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I Want In On That: Community-level Policies for Unconventional Gas Development in New York

Nikolaos Ziropiannis, Jessica Alcorn, Jayne Piepenburg, and John Rupp

We investigate geospatial and socio-demographic attributes that explain differences in community-level policies affecting unconventional gas development (UGD) in New York. We examine local policy decisions (i.e., municipal bans, moratoria, and pre-emptive resolutions supporting development) through ordered probit models and middle-inflated and zero-inflated ordered probits to account for communities without UGD policies and estimate a spatial ordered probit to address spatial correlations between communities' decisions. Our findings suggest that New York communities near Pennsylvania UGD are more likely to support UGD. Communities that are predominantly Democrat or have more citizens who have bachelor's degrees are more likely to adopt policies opposing UGD.

Key Words: local bans and moratoria, New York, ordered probit, unconventional gas development

Within the last decade, the northern Appalachian basin has seen significant development of natural gas from unconventional reservoirs. Activities associated with this production have been collectively termed unconventional gas development (UGD) (Graham, Rupp, and Mitchell 2013). Wang and Krupnick (2013) suggested that this increase in UGD is attributable to several key factors: economically advanced drilling and well-completion technologies,

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favorable geology in that region, a preponderance of private mineral rights that allow landowners to receive substantial financial benefits, an existing infrastructure of natural gas pipelines, and the federal open access policy that governs the use of pipelines.

Studies of UGD have identified many potential economic and environmental benefits and risks associated with shale gas extraction. Labor markets reap substantial economic benefits, although it is not yet clear whether the benefits remain within the boundaries of a county or spill over to neighboring counties (Kinnaman 2011, Weber 2012, Considine, Watson, and Blumsack 2010). Owners of the mineral rights can gain substantially from leasing agreements and royalties paid by shale gas developers (Gopalakrishnan and Klaiber 2014), and state and county governments can benefit via severance taxes assessed on developers. The effect on housing prices is not yet clear. Several studies have reported increases in prices for homes near shale gas wells but decreases in prices of homes that rely on private water wells (Muehlenbachs, Spiller, and Timmins 2012, Gopalakrishnan and Klaiber 2014). Boslett, Guilfoos, and Lang (2015) found that New York's statewide moratorium on UGD was associated with a decline in the value of homes in the shale region. The primary economic risk associated with UGD is similar to the risk associated with conventional fossil fuel extraction—the threat of creating a “boom and bust” economy. Several authors have questioned UGD's ability to provide sustainable incomes and economic development in communities rather than short-lived, fleeting economic gains (Albrecht 1978, Anderson and Theodori 2009, Jacquet and Stedman 2013, Stedman et al. 2012).

The environmental risks associated with UGD are also open to debate. Potential risks include degraded water quality commonly attributed to migration of methane, failures of well integrity that can allow chemicals to leach out, and contamination from waste water. These risk have been the subject of several studies (Osborn et al. 2011, Olmstead et al. 2013, Vengosh et al. 2014). In addition, recent studies have linked UGD to public health risks and to an increase in seismic events in extraction areas (Graham, Rupp, and Mitchell 2013, Hand 2014, Hill 2013, Kim 2013, McKenzie et al. 2014). UGD's net impact on climate change is another point of debate (Miller et al. 2013, Newell and Raimi 2014).

Background on Local-level Unconventional Gas Development Policies

Several federal environmental laws apply to the shale gas industry, but the federal government does not explicitly regulate the industry. Consequently, state and local governments have been at the forefront of regulatory policy design (Richardson et al. 2013), and consideration of the risks and benefits associated with UGD has spawned a variety of state and local policies.

An important question for many states is the extent to which cities and towns can use home-rule to impose local bans and moratoria and/or to restrict UGD through zoning regulations. In California, the state senate's attempt to pass a statewide moratorium on fracking failed to gather enough votes (McGreevy 2014), but a number of counties and municipalities have passed bans (Baker 2014, Schwartz 2014). In Colorado, the cities of Lafayette, Longmont, and Fort Collins banned UGD, but the bans were overturned after suit was brought by the Colorado Oil and Gas Association; Boulder and Broomfield adopted moratoria (Proctor 2014). Recently, Ohio's supreme court ruled that the state's

municipalities cannot use zoning regulations to block drilling activities (Smyth 2015, Knox 2015). In Texas, Denton was the state's first city to ban UGD via a ballot measure in November 2014 (Krauss 2014).

Pennsylvania and New York present an especially clear example of how state UGD policy approaches have differed. Both states fall within the boundaries of the Marcellus and Utica shale regions (see Figure 1), which have already yielded significant supplies of oil and gas. Conventional extraction from the Marcellus has yielded an extraordinary rate of return of 10 percent even with gas prices of less than \$3 per thousand cubic feet (Harpole 2013). The Utica shale lies below the Marcellus and thus involves a greater extraction cost since drilling must be deeper, but it may contain lucrative liquid natural gas. Generally, New York has proceeded with a cautious approach to the UGD policy question while Pennsylvania has allowed a considerable amount of development.

New York established a de facto moratorium on UGD in 2008 by prohibiting the New York Department of Environmental Conservation (NYDEC) from issuing UGD permits until a supplemental generic environmental impact statement (SGEIS) was completed under the State Environmental Quality Review Act. In 2010, the New York state legislature passed a one-year moratorium. Then-governor David Paterson vetoed the measure and instead issued an executive order prohibiting hydraulic fracturing of horizontal wells until July 1, 2011 (Esch 2010). Following that order, NYDEC completed an initial study and presented draft regulations in July 2011 that allowed hydraulic fracturing in 85 percent of New York's Marcellus shale and exempted areas associated with primary aquifers, state and national parks, and watersheds that supply surface drinking water (NYDEC 2011). The draft regulations were met with protests and strong public opposition so Andrew Cuomo's administration suggested

Figure 1. Extent of Utica and Marcellus Shales in New York and Pennsylvania

Source: Compiled by the authors using data from Penn State Marcellus Center for Outreach and Research (2014).

limiting hydraulic fracturing to counties along the Pennsylvania border, also known as the southern tier, with a goal of providing economic development for those counties (Hakim and Confessore 2011, Hakim 2012, Hargreaves 2011). Instead, the moratorium was extended for another year in 2011. In March 2013, The state assembly passed a two-year moratorium to allow more time to evaluate any health risks associated with UGD (Gralla 2013, Wiessner 2011). Finally, in December 2014, the New York Department of Health (2014) issued a public health review that, based on significant ongoing uncertainty regarding the risks, recommended continuing to refuse to allow UGD in New York. In response to the report, Governor Cuomo banned UGD (Kaplan 2014).

Pennsylvania already has extensive UGD, and residents have experienced both the benefits and the costs of the practice. After some negative impacts of UGD were covered in the popular press, the state in 2012 passed Act 13, which introduced a statewide impact fee in which developers pay a fixed amount per well drilled; the amount of the fee is indexed to the price of natural gas. The revenue is used to offset local and statewide impacts of UGD; 40 percent goes to state agencies and 60 percent goes to local governments in communities affected by development. In addition, municipalities that have no UGD wells but are contiguous to a developed area or are within five miles of a municipality that has wells receive a portion of the revenue (Pennsylvania Public Utility Commission 2015). The fee is somewhat unique since most states impose severance taxes that are based on the gross value of the natural gas produced (Graham, Rupp, and Mitchell 2013). Pennsylvania attempted to use Act 13 as evidence that it had pre-empted local governments in regulating UGD and that those governments were not permitted to use local zoning codes to restrict development (Ellis 2012). The state's assertion was challenged in court on the basis of home-rule (Dillon's rule), and in 2013, the state supreme court ruled that local zoning was not pre-empted by Act 13 (Cusick 2013).

Factors Affecting Local Policy Decisions

Several studies have investigated public perceptions of UGD through national and statewide surveys (Kohut et al. 2012, University of Michigan and Muhlenberg College 2012, Davis and Fisk 2014, Boudet et al. 2014) and through interviews and case studies at a local level (Anderson and Theodori 2009, Theodori 2012, 2013, Brasier et al. 2011). From these studies, it is evident that public opinion varies geographically and is influenced by characteristics of communities and individual residents. Therefore, "one size fits all" regulations cannot adequately represent local desires and concerns. In New York, Pennsylvania, Ohio, Colorado, and other states grappling with how to regulate a rapidly evolving technological enterprise, citizens have organized movements for localized control when their desires conflict with state regulatory decisions. These movements are manifested in local policy decisions that impose municipal bans or moratoria, restrictions on UGD based on zoning regulations, and, in the case of New York, pre-emptive resolutions that support UGD. Therefore, while numerous factors and stakeholders are inherently involved in the policymaking process, public opinion and the socio-demographic, political, and community characteristics that determine public opinion can play a significant role in what civic actions are taken and the nature of resulting regulations (Jacquet 2012, Stedman et al. 2012, Theodori 2013, Boudet et al. 2014, Davis and Fisk 2014).

Given the significance of local policy decisions in the debate, it is important for researchers and policymakers to understand the drivers behind a community's position for or against UGD. Few researchers have attempted to answer this question, and our work aims to fill this gap. The question we address relates to the factors and community-level attributes that determine local policy decisions for UGD.

Christopherson, Frickey, and Rightor (2013) were the first to examine this question by gathering data on 298 communities in New York, Pennsylvania, Ohio, and West Virginia that had passed some form of UGD statute or resolution. The local UGD regulations were assigned to one of four categories: (i) bans, (ii) moratoria that allowed communities to study the potential impacts of UGD further, (iii) restrictions on some aspects of UGD, such as zoning codes that limited where the wells could be drilled, and (iv) pre-emptive resolutions declaring community support for UGD. Of the 298 communities, 233 were located in New York. The authors noted that the pre-emptive resolutions were largely a result of efforts by Joint Landowners Coalition of New York (JLCNY), which circulated a draft resolution that could be passed without a public hearing and adopted as a resolution rather than as a statute to a number of local governments. The authors interviewed government officials in New York and Pennsylvania and collected socioeconomic data, such as household incomes and average level of education at the county level, to determine whether they explained differences in the policy responses of the communities. However, since the attributes were measured at a county level, they could not draw decisive conclusions regarding drivers of regulations at a community level.

Arnold and Holahan (2014) conducted a comparative analysis of civic engagement associated with UGD in New York and Pennsylvania that was focused on the five southern tier counties in New York (Broome, Chemung, Chenango, Steuben, and Tioga) and five counties in northeastern Pennsylvania because they have some of the largest natural gas reserves in the country. The authors collected information from local newspapers and minutes from municipal board meetings and public hearings. They found that citizens in New York's southern tier counties were more actively engaged in local deliberations regarding UGD than residents in the neighboring Pennsylvania counties, which they attributed in part to the value placed on home-rule in New York as evident from a ruling in 2014 by the New York court of appeals in favor of local governments' right to use home-rule to restrict UGD (Sullivan 2014). However, the authors also argued that Pennsylvania citizens demonstrated a lesser degree of civic engagement because they believed that the state controlled most UGD decisions. Furthermore, municipalities in Pennsylvania are required to establish a home-rule charter through the state assembly, which inhibits civic engagement.

In an approach similar to ours, Bird, Heintzelman, and Walsh (2014) used a spatial probit model to examine community-level attributes that affect local UGD policies in New York. They examined the presence of clusters of communities that had adopted restrictions on UGD and found that communities with more Democrats than Republicans were relatively likely to impose bans. In addition, wealthier and highly educated communities were also more likely to ban UGD.

Motivation and Research Question

We contribute to the literature on adoption of UGD policies by examining community-level attributes and geospatial factors that influence local opposition

to and support of UGD in New York, where the de facto moratorium motivated communities to adopt local statutes or resolutions as a way of influencing the final state decision, which was to ban UGD statewide in December 2014. Local bans and moratoria also may represent attempts to guard against state-level policies viewed as unfavorable in case the statewide moratorium was lifted. Other than this study and Bird, Heintzelman, and Walsh (2014) discussed earlier, there have been no studies analyzing socioeconomic and geospatial factors that drive local UGD policy decisions in New York. Given New York's UGD ban, we anticipate that the number of local efforts to restrict or ban UGD in other states will increase, in part to signal the communities' views to state governments. It is important, therefore, for policymakers to gain a better understanding of the drivers of such local policies.

Our primary model-specification strategy is an ordered probit with several variations and extensions. We envision that communities in New York can choose from a series of policy options regarding UGD ranging from the most positive (a pre-emptive resolution in support of UGD) to the most negative (an outright ban). Between those extremes, communities could choose to establish no policy, move toward adoption of a statute, or enact a local moratorium. Our research question aims to identify the community-level attributes and geospatial factors that best predict the probability of a locality adopting one of those five policy responses—pre-emptive resolution, no policy, movement for a statute, moratorium, ban. Specifically, we are interested in answering four questions:

- (1) Are New York communities near the state border with Pennsylvania more likely to support UGD?
- (2) Are New York communities that have experience with the fossil fuel industry more likely to support UGD?
- (3) How do various socioeconomic community characteristics—median incomes, rates of unemployment, population density, level of education, predominant political affiliation, and share of citizens who own their homes—affect local policies toward UGD?
- (4) Does proximity to valued environmental resources—watersheds that supply surface drinking water, primary aquifers, and state parks—increase the probability of community bans and moratoria for UGD?

Data

We compile data on New York communities and their local UGD policy decisions using information from FracTracker and JLCNY. Table 1 shows the number of communities in New York that have adopted each UGD policy and Table 2 presents the number of communities within each shale region that have UGD policies.¹ Note that we use the term “communities” to include all villages, cities, and towns in the state.

¹ We thank Karen Edelstein of FracTracker for her help in obtaining and understanding the data on local regulations in New York. We also thank Steve Hertz from JLCNY for his help in obtaining information on pre-emptive resolutions.

Table 1. Frequency Distribution of Local Statutes and Resolutions

Type of Community Statute or Resolution	Number of Observations	Percent Frequency
Pre-emptive resolution supporting development	40	2.6
No policy in place	1,242	81
Movement for a ban or moratorium	73	4.8
Moratorium	101	6.6
Ban	77	5.0

Notes: Total observations are 1,533. The types of policies are ranked from most supportive (pre-emptive resolution) to least supportive (ban). Sources: FracTracker Alliance (2014), Joint Landowners Coalition of New York Inc. (2012).

Table 2. Number of Unconventional Gas Development Policies by Shale

	Number of Communities with a Policy	Total Number of Communities	Percent Frequency
Communities overlying the Marcellus shale	215	637	34
Communities overlying the Utica but not the Marcellus	62	433	14
Communities outside of the Utica shale	14	463	3
Total	291	1,533	

Source: FracTracker Alliance (2014), Joint Landowners Coalition of New York Inc. (2012).

Dependent Variable

We use the five policy categories—pre-emptive resolutions, no UGD policy, movements toward statutes, moratoriums, and bans—as dependent variables in our models. As noted in Christopherson, Frickey, and Rightor (2013) and discussed by FracTracker Alliance (2014), pre-emptive resolutions in support of UGD do not require a public hearing and vote. They are simply a statement from the town board that the community does not intend to pass a statute that would restrict or prohibit UGD. Communities identified as moving toward a ban or moratorium have signaled that they are considering restricting or prohibiting UGD, in some cases through zoning regulations (FracTracker Alliance 2014). In fact, we identified fourteen communities in the data set that had both a pre-emptive resolution and a movement toward restrictions. Bans and moratoria involve local statutes that are subject to community input via town hall meetings and a subsequent vote of the governing body. Given these differences, we take a conservative approach when specifying the dependent variable and use seven iterations of the model, which are presented in Table 3 and vary in how different types of communities and policy actions are treated. The variable *LocalPolicies3* includes all five policy categories and drops the fourteen communities that have both a pre-emptive resolution and a movement for a statute. *LocalPolicies1* assigns those fourteen communities to the pre-emptive

Table 3. Descriptive Statistics

Variable	Mean	Std. Dev.	Label
Dependent Variables			
<i>LocalPolicies1</i> Ordinal, N = 1,547	2.708	0.840	0 = Pre-emptive resolution 1 = No policy 2 = Movement for ban or moratorium 3 = Moratorium 4 = Ban Fourteen communities that have both pre-emptive resolutions and movements for a ban or moratorium are classified as pre-emptive resolutions.
<i>LocalPolicies2</i> Ordinal, N = 1,547	2.690	0.834	0 = Pre-emptive resolution 1 = No policy 2 = Movement for ban or moratorium 3 = Moratorium 4 = Ban Fourteen communities with pre-emptive resolutions and movements for a ban or moratorium are classified as movements.
<i>LocalPolicies3</i> Ordinal, N = 1,533	2.696	0.835	0 = Pre-emptive resolution 1 = No policy 2 = Movement for ban or moratorium 3 = Moratorium 4 = Ban Fourteen communities with pre-emptive resolutions and movements for a ban or moratorium are dropped.
<i>LocalPolicies4</i> Ordinal, N = 1,420	0.180	0.506	0 = No policy 1 = Moratorium 2 = Ban Pre-emptive resolutions and movements for a ban or moratorium are dropped.
<i>LocalPolicies5</i> Binary, N = 1,420	0.125	0.331	0 = No policy 1 = Moratorium or ban Pre-emptive resolutions and movements for a ban or moratorium are dropped.
<i>LocalPolicies6</i> Ordinal, N = 1,547	0.165	0.487	0 = No policy, a pre-emptive resolution, or a movement for a ban or moratorium 1 = Moratorium 2 = Ban
<i>LocalPolicies7</i> Binary, N = 1,547	0.115	0.319	0 = No policy, a pre-emptive resolution, or a movement for a ban or moratorium 1 = Moratorium or ban
Independent Variables			
Productivity zone Binary, N = 1,547	0.133	0.340	1 = Community located over productivity zone 0 = Otherwise
20-mile buffer zone Binary, N = 1,547	0.089	0.285	1 = Community located within 20 miles of closest UGD well in Pennsylvania; 0 = Otherwise
15-mile buffer zone Binary, N = 1,547	0.061	0.240	1 = Community located within 15 miles of closest UGD well in Pennsylvania; 0 = Otherwise

Continued on following page

Table 3 (continued)

Variable	Mean	Std. Dev.	Label
10-mile buffer zone Binary, N = 1,547	0.034	0.182	1 = Community located within 10 miles of closest UGD well in Pennsylvania; 0 = Otherwise
5-mile buffer zone Binary, N = 1,547	0.016	0.126	1 = Community located within 5 miles of closest UGD well in Pennsylvania; 0 = Otherwise
City dummy Binary, N = 1,547	0.040	0.196	1 = Community is a city; 0 = Otherwise
Town dummy Binary, N = 1,547	0.602	0.490	1 = Community is a town; 0 = Otherwise
Village dummy Binary, N = 1,547	0.357	0.479	1 = Community is a village; 0 = Otherwise
Aquifer Binary, N = 1,547	0.115	0.319	1 = Community located within primary aquifer; 0 = Otherwise
Watershed Binary, N = 1,547	0.131	0.338	1 = Community located within surface drinking-water watershed; 0 = Otherwise
Marcellus dummy Binary, N = 1,547	0.421	0.494	1 = Community over Marcellus shale 0 = Otherwise
Utica dummy Binary, N = 1,547	0.701	0.458	1 = Community over Utica shale 0 = Otherwise
State park Continuous, N = 1,547	0.727	4.582	Percent of community land within a state park
Population density Continuous, N = 1,547	1,154.2	2,322.7	Population density (per square mile)
Pres. Dem/Rep ratio Continuous, N = 1,546	1.023	0.593	Ratio of Democrat to Republican votes in 2012 presidential election
NYSBE Dem/Rep ratio Continuous, N = 992	0.865	0.835	Ratio of Democrats to Republicans registered as voters based on information from NYSBE
Median family income Continuous, N = 1,546	72.181	33.027	Median family income (thousand dollars)
Unemployment rate Continuous, N = 1,547	4.968	2.245	Unemployment rate (percent)
Education Continuous, N = 1,547	26.193	15.822	Percent of community residents who have bachelor's degrees
Manufacturing Continuous, N = 1,546	10.791	6.044	Percent of community residents employed in manufacturing sector
Homeowners Continuous, N = 1,547	74.646	13.664	Percent of community residents who own home
Well count Continuous, N = 1,547	0.767	8.594	Number of active conventional oil and gas wells in the community

resolution category and *LocalPolicies2* assigns them to the movement category. *LocalPolicies4* and *LocalPolicies6* include only three categories—no policy, moratorium, and ban. For *LocalPolicies4*, we drop communities that had pre-emptive resolutions or movements from our sample; in *LocalPolicies6*, those communities are assigned to the no-policy category. A similar distinction is made in *LocalPolicies5* and *LocalPolicies7*, which include only two categories: (i) no policy and (ii) either a ban or a moratorium. In *LocalPolicies5*, we drop pre-emptive resolutions and movements; in *LocalPolicies7*, we assign them to the no-policy category.

Many of the communities in the data set (81 percent) had no UGD policy in place (see Table 1), which may be related to several factors:

- (1) The community has no potential for UGD because it is located outside the Utica and Marcellus shale boundaries and shale gas extraction is impossible.
- (2) The community has insignificant UGD potential because it is located close to the thin shallow boundaries of the shales. Though the resource can be developed, it would not be substantial enough to warrant local regulation.
- (3) The community has substantial potential for UGD but public opinion regarding its development is divided. There is no consensus that can lead to a resolution or statute.
- (4) Members of the community are uninterested and/or uninformed about issues associated with UGD.

It is informative to consider whether existence of a policy is related to the community's UGD potential. And since the Marcellus has provided a greater rate of return than the Utica, communities within the boundaries of the Marcellus potentially have the most to gain from UGD. As shown in Table 2, most of the local policies have been enacted by communities that are located over the Marcellus.

The distributions reported in Table 2 also capture something unexpected—fourteen communities that are located outside of the boundaries of both shales and have no potential for shale gas development have enacted some form of UGD policy. For example, Livingston in Columbia County banned UGD and New Bremen in Lewis County passed a pre-emptive resolution. We attribute such cases to two factors: (i) both citizens and local officials may not be fully aware of their community's potential for UGD (or lack thereof) and (ii) a community could instigate a local policy to express solidarity with other communities in the state.

Independent Variables

Table 3 presents descriptive statistics for the explanatory variables in the models. Our sample is comprised of 1,547 communities in New York identified through data from the U.S. census.² We plotted the data in ArcMap using latitudes and longitudes supplied by 2013 U.S. census gazetteer files.

² We exclude census-designated places because, although they could be incorporated places, they are not considered relevant in this study because they lack municipal governance structures. We also exclude the five New York boroughs (Bronx, Brooklyn, Manhattan, Queens, and Staten

Figure 2. Active Conventional Oil and Gas Wells in New York and Active Unconventional Gas Wells in Pennsylvania in 2013

Source: Compiled by the authors using data from Empire State Oil and Gas Information System (2014) and New York State GIS Clearinghouse (2014).

Since we want to test whether proximity to UGD in Pennsylvania influences policy decisions in New York communities, our primary spatial metric of interest is the distance from the centroid of each New York community to the closest active unconventional gas well in Pennsylvania.³ We model distance through a series of buffer zones extending 5, 10, 15, and 20 miles from active unconventional wells in Pennsylvania. Each buffer-zone variable assigns a value of 1 to each New York community that falls within the buffer distance and 0 to the other communities.⁴ We obtained the locations of active unconventional gas wells in the Marcellus shale from Pennsylvania's Bureau of Topographic and Geologic Survey, which identified the wells as part of its UGD monitoring efforts (Carter 2014).⁵

To assess the New York communities' familiarity with oil and gas extraction, we gathered data on the locations of active conventional oil and gas wells nearby.⁶ To assess each community's UGD potential, we used geological information to define potentially productive regions in New York (see Figure 2)

Island) since those localities are demographically different from the rest of the state. Finally, we exclude nine Indian reservations.

³ To ensure accurate measurements, we projected the geographic coordinates onto the U.S. 1983 Albers equal-area conic projection, which is currently the most commonly used projection.

⁴ We assigned 1 to localities in which any portion of their area intersects the buffer rather than requiring the centroid or a particular percentage of the area to fall within the buffer.

⁵ For the purposes of this analysis, a producing well is defined as a well that has been active within the preceding five years.

⁶ This data came from the Empire State Oil and Gas Information System (<http://esogis.nysm.nysed.gov>).

and created a binary variable in which communities located in productive regions were assigned a value of 1 and all other communities were assigned a value of 0. The regions were defined based on the depth, thickness, total organic content, and thermal maturity of the reservoirs in the Utica and Marcellus shales and productivity trends for UGD in Pennsylvania (U.S. Geological Survey 2012a, 2012b, Wrighstone 2009, Penn State Marcellus Center for Outreach and Research 2014, Nyahay et al. 2007).

We control for three geospatial attributes: percentage of the land area of a community that is occupied by state parks, whether a community is located within a watershed that supplies surface drinking water (a binary variable), and whether a community is located over a primary aquifer (a binary variable).⁷ We use two dummy variables to identify communities located over the Marcellus and Utica shales, which overlap (see Figure 1). The spatial metrics are matched with demographic control variables of interest using data from the U.S. Census Bureau's 2013 American Community Survey (ACS), a mandatory annual statistical survey of a small percentage of the U.S. population that assigns a unique identifier to each municipality in the census data⁸ (U.S. Census Bureau 2014).

The socio-demographic attributes in our models are (i) communities' unemployment rates, population densities, and median household incomes and (ii) the proportions of the communities' populations that are employed in the manufacturing sector, have attained an undergraduate degree, and own their homes. The main political variable of interest is the ratio of Democrats to Republicans in the community. That information comes from votes cast in the 2012 presidential election in each community and voter registrations, both provided by the New York State Board of Elections (NYSBE). Presidential election results typically are reported at a county or district level. Our data come from Naigles (2014), which collected municipal-level data for New York by contacting the individual counties. It is important to note that Naigles (2014) could not obtain village election results. Therefore, we assume that the ratios of Democrats to Republicans in the villages are the same as the ratios in the towns to which the villages belong when the villages are entirely included within the towns' boundaries. When villages traverse a town boundary, we weight the ratio using the approximate area of the village contained within the two towns. The same caveat applies to data from NYSBE since village-level data were not available. We therefore create two variables, one using data on votes cast in the presidential election, which includes villages, and the other using NYSBE data, which does not include villages.

Tables A.1 and A.2 in the appendix (available from the authors) present simple correlation coefficients and variance inflation factors (VIFs) for the independent variables. Except for a high correlation coefficient between education level and median family income (which is expected), none of the explanatory variables raise any concern about collinearity. In the case of education and income, the VIF values are well below 10.0, the threshold often used in the literature (Chatterjee and Hadi 2012).

⁷ The shape files were accessed via the New York State GIS Clearinghouse (<https://gis.ny.gov/gisdata>).

⁸ We manually corrected any inconsistencies found between the name of the location and the county listed in the FracTracker and ACS data.

Methods

We model local-level policy decisions in New York using three approaches. First, we examine factors that drive local policy decisions using a series of ordered probit models. Then, because the no-policy dependent variable covers 81 percent of our observations, we have reason to believe that this inflated category could bias our results, and we employ middle-inflated and zero-inflated ordered probit models (Bagozzi and Mukherjee 2012, Bagozzi et al. 2015, Harris and Zhao 2007). The third approach explores potential spatial correlations between communities using a spatial ordered probit model. We thus examine whether a UGD policy adopted in one community affects the likelihood of adoption of similar policies in neighboring communities. In each approach, we use the socio-demographic and geospatial community-level attributes as explanatory variables. The underlying notion is that the characteristics can influence people's attitudes toward UGD and that those attitudes can stimulate civic engagement, which may lead to adoption of policies. By controlling for these characteristics, we aim to explain how differences among communities affect adoption of each type of policy.

We test whether New York communities located near unconventional gas wells in Pennsylvania are more likely than other communities to enact some form of local UGD policy. We model proximity by constructing four binary variables that capture communities that are within four buffer zones extending 5, 10, 15, and 20 miles from the closest UGD well in bordering counties of Pennsylvania. Residents of New York communities located relatively close to a well in Pennsylvania could act to support UGD with a pre-emptive resolution because of a desire to share in positive economic effects witnessed in Pennsylvania. Or they might have observed negative externalities (e.g., health effects from local pollutants, adverse water quality, increased traffic) and little or no economic benefit (e.g., from lease and royalty payments and severance taxes paid by the industry) and consequently choose to adopt policies that restrict or prohibit UGD.

We also expect that local policies will be influenced by familiarity of citizens with the oil and gas industry. New York has a long history of conventional extraction of fossil fuels, particularly in the western and southern parts of the state (see Figure 2). We model this familiarity by recording the number of conventional oil and gas wells within a community and the proportion of the community's population employed in the manufacturing sector. People who are familiar with conventional oil and gas extraction or work in manufacturing could be relatively supportive of UGD. On the other hand, opposition to conventional extraction is likely to carry over to UGD.

We account for geospatial attributes as variables representing the communities' proximity to watersheds that supply drinking water and to state parks and being located over a primary aquifer. We expect that citizens who live close to those environmental resources may be particularly concerned about conservation and thus likely to oppose UGD, which could translate into policies restricting the practice.

Next, we consider each community's socio-demographic attributes: median family income, education level, unemployment rate, degree of home ownership, population density, and predominant political affiliation.

We expect that a high unemployment rate will have a positive impact on enacting of policies that support UGD; community members will want to

benefit from the employment opportunities that a booming shale gas industry offers. The expectation for the coefficient on median family income is less clear. On the one hand, we hypothesize that relatively poor communities will support UGD because of the economic opportunities it can provide. Using that same rationale of a negative relationship between median income and support for UGD, relatively wealthy communities might oppose UGD because of nuisances associated with it. At the same time, though, wealthier communities might be just as likely to support the practice given that higher income levels offer more opportunities to mitigate potential negative impacts.

Our expectations of the effect of the coefficient on home ownership are mixed. The results of prior studies suggest that UGD's effect on housing prices depends not only on proximity but also on the presence of drinking water wells on the property. We could not obtain data on private wells for drinking water so could not directly test hypotheses about the effect of UGD on the price of homes that rely on private water supplies. However, we expect that the potential for revenue from leases and royalties could induce communities that have a large proportion of homeowners to support UGD.

Affiliation with the Democratic Party is likely to be associated with opposition to UGD given the party's traditional pro-environmental stance. And based on the results of Bird, Heintzelman, and Walsh (2014), we anticipate that more advanced education will negatively affect support for UGD.

The coefficient on population density could run in both directions. A low population density would likely facilitate UGD since the industry would not have to negotiate with numerous landowners to secure access to mineral rights. A high population density would likely have a positive impact on support for UGD. Jacquet (2014) argued that rural areas that are densely populated can alleviate some of the need for increased housing and services generated by the influx of UGD workers. Therefore, gas shale developers might be attracted to such communities.

The Ordered Probit Model

We assume that the latent variable y_i^* captures community i 's attitude toward UGD (as manifested through the presence or absence of resolutions and statutes) where $-\infty < y_i^* < +\infty$. If we let $\mathbf{x}_i$ be a vector of community-level geospatial and socio-demographic attributes that affect UGD policies and assume that y_i^* depends linearly on $\mathbf{x}_i$, we can represent the ordered probit model as

$$(1) \quad \begin{aligned} y_i^* &= \mathbf{x}_i' \beta + \varepsilon_i \quad i = 1, \dots, n \\ \varepsilon_i &\sim N(0,1). \end{aligned}$$

In the model, β is a vector of parameters to be estimated. The observed dependent variable y_i , which captures the five UGD policy categories, is related to the latent variable y_i^* :

$$(2) \quad \begin{aligned} y &= 0 \text{ if } -\infty < y^* < \kappa_1 \\ y &= 1 \text{ if } \kappa_1 < y^* < \kappa_2 \\ y &= 2 \text{ if } \kappa_2 < y^* < \kappa_3 \\ y &= 3 \text{ if } \kappa_3 < y^* < \kappa_4 \\ y &= 4 \text{ if } \kappa_4 < y^* < \infty \end{aligned}$$

where $\kappa_j, j = 1, \dots, 4$ represents the cut points (the threshold parameters). Our model does not include an intercept because all of the cut points are parameters to be estimated (Daykin and Moffatt 2002). The expressions in equation 2 translate into the following probabilities for the ordered probit (OP) model:

$$(3) \quad \Pr(y_i) = \left\{ \begin{array}{lcl} \Pr(y_i = 0 | \mathbf{x}_i) & = & \Phi(\kappa_1 - \mathbf{x}_i' \beta) \\ \Pr(y_i = 1 | \mathbf{x}_i) & = & \Phi(\kappa_2 - \mathbf{x}_i' \beta) - \Phi(\kappa_1 - \mathbf{x}_i' \beta) \\ \Pr(y_i = 2 | \mathbf{x}_i) & = & \Phi(\kappa_3 - \mathbf{x}_i' \beta) - \Phi(\kappa_2 - \mathbf{x}_i' \beta) \\ \Pr(y_i = 3 | \mathbf{x}_i) & = & \Phi(\kappa_4 - \mathbf{x}_i' \beta) - \Phi(\kappa_3 - \mathbf{x}_i' \beta) \\ \Pr(y_i = 4 | \mathbf{x}_i) & = & 1 - [\Phi(\kappa_4 - \mathbf{x}_i' \beta)] \end{array} \right\}.$$

Our main specification is an OP model in which the dependent variable is comprised of the five policy categories: pre-emptive resolutions, no UGD policy, movements toward statutes, moratoriums, and bans. Communities that have not established a UGD policy, are moving toward a statute, or have enacted a moratorium signal a desire for more time to examine the impacts of UGD before taking a stance. We conduct additional OP and probit model runs using the specifications of the dependent variable presented in Table 3.

Middle-inflated and Zero-inflated Ordered Probit Models

As shown in Table 1, 81 percent of the communities represented in our data set have not enacted a UGD policy. The communities may have no UGD potential, insignificant UGD potential, a lack of consensus about such development, and/or little or no interest in the UGD debate. It is therefore plausible that our observations in the no-policy category arise from multiple regimes. Disregarding heterogeneity could introduce bias into our results so we need a distinct methodological approach.

Harris and Zhao (2007) were the first to propose a zero-inflated ordered probit model (ZiOP) as a solution to problems like ours. Their application consisted of a survey in which respondents were asked how often they used tobacco products. Individuals who identified themselves as nonsmokers (stated that they did not use tobacco products) could include people who had never smoked, people who had recently quit smoking, and smokers who currently were not smoking, and the large number of respondents who fell into the nonsmoker category motivated their use of a ZiOP model. Bagozzi and Mukherjee (2012) extended Harris and Zhao's (2007) methodology to account for an inflated middle category in a study of respondents' attitudes about whether their country benefitted from membership in the European Union (EU). A majority of the respondents chose the middle "neither good nor bad" category. The authors argued that two types of respondents selected the middle category: uninformed individuals who chose the middle category to avoid losing face and informed respondents who genuinely believed that EU membership was neither good nor bad. This distinction motivated their use of a first-stage inflation equation and an augmented ordered probit equation in the outcome stage.

Following Bagozzi and Mukherjee (2012), we identify two regimes based on whether a community adopts a resolution or statute. We let s_i be a binary variable that characterizes the split between regime 0 (no UGD policy) and regime 1 (any kind of UGD policy) where s_i is an observable manifestation of a latent variable, s_i^* , such that $s_i = 1$ for $s_i^* > 0$ and $s_i = 0$ for $s_i^* \leq 0$. The latent

variable captures the probability of a community being in regime 1 and is modeled by

$$(4) \quad s_i^* = \mathbf{z}_i' \gamma + u_i,$$

which Bagozzi and Mukherjee (2012) labeled as a split probit “inflation” equation. In this model, γ is a vector of parameters, $\mathbf{z}_i$ is a vector of covariates, and $u_i \sim N(0,1)$ is an error term. The augmented ordered-probit outcome equation for the middle-inflated ordered probit (MiOP) model, which is a variant of Bagozzi and Mukherjee (2012), is specified as

$$(5) \quad \Pr(y_i) = \left\{ \begin{array}{l} \Pr(y_i = 0 | \mathbf{x}_i, \mathbf{z}_i) = \Phi(\mathbf{z}_i' \gamma) \Phi(\mathbf{x}_i' \beta) \\ \Pr(y_i = 1 | \mathbf{x}_i, \mathbf{z}_i) = [1 - \Phi(\mathbf{z}_i' \gamma)] + \Phi(\mathbf{z}_i' \gamma) [\Phi(\kappa_1 - \mathbf{x}_i' \beta) - \Phi(-\mathbf{x}_i' \beta)] \\ \Pr(y_i = 2 | \mathbf{x}_i, \mathbf{z}_i) = \Phi(\mathbf{z}_i' \gamma) [\Phi(\kappa_2 - \mathbf{x}_i' \beta) - \Phi(\kappa_1 - \mathbf{x}_i' \beta)] \\ \Pr(y_i = 3 | \mathbf{x}_i, \mathbf{z}_i) = \Phi(\mathbf{z}_i' \gamma) [\Phi(\kappa_3 - \mathbf{x}_i' \beta) - \Phi(\kappa_2 - \mathbf{x}_i' \beta)] \\ \Pr(y_i = 4 | \mathbf{x}_i, \mathbf{z}_i) = \Phi(\mathbf{z}_i' \gamma) [\Phi(\kappa_3 - \mathbf{x}_i' \beta)] \end{array} \right\}$$

where Φ is the cumulative distribution function of the standard normal.

The second-stage OP illustrated in equation 1 models the probability of a community being included in one of the five policy action categories. The MiOP model specified in equation 5 assumes that the error terms in equations 1 and 4 are independent, which gives rise to Bagozzi and Mukherjee’s (2012) MiOP conditional model in which the error terms u_i and ε_i are correlated and follow a bivariate distribution with a correlation coefficient of ρ_{eu} . In this case, the augmented OP outcome equation is

$$\Pr(y_i) = \left\{ \begin{array}{l} \Pr(y_i=0|\mathbf{x}_i, \mathbf{z}_i) = \Phi_2(\mathbf{z}_i' \gamma, -\mathbf{x}_i' \beta; -\rho_{eu}) \\ \Pr(y_i=1|\mathbf{x}_i, \mathbf{z}_i) = [1 - \Phi(\mathbf{z}_i' \gamma)] + \Phi_2(-\mathbf{z}_i' \gamma, \kappa_1 - \mathbf{x}_i' \beta; -\rho_{eu}) - \Phi_2(-\mathbf{z}_i' \gamma, -\mathbf{x}_i' \beta; -\rho_{eu}) \\ \Pr(y_i=2|\mathbf{x}_i, \mathbf{z}_i) = \Phi_2(-\mathbf{z}_i' \gamma, \kappa_2 - \mathbf{x}_i' \beta; -\rho_{eu}) - \Phi_2(-\mathbf{z}_i' \gamma, \kappa_1 - \mathbf{x}_i' \beta; -\rho_{eu}) \\ \Pr(y_i=3|\mathbf{x}_i, \mathbf{z}_i) = \Phi_2(-\mathbf{z}_i' \gamma, \kappa_3 - \mathbf{x}_i' \beta; -\rho_{eu}) - \Phi_2(-\mathbf{z}_i' \gamma, \kappa_2 - \mathbf{x}_i' \beta; -\rho_{eu}) \\ \Pr(y_i=4|\mathbf{x}_i, \mathbf{z}_i) = \Phi_2(\mathbf{z}_i' \gamma, \mathbf{x}_i' \beta - \kappa_3; -\rho_{eu}) \end{array} \right\}$$

where Φ_2 is the cumulative distribution of the bivariate normal. This augmented OP equation accounts for cases in which the dependent variable involves the five policy action categories. We also run a ZiOP model in which the augmented OP equation uses a dependent variable with three categories (*LocalPolicies4* and *LocalPolicies6*).

Spatial Ordered Probit Model

In addition to the OP, ZiOP, and MiOP models, we incorporate potential spatial dependency within the policy-adoption decision using a Bayesian spatial OP model proposed by Wilhelm and de Matos (2013). Like other political events, policy adoption, by its very nature, involves shared actors, political and

cultural institutions, and news sources (Berry and Berry 1992, Beck, Gleditsch, and Beardsley 2006, Franzese and Hays 2007, Darmofal 2008). Modeling of the spatial relationships is essential to prevent biased and inconsistent parameter estimates. While accounting for spatial autocorrelation has been a common concern in many studies that involved geographic aspects, the ability to extend the traditional linear spatial autoregressive model to limited dependent variables, particularly ordered categorical variables, has been limited (Wang and Kockelman 2009). Methodological progress in modeling nonlinear relationships has occurred only in the last several years (Bukonya, Gebremedhin, and Schaeffer 2003, Wilhelm and de Matos 2013).

The basic spatial autocorrelation model can be represented as

$$(6) \quad y = \rho \mathbf{W}_z + \mathbf{X}\boldsymbol{\beta} + \varepsilon, \quad \varepsilon \sim N(0, \sigma_\varepsilon^2 I_n)$$

where $\mathbf{X}$ is a matrix of covariates with dimensions $(n \times k)$, $\boldsymbol{\beta}$ is a vector of coefficients for each variable of interest, $\mathbf{W}_z$ is a spatial weight matrix specifying the observations considered to be neighboring, and ρ is a coefficient representing the degree of spatial dependence. The spatial weight matrix can be specified in a variety of ways; however, in the absence of a theoretical rationale for more complicated spatial relationships, we simply chose all observations that share a border since that is the most commonly used strategy. Specifically, the spatial weight matrix, $\mathbf{W}_z$, is row-standardized (i.e., the weight is determined by dividing 1 by the number of communities). Therefore, communities with six observations instead of ten do not receive less weight in the model because the weights for each row of the matrix always sum to 1. For villages completely contained within the boundaries of a town, we specified the town as the sole neighbor of the village. Selection of the spatial weight assignment mechanism is not simply a modeling-specification decision; it is a substantive choice because it represents the expected relationships between the observations. Thus, it is important to recognize that, while we adopt a relatively straightforward, simplistic approach by choosing adjacent localities as neighbors, more complicated spatial dynamics could exist. Other potential spatial weight strategies include weighting communities based on the length of the shared border, consideration of second-order neighbors (i.e., all communities that border the neighbors immediately adjoining), and assigning weights to communities based on similar political orientations. However, without a greater understanding of how public policy adoption and public opinion surrounding the activity diffuse (i.e., the uncertain geographic context problem discussed in Kwan (2012)), we have few options other than to rely on existing local-level census designations.

In adapting the model for estimation in the Bayesian framework, we seek to sample from a posterior distribution of the model parameters, $p(y, \boldsymbol{\beta}, \rho | z)$, given data z and prior distributions for each parameter. The conditional density $p(y, \boldsymbol{\beta}, \rho | z)$ would be a truncated multinormal distribution:

$$y \sim N[(I_n - \rho \mathbf{W})^{-1} \mathbf{X}\boldsymbol{\beta} [(I_n - \rho \mathbf{W})' (I_n - \rho \mathbf{W})^{-1}]^{-1}].$$

As in the nonspatial OP model, the dependent variable in this model can be conceptualized as realization of an underlying continuous latent variable with a vector of threshold cut points. For identification purposes, σ_ε^2 is set to 1 and the first threshold, κ_1 , is set to 0.

Results

We report results for the three groups of models: OP models using different specifications of the dependent variable, two-step MiOP and ZiOP models to account for the high number of no-policy observations, and a spatial OP model to account for potential spatial autocorrelation between communities.

Table 4 presents the results of the OP models that use *LocalPolicies3* as the dependent variable and four specifications of the buffer zone variable (5, 10, 15, and 20 miles). Table 5 reports marginal effects for the OP model that uses a 20-mile buffer zone, which has the best Bayesian information criterion values of the four specifications.

As a robustness check, we ran additional probit and OP models using other specifications for the dependent variable. We report results for the 20-mile buffer zone and Democrat/Republican ratio from election data in Table 6. Results for the other specifications—buffer zones of 5, 10, and 15 miles, the Democrat/Republican ratio based on NYSBE data,⁹ and OP specifications restricted to communities within the Utica and Marcellus shales—are available in part B of the appendix.

Table 7 presents the results of the MiOP and ZiOP models. For each class of model, we also run specifications that allow for correlation between errors of the inflation equation and errors of the augmented OP equation, labeled as MiOP(C) and ZiOP(C). The dependent variables in the augmented OP equation are *LocalPolicies3*, *LocalPolicies4*, and *LocalPolicies6*. In each model, the dependent variable in the inflation equation takes a value of 0 if no policy is implemented and 1 if the communities have any type of policy in place.

The results of the Bayesian spatial OP using *LocalPolicies1* and *LocalPolicies2* as dependent variables are presented in Table 8. We do not use *LocalPolicies3* because dropping the fourteen communities that have both pre-emptive resolutions and movements for a statute would make specification of the spatial weight matrix cumbersome; it is impossible to have observations with no spatial neighbors.¹⁰ These results are obtained by Markov Chain Monte Carlo sampling using spatial probit packages in R with 30,000 iterations and a burn-in¹¹ of the first 5,000 iterations.

The trace plots, which show the posterior mean value at each iteration, and the autocorrelation plots, which typically have a relatively high bar at the first lag followed by almost no autocorrelation for further lags when well-behaved, do not show signs of lack of convergence.¹² Given that significance levels are not reported in the traditional Bayesian framework and in keeping with prior studies, we report posterior means, posterior standard deviations, and 95-percent highest posterior density (HPD) regions (also referred to as credible intervals (Box and Tiao 1992)). The primary difference between a Bayesian credible interval and a frequentist confidence interval is the way in which parameter estimates are discussed. In the Bayesian framework, the credible interval represents values between which the random parameter coefficient lies, based on the data, with a certain probability. For purposes of

⁹ Results for these models are available from the authors upon request.

¹⁰ Additional spatial OP models are presented in the appendix.

¹¹ Burn-in is a common practice in Bayesian analysis in which a set of first iterations is discarded to minimize the impact of the initial values on the posterior distribution.

¹² We do not present more extensive diagnostics (i.e., Geweke diagnostics) because the software at that time did not offer the ability to run multiple chains.

Table 4. Results of the Ordered Probit Model

Variable <i>Dependent variable: LocalPolicies3</i>	Model 1 20-mile Buffer	Model 1 15-mile Buffer	Model 3 10-mile Buffer	Model 4 5-mile Buffer
Productivity zone	-0.106 (0.119)	-0.133 (0.121)	-0.283** (0.119)	-0.302*** (0.117)
Buffer zone	-1.202*** (0.160)	-1.104*** (0.186)	-0.573*** (0.218)	-0.882*** (0.292)
Aquifer	-0.112 (0.118)	-0.105 (0.120)	-0.233** (0.119)	-0.255** (0.116)
Watershed	0.162 (0.109)	0.211** (0.108)	0.244** (0.107)	0.251** (0.107)
State park	0.000648 (0.00845)	0.00155 (0.00836)	0.000300 (0.00831)	3.47e-05 (0.00828)
Population density	-6.80e-06 (2.15e-05)	-7.07e-06 (2.13e-05)	-7.15e-06 (2.09e-05)	-7.10e-06 (2.09e-05)
Democrat/Republican ratio (pres.)	0.184** (0.0740)	0.196*** (0.0734)	0.216*** (0.0727)	0.223*** (0.0726)
Town dummy	0.560*** (0.105)	0.540*** (0.104)	0.525*** (0.103)	0.525*** (0.103)
City dummy	0.894*** (0.212)	0.876*** (0.211)	0.806*** (0.209)	0.791*** (0.209)
Median family income	-0.00832*** (0.00254)	-0.00751*** (0.00251)	-0.00756*** (0.00248)	-0.00767*** (0.00248)
Unemployment rate	-0.0271 (0.0178)	-0.0277 (0.0177)	-0.0250 (0.0175)	-0.0241 (0.0175)
Education	0.0278*** (0.00485)	0.0262*** (0.00482)	0.0267*** (0.00478)	0.0269*** (0.00478)
Manufacturing	-0.00100 (0.00714)	-0.00117 (0.00709)	-0.00241 (0.00704)	-0.00252 (0.00704)
Homeowners	0.00411 (0.00403)	0.00375 (0.00400)	0.00399 (0.00395)	0.00477 (0.00396)
Well count	-0.00874** (0.00377)	-0.0101*** (0.00363)	-0.0131*** (0.00367)	-0.0139*** (0.00364)
Marcellus dummy	0.424*** (0.0967)	0.358*** (0.0956)	0.318*** (0.0947)	0.311*** (0.0946)
Utica dummy	0.711*** (0.118)	0.706*** (0.116)	0.715*** (0.114)	0.723*** (0.114)
κ_1	-0.866** (0.347)	-0.829** (0.343)	-0.744** (0.339)	-0.680** (0.339)
κ_2	2.573*** (0.351)	2.547*** (0.348)	2.563*** (0.344)	2.634*** (0.345)
κ_3	2.839*** (0.352)	2.811*** (0.349)	2.823*** (0.346)	2.894*** (0.347)
κ_4	3.405*** (0.357)	3.373*** (0.354)	3.378*** (0.350)	3.449*** (0.352)
Log-likelihood	-983.55	-995.09	-1,009.75	-1,008.67
Pseudo R-square	0.13	0.12	0.11	0.11
Bayesian Info. Criterion	2,121.12	2,144.18	2,173.50	2,171.35
Observations	1,531	1,531	1,531	1,531

Notes: The dependent variable used in all models is *LocalPolicies3*, which is illustrated in Table 3. Standard errors are shown in parentheses. *** p < 0.01, ** p < 0.05, and * p < 0.1.

interpretation, the primary aspect of interest for HPD regions is whether 0 falls within the interval. Many of the coefficients in our OP model are relatively small. Furthermore, the spatial OP models include a spatial coefficient, ρ , that is quite large. Therefore, it is not surprising that the results of the Bayesian spatial OP models show that the intervals for many of the variables contain 0, including some cases in which the variables are significant according to the p-value in the

Table 5. Marginal Effects for the OP Model and a Twenty-mile Buffer

Variable	Y = 0	Y = 1	Y = 2	Y = 3	Y = 4
Productivity zone	0.003 (0.88)	0.018 (0.89)	-0.006 (0.88)	-0.009 (0.88)	-0.006 (0.88)
Buffer zone (20 miles)	0.037 (5.04)**	0.206 (6.89)**	-0.071 (5.86)**	-0.107 (6.48)**	-0.065 (5.75)**
Aquifer	0.003 (0.94)	0.019 (0.95)	-0.007 (0.94)	-0.010 (0.94)	-0.006 (0.94)
Watershed	-0.005 (1.45)	-0.028 (1.49)	0.010 (1.47)	0.014 (1.48)	0.009 (1.47)
State park	-0.000 (0.08)	-0.000 (0.08)	0.000 (0.08)	0.000 (0.08)	0.000 (0.08)
Population density	0.000 (0.32)	0.000 (0.32)	-0.000 (0.32)	-0.000 (0.32)	-0.000 (0.32)
Democrat/Republican ratio (pres.)	-0.006 (2.28)*	-0.031 (2.45)*	0.011 (2.39)*	0.016 (2.41)*	0.010 (2.38)*
City dummy	-0.027 (3.54)**	-0.153 (4.12)**	0.053 (3.84)**	0.079 (4.00)**	0.048 (3.88)**
Town dummy	-0.017 (4.07)**	-0.096 (5.21)**	0.033 (4.59)**	0.050 (4.96)**	0.030 (4.74)**
Median family income	0.0002 (2.92)**	0.001 (3.22)**	-0.0005 (3.08)**	-0.001 (3.16)**	-0.0005 (3.09)**
Unemployment rate	0.001 (1.49)	0.005 (1.52)	-0.002 (1.51)	-0.002 (1.52)	-0.001 (1.50)
Education	-0.001 (4.27)**	-0.005 (5.45)**	0.002 (4.86)**	0.002 (5.18)**	0.001 (4.86)**
Manufacturing	0.000 (0.14)	0.000 (0.14)	-0.000 (0.14)	-0.000 (0.14)	-0.000 (0.14)
Home ownership	-0.000 (1.01)	-0.001 (1.02)	0.000 (1.01)	0.000 (1.01)	0.000 (1.01)
Well count	0.0003 (2.18)*	0.001 (2.29)*	-0.001 (2.25)*	-0.001 (2.28)*	-0.0004 (2.23)*
Marcellus dummy	-0.013 (3.43)**	-0.072 (4.27)**	0.025 (3.92)**	0.038 (4.08)**	0.023 (3.93)**
Utica dummy	-0.022 (4.56)**	-0.122 (5.77)**	0.042 (5.06)**	0.063 (5.50)**	0.038 (5.17)**
Observations	1,531	1,531	1,531	1,531	1,531

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

Table 6. Results of Ordered Probit and Probit Models with Different Specifications of the Dependent Variable

Variable	Model 1 <i>LocalPolicies4</i>	Model 2 <i>LocalPolicies6</i>	Model 3 <i>LocalPolicies5</i>	Model 4 <i>LocalPolicies7</i>
Productivity zone	-0.125 (0.165)	-0.298* (0.153)	-0.199 (0.173)	-0.370** (0.159)
Buffer zone (20 miles)	-0.911*** (0.261)	-0.935*** (0.244)	-0.901*** (0.264)	-0.913*** (0.247)
Aquifer	-0.0199 (0.165)	-0.0493 (0.158)	-0.0187 (0.171)	-0.0524 (0.163)
Watershed	0.139 (0.144)	0.166 (0.139)	0.196 (0.152)	0.211 (0.145)
State park	0.00575 (0.0109)	0.00659 (0.0109)	0.00487 (0.0114)	0.00564 (0.0113)
Population density	-0.000209** (8.76e-05)	-0.000221** (8.75e-05)	-0.000178** (8.99e-05)	-0.000192** (8.95e-05)
City dummy	1.739*** (0.299)	1.701*** (0.297)	1.565*** (0.309)	1.533*** (0.306)
Median family income	-0.0134*** (0.00498)	-0.0131*** (0.00488)	-0.0143*** (0.00519)	-0.0139*** (0.00508)
Unemployment rate	-0.0247 (0.0266)	-0.0222 (0.0259)	-0.0257 (0.0274)	-0.0233 (0.0265)
Education	0.0337*** (0.00688)	0.0343*** (0.00677)	0.0338*** (0.00718)	0.0344*** (0.00705)
Manufacturing	-0.00578 (0.00998)	-0.00792 (0.00962)	0.00118 (0.0102)	-0.00179 (0.00980)
Homeowners	0.00621 (0.00602)	0.00448 (0.00587)	0.00430 (0.00624)	0.00267 (0.00606)
Well count	-0.0257 (0.0190)	-0.0204 (0.0185)	-0.0341* (0.0202)	-0.0281 (0.0200)
Marcellus dummy	0.468*** (0.121)	0.407*** (0.119)	0.444*** (0.125)	0.383*** (0.122)
Utica dummy	1.232*** (0.201)	1.247*** (0.200)	1.203*** (0.203)	1.217*** (0.202)
Democrat/Republican ratio (pres.)	0.317*** (0.106)	0.327*** (0.105)	0.249** (0.112)	0.262** (0.111)
Town dummy	0.953*** (0.188)	0.876*** (0.188)	1.004*** (0.192)	0.922*** (0.191)
κ_1	3.560*** (0.561)	3.433*** (0.551)	— —	— —
κ_2	4.195*** (0.566)	4.041*** (0.556)	— —	— —
Constant term	— —	— —	-3.367*** (0.577)	-3.239*** (0.565)
Observations	1,418	1,545	1,418	1,545

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

Table 7. Results of the MiOP and ZiOP Models

Variable	Model 1 MiOP LocalPolicies3		Model 2 MiOP(C) LocalPolicies3		Model 3 ZiOP LocalPolicies4	
	Augm'd OP	Inflation Equation	Augm'd OP	Inflation Equation	Augm'd OP	Inflation Equation
Productivity zone	-0.155 (0.139)	— —	-0.154 (0.139)	— —	-0.0570 (0.181)	— —
Buffer zone (20 miles)	-1.106*** (0.172)	— —	-1.105*** (0.172)	— —	-1.102*** (0.291)	— —
Aquifer	-0.244 (0.152)	— —	-0.239 (0.153)	— —	-0.0197 (0.178)	— —
Watershed	0.194 (0.135)	— —	0.193 (0.135)	— —	0.109 (0.157)	— —
State park	0.00426 (0.0111)	— —	0.00396 (0.0111)	— —	0.00906 (0.0111)	— —
Population density	-0.000178 (0.000126)	-0.000151 (9.93e-05)	-0.000185 (0.000127)	-0.000152 (0.000101)	-0.000557*** (0.000146)	0.000726* (0.000401)
Dem/Rep ratio (pres.)	0.441*** (0.149)	0.0724 (0.143)	0.444*** (0.147)	0.0730 (0.143)	0.736*** (0.147)	-0.723* (0.427)
City dummy	1.732*** (0.560)	0.836** (0.397)	1.815*** (0.628)	0.824** (0.405)	0.872 (0.562)	1.761** (0.843)
Town dummy	-0.447 (0.317)	2.190*** (0.426)	-0.275 (0.773)	2.208*** (0.448)	-1.094 (0.712)	10.85 (323.4)
Median family income	0.00101 (0.00763)	-0.0382*** (0.0143)	-0.00138 (0.0122)	-0.0383*** (0.0149)	-0.0146** (0.00589)	0.00368 (0.0223)
Unemployment rate	-0.0311 (0.0259)	-0.0498 (0.0476)	-0.0344 (0.0280)	-0.0477 (0.0493)	-0.0407 (0.0302)	0.0340 (0.0937)
Education	0.0356*** (0.00940)	0.0298** (0.0133)	0.0373*** (0.0110)	0.0299** (0.0135)	0.0408*** (0.00806)	-0.0169 (0.0304)
Manufacturing	-0.0107 (0.0110)	0.0451** (0.0207)	-0.00832 (0.0146)	0.0465** (0.0218)	-0.00424 (0.0112)	-0.00228 (0.0349)
Homeowners	0.0110* (0.00647)	-0.00981 (0.0114)	0.0105 (0.00658)	-0.0101 (0.0117)	0.0130* (0.00714)	-0.0294 (0.0226)
Well count	-0.00773 (0.00576)	— —	-0.00760 (0.00565)	— —	-0.0251 (0.0194)	— —
Marcellus dummy	0.374*** (0.129)	— —	0.374*** (0.129)	— —	0.516*** (0.134)	— —
Utica dummy	1.066*** (0.193)	— —	1.058*** (0.199)	— —	1.465*** (0.227)	— —
ρ	— —	— —	— —	0.128 (0.526)	— —	— —
Constant	-0.264 (0.617)	0.860 (1.236)	-0.342 (0.672)	0.863 (1.286)	-2.645*** (0.810)	0.396 (1.695)
Log-likelihood	-892.12384		-892.10028		-475.47058	
Observations	1,531	1,531	1,531	1,531	1,418	1,418

continued on following page

Table 7 (continued)

Variable	Model 4 ZiOP(C) LocalPolicies4		Model 5 ZiOP LocalPolicies6		Model 6 ZiOP(C) LocalPolicies6	
	Augm'd OP	Inflation Equation	Augm'd OP	Inflation Equation	Augm'd OP	Inflation Equation
Productivity zone	-0.0571 (0.181)	— —	-0.343* (0.186)	— —	-0.349* (0.179)	— —
Buffer zone (20 miles)	-1.102*** (0.291)	— —	-1.226*** (0.307)	— —	-1.152*** (0.286)	— —
Aquifer	-0.0204 (0.178)	— —	-0.0250 (0.183)	— —	-0.0171 (0.174)	— —
Watershed	0.109 (0.157)	— —	0.260 (0.175)	— —	0.276 (0.170)	— —
State park	0.00909 (0.0111)	— —	0.0127 (0.0138)	— —	0.0131 (0.0155)	— —
Population density	-0.000550*** (0.000157)	0.000738* (0.000423)	-0.000674*** (0.000158)	0.000549** (0.000237)	-0.000532*** (0.000140)	0.000537** (0.000242)
Dem/Rep ratio (pres.)	0.731*** (0.153)	-0.732* (0.439)	0.791*** (0.172)	-0.308 (0.214)	0.675*** (0.159)	-0.265 (0.226)
City dummy	0.924 (0.691)	1.760** (0.845)	1.304** (0.539)	1.060 (0.646)	1.646*** (0.426)	1.133* (0.612)
Town dummy	-1.011 (0.962)	11.31 (862.6)	-1.198** (0.590)	3.532*** (0.643)	-0.264 (0.445)	3.585*** (0.764)
Median family income	-0.0148** (0.00600)	0.00432 (0.0236)	-0.0343*** (0.00900)	0.0343* (0.0181)	-0.0273*** (0.00746)	0.0373** (0.0180)
Unemployment rate	-0.0411 (0.0304)	0.0388 (0.105)	-0.0995** (0.0416)	0.133 (0.0930)	-0.0769** (0.0326)	0.179* (0.0939)
Education	0.0409*** (0.00808)	-0.0171 (0.0314)	0.0556*** (0.0105)	-0.0123 (0.0213)	0.0489*** (0.00933)	-0.00134 (0.0234)
Manufacturing	-0.00435 (0.0112)	-0.00142 (0.0365)	-0.0459** (0.0187)	0.0910** (0.0371)	-0.0325** (0.0142)	0.127*** (0.0450)
Homeowners	0.0130* (0.00714)	-0.0301 (0.0240)	0.0241** (0.00991)	-0.0394** (0.0173)	0.0150* (0.00793)	-0.0337 (0.0206)
Well count	-0.0251 (0.0194)	— —	-0.0187 (0.0191)	— —	-0.0180 (0.0185)	— —
Marcellus dummy	0.517*** (0.134)	— —	0.437*** (0.141)	— —	0.446*** (0.135)	— —
Utica dummy	1.463*** (0.227)	— —	1.620*** (0.264)	— —	1.521*** (0.246)	— —
ρ	— —	0.0542 (0.445)	— —	— —	— —	0.696*** (0.242)
Constant	-2.711*** (0.949)	0.356 (1.761)	-1.711* (0.874)	-2.730** (1.377)	-2.450*** (0.717)	-4.421** (1.797)
Log likelihood	-475.46305		-495.27432		-493.7659	
Observations	1,418	1,418	1,545	1,545	1,545	1,545

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

Table 8. Results of the Spatial Ordered Probit Models

Variable	Model 1 LocalPolicies1				Model 2 LocalPolicies2			
	Posterior Mean	Posterior Std.Dev.	Lower HPD	Upper HPD	Posterior Mean	Posterior Std.Dev.	Lower HPD	Upper HPD
Intercept	0.3675	0.4295	-0.4769	1.2080	0.1173	0.4306	-0.7282	0.9499
Productivity region	-0.1385	0.1147	-0.3677	0.0816	0.0147	0.1142	-0.2078	0.2384
20-mile buffer	-0.6571	0.1426	-0.9452	-0.3870	-0.4292	0.1380	-0.7038	-0.1615
Aquifer	-0.0371	0.1164	-0.2746	0.1851	-0.1297	0.1147	-0.3532	0.0948
Watershed	0.0854	0.1045	-0.1198	0.2880	0.0554	0.1043	-0.1424	0.2663
State park	0.0013	0.0067	-0.0123	0.0137	0.0008	0.0067	-0.0122	0.0138
Population density	-0.0001	0.0001	-0.0002	0.0000	-0.0001	0.0001	-0.0002	0.0000
Dem/Rep ratio (NYSBE)	0.1155	0.0574	0.0033	0.2273	0.1211	0.0568	0.0060	0.2277
City	0.5048	0.2548	-0.0062	0.9970	0.5085	0.2548	0.0182	1.0103
Median family income	-0.0097	0.0033	-0.0162	-0.0033	-0.0101	0.0033	-0.0166	-0.0037
Unemployment	-0.0250	0.0202	-0.0636	0.0153	-0.0126	0.0201	-0.0525	0.0263
Education	0.0274	0.0056	0.0164	0.0382	0.0292	0.0056	0.0180	0.0402
Manufacturing	0.0056	0.0073	-0.0086	0.0200	0.0062	0.0073	-0.0079	0.0206
Homeowners	0.0033	0.0048	-0.0060	0.0127	0.0058	0.0048	-0.0035	0.0152
Well density	-0.0042	0.0037	-0.0116	0.0027	-0.0058	0.0036	-0.0129	0.0013
Marcellus dummy	0.2137	0.0958	0.0325	0.4056	0.1981	0.0954	0.0123	0.3860
Utica dummy	0.2853	0.1110	0.0754	0.5100	0.3073	0.1117	0.0954	0.5316
ρ	0.4628	0.0446	—	—	0.4355	0.0452	—	—

OP models. Because of the computational difficulties in estimating the models at this point, we present only a select few primary models for this approach.¹³

The signs of most of the coefficients in the specifications of the dependent variables and the three modelling approaches used (OP, ZiOP/MiOP, and spatial OP) are robust. However, we observe changes in the level of significance for some of the explanatory variables.

Proximity and Familiarity

The coefficients for the buffer zone are consistently negative and significant. The partial effects shown in Table 5 suggest that a New York community located within 20 miles of a shale gas well in Pennsylvania is relatively more likely to either adopt a pre-emptive resolution or have no UGD policy. This result supports our hypothesis that communities that are close to active shale gas extraction sites and potentially at risk of negative consequences from the wells still want an opportunity to benefit economically from UGD.

The negative coefficients for well count, our measure of familiarity with UGD, indicate that the number of active conventional oil and gas wells in a community positively affects the probability of adoption of a pre-emptive resolution. However, this result is not robust across all models; it is not significant in the MiOP, ZiOP, and spatial OP. The negative sign is as expected and confirms our hypothesis that familiarity with conventional oil and gas extraction translates into a positive attitude toward UGD.

Communities within watersheds that supply drinking water are more likely than other communities to oppose UGD. However, this effect is significant only in the OP models that use *LocalPolicies3* as the dependent variable. The coefficients for proximity to state parks and primary aquifers are not significant.

Socioeconomic Characteristics

In terms of political affiliation, regardless of the political variable used (ratio of Democrats to Republicans using NYSBE or 2012 presidential election data), the coefficients are consistently positive and significant. The partial effects reported in Table 5 suggest that a 1 percent increase in the Democrat/Republican ratio results in a 1 percent increase in the probability of a community adopting a ban. This agrees with our expectations since Democrats are more likely to identify with policies that safeguard the environment.

Education level also appears to influence UGD policies. The coefficient on the community level of education, which is measured by the proportion of the population that had obtained an undergraduate degree, is consistently positive and significant. This result is in line with Bird, Heintzelman, and Walsh (2014), which found that communities are more likely to oppose UGD when their citizens have relatively high levels of education.

The coefficients for median family income are negative and significant for all but the two MiOP models (see Table 7). As Table 5 indicates, a 1 percent increase in median income increases the probability of a pre-emptive resolution

¹³ The results of the Bayesian approach are consistent with the results of the OP and MiOP models in terms of the coefficients on the smaller buffers and the consistency of the presidential election results in place of the NYSBE variable. Coding for the entire set of models is available upon request.

by 0.02 percent. This could be indicative of wealthier communities having more options in mitigating the negative impacts of UGD.

Population density is consistently negative and significant except in OP models 1 through 4 (Table 4), the MiOP, and the spatial OP models. These results suggest that relatively densely populated communities are less likely than other communities to impose a policy to limit or prohibit UGD. The Marcellus and Utica dummies are positive and significant for all models. The town and city dummies are consistently positive and significant for the OP and spatial OP models, indicating that cities and towns have a higher chance of adopting a ban or moratorium than villages.

The coefficients for unemployment rate are consistently negative for all models, indicating that greater levels of unemployment make communities less likely to adopt bans and moratoria. However, this result does not attain significance in any of the models.

The proportion of homeowners in a community positively affects the probability that the community will oppose UGD but the result is not consistently significant. The signs of the coefficients for manufacturing employment are negative in the majority of the models but are not significant.

Potential for Unconventional Gas Development

The coefficients of the productivity-zone dummy variable are consistently negative but are not consistently significant. The negative signs are in line with our expectations. That is, communities within the productivity zone identified in Figure 2, which have high potential for shale gas development, are less likely than other communities to adopt a ban or moratorium.

Inflated Ordered Probit Results

The results of the inflation equation in the MiOP and ZiOP models, which are presented in Table 7, identify factors that make a community more likely to take any kind of action (pre-emptive resolutions, movements for a statute, moratoria, and bans). However, those results do not allow us to reach a consensus as to what factors increase the likelihood of a specific type of action being taken. To address that question, we would need additional information regarding the role of the local government in the municipality and the level of trust by citizens in local officials, of social cohesion in the community, and of civic engagement in the past. Nevertheless, we can draw some conclusions from the ZiOP and MiOP models.

An interesting result of this analysis is that communities with large proportions of residents employed in manufacturing are more likely than other communities to adopt a pre-emptive supporting resolution, although this is not confirmed by models 3 and 4 in Table 7. The results of the ZiOP models suggest that greater population density increases the likelihood that a community will adopt some kind of resolution or statute. However, this result is not confirmed by the MiOP models. The effect of political affiliation in the probability of adopting any policy or statute is not clear from the results. Models 3 and 4 suggest that communities with a relatively large proportion of Democrats are more likely than other communities to adopt some type of policy, but that result is not confirmed by the inflation equation in the other models. The effect of income is not clear. In the MiOP models, communities with relatively low median family

incomes are more likely to adopt some kind of policy while the opposite is true in the ZiOP models. Communities with relatively educated residents are more likely than other communities to vote for a supportive resolution according to the MiOP inflation equation results, something that is not confirmed by the ZiOP results. Finally, home ownership decreases the probability of adoption of a statute or resolution; the only significant coefficient is in model 5.

The most important result is that the spatial ρ coefficient is positive and significant according to the Bayesian p-value.¹⁴ A positive coefficient for the spatial lag indicates that the policy-adoption decision in a community covaries with the policy-adoption decision in neighboring areas.

Conclusions

The debate surrounding UGD in New York presents a unique case in the environmental policy literature. Despite substantial potential for shale gas production in New York, particularly in the southern tier counties that border Pennsylvania, the state recently banned shale gas development. Our analysis demonstrates significant heterogeneity in communities' UGD policy preferences based on geospatial and socio-demographic characteristics. New York's recent decision to ban UGD could perhaps be viewed as in line with public opinion in the state. However, the ban does not represent the diversity of interests among communities. In fact, following imposition of the ban, towns along the southern tier began raising the idea of seceding from New York and joining Pennsylvania (*The Economist* 2015). While such a transfer is unlikely, it speaks to the heterogeneous attitudes toward UGD in New York.

Local UGD policy decisions in New York and other states point to the complexity faced by state policymakers. Pennsylvania and Ohio have attempted to pre-empt local governments from using zoning regulations to control UGD. In Colorado, municipal bans have been overturned following lawsuits filed by the Colorado Oil and Gas Association. Our research indicates that differences in community characteristics result in a wide heterogeneity of local policy decisions, yielding implications for the relevance of bottom-up policymaking approaches. State policymakers should better understand these local differences and design UGD policies that allow communities to be a contributing stakeholder to the regulatory environment.

Our analysis contributes to the literature on local policymaking by examining socio-demographic characteristics and geospatial attributes that affect the local policies introduced in a community in the case of UGD. The results of our OP, MiOP/ZiOP, and spatial OP models consistently show that New York communities located near active shale gas production wells in Pennsylvania are more likely to support UGD than other communities in the state. We hypothesize that this relationship can be attributed to the fact that New York communities that are closer to active UGD wells in Pennsylvania potentially experience some negative impacts of drilling and therefore want to have access to the economic benefits from UGD. In addition, communities with higher levels of education and a higher ratio of Democrats are more likely to oppose UGD through bans and moratoria. Finally, higher median family income makes a

¹⁴ Currently, readily accessible functions do not allow one to extract the HPD for the spatial coefficient; however, the Bayesian p-values (not shown in the tables) can be readily extracted via the code. Calculation of marginal effects or predicted probabilities was beyond the scope of this study.

community less likely to oppose UGD. We also find evidence of positive spatial correlation between communities, indicating that a decision to adopt a ban or a moratorium in one community positively influences the probability of similar decisions in neighboring communities.

Potential extensions of our work include addition of a variable to capture a community's access to piped drinking water and reliance on private wells. In addition, future analyses could extend the MiOP and ZiOP models to include variables that can better elucidate the probability of a community voting for any type of resolution or statute. Alternative spatial OP models could use different specifications of the spatial weight matrix.

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