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Working Paper Series

Working Paper # 12-02
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Abstract

To guard against urban sprawl, many communities in the United States have begun enacting policies to preserve open space, often through local voter referenda. New Jersey sponsors such municipal action through the Green Acres Program by providing funding and low interest loans to towns that choose, through a referendum, to increase property taxes and spend the money raised on open space preservation for the purposes of conservation and/or recreation. Understanding which factors contribute to the appearance and success of these measures is important for policy makers and conservation advocates, not only in New Jersey, but across the United States. Although previous literature has examined this issue, this is the first study to account for spatial dependence/spatial autocorrelation and to explore dynamic issues through survival analysis. The traditional two stage model from the literature is extended by incorporating a Bayesian spatial probit for the first stage and a maximum-likelihood spatial error model in the second stage. A Cox – proportional hazard model is used to examine the timing of referenda appearance. Spatial dependence is found in the second stage of the analysis, indicating future studies should account for its influence. There is not strong evidence for spatial dependence or correlation in the first stage. The survival model is found to be a useful complement to the traditional probit analysis of the first stage.

**KEYWORDS:** Environmental Referenda, Open Space, Survival Model, Spatial Econometrics, Bayesian Probit

**JEL Classifications:** Q50, Q57, Q58, C11, C21

## 1. Introduction

In the face of increasing urban sprawl, communities around the country have taken an active role in preserving open space. There are many approaches to preservation, including outright purchase of undeveloped land, the purchase of development easements, and public/private partnerships with land trusts or other preservation organizations. All of these approaches, however, require financing, and many communities have turned to voter-approved tax increases or bond issues to finance preservation. There have been 2,299 voter referenda on this issue since 1988 in the United States, of which 1,740 have passed. These measures have raised more than $56 Billion for land preservation (Trust for Public Land's Landvote database, www.landvote.org).

These referenda are quite diverse. They range from statewide referenda on major bond issuances to municipal level referenda on small land acquisitions. They often target multiple issues at once, including open space acquisition, the creation of recreational facilities, historic preservation, and the provision of affordable housing. Sometimes the targets and outcomes are specific and well-known, as in the case of the acquisition of a particular parcel of land. In other cases they are more ambiguous, raising funds which will then be set aside in a trust fund for future actions. In at least two states, matching funds or low-interest loans are made available to local communities who choose to undertake preservation programs.

There are many factors which might influence whether or not a community holds and/or passes preservation referenda. Most basically, voting behavior in referenda resembles purchasing behavior; voters are choosing yes or no on a measure that would provide some benefits at some cost. Voters should vote yes or no on the question depending on whether or not, on balance, the benefits that the voter expects to receive exceed the costs that she expects to pay.

These benefits and costs may depend on existing levels of consumption of both private and public goods that are related to the good in question, will include any direct expected tax costs which may or may not depend on income or the value of one's property, as well as indirect benefits or costs in the form of changes in property values or other macroeconomic effects. Finally, individual preferences will also play a role in determining an individual's voting behavior.

Since we cannot observe individual voting behavior, we are forced to rely on aggregations to the level of the municipality. We can also only view aggregate measures which are likely to be correlated with the costs, benefits, and associated preferences towards the propositions in question rather than the actual distributions of costs and benefits faced by voters and their associated preferences. These measures include the socio-demographic profile of a community, the existing land cover and relative amount of developed, undeveloped, or preserved space in a community, existing levels of taxation, and, of course, the parameters of the program under consideration - the mechanism through which funds are raised may be important, for instance, if the public discounts the necessity to eventually increase taxes to pay back bonds. In addition, once an issue is on the ballot, the timing of the election may play an important role as that will effect voter participation and, perhaps, the level of media coverage. It is important for policymakers and conservation advocates to understand how these factors influence the demand for conservation as revealed through these referendum results in order to efficiently allocate resources to areas where conservation is a higher priority and at times when communities are willing to move forward in this area.

Deacon and Shapiro (1975) laid the groundwork for this sort of analysis by developing a theoretical model of voter behavior in the context of referenda and applying that model to an empirical analysis of two referenda in California, one of which aimed to control development along the California Coast. Using voting data for 334 cities, they found evidence that conservation is a normal good and that the likelihood of voting for conservation is increasing in education and decreasing in the share of employment in a county that is in construction or related industries. Using voting data aggregated to the county level, Kahn and Matsusaka (1997) find a concave relationship between income and the proportion of votes for environmental propositions. Their results also confirm the findings of Deacon and Shapiro (1975) regarding the effects of education and the composition of the local economy. Wu and Cutter (2011) improve on these analyses by using census block-group level data (a much finer scale) and spatial error and lag models similar to those used in this paper to account for spatial dependence and autocorrelation. Finding that this more disaggregated data as well as the spatial controls matter, they find evidence that income has a convex relationship with the proportion of yes votes, but confirm the results of Kahn and Matsusaka (1997) as regards education. They also show that older populations seem less likely to support environmental referenda, but that denser and more urban populations are more likely to be supportive.

A related set of papers focuses on local referenda as opposed to local voting results on statewide referenda. These referenda may give a better picture of demand for conservation since the costs and benefits of these programs are more closely tied to the voting populations. Howell-Moroney (2004) used a sample of communities in the Delaware Valley of Pennsylvania and New Jersey to look at the decision to hold referenda. Kotchen and Powers (2006) and Nelson, Uwasu, and Polasky (2007) expanded this analysis by simultaneously examining not only the decision to hold a referendum, but, like the studies above, the proportion of votes for such measures in studies of referenda across the United States. Kotchen and Powers (2006) also provide more detailed analyses of referenda in Massachusetts and New Jersey, two of the most active states in the land conservation movement. Banzhaf et al.(2010) provide a similar nationwide analysis but are careful to control for two facts; that communities that hold referenda are likely to be those jurisdictions that are most likely to pass referenda and that the chosen financing mechanism (e.g. municipal bond or tax) is also likely to be the mechanism most likely to pass. These studies largely find that communities with higher income and more educated populations, and which have experienced more loss of open space, are more likely to hold and pass conservation referenda.[1]

We use municipal-level data on municipal referenda in New Jersey to answer many of the same questions addressed in the papers discussed above. However, we make two notable contributions to this literature. First, we use spatial error models to explicitly account for spatial autocorrelation. The traditional two stage model from the literature is extended by incorporating a Bayesian spatial probit for the first stage and a maximum-likelihood spatial error model in the second stage. Spatial factors come into play when the appearance or passage of a referendum is either partially determined by the decisions of nearby communities, or is subject to the same unobserved factors which drive these decisions in nearby communities. In addition, we use a Cox – proportional hazard model to take advantage of the time span over which referenda are held in our sample. Whereas the previous literature has largely thought of these referenda as static phenomena, we look to explain not only the static question of whether or not a municipality holds or passes a referendum, but also the dynamic question of why some towns adopt before others.

[1] Additional contributions to this literature include Kline and Wichelns (1994), Nelson et al. (2007), Kline (1994), Sundberg (2006) and Vossler et al (2006).

We find that accounting for spatial effects is important in the second stage model of referenda voting. There is strong evidence of spatial autocorrelation at this stage that is controlled for in the spatial error model. We also find the survival model to be a useful complement to traditional approaches, as, qualitatively, the results match up very closely with those in the first stage (appearance) models. Overall, we find mixed impacts of income on referenda, although referenda appear less often in periods of high unemployment. Referenda are also significantly impacted by existing property taxes, as well as the age distribution of the population. Finally, voters are more likely to support referenda geared towards farmland preservation and less likely to support those directed at recreation.

Section II provides more details about our study area and the referenda under consideration. Section III describes our dataset. Section IV goes into detail on our methodology and Section V presents our results. Section VI concludes the paper.

## 2. Study Area and Policy Details

New Jersey, sandwiched between two of the six largest cities in the United States, is the most densely populated state in the United States according to the 2010 census. Hasse and Lathrop (2008; 2010) state that if 2007 rates of development and urbanization were to continue, the state would develop all available land by 2053. In response to this increasing density and growth in urban development, New Jersey has been a leader in preservation of open space through voter referenda. This leadership can, in part, be attributed to a statewide initiative, the Green Acres Open Space Land Conservation Program. Begun in 1961, there have been 13 statewide ballot measures that have provided funding for open space preservation in New Jersey, with the most recent in 2009. Much of the money raised through these initiatives has been used to match funds raised through local ballot measures that have provided additional resources for preservation. Since 1989, these statewide programs have resulted in 493 municipal referenda on conservation. Of these, 389 measures have passed which have raised approximately $1.3 Billion for land conservation.[2]

The Green Acres Program, broadly speaking, has four program areas: State Park and Open Space Acquisition, Local Governments and Non-Profit Funding, Stewardship – Keeping it Green, and Planning and Information Management. The second of these is what we address in this paper. The Green Acres program provides funding and low interest financing to local authorities for the protection and/or acquisition of existing open space as well as for the provision of recreation facilities. A substantial portion of this funding depends on the local governments having put in place an "open space tax" and associated implementation plan. The program also supports non-profit organizations which often work with local communities to acquire undeveloped land or the associated development rights.[3] Also, any land acquired through the use of Green Acres funding must be used solely for conservation or recreation. In these ways, the program provides substantial incentives for municipalities to actively engage in land preservation programs.

We look at those referenda held at the municipal level and which proposed a property tax increase to fund preservation (this excludes only 9 referenda which used Bonds or other financing mechanisms) and exclude those at the County or State levels from our analysis. In total, 253 municipalities held at least one referendum. This represents about 44% of all municipalities in New Jersey. These referenda, on average, proposed raising $3.97 Million for conservation by increasing property taxes by 1.62 cents per $100 dollars of property value. On

[2] TPL LandVote Database (http://www.landvote.org).
[3] For more details on the program, see the Green Acres website at: http://www.nj.gov/dep/greenacres.

average, these referenda received support from 58% of voters. All of those referenda for which information on the purpose was provided mentioned open space preservation as the primary purpose. Of those, 195, or not quite 50% mentioned recreation and 182, or 42%, mentioned farmland preservation. Figure 1 provides a map of the referenda included in our dataset. While eyeballing the map does not reveal strong evidence of spatial clustering, there are areas near New York City and in the south of the state where clusters of municipalities do not hold referenda. Additionally, there appears to be some minor clustering of rejected referenda directly to the west of New York City.

## 3. Data

Several data sets were combined to create the data used here. First, the open space referendum data was obtained from the Trust for Public Land's (TPL) Landvote Database (www.landvote.org). These data contain information about the dates, voting results, finance mechanisms, matching funds, and property tax rates of the proposed measures. It also contained information on how the funds raised were to be used - for general open space preservation, farmland preservation, recreation, parks, trails, wildlife habitat, greenways, or watershed protection. Out of 493 open space referenda occurring between 1989 and 2009, 389 passed. The municipality-level Green Acres program of open space purchases officially began in 1997, although there were 18 similar open space referenda prior to that date. Figure 1 presents a map of New Jersey's municipalities that have passed referenda (indicated in green). Data on referenda from TPL are summarized in Table 1. Note that the funds from a particular referendum can be designated for several purposes, so those categories in Table 1 are not mutually exclusive.

Municipality-level demographic data was obtained from the 2000 US Census. Measures of income are traditionally used in voting analysis, for it can indicate whether the environmental good is a normal or inferior good (Kahn and Matsusaka, 1997). The income distribution can also be important to the analysis, since a voter's relative position in the income distribution may impact their voting (Wu and Cutter, 2011). Median home value and the homeownership rate are included since the majority of the referenda use property taxes to solicit funds. Population density is included; along with the land use data described below, this is an indicator of the scarcity of land in a municipality. Variables representing the percentage of older (over 65) and younger (under 18) residents are also included to examine the impact of the municipality's age distribution. Educational achievement (proportion of municipality with a Bachelor's degree) is also included, since more educated people may be more aware of environmental problems and the risks and long term consequences associated with them (Wu and Cutter, 2011). Additional demographic variables include water area, the number of males per 100 females, and race.  Table 2 summarizes these variables, split into three categories: held a referendum and passed at least one (218 municipalities), held a referendum but never passed (39 municipalities), and never held a referendum. From the Table we see that municipalities that never held referenda are, on average, less educated, poorer, have lower home values and less homeownership, and have higher property tax rates, as well as higher population density.

Effective property tax rates were obtained from the New Jersey Department of the Treasury's Division of Taxation. The mean municipal property tax across New Jersey was 2.59 percent, although there were districts with taxes as high as 11.85 percent. Since the majority of the referenda use property taxes to purchase open space, previously high taxes may be an impediment to the appearance or passage of referenda. The New Jersey Department of

Environmental Protection was the source of the land use data, which was used to construct the open space and urban area variables. County-level average (1997-2009) unemployment rates came from the US Bureau of Labor Statistics, which may serve as an indicator of the opportunity cost of the referenda (Nelson et al., 2007). Finally, information about the 2000 presidential election was obtained from the New Jersey Division of Elections. Those data are at the county level and serve as an indication of general voter preferences.

**4 Methodology**

The analysis of open space referenda requires a two stage procedure (Nelson et al., 2007). A first stage analysis of referenda appearance is required to confront potential sample selection bias in the second stage analysis of voting results. Municipalities that hold referenda may be consistently different than others, which may bias the results of the second stage analysis. In particular, following Banzhaf et al. (2010), municipalities that hold referenda are more likely to pass them. Evidence from past literature on the influence of the first stage is mixed; Kotchen and Powers (2006) and Nelson et al. (2007) do not find selection bias, while Banzhaf et al. (2010) do find evidence of this effect. Even if sample selection is not found, however, the first stage still provides useful information about open space referenda. A Heckman two-stage regression is used to detect sample selection in the present paper (Greene, 2000).

In the first stage, the focus is factors that influence a municipality’s decision to hold a referendum. Assume that the underlying propensity for a municipality to host a referendum is given by:

$$R_i{*} = c_0 + \beta_1 \mathbf{demo}_i + \beta_2 \mathbf{econ}_i + \beta_3 \mathbf{LU} + e_i \qquad (1)$$

In equation (1), ***demo*** represents demographic variables—such as population, age, or race. Economic variables, like median household income and unemployment rate, appear in ***econ***. Land use variables, such as amount of open space, open space change, and urban area, appear in ***LU***, and *e* is an error term. Since we do not have data on the latent variable $R_i$*, only on whether a referenda actually occurred, the appearance of referenda can instead be estimated by the probit model in (2).

$$\Pr(R_i = 1) = \Phi(c_0 + \beta_1 \mathbf{demo}_i + \beta_2 \mathbf{econ}_i + \beta_3 \mathbf{LU}) + \varepsilon_i \tag{2}$$

In this model $R_i$ = 1 if $R_i$* > 0 and the municipality held a referenda and 0 otherwise.

The second stage of the analysis focuses on the passage of referenda. There exists a wide literature on municipal, county, state, and national voting outcomes. While some papers model the proportion of yes votes directly, this paper follows the analyses of Deacon and Shapiro (1975), Kotchen and Powers (2006), and Nelson et al. (2007) and uses the logodds variable for estimation:

$$logodds_i = \ln\left(\frac{P_i}{1-P_i}\right) \tag{3}$$

with $P_i$ representing the proportion of yes votes in referendum *i*. The resulting model for referenda passage is as follows:

$$logodds_i = c_o + \delta_1 \mathbf{demo}_i + \delta_2 \mathbf{econ}_i + \delta_3 \mathbf{LU}_i + \delta_4 \mathbf{ref}_i + \mathbf{t}_i + u_i \tag{4}$$

where *ref* is a vector of variables related to the referendum, *t* is a vector of binary year fixed effects, and $u_i$ is an error term.[4]

[4] Note that several specifications explored also included matching municipality funds. In the end, these variables were not included due to data concerns, such as large numbers of missing observations, errors in observations, and induced multicollinearity.

To conduct the Heckman procedure (Deacon and Shapiro, 1975; Kotchen and Powers, 2006; Nelson et al., 2007) the residuals from the first stage are used to construct the inverse Mills ratio, which is inserted in the second stage regression as an additional variable. A standard *t* test of the inverse Mills ratio coefficient serves as a valid test of the null hypothesis of no selection bias (Heckman, 1979), or independence between the first (appearance) stage and the second (voting) stage.

*4.1 Spatial Dependence in Referenda*

The appearance or result of a referendum may depend on referenda in nearby counties, and there may be similar unobserved influences in nearby municipalities that impact the appearance or passage of a referendum. In Figure 1, for example, there appears to be some spatial clustering of municipal referenda results; to the west of New York City a cluster of contiguous municipalities rejected referenda.[5] In recent years, a variety of spatial econometric tools have arisen to address these kinds of problems (Wooldridge, 2002), which regularly appear in environmental and urban applications (Brasington and Hite, 2005; Anselin and Le Gallo, 2006; Bourassa et al., 2007), including analyzing the effects of open space on home prices (Brasington and Hite, 2005; Anselin and Le Gallo, 2006; Bourassa et al., 2007; Heintzelman, 2010).

The two most common ways to model spatial dependence are through the dependent variable, in a spatial lag model, or through the disturbance term, using the spatial error model. The former approach uses a spatially-lagged dependent variable on the right side of the equation, as in equation (5):

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[5] Some of the spatial clustering may be a result of unobserved attributes common to particular regions, such as the undeveloped "Pine Barrens" in south New Jersey, or high opportunity cost of land near New York City.

$$y = \rho W y + X\beta + \varepsilon \qquad (5)$$

Where $\rho$ is a spatial autocorrelation parameter to be estimated and $W$ is a spatial weights matrix (SWM), an $n \times n$ weighting matrix that expresses the spatial relationships between each observation in the study. There are several ways to configure the SWM; this paper uses a version commonly encountered in the literature, the inverse distance specification (Anselin and Le Gallo, 2006; Mueller and Loomis, 2008; Wu and Cutter, 2011).[6,7] The spatial error model instead incorporates spatial dependence through a non-spherical error term:

$$\begin{aligned} y &= X\beta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + u \end{aligned} \qquad (6)$$

Where $\lambda$ is a parameter to be estimated and $u$ is a normally distributed error term.

To test for spatial dependence, normal and robust versions of the Lagrange multiplier (LM) test (Anselin and Le Gallo, 2006; Mueller and Loomis, 2008; Wu and Cutter, 2011) are used, for both lag and error specifications. LM tests have clear asymptotics, and the robust versions have power even in the presence of lag and error forms of spatial dependence (Mueller and Loomis, 2008; LeSage and Pace, 2009). In the passage data, the null hypothesis of no spatial correlation is strongly rejected, with the robust tests supporting the spatial error model.[8]

*4.1.1 Bayesian Probit*

Spatial dependence is also a concern for the referenda appearance regressions. For instance, Figure 1 shows a cluster of municipalities in the south of the state that have not yet held referenda. The normal maximum likelihood spatial econometric techniques are not suited to a

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[6] Contiguity, "nearest neighbor," and inverse distance squared specifications were also estimated, with similar results.

[7] SWMs are row standardized.

[8] Parallel tests for spatial dependence have not yet been developed for the case of a discrete dependent variable, as in the appearance regression.

binary dependent variable since, among other things, probit probabilities do not have a closed form and therefore require numerical approximation (Anselin, 2002; Fiva and Rattsø, 2007). Bayesian methods represent a better approach to the spatial probit, since they are flexible, can accommodate both lag and error specifications, and can account for heteroskedasticity (LeSage, 2000; Fiva and Rattsø, 2007; LeSage and Pace, 2009). These methods use a Markov Chain Monte Carlo (MCMC) approach to estimate the parameters of the model. For a full treatment of the Bayesian spatial econometric model, the reader is referred to (LeSage, 2000; Fiva and Rattsø, 2007; LeSage and Pace, 2009).

The Bayesian spatial probit approach has its foundations in the non-spatial methods of Albert and Chib (1993), who treat the binary dependent variable ($y$) as an indicator of latent unobservable utility ($y$*)(LeSage and Pace, 2009). In this case, we only observe $y_i = 1$ when $y_i* \geq 0$ and $y_i = 0$ when $y_i* < 0$.[9] We can therefore take advantage of the result that $p(\beta,\sigma^2|y*) = p(\beta,\sigma^2|y*,y)$, since once you have $y$* you automatically have $y$. Consequently, if $y$* is added as an additional parameter to be estimated, then the joint conditional posterior distribution of the parameters will be the same as that of a Bayesian regression with a continuous dependent variable. Gibbs sampling is used to draw from a multivariate truncated normal (TMVN) distribution to simulate $y$* (LeSage and Pace, 2009).[10]

In Bayesian estimation, the posterior distribution is formed by multiplying the likelihood function by the prior. In the case of a spatial error model, the likelihood function is

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[9] For instance, in the case of a referendum, $y_i = U_{1i} – U_{0i}$, so that when net utility is positive, a referendum is held, and when net utility is negative the vote is not held.

[10] Methods from Geweke (1991) are used to sample from the conditional distribution p($y*|\beta,\rho$). Essentially, a Gibbs sampling algorithm pulls draws from the conditional distribution for each individual $y_i$*, conditional on all other n-1 components of the n x 1 vector $y$*, For the probit model, this takes the form of a TMVN distribution, or $y*\sim$TMVN($\mu, \Omega$), where $\mu = (I-\lambda W)^{-1}X\beta$, and $\Omega = [(I-\lambda W)' (I-\lambda W)]^{-1}$. The Geweke (1991) approach uses the precision matrix, which is the inverse of the variance-covariance matrix of them TMVN distribution. Similar to the case of the non-spatial probit, identification restrictions require us to set $\sigma_\varepsilon^2 = 1$. See LeSage and Pace (2009) for additional details.

$$L = (2\pi\sigma^2)^{-(n/2)} \left| I - \lambda W \right| \exp\left( -\frac{1}{2\sigma^2} (y - X\beta)'(I - \lambda W)'(I - \lambda W)(y - X\beta) \right) \tag{7}$$

Following LeSage and Pace (2009), we use a normal prior distribution for *β*, which is conditional on an inverse gamma distribution for $\sigma^2$. The spatial dependence parameter, *λ*, uses a uniform prior distribution.

$$\begin{aligned} \pi(\beta,\sigma^2) &\sim NIG(c,T,a,b) \\ &= \pi(\beta \mid \sigma^2)\pi(\sigma^2) \\ &= N(c,\sigma^2 T) IG(a,b) \end{aligned} \tag{7}$$

$$\pi(\lambda) \sim U(l_{\min}^{-1}, l_{\max}^{-1}) \tag{7}$$

Since there is uncertainty regarding the parameters, we use diffuse priors by setting c = 0, T = $I_H$ *x* $10^{10}$, and a = b = 0. In the prior for *λ*, $l_{min}$ and $l_{max}$ refer to the largest and smallest eigenvalues of the SWM. While Gibbs sampling can be used for the other parameters, since their conditional distributions take known forms, the conditional distribution for λ (in the spatial error model), appearing in (10), does not take a known form.

$$p(\lambda \mid \beta, y^*) \propto \left| I_n - \lambda W \right| \exp\left( -\frac{1}{2}\left(y^* - X\beta\right)'\left(I_n - \lambda W\right)'\left(I_n - \lambda W\right)\left(y^* - X\beta\right) \right) \tag{7}$$

The Metropolis-Hastings algorithm is instead used to sample from (10).

The results presented below use 10,000 draws along with a 2,500 draw "burn-in" period.[11] Since sufficient spatial tests—such as the LM or Moran's I tests—have not yet been developed for a spatial probit model, both error and lag models are used for the spatial probit appearance regressions, although since the results turn out to be quite similar, we only report results of the spatial error models here. The resulting estimates of the *λ* and *ρ* coefficients serve as proxy measures for the degree of spatial correlation and dependence in our models.

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[11] The "burn-in" period is discarded to prevent dependence on initial values. Estimation was also performed under 20,000, 50,000, and 70,000 draws with equivalent results. Furthermore, Raferty-Lewis convergence diagnostics indicated convergence for most regressions at above 3,000 observations (with some converging much sooner)

*4.2 Survival Model*

We are also interested in factors that affect the timing of referenda, to see which variables may lead to early adoption, in terms of appearance and passage. This is the first paper to use a survival model to analyze referenda results. Also referred to as hazard or duration models, survival models are widely used in the fields of biology (LeSage and Pace, 2009) and medicine (Ma and Huang, 2007); they are only recently starting to appear in economic applications (Vance and Geoghegan, 2002; Box, 2008). In survival models, the focus is on the length of time to an event, such as time until a home sells or goes into foreclosure (Vance and Geoghegan, 2002; Box, 2008). These models estimate the conditional probability that a unit (such as a home or cancer patient) exits a particular state (such as "on the market" or "alive"), where observations represent time periods. The dependent variable is the length of time from the beginning to the end of the specified state, or until the end of the sample period (in which case the observation is "right censored") (Simmons-Mosley and Malpezzi, 2006; Bellotti and Crook, 2009). In this paper, two periods of interest are investigated with survival models. The first is the time between the beginning of the open space program and the occurrence of the first referendum vote. The second model analyzes the time to the first successfully passed referendum. Since not all municipalities hold referenda by the end of the sample period, the data used in both models contain right censored observations, a common feature of survival data.

Instead of focusing on the cumulative distribution function (CDF), $F(t) = Pr(T \leq t)$, for $t \geq 0$ (where $T$ is the duration and $t$ denotes a particular value of $T$), the emphasis is on the survival function $S(t) = 1 - F(t) = Pr(T > t)$ and the hazard function. The hazard function, ($h(t)$), is equal to the instantaneous rate of exiting the state, per unit of time. The hazard function can be written in terms of the density (*f(t)*), which is equal to –S'(*t*)), and CDF, as follows:

$$h(t) = \frac{P(t \le T < t+b)}{P(T \ge t)} = \frac{F(t+b) - F(f)}{1 - F(t)} \tag{8}$$

Taking the limit as *b* approaches zero,

$$h(t) = \lim_{b \to 0} \frac{F(t+b) - F(t)}{h} \frac{1}{1 - F(t)} = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} \tag{9}$$

A survival analysis allows us to take a novel look at the dynamics of appearance and passage of referenda. A Cox proportional hazard model (Vance and Geoghegan, 2002) is used to model the time periods of interest—in this case, the time until referendum appearance and the time until passage--of the form:

$$h(t) = h_0(t) \exp(\gamma_1 \mathbf{demo}_i + \gamma_2 \mathbf{econ}_i + \gamma_3 \mathbf{LU}_i) \tag{10}$$

Where the baseline hazard is $h_0(t)$, and the independent variables are the same as those in the appearance model.[12] The Cox Proportional hazard model is a widely used semi-parametric model that does not require an a-priori specification of the baseline hazard (Cox, 1972).[13] To account for non-constant variance, a heteroskedasticity-robust form of the model is employed (Cleves et al., 2008).[14] The same variables from the probit appearance regressions are used here.[15]

## 5. Results

[12] Note that the Cox proportional hazards model does not have an intercept, since it gets subsumed into the baseline hazard $h_0(t)$.
[13] For this specification, we assume that the coefficients are constant over the sample period.
[14] The heteroskedasticity robust version of the model was developed by Lin and Wei (1989), which is simply a variant of the traditional Huber-White robust model.
[15] The beginning of the Green Acres municipal program is used as the initial time for all observations (time periods). The 18 referenda between 1989 and 1997are discarded to ensure consistency in the survival model.

*5.1 Appearance*

The results of the appearance regressions appear in Table 3. We present results for standard Probit, Spatial Error, and Survival models, and in each case report specifications with and without a quadratic term for the tax rate variable. [16] Estimated coefficients are mostly consistent with expectations across the three models. Municipalities with higher average property taxes are less likely to hold a referendum. Education is positive and significant suggesting that higher education levels in a municipality, and potentially greater awareness of environmental issues (Lin and Wei, 1989), increase the likelihood of a referendum. Municipalities with a large number of residents under 18 are less likely to hold a referendum; they may prioritize education or other spending over open space funding. The number of men per 100 females is negative but insignificant, implying no gender effect. The positive (though small) and significant population density coefficient indicates that higher density areas are more likely to hold a referendum. Unemployment is negative and significant, perhaps suggesting that areas with unemployment problems have greater concerns for their scarce resources. Median household income has a very small positive coefficient and standard error, although it is insignificant in this specification.[17]

In specifications including the quadratic tax rate term, both the regular and squared versions of the variable are highly significant. Their signs indicate a “hill-shaped” relationship between taxes and referenda appearance. Consistent with expectations, at low levels of existing taxation, the probability of holding a referendum is increasing with taxation, but above a certain point, estimated to be where property tax rates equal 2.3%, this probability begins to decline with

[16] Squared terms were explored for several other variables, with others producing either insignificant results or multicollinearity problems. Variance inflation factors and characteristic numbers were used to detect multicollinearity.

[17] Several specifications were estimated that included the income distribution variables instead of the median household income variables. Similar to the insignificant results on the latter, the former did not add much to the model.

additional taxation. This implies that at a tax rate of 2.3% the probability of holding a referendum is maximized, which is slightly below the median tax rate of 2.5%.

As noted above, the results of the spatial error model are also presented here.[18,19] There are some minor differences in magnitude and significance between the spatial and non-spatial specifications. In the basic model (with no squared variable), *Over 65* is no longer significant, while the male to female ratio, open space area, and median household income are now significant, which may illustrate improved estimation through spatial corrections. However, the spatial coefficients ($\lambda$ in this model and $\rho$ in the spatial lag model) were insignificant in all estimated models, indicating that spatial dependence and spatial autocorrelation may not be a concern in the appearance models.

The last four columns of Table 3 contain the results of the survival models for referendum appearance.[20] The reported estimates are hazard ratios, which are interpreted differently than regression coefficients. For the Appearance data, for instance, an estimate greater than one indicates that variable increases the probability of holding a referendum, and hence the probability that the event will occur sooner. Reported ratios less than one decrease the hazard, making the referendum less likely to happen. For example, in the first column of these results, the hazard ratio on *Pct Own* is 1.015, which means that an increase in homeownership of one unit (one percent) will increase the hazard by 1.5%. Consequently, municipalities with higher homeownership rates are predicted to hold referenda sooner, since the hazard of appearance increases. Conversely, the hazard ratio on *Tax Rate* is 0.732, which means that an

[18] Spatial lag models were also estimated, with similar results.
[19] The results presented use an inverse-distance SWM based on a threshold of 30,000 feet. Other SWMs were also estimated, including nearest neighbor and inverse distance squared specifications, with comparable results.
[20] Note that there is no constant in the Cox Proportional model since the constant gets subsumed into the baseline hazard.

increase in the tax rate of one unit decreases the hazard by 2.68%. So in the first specification, municipalities with high tax rates are likely to hold referenda later.

Similar to the appearance regressions, the tax variables exhibit a significant "hill-shaped" relationship. More importantly, comparing the hazard ratios to the previous probit coefficients, they all agree about the qualitative influence of each independent variable. All hazard ratios that are less than one correspond to negative probit coefficients, and all ratios greater than one match to positive variables. Also, the male to female ratio is significant in the survival models, implying that, given the referendum appears, a larger concentration of females may cause earlier appearance.[21]

We can also plot the survivor function, which graphically illustrates the impact of a particular variable. Figures 2-5 show the impact of several variables on the estimated survivor function. In each case, the survivor curve is shown with all variables at their mean levels, as well as plus and minus one standard deviation for the variable of interest. For instance, Figure 2 has three curves corresponding to education at its mean level (0.31) and one standard deviation above (0.47) and below (0.15) the mean. Given its high hazard ratio, the graph shows that education can have a considerable impact on the predicted timing of the referendum. At 12 years from the start of the open space program, the higher education municipality only has a survival probability of around 50%, whereas the low education municipality has a survival probability of around 77%. Figure 3 graphs the survival function as tax varies, where the quadratic relationship between tax and appearance is apparent.[22] Finally, Figure 4 graphs the impact of unemployment on the survival function.

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[21] Although we must interpret this result with caution, as it is likely that the male to female ratio is correlated with other unobservables.

[22] Note that the mean survival curve in this graph is different than the other three. That is because we fix the squared tax variable at $(2.59)^2 = 6.7081$, instead of the mean of $Tax^2$, which is 7.32.

*5.2 Passage*

Table 4 contains the results of the passage regressions. Tests of sample selection bias, based on the Heckman test, were not significant.[23] In the first four models the dependent variable is *logodds*, as described above. We see that there are several parallels with the appearance regressions. Home values have a small, positive, and significant impact on referenda passage. Education has a strong positive impact on referenda passage, indicating that higher levels of environmental awareness increase the probability that a vote passes. A larger proportion of votes for Bush in the 2000 election are negatively correlated with passage. Surprisingly though, the existing property tax rate is insignificant in both OLS specifications. Also, *Over65* and *Under18* are now both significant and positive, so that larger proportions of older and younger residents increase the probability of passage. Kahn and Matsusaka , Kotchen and Powers (2006), and Nelson et al. (2007) (Kotchen and Powers, 2006; Nelson et al., 2007)also find a positive relationship between environmental voting results and the percentage of residents over 65, and hypothesize that it could be due to increased health impacts and a lower tax burden.

Although population density was a significant determinant of referenda appearance, it is not significant in the passage regressions. Also, notice that the tax (*Tax ¢/$100*) is negative but insignificant. This could be due to lack of variation; there are 142 observations with 1 cent per 100 dollars and 108 observations with 2 cents.(1997). Similar to Nelson et al., results indicate that the timing of the referendum is not significant, although this is no surprise since there were only five that occurred outside of November. The amount of open space change in a county increases the odds of passing the referenda, so counties that lost open space from 1997 – 2002

[23] Therefore the regressions presented here do not contain the inverse mills ratio to control for sample selection bias.

are likely to pass referenda—perhaps due to the increased opportunity cost of land. By and large, the open space land use variables were less important to the results that expected. This may be a result of the land use data only being available at the county level, as stressed in Kotchen and Powers (2007).

The stated purpose of open space funds has a significant effect on the odds of passage. The use of funds for farmland and wildlife habitat purchase has a positive effect, while use for recreation facilities and maintenance has a negative effect. Finally, although not shown, the year dummies were positive in the earlier years of the sample and negative after 2003, with years 2006 and 2007 significant in all specifications.

Note that the lambda coefficients are now highly significant, confirming the previous LM tests. This suggests a substantial amount of spatial autocorrelation in our dataset as regards referendum passage. Also, the goodness-of-fit measures indicate an improvement with the spatial models, and the standard error of each variable in the spatial regressions is less than or equal to its OLS counterpart. In the spatial models, the significance and magnitude of the farm and recreation funding variables both increase relative to the traditional OLS approach. More importantly, the unemployment rate, which was insignificant in the OLS models, is now negative and significant, illustrating a link between the performance of the economy and the importance of the environment. On the whole, the spatial corrections improve the regressions and illuminate important relationships in the analysis of open space referenda, akin to the analysis of ballot measures in Wu and Cutter (2006).

The results of the survival models of first passage, although not presented here, offered only minor contributions to the analysis. The results were similar to the appearance survival models, with several minor differences in significance and sign. Since the model could not easily account for referenda-specific variables (such as funding purposes, time of year, and cost), which occur at the referendum, its utility was somewhat limited.

## 6. Conclusion

Throughout the country, open space referenda have become a popular avenue for land conservation, with over $56 billion in funds approved in the US since 1988.[24] It is therefore important to understand the factors that contribute to the appearance and passage of these referenda. This paper improves the analysis of open space referenda through two novel approaches. First, spatial econometric models are employed for each stage of the traditional two stage analysis of referenda. Second, the timing of referenda is analyzed through a survival model: the Cox proportional hazard model. We use a dataset that includes all open space referenda that occurred in New Jersey since 1989, which contributed over $1.3 billion to land conservation. Since New Jersey is the most densely populated state in the US, land management issues are important to voters, and provide a robust area of study.

Although a Bayesian spatial probit model failed to find convincing evidence for spatial effects in the first stage (appearance), a maximum likelihood model detected highly significant effects in the second (voting) stage. Overall, the spatial model improved the standard errors in the analysis and uncovered several important relationships. For instance, the non-spatial model did not detect the significant effect of the unemployment rate on referenda passage, which provides an important link between economic performance and environmental voting patterns.

In our survival estimates, we find that survival models can be useful complements to the appearance regression, with the signs of all coefficients in the Cox models matching those of the appearance models. Furthermore, several variables were found to significantly affect the timing

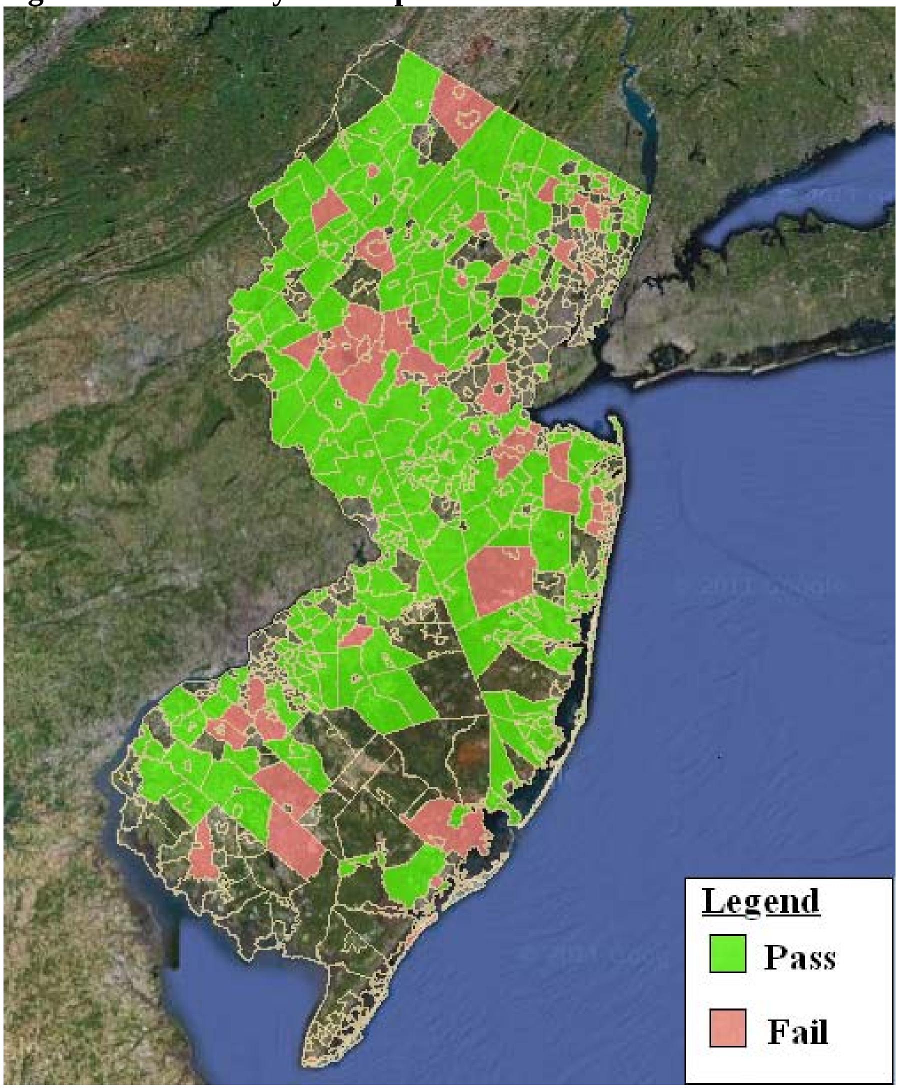
[24] For additional national referenda information, see www.landvote.org.

of referenda but not their appearance, suggesting that there may be some minor effects that impact the timing of adoption but not overall appearance. These smaller influences could allow a further refining of targets for open space advocates and local governments. Overall, the results of these models illustrate the utility of survival models in analyzing voting outcomes. The signs of the results are consistent with a traditional probit model, but the focus on time allows additional results to be culled from the data. In particular, survival curves represent a promising tool for future analysis.

Given the large amount of money involved in open space referenda, local and national advocates, as well as policy makers, have been active in the process of getting these referenda on ballots and subsequently passed. (2011) find considerable evidence that conservation advocates actively target communities based on observable factors. For instance, the state of New Jersey has a pamphlet on its website about designing winning referenda, which was created by the Trust for Public Land.[25] However, (Banzhaf et al., 2010) suggest that future conservation advocacy should target less affluent or educated communities, since the richer, more educated communities have been independently successful at securing open space. Since the present paper allows a more robust analysis of open space referenda, it is our hope that these tools can be used to uncover previous advocacy and policy gaps, for a more balanced approach to conservation.

[25] http://www.state.nj.us/dep/greenacres/pdf/nj_self.help.guide_4.1.08.pdf

**Figure 1: New Jersey Municipal Referenda**




Source: Trust for Public Land Landvote Database (www.landvote.org)

**Figure 2: Survival Function and Education**

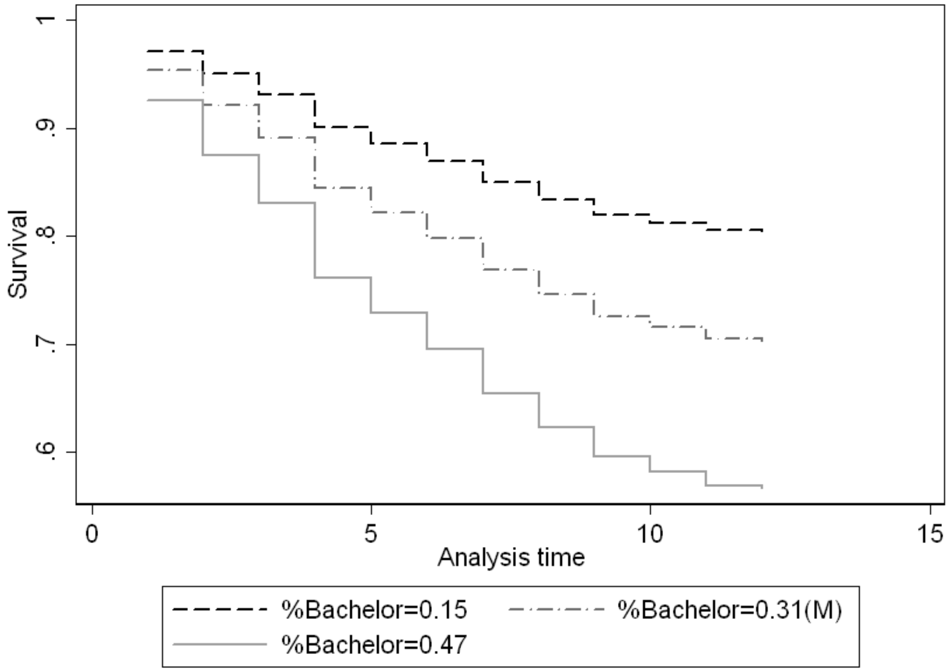



**Figure 3: Survival Function and Taxes**

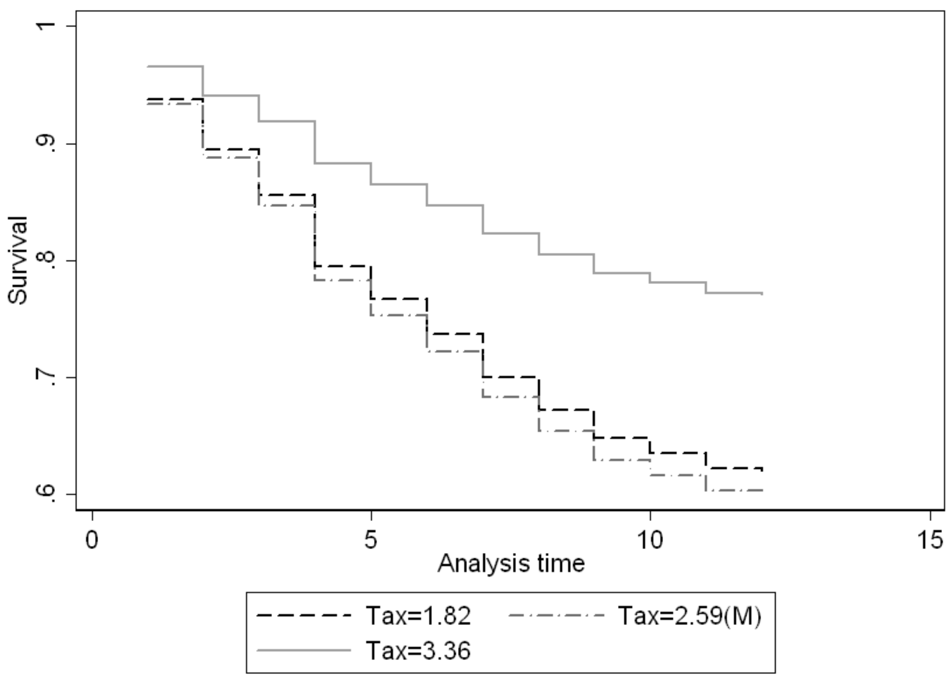


**Figure 4: Survival Function and Unemployment**

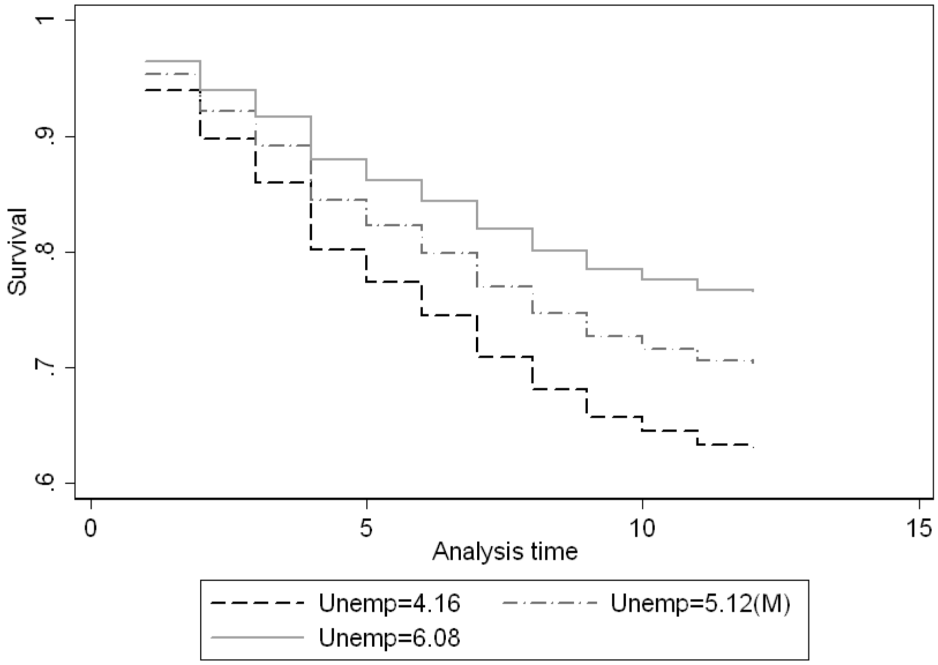


**Table 1: Referenda Summary Statistics**

| Variable (n = 406) | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Tax rate (¢/$100 of Property) | 1.63 | 1.20 | 0.01 | 8 |
| Vote not in November | 0.01 | 0.11 | 0 | 1 |
| Funds for General OS | 0.93 | 0.25 | 0 | 1 |
| Funds for Farming | 0.55 | 0.50 | 0 | 1 |
| Funds for Recreation | 0.57 | 0.50 | 0 | 1 |
| Funds for Parks | 0.06 | 0.23 | 0 | 1 |
| Funds for Trails | 0.01 | 0.09 | 0 | 1 |
| Funds for Habitat | 0.01 | 0.12 | 0 | 1 |
| Funds for Watersheds | 0.04 | 0.19 | 0 | 1 |
| County First | 0.87 | 0.34 | 0 | 1 |
| Repeat Referenda | 0.42 | 0.49 | 0 | 1 |
| Pre-1997 | 0.03 | 0.18 | 0 | 1 |
| 1998 | 0.14 | 0.34 | 0 | 1 |
| 1999 | 0.08 | 0.28 | 0 | 1 |
| 2000 | 0.07 | 0.26 | 0 | 1 |
| 2001 | 0.13 | 0.34 | 0 | 1 |
| 2002 | 0.07 | 0.26 | 0 | 1 |
| 2003 | 0.09 | 0.29 | 0 | 1 |
| 2004 | 0.10 | 0.30 | 0 | 1 |
| 2005 | 0.07 | 0.26 | 0 | 1 |
| 2006 | 0.06 | 0.23 | 0 | 1 |
| 2007 | 0.06 | 0.24 | 0 | 1 |
| 2008 | 0.05 | 0.22 | 0 | 1 |
| 2009 | 0.02 | 0.13 | 0 | 1 |

**Table 2: Municipality Summary Statistics**

| | Held a Referendum | | | | No Referendum | |
|---|---|---|---|---|---|---|
| | Passed at Least 1 N = 218 | | Never Passed N = 39 | | N = 309 | |
| Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Med Home Values | 231.21 | 114.68 | 222.99 | 119.71 | 177.45 | 115.56 |
| Homeownership | 81.91 | 11.70 | 76.25 | 16.12 | 68.01 | 19.37 |
| Property Tax Rate (%) | 2.42 | 0.47 | 2.45 | 0.49 | 2.73 | 0.93 |
| % Muni with Bachelor | 0.38 | 0.16 | 0.34 | 0.14 | 0.26 | 0.15 |
| % Muni over 65 | 0.13 | 0.06 | 0.15 | 0.06 | 0.15 | 0.06 |
| % Muni Under18 | 0.24 | 0.04 | 0.22 | 0.04 | 0.21 | 0.05 |
| Men per 100 Females | 95.22 | 5.37 | 94.49 | 5.71 | 97.13 | 25.72 |
| % Black | 3.77 | 5.37 | 6.88 | 7.77 | 9.49 | 15.58 |
| Pop Density/Sq mi. | 1,767.68 | 2,619.28 | 2,415.39 | 1,819.81 | 4,560.57 | 6,211.44 |
| % Area Open Space (2002) | 42.30 | 17.94 | 38.74 | 15.13 | 35.99 | 17.75 |
| % Chg. Open Space(95-02) | -5.76 | 3.13 | -5.65 | 2.98 | -5.98 | 3.89 |
| % Urban Area (2002) | 8.58 | 4.37 | 7.74 | 3.91 | 7.16 | 4.41 |
| % Muni Area Water | 0.07 | 0.24 | 0.07 | 0.17 | 0.16 | 0.87 |
| % County Vote Bush (2000) | 0.32 | 0.07 | 0.32 | 0.06 | 0.29 | 0.07 |
| Unemployment Rate | 4.80 | 0.75 | 5.07 | 1.13 | 5.34 | 1.00 |
| Median HH Income | 74,733.24 | 20,187.93 | 66,692.62 | 22,686.27 | 55,298.82 | 20,144.50 |
| Inc. % < 10,0000 | 3.51 | 2.02 | 4.76 | 2.73 | 6.24 | 4.18 |
| Inc. % 10,000-14,999 | 2.94 | 1.65 | 3.83 | 1.75 | 5.00 | 2.73 |
| Inc. % 15,000-24,999 | 6.65 | 3.11 | 7.98 | 3.28 | 10.32 | 4.24 |
| Inc. % 25,000–34,999 | 7.48 | 2.82 | 8.64 | 3.06 | 10.84 | 3.75 |
| Inc. % 35,000-49,999 | 12.19 | 3.57 | 13.60 | 3.98 | 15.54 | 5.02 |
| Inc. % 50,000-74,999 | 20.09 | 4.63 | 20.53 | 4.56 | 20.89 | 4.70 |
| Inc. %75,000-99,999 | 15.77 | 3.25 | 14.39 | 2.91 | 12.96 | 4.08 |
| Inc. % 100,000-149,999 | 17.23 | 4.89 | 14.57 | 5.11 | 10.99 | 5.57 |
| Inc. % 150,000-199,999 | 6.48 | 3.80 | 5.30 | 3.80 | 3.46 | 3.41 |
| Inc. % > 200,000 | 7.66 | 7.58 | 6.40 | 8.18 | 3.76 | 6.35 |

**Table 3: Appearance Regression Results**

| | Probit | | Probit Tax$^2$ | | SEM | | SEM Tax$^2$ | | Survival | | Survival Tax$^2$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Coeff | SE | Coeff | SE | Coeff | SD | Coeff | SD | Haz Ratio | SE | Haz Ratio | SE |
| Constant | 2.293 | 1.832 | -0.545 | 2.015 | 1.150 | 1.989 | 0.840 | 2.157 | --- | --- | | |
| Home own | 0.012$^{*}$ | 0.007 | 0.012$^{*}$ | 0.007 | 0.012$^{*}$ | 0.008 | 0.013$^{*}$ | 0.008 | 1.015$^{**}$ | 0.008 | 1.014$^{*}$ | 0.008 |
| Home Value | 0.000$^{**}$ | 0.000 | 0.000 | 0.000 | -0.003$^{**}$ | 0.001 | -0.003$^{**}$ | 0.002 | 1.000$^{**}$ | 0.000 | 1.000 | 0.000 |
| Tax Rate | -0.273$^{**}$ | 0.136 | 2.261$^{***}$ | 0.734 | -0.232$^{*}$ | 0.165 | -0.044 | 0.621 | 0.732$^{*}$ | 0.121 | 16.812$^{***}$ | 15.624 |
| Tax Rate$^2$ | --- | --- | -0.490$^{***}$ | 0.141 | --- | --- | -0.037 | 0.110 | --- | --- | 0.538$^{***}$ | 0.098 |
| Education | 2.825$^{***}$ | 0.790 | 2.875$^{***}$ | 0.826 | 2.695$^{***}$ | 0.919 | 2.711$^{***}$ | 0.922 | 19.068$^{***}$ | 16.204 | 19.987$^{***}$ | 17.289 |
| Over 65 | -2.966$^{*}$ | 1.701 | -3.087$^{*}$ | 1.734 | -2.454 | 2.145 | -2.487 | 2.150 | 0.017$^{*}$ | 0.039 | 0.020$^{*}$ | 0.046 |
| Under 18 | -2.658 | 2.146 | -3.151 | 2.188 | -1.410 | 2.527 | -1.536 | 2.538 | 0.138 | 0.256 | 0.113 | 0.212 |
| Male/Fem | -0.012 | 0.008 | -0.012 | 0.008 | -0.009$^{**}$ | 0.006 | -0.009$^{**}$ | 0.006 | 0.977$^{**}$ | 0.011 | 0.975$^{**}$ | 0.011 |
| % Black | -0.006 | 0.007 | -0.003 | 0.008 | -0.004 | 0.008 | -0.003 | 0.008 | 0.993 | 0.008 | 0.996 | 0.008 |
| Pop Density | 0.000$^{**}$ | 0.000 | 0.000$^{***}$ | 0.000 | 0.000$^{*}$ | 0.000 | 0.000 | 0.000 | 1.000$^{**}$ | 0.000 | 1.000$^{**}$ | 0.000 |
| % Urban02 | 0.000 | 0.007 | -0.001 | 0.007 | -0.002 | 0.008 | -0.002 | 0.008 | 1.008 | 0.010 | 1.006 | 0.010 |
| % OS 02 | 0.016 | 0.010 | 0.015 | 0.011 | 0.017$^{*}$ | 0.012 | 0.017$^{*}$ | 0.012 | 1.026$^{**}$ | 0.013 | 1.024$^{**}$ | 0.013 |
| % Chg. OS | -0.024 | 0.030 | -0.021 | 0.030 | -0.024 | 0.035 | -0.025 | 0.036 | 0.955 | 0.033 | 0.960 | 0.033 |
| % Water | -0.130 | 0.218 | -0.073 | 0.218 | -0.156 | 0.227 | -0.159 | 0.256 | 0.916 | 0.250 | 0.970 | 0.249 |
| Bush Vote | -3.342$^{**}$ | 1.675 | -3.567$^{**}$ | 1.718 | -3.019$^{*}$ | 1.938 | -3.026$^{*}$ | 1.974 | 0.005$^{***}$ | 0.011 | 0.004$^{***}$ | 0.009 |
| Unemp. | -0.207$^{*}$ | 0.114 | -0.195$^{*}$ | 0.115 | -0.197$^{*}$ | 0.132 | -0.192$^{*}$ | 0.132 | 0.754$^{**}$ | 0.104 | 0.752$^{**}$ | 0.103 |
| Med HH Inc. | 0.000 | 0.000 | 0.000 | 0.000 | 0.000$^{*}$ | 0.000 | 0.000 | 0.000 | 1.000 | 0.000 | 1.000 | 0.000 |
| Lambda | --- | --- | --- | --- | -0.032 | 0.098 | -0.033 | 0.095 | --- | --- | | |
| N | 566 | | 566 | | 566 | | 566 | | 543 | | 543 | |
| $R^2$ | 0.23 | | 0.25 | | 0.62 | | 0.64 | | --- | | --- | |

## Table 4: Passage Regression Results

| | OLS | | OLS Tax$^2$ | | SEM | | SEM Tax$^2$ | |
|---|---|---|---|---|---|---|---|---|
| Variable | Coeff | SE | Coeff | SE | Coeff | SE | Coeff | SE |
| constant | 1.264 | 0.783 | 1.425 | 0.913 | 1.222*** | 0.333 | 1.335*** | 0.233 |
| Home Own | -0.002 | 0.003 | -0.002 | 0.003 | -0.002 | 0.003 | -0.002 | 0.003 |
| Home Values | -0.001** | 0.001 | -0.001** | 0.001 | -0.001** | 0.001 | -0.001** | 0.001 |
| Tax Rate | -0.081 | 0.070 | -0.218 | 0.404 | -0.087 | 0.069 | -0.185 | 0.339 |
| Tax Rate^2 | --- | --- | 0.027 | 0.080 | --- | --- | 0.020 | 0.068 |
| Education | 0.832*** | 0.332 | 0.831*** | 0.332 | 0.759** | 0.329 | 0.758** | 0.330 |
| Over 65 | 0.015** | 0.006 | 0.015** | 0.006 | 0.016*** | 0.006 | 0.016*** | 0.006 |
| Under 18 | 0.020** | 0.010 | 0.021** | 0.010 | 0.020** | 0.010 | 0.021** | 0.010 |
| Male/Fem. | -0.007 | 0.005 | -0.007 | 0.005 | -0.005 | 0.004 | -0.005 | 0.004 |
| % Black | -0.003 | 0.005 | -0.004 | 0.005 | -0.004 | 0.004 | -0.004 | 0.005 |
| Pop Density | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| % Urban 02 | -0.001 | 0.003 | -0.001 | 0.003 | 0.000 | 0.003 | 0.000 | 0.003 |
| %OS 02 | 0.003 | 0.005 | 0.003 | 0.005 | 0.004 | 0.005 | 0.004 | 0.005 |
| % Chg. OS | 0.019* | 0.011 | 0.019* | 0.011 | 0.018 | 0.011 | 0.018 | 0.011 |
| % Water | 0.141 | 0.121 | 0.141 | 0.121 | 0.135 | 0.116 | 0.135 | 0.116 |
| Bush Vote | -1.563** | 0.688 | -1.561** | 0.689 | -1.787*** | 0.476 | -1.789*** | 0.581 |
| Unemp. | -0.067 | 0.045 | -0.068 | 0.045 | -0.073** | 0.035 | -0.074** | 0.037 |
| Med. HH Inc. | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Tax ¢/$100 | -0.005 | 0.022 | -0.005 | 0.022 | -0.012 | 0.021 | -0.012 | 0.021 |
| Not Nov. | 0.208 | 0.244 | 0.206 | 0.245 | 0.163 | 0.224 | 0.161 | 0.224 |
| County First | 0.014 | 0.093 | 0.013 | 0.093 | 0.033 | 0.085 | 0.033 | 0.085 |
| Repeat | -0.040 | 0.052 | -0.039 | 0.053 | -0.028 | 0.049 | -0.028 | 0.049 |
| OS Funds | -0.048 | 0.104 | -0.048 | 0.105 | -0.058 | 0.098 | -0.058 | 0.097 |
| Farm Funds | 0.085* | 0.048 | 0.087* | 0.049 | 0.097** | 0.046 | 0.098** | 0.046 |
| Rec Funds | -0.089* | 0.049 | -0.089* | 0.049 | -0.089** | 0.046 | -0.089** | 0.046 |
| Park Funds | -0.113 | 0.101 | -0.113 | 0.101 | -0.103 | 0.095 | -0.102 | 0.095 |
| Trail Funds | -0.006 | 0.255 | 0.000 | 0.256 | 0.025 | 0.236 | 0.029 | 0.236 |
| Wild Funds | 0.369* | 0.209 | 0.371* | 0.209 | 0.367* | 0.192 | 0.368* | 0.192 |
| Wtr. Shed Funds | 0.076 | 0.130 | 0.074 | 0.131 | 0.091 | 0.120 | 0.090 | 0.120 |
| pre1997 | 0.206 | 0.197 | 0.212 | 0.198 | 0.170 | 0.182 | 0.173 | 0.183 |
| 1998-2009 Vars. | *Jointly Significant* | | *Jointly Significant* | | *Jointly Significant* | | *Jointly Significant* | |
| lambda | --- | --- | --- | --- | 0.132*** | 0.048 | 0.134*** | 0.043 |
| $R^2$ | 0.336 | | 0.337 | | 0.354 | | 0.355 | |
| N | 358 | | 358 | | 358 | | 358 | |

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