the vote to ban fracking, while considering other possible confounding variables. For example, to capture the effect of party affiliation on the vote to ban fracking, we consider party affiliation as an independent variable and several other confounding variables, according to the double-selection post-LASSO methodology, to explain the voting outcome. To capture the effect of birthplace on voting outcome, we run a similar procedure as discussed above but instead consider birthplace as the primary independent variable. We do that for each of our primary variables of interest in Table 1. These primary variables of interest are ones we would have selected for a regular OLS regression based on *a priori* theorizing. Therefore, we observe the mechanism effect of each legislator's observable characteristics to explain voting outcome while considering other confounders.

Table 1 about here.

Table 2 presents the double-selection post-LASSO results for the legislator's observable characteristics mechanism effect and also for confounding variables. As a reminder, to make a clear distinction between the legislator's characteristics and median voter characteristics, we include the prefix *LEG* for legislator specific characteristics. For instance, column (1) of Table 2 represents the party affiliation (LEG.Party) mechanism effect on voting outcome while considering other confounding variables, such as Environmental Studies (LEG.Environmental Studies) and Graduate or professional degree (%). In column (2), we observe the incumbent (LEG.Incumbent) mechanism effect on voting outcome, considering Party (LEG.Party), Contributions (LEG.Contributions) and Graduate or professional degree (%) as confounding variables, and so forth.

Table 2 about here.

One caveat is necessary before discussing our results. Variable scaling could lead to coefficient shrinkage. Since we are more interested in the direction of the effect here rather than the magnitude, our results should be interpreted in terms of mechanism, not size.

In Column 1 of Table 2 we observe the effect of party affiliation (LEG.Party) on the decision to vote "Yea" on banning fracking in Vermont. Based on the sign of our LPM, it appears that Democratic legislators were more likely to vote "Yea." This result is consistent with the findings of Arnold and Neupane (2017). Since the Democratic Party proposed the Act and there exists institutional ways of enforcing party discipline, this result is not surprising. What is interesting here, however, is that being a Democrat is highly significant as a confounding variable for Columns (2) – (6).

The effect of being an incumbent (LEG.Incumbent) is shown in column (2) of Table 2. Here we find that this is not related to voting for the ban in a statistically significant manner. Column (3) shows that legislators receiving higher levels of campaign contributions (LEG.Contribution) is related to voting to ban fracking, but the magnitude is small. Contrary to our priors, being a native legislator (LEG.Birthplace) decreases the likelihood of voting in favor of the ban (Column 4). Finally, being either economics or environmental education major has no statistically significant relationship with voting on fracking (Column 5 and 6).

We do find, however, that the education level of district residents has a strong confounding effect, showing up as significant when all six variables of interest are considered as primary in Columns 1-6 of Table 2. It is important to highlight that confounders only show up in the Tables 2 and 3 as a result of the double-selection post-LASSO. The fact that only Graduate and professional degree (%) consistently appears in all six columns of Table 2 is because that is the only confounder from all potential confounders. Additionally, we perform a robustness check considering a larger data set. We consider the cross-interactions and squared value of each variable, resulting in 3320 potential control variables. We run the same procedure with similar findings, with the exception of Economics training, which is now statistically significant. (These results, highlighting only the coefficients on the variables of interest in each specification, are presented in Appendix Table A1.)

Table 3 presents the results considering possible median voter mechanisms. We find evidence that the poverty rate (Table 3–Column 1) and population with retirement income (Table 3–

Column 3) are statistically significant in explaining how their legislator voted on the fracking ban. Legislators that represent districts with a higher poverty rate were more likely to vote "Nay" on the fracking ban. This result is consistent with the findings of Arnold and Neupane (2017), in which districts that have a higher poverty rate might favor fracking as an opportunity to expand employment and income. Recall, however, that there are zero known natural gas reserves in Vermont and so this should be viewed as largely as expressive voting in favor of being growth.

Table 3 about here.

Conversely, legislators that represent districts with a larger population with retirement income are more likely to vote to ban fracking.[7] Areas with a higher retirement income have less of a need for localized economic benefits and are more sensitive to environmental, health, and nuisance concerns. As a result, these areas likely perceive shale development as a net cost.

We note that graduate or professional degree was positive significant as a confounding variable to explain the effect mechanism of legislator's observable characteristics in Table 2. In Table 3, however, districts with more educated populations do not explain legislator voting in a statistically significant manner. Party affiliation (LEG.Party) has a positive and significant effect as a confounding variable across all the median voter mechanism columns, shedding light on the importance of party affiliation in expressive voting. Other variables such as population working on the natural resource sector (NRCM), Population with Supplemental Nutrition Assistance Program (SNAP) are positively significant as confounding variables for a few median voter mechanism effect. As a reminder, recall that potential confounders only appear in Table 3 when selected as part of the double-selection post-LASSO process. It is for that reason that the included variables and reported coefficients vary across columns.

We again perform a robustness check considering a larger data set of cross-interactions and squared value of each variable. In these results, presented in Appendix Table A2, the effect of the poverty rate and population with retirement income becomes insignificant. The other hand, the graduate or professional degree mechanism effect became significant, suggesting that legislators that represent district with larger populations with graduate or professional degree

[7] Median income was not statically significant as a mechanism effect to explain voting outcome. In our view, this highlights the benefit of our method, as an *a priori* approach would just select mean or median household income under the assumption that all income measures are essentially capturing the same effect.

are more likely to vote in favor of the ban. Given the expressive context, this suggests that highly educated individuals may be more like to be in favor of expressive voting in the fracking context. These robustness checks, combined with our other results, suggest that legislator characteristic primarily drove voting on the fracking ban.

6 Conclusion

Vermont's General Assembly voting on to ban fracking is an ideal setting to study expressive voting because the state of Vermont has no known natural gas or oil reserves. We use this fact to understand the factors influencing legislator voting in an expressive context. Are they voting to ban fracking because their constituents demand it, or are they expressing personal preferences related to their background, education, or party identity? Our results suggest that the primary factor influencing the voting behavior of members of the Vermont General Assembly is party affiliation.

In this respect, our results are not surprising and match the literature on fracking bans (Boudet et al., 2014; Davis, 2017). Given that the bill was introduced by a Democrat, this suggests that in an expressive context there is little that can overcome party affiliation. Clarke et al. (2016) show that political ideology is weighted heavier the more geographically removed the population is from the fracking activity. Since Vermont does not have commercial production of natural gas nor oil, voting on fracking should reflect the expressive, not instrumental views, of legislators and voters. That is largely what we find for legislators, while finding that characteristics of the median voter characteristics are largely insignificant in explaining their legislator's votes to ban fracking in Vermont.

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Table 1: Descriptive Statistics

Variable	Min	Max	Mean	Std dev
Vote (% of "Yea")	0	1	0.78	0.42
Party (% of "Democrats")	0	1	0.67	0.47
Incumbent (%)	0	1	0.79	0.41
Log of $ Contribution	0	10.57	6.56	3.2
Birthplace (% born in Vermont)	0	1	0.31	0.46
Economics (% who study)	0	1	0.02	0.13
Environmental studies (% who study)	0	1	0.04	0.2
Population in poverty (%)	0	29.5	7.25	4.38
Unemployed population (%)	0	8.8	4.02	1.34
Population with retirement income (%)	5.3	26.6	16.65	3.67
Bachelors degree (%)	6.7	35.7	20.22	6.75
Some college but no degree (%)	11.5	26.9	16.81	2.23
Graduate or professional.degree (%)	4	42.2	13.2	6.3

n = 167

Table 2: Estimation result for Legislator's characteristics mechanism effect

	Dependent variable					
	Vote					
	(1)	(2)	(3)	(4)	(5)	(6)
LEG.Party	**0.521*****	0.545***	0.545***	0.504***	0.523***	0.521***
	(0.073)	(0.071)	(0.071)	(0.074)	(0.072)	(0.073)
LEG.Incumbent		**0.035**				
		(0.057)				
LEG.Contributions		0.00001***	**0.00001*****			
		(0.00000)	(0.00000)			
LEG.Birthplace				**−0.106***		
				(0.062)		
LEG.Economics				0.171	**0.204**	
				(0.123)	(0.125)	
LEG.Environmental studies	0.006			−0.015		**0.006**
	(0.028)			(0.029)		(0.028)
Graduate or professional degree (%)	0.009**	0.008**	0.007**	0.008**	0.009**	0.009**
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Constant	0.313***	0.234***	0.267***	0.366***	0.312***	0.313***
	(0.073)	(0.089)	(0.075)	(0.081)	(0.073)	(0.073)
Observations	167	167	167	167	167	167
R^2	0.423	0.452	0.451	0.440	0.427	0.423
Adjusted R^2	0.413	0.438	0.440	0.423	0.417	0.413
Residual Std. Error	0.319	0.312	0.312	0.316	0.318	0.319
Degrees of freedom	(df = 163)	(df = 162)	(df = 163)	(df = 161)	(df = 163)	(df = 163)
F Statistic	39.853***	33.347***	44.546***	25.343***	40.552***	39.853***
Degrees of freedom	(df = 3; 163)	(df = 4; 162)	(df = 3; 163)	(df = 5; 161)	(df = 3; 163)	(df = 3; 163)

Note: ***, **, * represents significant in 10%, 5% and 1% level of significance. Enclosed values in (.) are heteroscedasticity consistent robust standard errors. The estimates of interest (mechanism) are highlighted bold for each model presented from column (1) to (6) while covariates are selected using the double-selection post-LASSO method from a list of 80 possible confounders from the ACS (see text for more details).

Table 3: Estimation result for median voter characteristics mechanism effect

	Dependent variable					
	vote					
	(1)	(2)	(3)	(4)	(5)	(6)
Population in poverty (%)	**−0.018***					
	(0.010)					
Unemployed population (%)		**−0.0003**				
		(0.020)				
Population with retirement income (%)			**0.022****			
			(0.011)			
Bachelor's degree (%)				**0.018**		
				(0.014)		
Some college but no degree (%)				−0.006	**−0.010**	
				(0.013)	(0.013)	
Graduate or professional.degree (%)	0.009**	0.012	0.016***	0.014	0.010**	**0.006**
	(0.004)	(0.009)	(0.005)	(0.009)	(0.004)	(0.010)
Population with SNAP (%)	0.006			0.015*		
	(0.007)			(0.008)		
NRCM occupations (%)			0.015	0.031***		
			(0.012)	(0.009)		
LEG.Party	0.517***	0.528***	0.524***	0.517***	0.515***	0.529***
	(0.073)	(0.073)	(0.070)	(0.073)	(0.073)	(0.071)
Constant	2.052	−1.051	−0.431	−2.004	0.712	1.744
	(1.871)	(1.792)	(0.806)	(2.508)	(0.470)	(2.221)
Observations	167	167	167	167	167	167
R^2	0.438	0.433	0.477	0.477	0.429	0.471
Adjusted R^2	0.421	0.408	0.450	0.432	0.407	0.430
Residual Std. Error	0.317	0.321	0.309	0.314	0.321	0.314
DF	(df = 161)	(df = 159)	(df = 158)	(df = 153)	(df = 160)	(df = 154)
F Statistic	25.135***	17.333***	17.988***	10.717***	20.000***	11.444***
DF	(df = 5; 161)	(df = 7; 159)	(df = 8; 158)	(df = 13; 153)	(df = 6; 160)	(df = 12; 154)

Note: ***, **, * represents significant in 10%, 5% and 1% level of significance. Enclosed values in (.) are heteroscedasticity consistent robust standard errors. The estimates of interest (mechanism) are highlighted bold for each model presented from column (1) to (6) while covariates are selected using the double-selection post-LASSO method from a list of 80 possible confounders from the ACS (see text for more details).

Table A1: Estimation result for Legislator's characteristics mechanism effect considering cross interaction and lagged variable

	Dependent variable					
	vote					
	(1)	(2)	(3)	(4)	(5)	(6)
LEG.Party	0.511***					
	(0.077)					
LEG.Incumbent		−0.005				
		(0.056)				
LEG.Contributions			0.00001**			
			(0.00000)			
LEG.Birthplace				−0.109*		
				(0.061)		
LEG.Economics					0.173*	
					(0.097)	
LEG.Environmental studies						−0.022
						(0.030)
Observations	167	167	167	167	167	167
R^2	0.445	0.480	0.499	0.494	0.483	0.480
Adjusted R^2	0.413	0.443	0.464	0.451	0.446	0.443
Residual Std. Error	0.319	0.311	0.305	0.309	0.310	0.311
Observations	(df = 157)	(df = 155)	(df = 155)	(df = 153)	(df = 155)	(df = 155)
F Statistic	13.998***	13.001***	14.054***	11.475***	13.158***	13.005***
Observations	(df = 9; 157)	(df = 11; 155)	(df = 11; 155)	(df = 13; 153)	(df = 11; 155)	(df = 11; 155)

Note: ***, **, * represents significant in 10%, 5% and 1% level of significance. Enclosed values in (.) are heteroscedasticity consistent robust standard errors. Covariates selected from the double-selection post-LASSO method included but not reported for space considerations.

Table A2: Estimation result for median voter characteristics mechanism effect cross interaction and lagged variable

	Dependent variable					
	vote					
	(1)	(2)	(3)	(4)	(5)	(6)
Population in poverty (%)	−0.015					
	(0.012)					
Unemployed population (%)		−0.009				
		(0.023)				
Population with retirement income (%)			0.011			
			(0.013)			
Bachelors degree (%)				0.015		
				(0.016)		
Some college but no degree (%)					−0.017	
					(0.014)	
Graduate or professional.degree (%)						0.024**
						(0.011)
Observations	167	167	167	167	167	167
R^2	0.507	0.503	0.501	0.573	0.486	0.553
Adjusted R^2	0.444	0.443	0.429	0.467	0.446	0.458
Residual Std. Error	0.311	0.311	0.315	0.304	0.310	0.307
Observations	(df = 147)	(df = 148)	(df = 145)	(df = 133)	(df = 154)	(df = 137)
F Statistic	7.971***	8.330***	6.939***	5.400***	12.122***	5.833***
Observations	(df = 19; 147)	(df = 18; 148)	(df = 21; 145)	(df = 33; 133)	(df = 12; 154)	(df = 29; 137)

Note: ***, **, * represents significant in 10%, 5% and 1% level of significance. Enclosed values in (.) are heteroscedasticity consistent robust standard errors. Covariates selected from the double-selection post-LASSO method included but not reported for space considerations.