# Understanding Local Regulation of Fracking: A Spatial Econometric Approach

**Patrick J. Walsh, Stephen Bird, and Martin D. Heintzelman**

Fracking is a controversial practice but is thriving in many areas. We combine a comprehensive data set on local bans and moratoria in the state of New York with local-level census data and spatial characteristics in a spatial econometric analysis of local fracking policies. Some factors, including location in the Utica shale, proportion of registered Democrats, and education level, increase the probability of restrictions on fracking. Extent of local land development, location in highly productive petroleum areas, and number of extant oil and gas wells are among factors that have a negative impact on the likelihood of a ban or moratorium.

***Key Words***: fracking, local policy analysis, spatial econometrics, survival analysis

High-volume hydraulic fracturing, also known as fracking, of underground shale gas deposits to capture natural gas is a controversial practice but one that is thriving in many areas of the United States. Concerns regarding fracking include local air and water quality, impacts on traffic from trucks required to move waste water and other materials, and social impacts related to a "boomtown" mentality. In recent years, several states have scrambled to address a lack of coherent fracking and shale gas regulation. Wyoming, Texas, Colorado, Illinois, Pennsylvania, and Maryland have all significantly revised and strengthened their fracking regulations. Other states are in the middle of significant revisions that could result in some of the most forceful and comprehensive fracking regulations in the United States. Despite this, one can argue that no state yet

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has a comprehensive set of regulations, and states and municipalities can learn much from each other and from better information and analyses.

Thirty home-rule states (and nine states with limited home-rule status) allow local communities to pass laws that extend restrictions on fracking beyond limits established by the state legislature. As a result, municipalities, townships, and counties can establish more effective, locally focused strategies and create variation in policy responses to potential negative impacts of shale gas drilling in their jurisdictions. We combine a comprehensive data set on local bans and moratoria in the state of New York with local-level census data and spatial characteristics linked through a geographic information system (GIS) in a spatial econometric analysis of local fracking policies. These data allow us to explore the determinants of local regulations that allow (or ban) fracking activities in New York, our test-case state. Despite New York's decision in December 2014 to maintain its state-level moratorium indefinitely (Kaplan 2014), this research is important given the prevalence of home-rule legislation in many states where fracking is occurring.

A variety of factors can account for variation in local-level and state-level policymaking. For instance, adoption of policies related to renewable resource portfolio standards has been shown to be associated with economic, resource-based, geographic, competitive, and political characteristics (Huang et al. 2007, Chandler 2009, Carley and Miller 2012). We expect that extensive state and local variation similarly will play a part in accounting for variation in fracking regulations.

Understanding the determinants of local decision-making allows scholars and policymakers to differentiate the economic, cultural, risk, geographic, and socio-demographic factors underlying acceptance and resistance (Wüstenhagen, Wolsink, and Bürer 2007). With that information, stakeholders, government agencies, and resource developers can craft better solutions via bargaining, negotiations, improved mitigation measures, and education efforts or refuse development when such solutions are not available. Improved understanding also can alert policymakers to potential coopting of the process and concerns regarding environmental justice and/or make it easier for developers to craft better implementation plans that incur less opposition and produce more effective and efficient outcomes. Knowledge about the determinants of local policymaking, in this case related to fracking, can be applied broadly to acceptance of other energy facility and infrastructure projects (e.g., wind turbines) and to other public policy questions.

Our econometric approach and GIS data set allow us to account for spatial clustering to determine the extent to which local policy actions are correlated with actions of nearby communities. This analysis allows us to determine whether spatially correlated unobserved influences have an effect on community actions even after controlling for demographic characteristics and other features. Past research has shown that a community's policy decisions can be influenced by the decisions made by nearby communities through processes of policy diffusion (Andrews 2000, Karch 2007, Rogers 2003). A spatial econometric approach allows us to better explore these effects. In addition, we use a hazard/survival analysis to take advantage of variation in the timing of local policy actions.

Our analysis suggests that several factors influence whether a local municipality implements a ban or moratorium on fracking. Factors that increase the probability of local restrictions include the community being located in the Utica shale region, the relative leaning of the community toward the Democratic Party, and the local average level of education. Factors that decrease the probability of a ban or moratorium include the degree of local land development, being located in highly productive areas of the Marcellus shale region, the number of extant oil and gas wells, the presence of priority watersheds for drinking water, being an incorporated village rather than a town, and the percentage of the community's land area occupied by wetlands. In addition, the results of our spatial error model indicate that there are significant spillover effects across communities, pointing to the importance of a spatial econometric approach.

## Policy Background

The expansion of high-volume fracturing is a relatively new phenomenon. The technology is not new, but improvements in the process over the last ten years led to an explosion of fracking activity across the United States. New York, like most states, has enacted a variety of regulations governing production of fossil fuels in the state.[1] Many of these regulations, however, cannot be applied to contemporary fracking operations, which are quite different from conventional fossil fuel extractions and even from earlier fracturing methods. In 2008, Governor David Patterson issued a statewide moratorium on all new fracking activities while the state prepared a new set of regulations (and simultaneously allowed a very few small-scale fracking efforts already under way to continue). His actions were a response to concerns about environmental protection and public health and the need for regulations that addressed the current state of the technology. This began as a process for development of a new regulation, known as the Supplemental Generic Environmental Impact Study (SGEIS) (New York State Department of Environmental Conservation (NYSDEC) 2011). Governor Andrew Cuomo continued those fracking policies and added a requirement for a comprehensive national study of fracking's health impacts to help inform the policy development process. In December 2014, Governor Cuomo converted the moratorium into a permanent ban in what many view as a surprising decision (Bagley and Hirji 2014, Phillips 2014).

In New York, local self-governance is promoted by the state's constitution, and there is a strong home-rule tradition granting legislative authority to counties, cities, villages, and towns (Stinson 1997). As a result, many jurisdictions in New York have enacted a ban or moratorium (usually via zoning regulations) on fracking activity as a pre-emptive action. Local bans currently are redundant under the statewide ban, but they have full legislative weight and new legislation would be needed to remove them. The simple fact that such local restrictions have been resisted so vociferously by the petroleum industry in New York, Texas, Colorado, and other states demonstrates their potential efficacy (Healy 2015). Generally, home-rule has been supported by the courts. In New York, fracking supporters filed suit in 2012 to contest the right of local communities to take these actions, and in 2013 an appellate court of appeals ruled in favor of municipal home-rule oversight. In June 2014, the New York State Supreme Court ruled in favor of local communities and reinforced the

[1] The Generic Environmental Impact Statement (GEIS) on the Oil, Gas, and Solution Mining Regulatory Program was initially prepared in 1992 by New York's Department of Environmental Conservation (2011).

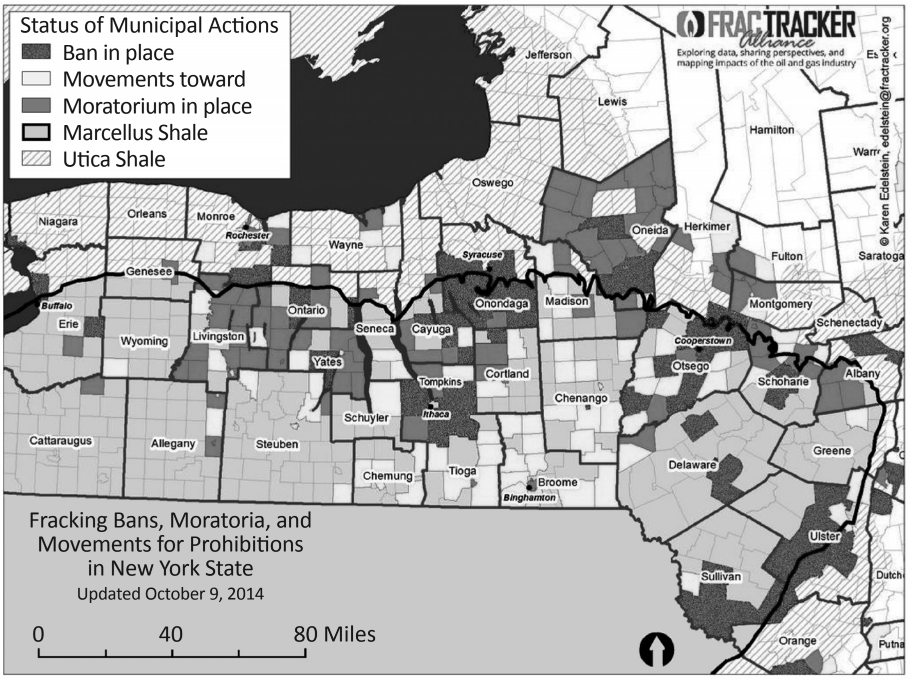


**Figure 1. Locations of Bans and Moratoria in New York**

Map created by FracTracker Alliance on *FracTracker.org* (www.fractracker.org/map/us/new-york).

capacity of municipalities to oversee fracking activity (De Avila, Vilensky, and Gold 2014). Figure 1 illustrates the locations of current bans and moratoria in the region of New York near the Marcellus and Utica shale formations.

There has been considerable interest (including monetary resources) from lobbyists and organizations associated with both banning and endorsing fracking. For instance, the group Food and Water Watch has an online pamphlet titled "How to Get Your Resolution Passed to Ban Fracking."[2] Pre-emptive resolutions supporting fracking have also sprung up, primarily in the six counties along the southern tier, and the Joint Landowner's Coalition of New York provides resolution documents that can be adapted for any town.[3] Generally, home-rule is seen as an opportunity by its proponents to increase civic participation, including in environmental policy. Advocates on both sides have characterized it as an opportunity for municipalities to take control of their responses to fracking and to develop locally appropriate solutions.

Implementation of the local bans and moratoria varies in terms of governance procedures. The process is not complicated; it is possible for a citizen to present a proposal and the town council to vote on it at the same meeting. The vast majority of the time, however, these proposals and their adoption are highly politicized and contentious and often take many months and multiple discussions to pass.[4]

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2 See http://documents.foodandwaterwatch.org/doc/localResolutionGuide-fracking.pdf.

3 See www.jlcny.org/site/index.php/town-resolutions-efforts-and-landowner-info/1347-town-resolution-to-support-nydec-efforts-and-findings.

4 For several examples of how bans and moratoria arise, see www.fractracker.org/a5ej20sjfwe/wp-content/uploads/2012/04/Court-of-Appeals-Decision.2014-06-30.pdf.

Because pre-emptive resolutions in favor of fracking have no binding effect on policy, we do not consider them in our analysis. These resolutions have no legislative weight other than to indicate a community's support and are largely symbolic. We similarly do not include reported "movements" toward bans or moratoria because it is difficult to know what constitutes such a movement and how well they represent the opinions within the community. Zirogiannis et al. (2014) studied the broad range of actions for and against fracking in an analysis similar in spirit to this one. They used a nonspatial ordered probit approach that included positive resolutions, movements, and actual moratoria and bans.

## Motivation and Existing Literature

It is a challenge to explain factors that may influence local policymaking for any issue. We characterize five categories of potential drivers of local fracking policies: spatial diffusion and proximity effects, social and economic effects, political characteristics, land characteristics, and geological characteristics.

Local policies in a community may influence policies in nearby communities and may influence and be influenced by policies at the state and federal level (Brueckner 1998, Brueckner and Saavedra 2001). Shipan and Volden (2008), in a study of U.S. cities, found that small municipalities often adopted regulations in response to pressure from the state government. In our current context, one can interpret pre-emptive adoption of a ban or moratorium on fracking as a clear rejection of state policy rather than succumbing to pressure. Adoption of regulation in this manner points to a nuanced process in which sub-governments can respond to broader regulations in the affirmative or the negative. There is also evidence of policy learning, experiential diffusion from proximity, and geographic perspectives (Sabatier and Jenkins-Smith 1993, Borgatti and Cross 2003). The principal causal mechanism for policy learning and diffusion in a geographic context is most obviously via simple exposure by proximity. After such exposure, adoption can occur for a variety of reasons that include influence mechanisms, mimicry, and simple learning (Bird 2010, Karch 2007). These are the primary motivations for our spatial econometric approach, which adapts the standard regression model by allowing explicitly for the spatial interactions between communities in policymaking.

The most obvious tension in the literature on fracking is the connection between pro-fracking attitudes and concerns about economic development (e.g., jobs, opportunities, leases) and the association of anti-fracking attitudes with economic and environmental harm (negative impacts on amenity and land values, environmental damage). An important concern in debates about community acceptance of potential environmental harm and cooption relates to environmental justice and potential for economic development. Jurisdictions that have few financial resources, expertise, or capital may be highly motivated by the promise of economic development and thus may be more vulnerable or likely to be exploited in terms of willingness and/or ability to oversee environmental and community impacts from energy extraction effectively (White 1998, Environmental Protection Agency (EPA) 2014, Wermuth 2003, Timmins and Vissing 2014). Alternately, there is evidence of economic impacts from fracking on land values and economic activity, though the results vary in terms of the degree of impact and are sometimes conflicting (Barth 2013, Boslett, Guilfoos, and Lang 2014, Cosgrove et al. 2014, Hardy and Kelsey 2014). Attitudes about energy and the environment also may be derived from individuals' identities and political affiliations (Daniels et al. 2012, Pew Research Center for the People and the Press 2012, McCright et al. 2013, Miller, Atems, and Bird 2014). Typically, anti-regulation and pro-economic attitudes are affiliated with Republican, right wing, and conservative citizens while regulatory, pro-environmental, and public good concerns are affiliated with Democrat, left wing, and liberal individuals.

We include political, economic, and social values as variables in our analysis. Political values are represented by the ratio of registered Democrats to registered Republicans. Economic and social values are incorporated through data on rates of unemployment, median income, and level of education, which we measure as the percentage of citizens older than 25 who have only a high school diploma (inversely related to the percentage who have at least a bachelor's degree). We also include data on share of local employment attributable to three industries: arts and tourism, manufacturing, and natural resources and construction. Demographic factors in the analysis are race and age. Finally, we include population densities with the expectation that residents of densely populated areas will be relatively resistant to fracking because it would occur in relatively close proximity to homes.

We also assess the communities' prior relationships and experience with different energy production systems. We include data on the number of oil and gas wells already drilled in a jurisdiction because there is extensive evidence of visual impacts that correspond to environmental concerns and actions to address them (Forsyth et al. 2004, Blake 2001, Baldassare and Katz 1992). We use information on the share of homes that rely on residential solar energy systems as a proxy variable to control for general attitudes toward renewable energy, which may be correlated with attitudes toward the environment and/or fossil fuels. A count of recently drilled water wells in each community is an indicator of local investments in ground water resources that could be put at risk by fracking.

The characteristics of different types of land logically should affect how much effort is needed to produce oil and gas through fracking, the resulting rate of return, and the value of competing amenities and other land uses. Some land uses, such as open waters and wetlands, likely reflect areas that are already protected from development and, consequently, from fracking. Thus, we include data on a variety of land uses that could increase or decrease the cost of fracking and access to potential drilling sites. In addition, some types of land (developed land, wetlands) may be better or worse suited to other uses, motivating community decisions about fracking.

Should the state ban be lifted, local geologic conditions are likely to be critical determinants of where fracking would occur so we include data on two geological characteristics—depth to the shale reserve and access to areas expected to be highly productive—that could improve producers' financial returns and, in turn, influence the economic outcomes of fracking for local communities. These areas, known as the Marcellus prime and the Utica sweet spot, are illustrated in Figure 2.[5]

Lastly, we include data on watersheds that are considered to be critical in providing drinking water for New York City and Syracuse. Drilling in those areas is almost certain to be banned even if fracking is allowed elsewhere.

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[5] The Marcellus prime counties are Broome, Chemung, Cortland, Schuyer, Steuben, Tioga, and Tompkins.

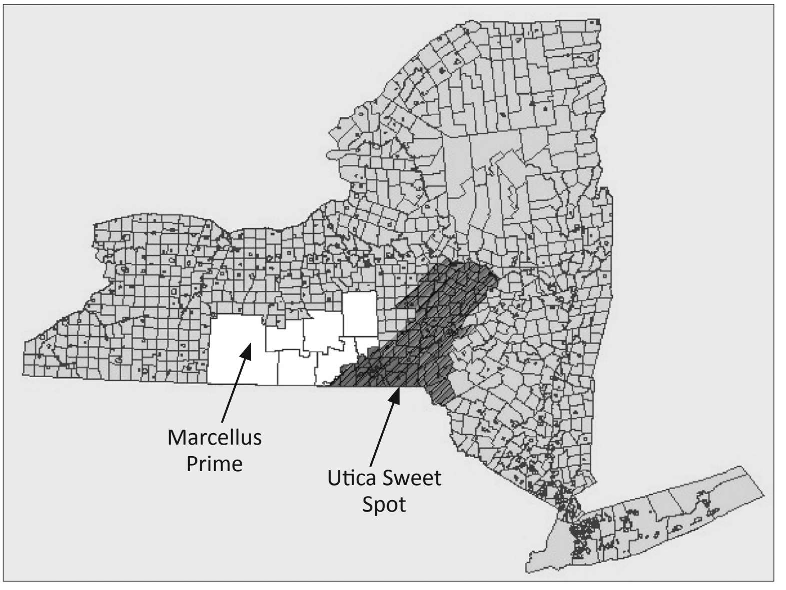


**Figure 2. Location of Marcellus Prime and Utica Sweet Spot Areas in New York**

Thus, we expect that local communities within those watersheds will view local regulations as superfluous and unnecessary. However, they may still adopt bans for symbolic reasons.

## Empirical Approach and Data

This study is similar in spirit to studies of voting on environmental propositions, a literature that dates back to Deacon and Shapiro (1975). Those studies (Heintzelman, Walsh, and Grzeskowiak 2013, Banzhaf, Oates, and Sanchirico 2010, Wu and Cutter 2011, Kotchen and Powers 2006, Nelson, Uwasu, and Polasky 2007) examined voting data sets that were aggregated to various levels in local and statewide referenda on environmental, conservation, and other issues. Our study looks at policies implemented at the local level through actions of town councils rather than popular votes and follows an approach similar to ones used in the context of land use policies by Meltzer and Schuetz (2010), Cheung and Meltzer (2013), Hawkins (2014), and Feiock (2004). In our context, there is a degree of separation between policy actions and the will of voters and residents but we can still expect that municipal councils will work mostly in the interest of or in response to the desires of voters. Nonetheless, we can draw only limited conclusions about popular sentiment based on adoption of fracking policies by local governing bodies.

Because these policy decisions are made by elected representatives, we do not have data in the form of continuous vote shares as in Deacon and Shapiro (1975), Heintzelman, Walsh, and Grzeskowiak (2013), and Banzhaf, Oates, and Sanchirico (2010). Instead, we have to implement a limited dependent variable approach similar to Meltzer and Schuetz (2010). In addition, we follow Heintzelman, Walsh, and Grzeskowiak (2013) and Wu and Cutter (2011) in accounting for spatial dependence. This is in keeping with Brueckner (1998) and Brueckner and Saavedra (2001), which found early evidence of spatial interdependence across jurisdictions in local policy settings.

Home-rule communities can prevent fracking with bans and moratoria, which differ only in how they end. A moratorium generally has a known sunset date and must be renewed to remain in effect. A ban, on the other hand, generally does not expire but can be terminated by the local governing body at any time. Because the effects of the policies are the same, particularly in our context in which there has been a statewide moratorium (now ban) in place, and because the data from FracTracker on moratorium expirations are not complete, we treat moratoria and bans as equivalent. As a result, our preferred dependent variable is whether a community enacted either policy.[6]

*Probit Model*

Assume that the underlying propensity for a municipality to implement a ban or moratorium on fracking is given by

$$(1) \qquad \beta_i^* = \beta_0 + \beta_1\mathbf{demo}_i + \beta_2\mathbf{econ}_i + \beta_3\mathbf{geol}_i + \beta_4\mathbf{other}_i + \varepsilon_i$$

where $\mathbf{demo}_i$ represents demographic and political attributes of municipality *i*, including population density, age distribution, racial distribution, Democrat-Republican ratio, and distribution of educational attainment; $\mathbf{econ}_i$ represents economic variables, including median household income, unemployment rate, and distribution of employment across industries; $\mathbf{geol}_i$ represents geological characteristics, including whether municipality *i* lies above the Marcellus or Utica formations and/or their sweet spots, and the number of existing, active oil and gas wells in the municipality; $\mathbf{other}_i$ represents a series of miscellaneous explanatory variables, including data on land cover and the number of recently drilled water wells in the municipality; and $\varepsilon_i$ represents an idiosyncratic error term. It is not possible to observe the latent variable $\beta_i^*$; we can only observe whether the municipality chose to implement a ban or moratorium on fracking. Thus, we estimate the probability of a ban or moratorium using the following probit model.

$$(2) \qquad \Pr(B_i = 1) = \Phi(\beta_0 + \beta_1\mathbf{demo}_i + \beta_2\mathbf{econ}_i + \beta_3\mathbf{geol}_i + \beta_4\mathbf{other}_i) + \varepsilon_i$$

This model assumes that $B_i = 1$ if $B_i^* > 0$ and 0 otherwise. That is, a ban is put in place only if the latent propensity to ban fracking is greater than 0.

Figure 1 shows several ban and moratorium clusters (e.g., Onondaga and Livingston counties), and the presence of clustering of local fracking policies is supported by the studies of local policy diffusion discussed previously. To formally explore the presence of spatial clustering, we use two tests. First, we calculate the local Moran's I spatial statistic (Anselin 1995), which tests for clustering of values—in this case, whether bans or moratoria were implemented in municipalities that are in close proximity to each other. We present the results of this test in Figure 3. In the figure, HH indicates statistically significant (at least 95 percent) clustering of bans and moratoria, LL indicates clustering of no bans or moratoria (there are none of these in the map), and HL and LH

[6] We also ran regressions for bans and moratoria individually; results of those regressions are available online at Social Science Research Network (*www.ssrn.com*).

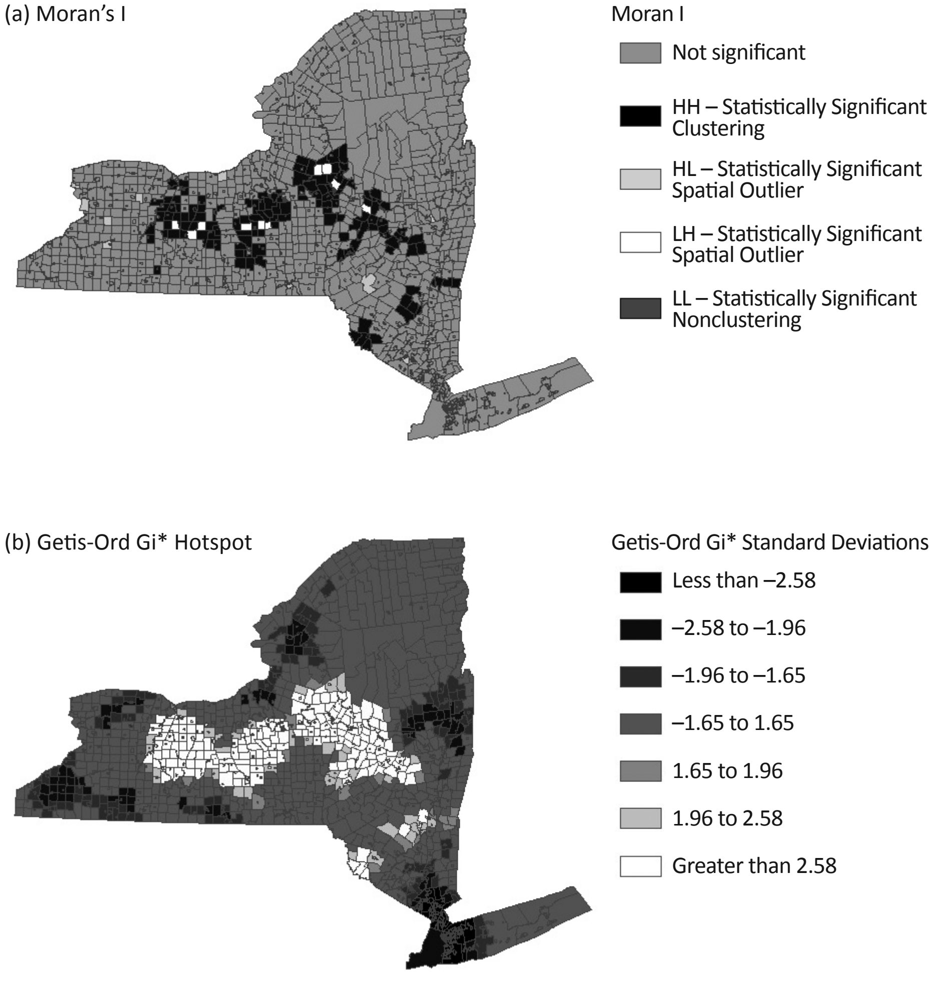


**Figure 3. Local Spatial Statistic Tests for Bans and Moratoria**

indicate statistically significant spatial outliers. Figure 3 also shows the results of a Getis-Ord Gi* hot spot analysis. Both tests indicate spatial clustering of bans and moratoria in central New York that loosely follows Interstate 90, which crosses several major cities, including Syracuse, Rochester, and Utica. There is evidence of clustering around Ithaca as well. However, the prime fracking areas (having the most geologic potential) are located just north of the Pennsylvania border near the center of these states. We detect no ban/moratorium hot spots in that area. In fact, the Getis-Ord Gi* map shows a "cold spot" there, indicating a dearth of bans and moratoria.

Given the clustering observed in Figure 3, it is important to control for spatial dependence, which could be caused by a variety of unobserved factors. For models involving a binary dependent variable, the normal approach of maximum-likelihood spatial econometric tools is not feasible. The probit model does not have a closed-form solution, so numerical methods must be combined with Bayesian techniques (LeSage and Pace 2009). We estimate both spatial lag and spatial error models that are in the same form as the preceding normal probit except that the spatial lag model contains a lagged dependent variable (equation 3) and the spatial error model contains a nonspherical error term (equation 4):

$$(3)\quad \Pr(B_i = 1) = \Phi(\rho \mathbf{W}B + \beta_0 + \beta_1\mathbf{demo}_i + \beta_2\mathbf{econ}_i + \beta_3\mathbf{geol}_i + \beta_4\mathbf{other}_i) + e_i$$

$$(4)\quad \begin{aligned} &\Pr(B_i = 1) = \Phi(\beta_0 + \beta_1\mathbf{demo}_i + \beta_2\mathbf{econ}_i + \beta_3\mathbf{geol}_i + \beta_4\mathbf{other}_i) + e_i \\ &e_i = \lambda \mathbf{W} e_i + u \end{aligned}$$

where $\lambda$ and $\rho$ are parameters to be estimated and $\mathbf{W}$ is an $n$ x $n$ spatial weight matrix that exogenously specifies the neighbor structure in the data.

The Bayesian spatial probit approach uses repeated Markov Chain Monte Carlo (MCMC) sampling along with Gibbs sampling (for full details, see LeSage and Pace (2009)). This approach treats the binary dependent variable as an indicator of an unobservable continuous latent utility variable. Following Albert and Chib (1993), this latent utility variable can be estimated through Gibbs sampling by drawing from a multivariate truncated normal distribution. For example, in the spatial error model, the likelihood function is

$$(5)\quad L = (2\pi\sigma^2)^{-(n/2)}\,|\,I - \lambda W\,|\,\exp\left(-\frac{1}{2\sigma^2}(y - X\beta)'(I - \lambda W)'(I - \lambda W)(y - X\beta)\right).$$

The posterior distribution for each parameter in a Bayesian setting is obtained by multiplying the likelihood by the prior. Following convention (LeSage and Pace 2009), we use a normal prior distribution for $\beta$, an inverse gamma distribution for $\sigma^2$, and a uniform prior distribution for $\lambda$. Gibbs sampling can be used to sample from the posterior distributions of $\beta$ and $\sigma^2$ since they take known forms. However, the Metropolis-Hastings algorithm (a type of MCMC) must be used to sample from the conditional distribution for $\lambda$ and $\rho$.

We explore several spatial weight matrices, including nearest neighbor, contiguity, and inverse distance-based variations. The matrix is $n$ x $n$ where a nonzero $\mathbf{W}_{ij}$ indicates that elements $I$ and $j$ are neighbors. The nearest neighbor spatial weight matrix sets $\mathbf{W}_{ij} = 1$ (before standardization, which makes all rows sum to 1) for the closest $X$ neighbors. The contiguity-based matrices set $\mathbf{W}_{ij} = 1$ if the two observations share a border. The inverse distance-based matrices use $\mathbf{W}_{ij} = 1 / d_{ij}$ within a certain radius where $d_{ij}$ is the distance between the observations.

To choose between these spatial weight matrices and between the error and lag models, we use the posterior probabilities from the Bayesian regressions. This represents another advantage of using Bayesian models. If there are no theoretical or other reasons to favor one model over others, the model with the highest posterior probability, post-analysis, should be chosen (Mueller and Loomis 2010).[7] The background for choosing a Bayesian model is more thoroughly described in Mueller and Loomis (2010); we present only some of the basic set-up here.

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[7] Spatial weight matrices were also compared using the deviance information criterion (DIC) (LeSage et al. 2011). The DIC test selected the same spatial weight matrices as the posterior probabilities. However, the DIC cannot choose between the error and lag models. Thanks are due to an anonymous reviewer for suggestions regarding the posterior probabilities.

Assume one wants to compare two Bayesian models, $B_i$ and $B_j$. Using Bayes' theorem,

$$(6) \qquad p(B_i \mid Data) = \frac{P(Data \mid B_i)}{P(B_i \mid Data) + p(Data \mid B_j)} \frac{p(B_i)}{p(B_j)}.$$

In equation 6, the marginal likelihood of the data given $B_i$ is represented by $p(Data \mid B_i)$ while the prior probability is $p(B_i)$. In Bayesian analysis, the posterior odds ratio $O_{ij} = \pi_i / \pi_j$ can be used to examine whether the data favor one model over another; $\pi_i$ is the posterior probability of model $i$. To compare more than one alternative model, each with equal prior probability, the posterior probability for model $k$, $\pi_k$, is given as

$$(7) \qquad \pi_k = \frac{p(Data \mid B_k)}{\sum_{x=1}^{P} p(Data \mid B_x)}$$

where $P$ is the number of alternate models. After computing the Bayesian regressions, the model with the highest posterior probability should be chosen (Mueller and Loomis 2010). We compare the contiguity matrix to three nearest-neighbor models (the number of nearest neighbors, $N$, is set to 10, 15, and 20) and two inverse-distance models using a distance cut-off radius of 20,000 and 30,000 feet. All five spatial weight matrices are employed in the error and lag models.

*Survival Model*

Another useful approach for modeling the local policy process is survival analysis, which emphasizes the timing of policy actions. Much of the literature on determinants of local policy actions has treated events as static phenomena (Heintzelman, Walsh, and Grzeskowiak 2013). In addition to identifying factors that lead to bans and moratoria, we are interested in the timing of these events. What causes some towns to pass bans or moratoria earlier than others? Survival analysis (sometimes called hazard or event history analysis) can be used to estimate the conditional probability of leaving a "state" of being, conditional on the amount of time that the state has been occupied (Vance and Geoghegan 2002). In this case, we are interested in the probability of passing a ban or moratorium—of exiting the "state" of not having a ban/moratorium. For obvious reasons, survival models are popular in medical studies in which the focus is, for instance, the impact of a particular drug on a medical condition (Albertsen et al. 1995, Cleves et al. 2008, De Bruyne et al. 2012). The temporal nature of these methods makes them useful for analyzing impacts over time. Furthermore, survival models control for explanatory variables that are unobservable but vary over time (Vance and Geoghegan 2002). These models are increasingly used in economics (Vance and Geoghegan 2002, Pinto and Nelson 2007, Busch and Vance 2011, Heintzelman, Walsh, and Grzeskowiak 2013).

The focus in such models is on the survival and hazard functions. If we define $F(t) = \Pr(T \leq t)$ as a cumulative distribution function in which $T$ represents the length of time without a ban or moratorium and $t$ denotes a specific point in time, the survival function is $S(t) = 1 - F(t) = \Pr(T > t)$, the probability of a state (no ban or moratorium) "surviving" beyond that specific time $t$ (Cleves et al. 2008). The probability density function therefore is

(8) $$f(t) = dF(t) / dt = -dS(t) / dt = -S'(t).$$

The hazard function, which plays a prominent role in most survival analyses, is the probability that the state will be vacated—that a ban or moratorium will be implemented—in a given interval (conditional on reaching that point) divided by the width of that interval:

(9) $$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t + \Delta t > T > t \mid T > t)}{\Delta t} = \frac{f(t)}{S(t)}.$$

We use the Cox (1972) proportional hazard model, which is frequently used in economics (Vance and Geoghegan 2002, Busch and Vance 2011, Heintzelman, Walsh, and Grzeskowiak 2013), medical sciences (Albertsen et al. 1995), and ecology (Tenhumberg, Keller, and Possingham 2001). It assumes that the hazard rate for the $i$th subject is

(10) $$h(t \mid x_i) = h_0(t)\exp(x_i\beta_x).$$

In this formulation, the covariates multiplicatively shift the baseline hazard function $h_0(t)$ (Cleves et al. 2008). One of the main advantages of the Cox proportional hazard model is that the baseline hazard is given no particular parameterization and thus no assumptions about its shape are needed.[8] We can use the same variables that we employ in the probit model in the hazard model:

(11) $$h(t) = h_0(t)\exp(\delta_1\mathbf{demo}_i + \delta_2\mathbf{econ}_i + \delta_3\mathbf{geol}_i + \delta_4\mathbf{other}_i).$$

This specification is robust to heteroskedasticity (Cleves et al. 2008). The initial "exposure" time, from which we measure subsequent periods, is passage of New York's statewide moratorium on July 23, 2008.[9]

*Data*

We collected data for this analysis from a number of sources. Information on municipal policy actions came from the November 22, 2013, update of the website of FracTracker Alliance (*FracTracker.org*); any policies enacted after that date were not included. We also used FracTracker GIS maps of geologic layers to calculate the share of each municipality that intersected those and the proximity of each community to the various layers of interest. Our demographic and economic data are from five-year estimates from the U.S Census American Community Survey. Data on existing oil and gas wells and recently drilled water wells came from NYSDEC through the state's GIS clearinghouse. Data on land

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[8] As explained in Cleves et al. (2008), since we confine our analysis to times when failure occurs (conditional on those failures only occurring then), the baseline hazard drops out of the calculations.

[9] Several other exposure times were considered, including 2005, when Congress passed the Energy Policy Act and the exemption from the Safe Drinking Water Act for fracking was made explicit. The results were robust to these changes.

**Table 1. Descriptive Statistics**

| | Full Sample | | Shale-deposit Sample | | Marcellus Prime Sample | |
|---|---|---|---|---|---|---|
| Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Ban | 0.04 | 0.20 | 0.06 | 0.23 | 0.04 | 0.20 |
| Moratorium | 0.07 | 0.25 | 0.09 | 0.29 | 0.05 | 0.22 |
| Ban or moratorium | 0.11 | 0.31 | 0.15 | 0.35 | 0.09 | 0.29 |
| Share over Marcellus | 38.65 | 47.73 | 55.43 | 48.34 | 1 | — |
| In prime Marcellus region | 0.09 | 0.28 | 0.13 | 0.33 | 1 | — |
| Share over Utica | 66.43 | 46.23 | 95.27 | 17.76 | 0 | — |
| Share over Utica sweet spot | 5.14 | 21.24 | 7.37 | 25.11 | 0 | — |
| Percent manufacturing employment | 11.02 | 6.29 | 12.60 | 6.19 | 14.93 | 5.80 |
| Percent arts and tourism employment | 7.90 | 4.35 | 7.92 | 4.24 | 6.51 | 3.10 |
| Percent natural resource and construction employment | 10.97 | 5.29 | 11.41 | 4.99 | 10.95 | 5.07 |
| Percent developed land area | 15.19 | 21.61 | 11.66 | 17.13 | 10.89 | 16.39 |
| Count of recent water wells (since 2000) | 10.35 | 17.23 | 11.20 | 17.57 | 12.85 | 18.68 |
| Percent open water | 2.94 | 6.14 | 2.26 | 5.51 | 0.65 | 2.25 |
| Percent wetlands | 6.69 | 7.05 | 6.45 | 6.71 | 3.03 | 3.00 |
| Ratio of Democrats to Republicans | 0.89 | 0.67 | 0.82 | 0.65 | 0.75 | 0.61 |
| Existing oil and gas wells | 4.27 | 21.97 | 6.13 | 26.10 | 0.70 | 2.09 |
| Share within priority watershed | 3.11 | 15.98 | 3.28 | 16.35 | 0.74 | 6.36 |
| Homes with solar systems | 0.03 | 0.20 | 0.03 | 0.19 | 0.03 | 0.13 |
| Civilian unemployment rate | 4.97 | 2.24 | 5.01 | 2.12 | 5.22 | 2.44 |
| Median household income ($1,000) | 59.387 | 28.438 | 52.081 | 12.545 | 49.343 | 9.052 |
| Percent over 65 years of age | 15.98 | 5.45 | 15.70 | 4.60 | 15.21 | 3.30 |
| Population density | 859.82 | 1,231.10 | 755.40 | 1,114.17 | 1,708.93 | 8,551.21 |
| Percent over 25 with with high school diploma | 13.94 | 6.35 | 12.74 | 5.41 | 11.61 | 5.10 |
| Incorporated village | 0.39 | 0.49 | 0.33 | 0.47 | 0.32 | 0.47 |
| Percent American Indian | 0.33 | 0.91 | 0.34 | 0.85 | 0.34 | 0.65 |

use and cover came from the U.S. government's National Land Cover Database. Information on residents' political affiliations was provided by the New York State Board of Elections. Areas likely to be the most productive geologically in the near term were identified through personal conversations with and data from geologist Tim Carr of West Virginia University.

Table 1 presents summary statistics for the variables included in our analysis. Note that a relatively small percentage of communities both statewide and in our restricted sample (communities overlying a shale deposit) have established anti-fracking policies—11 percent in the full sample and 15 percent in the restricted sample.

## Results

The posterior probabilities from the Bayesian model choice exercise are presented in Table 2. For a given set of alternate models, all of the probabilities should sum to 1. For both the full sample and the shale-community sample, we find strong evidence for nearest-neighbor effects at 20 nearby communities (*NN20 SWM*) in the spatial error model[10] and the posterior probability is close to 1 while the others approach 0. In the Marcellus prime sample, the difference is less stark; the inverse distance, *SWM InvDist30*, is favored, again in the error model.[11]

Table 3 presents the results for the full and restricted samples when we use the favored *NN20 SWM* in the spatial error models.[12] Starting with the shale-deposit sample for which bans and moratoria are most salient, we find that communities in prime regions where good shale gas production is anticipated are significantly less likely than other communities to pass a policy restricting fracking. Being located above the Marcellus and Utica formations does not

**Table 2. Posterior Probabilities**

| | Shale-deposit Sample | | Full Sample | | Marcellus Prime Sample | |
|---|---|---|---|---|---|---|
| **Variable** | **Error** | **Lag** | **Error** | **Lag** | **Error** | **Lag** |
| Contiguity | –2.54E-112 | 0.00E-00 | –4.94E-153 | 0.00E-00 | 0.007508 | 2.82E-56 |
| NN10 | 7.01E-64 | 0.00E-00 | 7.74E-80 | 0.00E-00 | 0.028741 | 3.15E-55 |
| NN15 | 7.75E-17 | 0.00E-00 | 3.82E-19 | 0.00E-00 | 0.030327 | 3.62E-55 |
| NN20 | 1.00E+00 | 0.00E-00 | 1.00E+00 | 0.00E-00 | 0.065738 | 1.15E-56 |
| InvDist20 | –1.49E-116 | 0.00E-00 | –1.09E-149 | 0.00E-00 | 0.038900 | 2.64E-56 |
| InvDist30 | –2.44E-100 | 0.00E-00 | 1.20E-113 | 0.00E-00 | 0.157847 | 4.58E-56 |

[10] Although 20 nearest neighbors may seem like a large number, the towns, villages, and municipalities represented in our data can be quite small. For example, the Ithaca urban and surrounding area is composed of approximately 24 observations.

[11] If we used lag models, marginal effects would not be represented by the coefficients and would need to be calculated because of the presence of the spatially weighted dependent variable on the righthand side (LeSage and Pace 2009).

[12] There are only minor differences in the coefficients from the spatial error and lag models. The results of the lag model are available in an appendix upon request.

**Table 3. Results of Primary Regression**

| Variable | Coefficient (Standard Error) Shale-deposit Sample | Full Sample | Marcellus Prime Sample |
|---|---|---|---|
| Constant | 0.6795<br>(1.0571) | −0.1165<br>(0.7040) | −1.7130<br>(4.3964) |
| Share over Marcellus | 0.0028<br>(0.0022) | 0.0031***<br>(0.0020) | — |
| In prime Marcellus region | −0.6566***<br>(0.2602) | −0.6327***<br>(0.2496) | — |
| Share over Utica | 0.0012<br>(0.0041) | 0.0062***<br>(0.0019) | — |
| Share over Utica sweet spot | 0.0008<br>(0.0031) | 0.0008<br>(0.0028) | — |
| Percent manufacturing employment | −0.0080<br>(0.0137) | −0.0066<br>(0.0121) | −0.0514<br>(0.0575) |
| Percent arts and tourism employment | −0.0233<br>(0.0192) | −0.0209**<br>(0.0152) | 0.0493<br>(0.0968) |
| Percent natural resource and construction employment | 0.0209<br>(0.0172) | 0.0077<br>(0.0140) | 0.0724<br>(0.0774) |
| Percent land area | −0.0106**<br>(0.0064) | −0.0075*<br>(0.0046) | 0.0040<br>(0.0265) |
| Count of recent water wells (since 2000) | 0.0057<br>(0.0047) | 0.0042<br>(0.0037) | 0.0224**<br>(0.0145) |
| Percent open water | 0.0076<br>(0.0103) | −0.0003<br>(0.0092) | 0.2401***<br>(0.1115) |
| Percent wetlands | −0.0331***<br>(0.0137) | −0.0211**<br>(0.0110) | 0.0686<br>(0.1150) |
| Ratio of Democrats to Republicans | 0.3214***<br>(0.1142) | 0.2467***<br>(0.0906) | 0.0691<br>(0.7125) |
| Existing oil and gas wells | −0.0106***<br>(0.0037) | −0.0105***<br>(0.0034) | −0.1117<br>(0.1461) |
| Share within priority watershed | −0.0100***<br>(0.0051) | −0.0084**<br>(0.0040) | −0.0222<br>(0.0564) |
| Percent homes with solar systems | −0.1218<br>(0.3530) | −0.0828<br>(0.2743) | −0.8641<br>(2.3101) |
| Civilian unemployment rate | −0.0117<br>(0.0343) | −0.0187<br>(0.0272) | 0.1292<br>(0.1339) |
| Median household income | 0.000007<br>(0.0000) | 0.000004*<br>(0.0000) | 0.0000<br>(0.0000) |
| Percent over 65 years of age | 0.0024<br>(0.0160) | −0.0017<br>(0.0138) | 0.0219<br>(0.0966) |
| Percent under 18 years of age | 0.0000<br>(0.0160) | −0.0030<br>(0.0126) | 0.0675<br>(0.0751) |

*continued on following page*

**Table 3 (continued)**

| Variable | Coefficient (Standard Error) Shale-deposit Sample | Full Sample | Marcellus Prime Sample |
|---|---|---|---|
| Population density | 0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0001) |
| Percent over 25 with high school diploma | –0.0462 *** | –0.0309 *** | –0.0841 *** |
| | (0.0125) | (0.0095) | (0.0499) |
| Incorporated village | –0.6815 *** | –0.5814 *** | –0.8230 |
| | (0.2035) | (0.1520) | (1.0111) |
| Percent American Indian | –0.0795 | –0.0431 | –0.1125 |
| | (0.0961) | (0.0727) | (0.4444) |
| Rho/Lambda | 0.6012 *** | 0.5153 *** | –0.0038 |
| | (0.0842) | (0.0641) | (0.1047) |
| Pseudo R-square | 0.5284 | 0.561 | 0.8501 |
| N | 1,122 | 1,564 | 142 |

Notes: Standard errors are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

appear to affect the probability of anti-fracking measures significantly. For the full data set that contains all New York municipalities, the coefficients of the general Marcellus and Utica variables are positive and significant, but the coefficient of the prime variable remains negative and its magnitude is similar to the magnitude of the coefficient for the deposit sample.

In the full sample, communities with a relatively large share of employment in arts and tourism are significantly less likely than other communities to pass a ban or moratorium, all else being equal. This is a particularly surprising result and may stem from an omitted-variable problem associated with the types of areas that have tourism industries. Alternately, local residents may be assuming that those areas are "safe" from fracking because of their reliance on tourism. We find no significant effects from shares of employment in manufacturing and natural resource / construction industries. However, areas that already have a relatively large number of conventional oil and gas wells are significantly less likely to pass anti-fracking policies. This is consistent with the theory that communities in such areas have more experience with these industries and are likely to be more dependent on them economically. In addition, oil and gas workers there would benefit more than other workers from fracking since they have skills and experience in the field.

In both samples, areas with greater development, larger areas of wetlands and priority watersheds, and incorporated villages are significantly less likely to pass bans or moratoria on fracking. These results, taken together, are not surprising. Wells generally are not drilled in urban and developed areas. Thus, areas in which the land has mostly been developed are less likely than rural areas to be in close proximity to drilling facilities and, consequently, less likely to be negatively impacted. In New York, smaller-scale rural municipalities can be confusing. Both "towns" and "villages" exist, but incorporated villages often are subsidiary components of towns. A village can exist within the jurisdiction of a town, and they can have overlapping or separated jurisdictional control. Further, some "towns" are actually quite large "townships" that can include hundreds of square miles of rural land.

In addition, incorporated villages, which have larger populations than more rural areas, may be more able to reap economic benefits from nearby fracking (while avoiding negative environmental impacts). Municipalities in close proximity to priority watersheds also likely expect that drilling will not be allowed. We consider two potential explanations for the relatively small probability of bans and moratoria being enacted in areas containing more wetlands. Wetlands typically are environmentally sensitive areas so municipal leaders may believe that they will be protected by other environmental policies. Or, perhaps areas with extensive wetlands offer few other uses that directly benefit residents, who thus are more willing to allow fracking to occur. Our analysis cannot distinguish between these motivations.

As expected, areas in which a relatively large number of registered Democrats reside are much more likely to pass local fracking bans and moratoria than areas in which most voters register as Republicans. This pattern is well documented; by and large, Republican voters are more likely to support pro-drilling policies while Democrats are more likely to prioritize environmental issues.

We find no significant impact from unemployment rates. However, communities in which most residents have limited education (people older than 25 who have only high school diplomas) are less likely than communities with higher average levels of education to pass bans or moratoria. In the full sample, communities that have relatively high incomes are more likely to pass anti-fracking policies (the results for the other samples are insignificant). Since one would expect relatively wealthy communities to rank local economic benefits from fracking lower than other concerns, such as environmental protection, this result is supported by theory (Cosgrove et al. 2014, Hardy and Kelsey 2014, Miller, Atems, and Bird 2014).

The results of the model in which we restricted the sample to prime areas also are presented in Table 3. Since potential bans and moratoria are most relevant in these areas, we are particularly interested in whether these results differ from the results of the larger samples. Unfortunately, the small sample size (142 observations versus 1,122 for all shale-deposit communities and 1,564 for the full sample) produced much less significance in the coefficients. The count of recent wells established and the percent of open water in the area both significantly increase the probability of anti-fracking measures, indicating that municipalities were concerned about protecting natural resources in those areas. The coefficient on the education variable was similar to the coefficients for the other two samples.

To further investigate differences in areas where fracking is the most probable (and potentially profitable), we introduced interactions between the ratio of Democrats to Republicans and location in either the Marcellus prime or Utica sweet spot. The results of these regressions are provided in Table 4. The interaction variables indicate that the presence of mostly Democrats has the smallest effect for the Marcellus prime region in both the shale-deposit and the full sample. The opposite is true for the Utica sweet spot; there, the interaction with the presence of Democrats is negative and significant, though much smaller in magnitude relative to the Marcellus. However, the

**Table 4. Political Interactions**

| Variable | Deposit Sample | Full Sample | Variable | Depost Sample | Full Sample |
|---|---|---|---|---|---|
| Constant | 0.576 | –0.009 | UtSweetDEMREP | 0.026*** | 0.027*** |
| | (1.135) | (1.010) | | (0.010) | (0.010) |
| MarcellusCoverage | 0.005** | 0.007*** | Exist_GasOilWellCount | –0.020*** | –0.016*** |
| | (0.003) | (0.003) | | (0.008) | (0.009) |
| MarcellusPrime | –0.650** | –0.651** | Pct_Watersheds | –0.015*** | –0.014*** |
| | (0.412) | (0.410) | | (0.006) | (0.006) |
| Utica_Coverage | 0.001 | 0.005** | PctSolar | –0.128 | –0.193 |
| | (0.004) | (0.003) | | (0.297) | (0.261) |
| Utica_Sweet | –0.022*** | –0.023*** | PctCivilianUnemployed | –0.003 | –0.020 |
| | (0.009) | (0.009) | | (0.040) | (0.035) |
| PctManuEmployment | –0.003 | –0.005 | MedianHHIncome | 0.000 | 0.000 |
| | (0.014) | (0.014) | | (0.000) | (0.000) |
| PctArtTourEmploym. | –0.013 | –0.026* | PctOver65 | 0.000 | 0.002 |
| | (0.022) | (0.020) | | (0.018) | (0.017) |
| PctNatRes_Construct | 0.038** | 0.023* | PctUnder18 | 0.007 | 0.001 |
| | (0.017) | (0.016) | | (0.016) | (0.015) |
| Developed | –0.015** | –0.010* | PopDensity | 0.000** | 0.000** |
| | (0.007) | (0.007) | | (0.000) | (0.000) |
| WellCount | 0.009** | 0.009** | PctOver25_HSG | –0.062*** | –0.049*** |
| | (0.005) | (0.004) | | (0.013) | (0.011) |
| OpenWater | 0.004 | –0.007 | VillageDummy | –1.227*** | –1.360*** |
| | (0.012) | (0.012) | | (0.216) | (0.212) |
| Wetlands | –0.046*** | –0.037*** | PctAmerIndian | –0.109 | –0.091 |
| | (0.016) | (0.017) | | (0.126) | (0.111) |
| DEMtoREP | 0.504*** | 0.445*** | Lambda | 0.814*** | 0.841*** |
| | (0.132) | (0.121) | | (0.041) | (0.032) |
| MPrimeDEMREP | –0.435** | –0.434* | N | 1,122 | 1,564 |
| | (0.279) | (0.298) | Pseudo R-square | 0.6609 | 0.6823 |

Notes: Standard errors are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

noninteracted Utica sweet spot variable is now negative and significant in both models. Overall, these results illustrate the importance of local political affiliation in decisions about bans and moratoria.

*Survival Model Results*

The results of our nonspatial survival analysis, presented in Table 5, are largely consistent with the spatial results. The reported coefficients are hazard ratios that represent multipliers on the period-by-period probability of a ban or moratorium being passed. Coefficients that are greater than 1 represent an increased probability of passage while coefficients that are less than 1 represent a decreased probability of passage. A relatively large ratio of Democrats to Republicans and relatively greater share of individuals who have at least a bachelor's degree correlate to a greater probability of anti-fracking measures in both samples. Alternately, art and tourism employment, share

**Table 5. Results of Survival Model**

| Variable | Shale-deposit Sample | Full Sample |
|---|---|---|
| Share over Marcellus | 1.0012<br>(0.0026) | 1.0010<br>(0.0025) |
| In prime Marcellus region | 0.3098***<br>(0.0967) | 0.2961***<br>(0.0919) |
| Share over Utica | 1.0059<br>(0.0050) | 1.0191***<br>(0.0034) |
| Share over Utica sweet spot | 1.0030<br>(0.0032) | 1.0026<br>(0.0032) |
| Percent manufacturing employment | 0.9802<br>(0.0171) | 0.9800<br>(0.0167) |
| Percent arts and tourism employment | 0.9498*<br>(0.0253) | 0.9350***<br>(0.0240) |
| Percent natural resource and construction employment | 1.0369*<br>(0.0222) | 1.0203<br>(0.0202) |
| Percent developed land area | 0.9798**<br>(0.0099) | 0.9841<br>(0.0096) |
| Count of recent water wells (since 2000) | 1.0036<br>(0.0052) | 1.0068<br>(0.0049) |
| Percent open water | 1.0227<br>(0.0148) | 1.0118<br>(0.0142) |
| Percent wetlands | 0.9252***<br>(0.0185) | 0.9305***<br>(0.0175) |
| Ratio of Democrats to Republicans | 1.3402***<br>(0.1350) | 1.3256***<br>(0.1245) |
| Existing oil and gas wells | 0.9605***<br>(0.0140) | 0.9603***<br>(0.0140) |
| Share in priority watersheds | 0.9809***<br>(0.0070) | 0.9810***<br>(0.0069) |
| Percent homes with solar systems | 1.0632<br>(0.3535) | 1.0261<br>(0.3409) |
| Civilian unemployment rate | 0.9428<br>(0.0421) | 0.9412<br>(0.0403) |
| Median household income | 1.0000<br>(0.0000) | 1.0000**<br>(0.0000) |
| Percent over 65 years of age | 1.0109<br>(0.0200) | 1.0092<br>(0.0188) |
| Percent under 18 years of age | 1.0092<br>(0.0192) | 1.0056<br>(0.0188) |
| Population density | 0.9999<br>(0.0001) | 0.9999<br>(0.0001) |
| Percent over 25 with high school diploma | 0.9146***<br>(0.0132) | 0.9222***<br>(0.0122) |
| Incorporated village | 0.1482***<br>(0.0563) | 0.1455***<br>(0.0522) |
| Percent American Indian | 0.8607<br>(0.1193) | 0.8787<br>(0.1140) |
| N | 1,122 | 1,564 |

Notes: Standard errors are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

of developed land, amount of wetland area, quantity of oil and gas wells, presence in a priority watershed, and incorporation as a village all result in a smaller probability of such measures. The effect of income is negative, which is consistent with the results of our spatial models. The positive coefficients for most of the spatial results reported in Table 3 correspond to hazard ratios that exceed 1 in the survival models; similarly, negative coefficients in the spatial models correspond to hazard ratios of less than 1 in the survival models. There are a few notable differences in the significance of these coefficients. Percent of employment in natural resources / construction is significant in the shale-deposit sample in the survival model and thus increases the probability of anti-fracking measures. In the survival model, a community being located in the prime productive area of the Marcellus shale decreases the probability of passage by more than 69 percent (1 – 0.3098). In turn, being in the prime area of the Utica shale increases the probability of a ban or moratorium by about 1.9 percent in the full sample (the effect is not significant in the deposit-only sample).

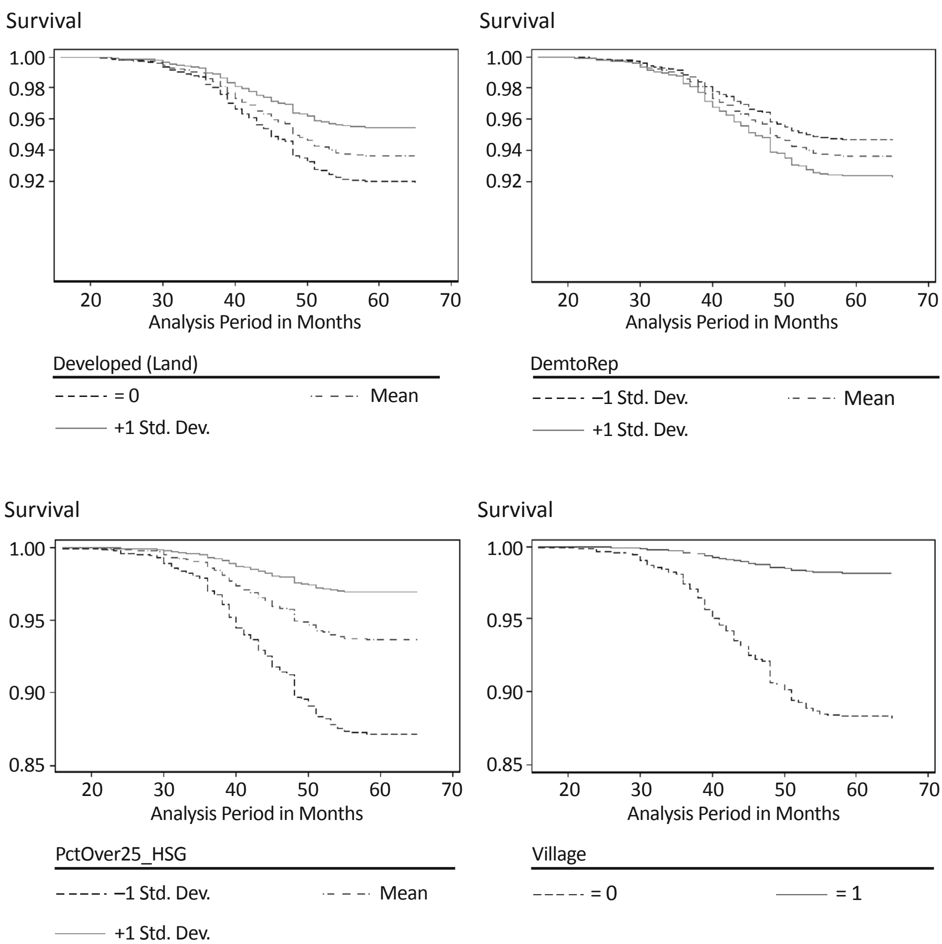


**Figure 4. Survival Curves for Shale-deposit Sample**

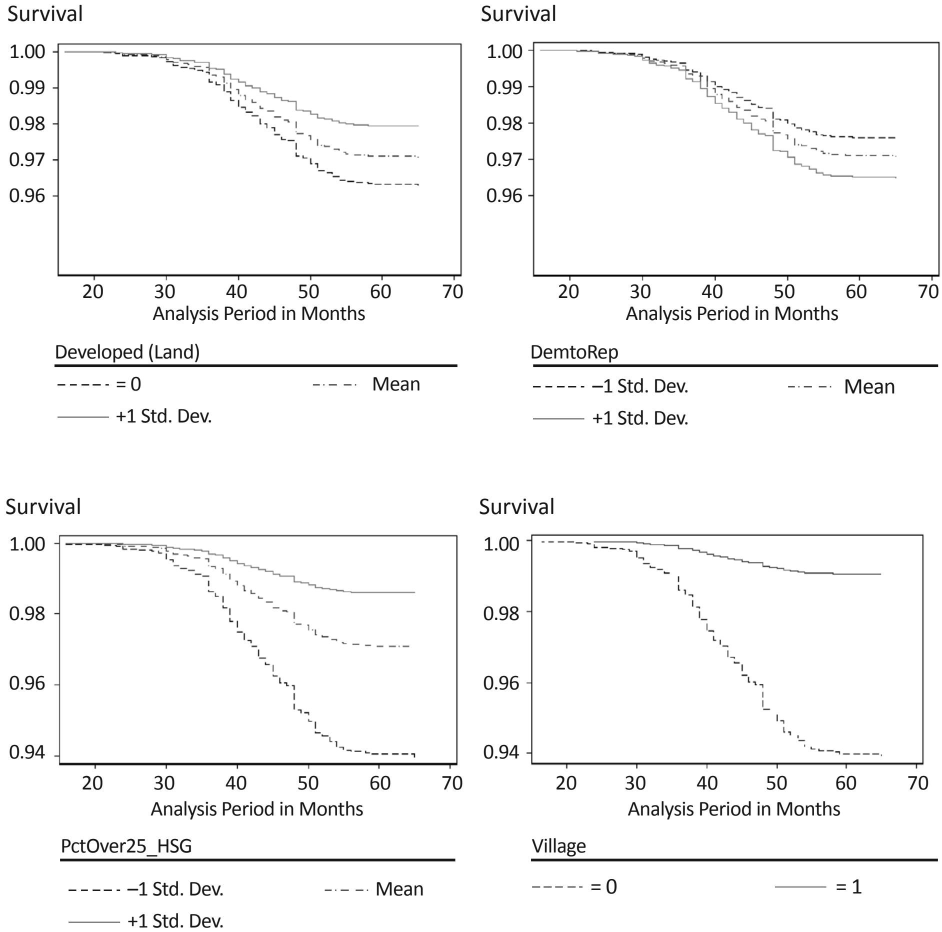


**Figure 5. Survival Curves for Full Sample**

A primary advantage of survival models is their ability to portray impacts over time. Small changes in the instantaneous probability of passage can add up to large differences in the cumulative probability of passage over time. We plot the effect of the cumulative probability of survival over time for several variables for the shale-deposit sample in Figure 4 and for the full sample in Figure 5. The three curves for the continuous variables represent the initial values, which correspond to the means, and plus-one and minus-one standard deviations. For the dummy variable *Village*, the curves correspond to initial values of 0 and 1. The units of time on the x-axis are months.

The figures illustrate how the probability of passing a fracking ban or moratorium changes over a five-year (60-month) period based on some key factors. For example, the high- and low-education survival (*PctOver25_HSG*) curves show that communities in the shale-deposit sample that have relatively low levels of education are approximately 10 percent less likely to pass a ban or moratorium after five years. The survival curve for the *Village* dummy variable also indicates a large compounding effect over time. As suggested by the probit coefficients, areas that are not incorporated in a village are much more likely to pass a ban or moratorium, probably because of the greater likelihood of fracking activity in those areas. The survival curves highlight differences in responses for the shale-deposit and full samples. For example, the probability of passing an anti-fracking measure in the regression on the education variable for the full sample is half that of the probability for the shale-deposit sample.

## Policy Implications and Conclusions

A number of policy implications and options emerge from this analysis. We find that the demographic nature of an area affects the likelihood of bans and moratoria and that limited education in a community decreases the likelihood of passage of such measures. A strong relationship between wealth and education is well established (e.g., Barro and Lee 1994, Filmer and Pritchett 1999), and we find further support for that relationship in our full sample; higher median household incomes in that model had a positive impact on the likelihood of anti-fracking measures. At a minimum, these results suggest that environmental authorities at the state and federal level should be concerned about potential negative impacts of fracking from an environmental justice perspective. The results also point to opportunities for the fracking industry to improve its reputation and/or address such concerns in a pre-emptive manner.

An important concern is that less educated communities may end up absorbing a greater share of negative impacts from fracking, both in New York if fracking is implemented and in other states. Much can be done to improve transparency and the availability of information, especially for communities that have limited resources (Piotrowski and Liao 2012, Miller, Atems, and Bird 2014). In the case of fracking, some limited transparency mechanisms have emerged in the past two years. These include FracFocus, a voluntary industry-led group that operates a website that tracks specific information about drilling sites (*www.fracfocus.org*). Certain aspects of FracFocus have been criticized as compromised in terms of oversight by state agencies or as lacking in terms of stringent submission rules (Konschnik, Holden, and Shasteen 2013). Independent organizations such as FracTracker are attempting to bring greater transparency to the process and to make resources available to the public. Indeed, we use FracTracker as our central data point for information on bans, moratoria, and resolutions. Regional leaseholder and landowner groups have also emerged in some places to provide best practices for protecting landowner rights in negotiating leases and to advocate for fracking generally. While all of these approaches offer useful information, other types of data could be much more valuable in ensuring that communities have access to appropriate resources so they can make informed decisions. State and federal agencies could provide information that would benefit residents and municipal areas in addressing fracking.

States can contribute to transparency and public education as well through up-to-date internet-based databases of environmental problems caused by specific drilling operators and/or problematic leaseholders (in the same way that New York City provides public “grades” from health inspections of restaurants). By assisting local communities in obtaining such additional information, community stakeholders could much more effectively address concerns about fracking activity in their areas.

We see value in this analysis for fracking operators as well. Our study and analyses that follow it can inform operators about factors that drive the opposition, perhaps allowing them to determine where challenges are likely to occur and to proactively address those concerns. This analysis also may help fracking operators to identify factors that drive well-to-do communities to oppose drilling. It could lead to positive changes to practices currently used by gas drilling operators.

While this analysis is specific to fracking in New York, this type of analysis is applicable to other local energy and policy issues. In particular, the siting of wind turbines has stirred considerable controversy in many places (Cape Cod, for example). Many of the issues associated with fracking also would apply to wind turbines. Areas (and individual landowners) that offer the greatest potential for wind energy may be more accepting of wind turbines while nearby residents and communities may be opposed, and there could be similar income effects. This is a fruitful area for further research.

Local control is an important factor in fracking and in other energy and natural resource issues. Our analysis is the beginning of a stream of research aimed at increasing our understanding of determinants of local intervention in energy extraction activities and the ramifications of those determinants for policy.

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