Local choice of property taxation: Evidence from Norway

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Abstract. Fiscal competition may influence the design of tax systems. The tax competition literature has concentrated on mobility of tax base and tax levels, while we turn the attention to the political decision-making system and the determination of tax structure. In the Norwegian setting local governments make a discrete choice whether to have property tax. The local choice is investigated in an econometric model allowing for yardstick competition. Our results indicate that yardstick competition explains the distinct geographic pattern in local property taxation observed. Grants have no effect on the propensity to have property taxation, consistent with the flypaper effect. The main methodological challenge handled concerns spatial interaction with discrete choice.

Keywords: property taxation · yardstick competition · Bayesian spatial probit

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1. Introduction

The positive analysis of tax systems has integrated political economy analysis and assumes that fiscal competition may affect the tax design. Strategic interaction among governments may lead to a tax system that differs substantially from a tax system based on an evaluation of social costs and benefits. The tax competition literature has concentrated on mobility of tax base and tax levels, while we turn the attention to the political decision-making system and the determination of tax structure. We attempt to show that yardstick competition affects the choice of tax structure. The institutional context is the local choice of having property taxation in Norway. Local governments choose whether to have property taxation and the influence of neighbors is analyzed in a spatial econometric analysis with discrete dependent variables.

Our approach assumes a political economy model of the local decision to tax. Inman (1989) and Hettich and Winer (1999) advocate the understanding of tax structure as a political equilibrium. We extend their frameworks by embedding the analysis in a spatial interaction model. The local choice of having property taxation is possibly influenced by the choices of neighboring municipalities and this interdependency must be taken into account in a complete positive model of local taxation. Wilson and Wildasin (2004) offer a recent overview of fiscal competition and discussion of the empirical literature. We read the empirical studies as an overwhelming support of the existence of strategic interaction at the local government level, and that both tax base mobility and information asymmetries may be of importance. In our setting, since property taxation relates to immobile factors, yardstick competition is the most realistic form of fiscal competition.

Yardstick competition implies that voters make use of information about the political choices in neighboring local governments. The decisions of the neighbors carry an information externality, they represent information to evaluate the performance of own government. It follows that voters condition their electoral choices on the relative fiscal performance of their own versus neighboring local governments. The understanding of the mechanism was first developed by Salmon (1987) and formalized by Besley and Case (1995).

We are aware of three different studies of strategic interaction in property tax decisions within European countries. They all try to separate yardstick competition from competition for a mobile tax base, and they all point in the direction of the former. Bordignon et al. (2003) find that business property tax interdependence in Italian cities is present only in those cities where mayors can run for reelection and are not backed by strong majorities. Solé-Ollé (2003) finds that property tax mimicking among Spanish municipalities is stronger in election years and when the majority of the ruling parties is smaller. Finally, Allers and Elhorst (2005) study strategic interaction in residential property taxation in Dutch municipalities and find that interaction is weaker when the electoral margin is high. The Dutch setting is very similar to the Norwegian and is characterized by low mobility of the tax base and politically highly visible decisions. Compared to these studies we draw the attention to the tax structure and the discrete decision to have property tax.

Section 2 presents the empirical context and the data. The empirical approach is discussed in section 3 and section 4 presents our econometric strategy. The discrete choice to have property taxation (probit analysis) is analyzed in section 5. Section 6 offers concluding remarks.

2. Local Property Taxation in Norway

Local governments in Norway can choose to have residential property taxation. The financing of the local governments is highly centralized, and more than 80 percent of the revenues are generated from central government grants and regulated income taxes. The grants are distributed as block grants and are based on objective criteria, partly as tax equalization and partly as spending equalization. The income tax revenue is shared between local, county and central governments with the maximum income tax rate at the local level set by the central government. All local governments apply the maximum income tax rate and their grants and income tax revenue consequently appear as given. Local governments have some discretion in setting fees for infrastructure services and welfare services, but also the fees are regulated and with the general rule that they can only cover costs. Borge (1995) and Borge and Rattsø (2005) analyze the fee setting, and Carlsen et al. (2005) investigate the role of mobility for the determination of fees for infrastructure services. The choice of having property tax is the key local decision to tax. Borge and Rattsø (2004) analyze determinants of the tax structure, the mix of revenues from property taxation and fees. We will have a closer look at the discrete choice of having property tax. Oates (2001) offers a broad background on the role of property tax financing of local governments.

The property tax is defined by law (of June 6, 1975) and the decision to have the tax is fully in the hands of the local government. The law describes the property that can be taxed, the tax base assessment, and limits to the tax rate. Residential property taxation is restricted to urban areas, defined as towns and areas under construction that will appear as towns. This definition of an urban area is not very clear, and there are many court cases where property owners have argued that the area under taxation is not urban.

Local governments in Norway are heterogeneous with respect to population size, with many small municipalities up valleys and along fjords. The median municipality has about 4.500 inhabitants, while the average is a population of 10.000. Since we study the choice of having property tax, we exclude local governments that cannot have property tax because they have no urban areas. Based on experiences from other studies the cut off point is set to 2.500 inhabitants and exclude local governments with population below this. Given the 434 local governments in all in 2001, we apply data for 301 local governments, and 105 of them levy residential property taxation.[1]

We have access to survey data that allows us to calculate how much a standardized household will have to pay in property taxation in each local government levying residential property taxation. The standardized house is assumed to be 160 sq. meters with a market value of NOK 1 million (USD 160 000). The average effective tax for the standardized house is NOK 1820 (USD 290), varying from NOK 4312 to NOK 130. A majority of the local governments levy effective taxes between NOK 1000 and NOK 2000.

All local governments have an assessment of house values related to the income tax. The assessment value is on average about 30 percent of the market value. The locals differ in their assessment, although most of them have assessed values in the area of 15-40 percent of market value. In addition to differences in the assessment practice, there are also variations in deductions (14 out of 105 local governments use different forms of deductions). The property tax rate is restricted to the interval between 0.2 and 0.7 percent of the assessed housing value. 72 of the 105 local governments with residential property taxation apply the maximum rate, and the average tax-rate is 0.61 percent. In addition to the residential property tax about 120 other local governments have a commercial property tax. This is basically a tax on electric power stations and part of a system of distributing the resource rent of electricity based on waterfalls. The commercial property tax is excluded here.

3. Empirical Modeling

We study a situation where local governments can choose to have property taxation or not. Our approach is to study this as a discrete choice between two alternatives: with and without the tax. The dummy variable dptax is our dependent variable, and dptax = 1 when the local government has residential property taxation.

The standard fiscal demand model assumes that taxes are chosen in an evaluation of the benefits of the increased public services financed by the new tax against the costs of raising the new revenue. Local governments choosing not to have property taxation are allowed higher private consumption and lower public consumption compared to those with property taxation. Two key economic determinants of the fiscal demand model are the private income level ($\overline{y}$) and the central government grants (G), both measured in NOK 1000 per capita. The private income level also works as a proxy for the property tax base here, since data about property valuation at the local level are not available.

The fiscal demand model includes variables describing the political structure. Based on earlier Norwegian studies we include measures of political ideology and political fragmentation. The socialist share of the local council (SOC) is a measure of ideological orientation. Socialist oriented municipalities tend to have higher tax and spending levels. The importance of political fragmentation for fiscal demand is argued by Roubini and Sachs (1989) in an analysis of fiscal balance in OECD-countries. In the Norwegian local government setting Borge and Rattsø (2005) show that fragmentation increases the fee level. We hypothesize that local governments with more fragmented political system is more likely to have property taxation. Political fragmentation is measured by a Herfindahl-index of party fragmentation of the local council. When SH_p is the share of representatives from party p, then the Herfindahl index for party fragmentation (HERF) is given by:

$$\text{HERF} = \sum_{p=1}^{P} SH_p^2 . \tag{1}$$

The Herfindahl-index is generally given by 1/P, when the representatives are equally divided among P parties. The index has maximum value of 1 when there is only one party in the council. The Herfindahl index ranges from 0.14 to 0.60 in our sample, with a sample mean of 0.24.

The data are documented in Appendix Table 1. As control variables in all regressions we include population size (POPULATION), a measure of the income distribution (ratio of median to mean income, $\frac{y_m}{\bar{y}}$), the age distribution of the population (CHILDREN (below 5 years), YOUNG (between 6 and 15 years) and ELDERLY (above 66 years)), share of the population living in rural areas (RURAL) and a constant term.

4. Spatial Econometric Issues

Different approaches for undertaking estimation and inference in linear regression models with spatial effects are well developed. However, spatial models with discrete dependent variables have received little attention in the literature and empirical implementation of such models is an area of active research. The underlying problem is the (potential) interdependence in the endogenous variable giving rise to simultaneity. Case et al. (1993) innovated the econometric investigation of this type of strategic interaction in a study of the expenditure levels among US state governments (in the continuous setting). To solve the simultaneity problem in the discrete setting we need to rely on a spatial latent variable approach.[2] The latent model specification with spatial dependence can be expressed as:

$$\mathbf{dptax^*} = \rho\mathbf{W}\mathbf{dptax^*} + \mathbf{x}\boldsymbol{\beta} + \mathbf{u}, \tag{2}$$

or equivalently on reduced form:

$$\mathbf{dptax^*} = (\mathbf{I}-\rho\mathbf{W})^{-1}\mathbf{x}\boldsymbol{\beta} + (\mathbf{I}-\rho\mathbf{W})^{-1}\mathbf{u}. \tag{3}$$

The observed variable, $dptax_i$, is a dummy variable identifying local governments with residential property taxation and $dptax_i^*$ is its unobserved latent counterpart. The observed $dptax_i$ equals unity when $dptax_i^*>0$, and zero otherwise. **W** is a symmetric 301x301 weight matrix, with zeros in the diagonal and with elements w_{ij} different from zero if the two local governments are considered to be neighbors.[3] **X** is a matrix of property tax determinants of every local government, **β** is a vector of parameters and **u** is a vector of error terms which we for now assume to be normally distributed with homoscedastic variance:

$$\mathbf{u} \sim N(0, \sigma_u^2). \tag{4}$$

The spatial weights matrix, **W**, is determined apriori and can be considered as part of local government i's basic characteristics. In this analysis we follow the literature on fiscal competition and choose a definition of neighbors as municipalities with a common border. $W_{ij} = 1/m_i$ for all municipalities that are contiguous to municipal i, where m_i is the number of observations that are contiguous to municipal i. We expect ρ to be statistically different from zero if yardstick competition is a relevant aspect of the choice of having property taxation.

The spatial autoregressive probit gives rise to a non-spherical variance-covariance matrix given by:

$$\mathbf{Cov(u)} = \left[(\mathbf{I} - \rho\mathbf{W})(\mathbf{I} - \rho\mathbf{W})'\right]^{-1} \sigma_u^2 . \tag{5}$$

The error terms will consequently be homoscedastic only if ρ=0. Heteroscedasticity can be relatively benign in models with continuous dependent variables, but it is a serious problem in discrete dependent variable models, causing estimates to be inconsistent (McMillen, 1992). There are basically two potential remedies to this problem. Some authors, such as Case (1992) and Pinkse and Slade (1998), have proposed to ignore the off-diagonal elements of the variance-covariance matrix and focus on the heteroscedasticity induced by spatial dependence. This method yields consistent, but not fully efficient estimates of the spatial probit model. To obtain consistent and fully efficient estimators, one has to deal with multidimensional integrals (Anselin, 2002, Fleming, 2004). Fleming (2004) presents a survey of different simulation techniques available for solving this problem. He concludes that the Bayesian approach based on Lesage (2000) is the most flexible method. We follow the Bayesian approach when empirically analyzing yardstick competition in section 5.[4]

The Bayesian approach is a Markov Chain Monte Carlo (MCMC) method based on the Gibbs Sampler.[5] This is a data augmenting procedure suggested by Albert and Chib (1993) which provides the linkage between the discrete dependent variable and its latent continuous counterpart. We refer the reader to Lesage (2000) and Fleming (2004) for a complete presentation of the method. The Bayesian approach allows for heteroskedastic error terms after controlling for spatial dependence, ensuring that parameter inconsistency is not driven by heteroskedastic influences. This allows equation (4) to be generalized as:

$$\mathbf{u} \sim N(0, \sigma_u^2 \mathbf{V}),\ \mathbf{V} = diag(v_1, v_2, ..., v_n)\,. \tag{6}$$

Technically the Gibbs sampler proceeds as follows:

1. Start with arbitrary initial values for the parameter vector: $\left(\sigma_u^2, \rho, \beta_1, \beta_2, ..., \beta_k, v_1, v_2, ..., v_n\right)$.
2. Estimate σ_u^2 given all other parameters and the data.
3. Estimate $(\beta_1, \beta_2, ..., \beta_k)$ given all other parameters and the data.
4. Estimate $\left(v_1, v_2, ..., v_n\right)$ given all other parameters and the data.
5. Estimate ρ given all other parameters and the data.
6. Sample the conditional distribution for the latent variable (dptax*) given all parameter values.

This completes one pass of the Gibbs sampler process. The Gibbs sampler process is then repeated a large number of times to derive conditional distributions for all the parameters. Lesage (2000) has derived all the conditional distributions for the limited dependent Bayesian spatial models and it is this sampling procedure that is used to obtain parameter estimates. The mean of the conditional distribution is the final parameter estimate and the standard deviation of the distribution is used for inference. All MCMC sampling procedures reported below are based on 10000 draws with the first 2000 draws omitted. The first draws are omitted to allow the sampler to achieve a steady-state (the so called ‘burn-in period’). The estimates based on 1000 draws with the first 200 draws omitted were close to identical to the reported estimates, suggesting that one need not carry out an excessive number of draws in practice.[6] Note that we need to fix one of the unknown parameters in order to identify the other unknowns in the model (Holloway et al. 2002, p.394). We adopt the usual practice and fix σ_u^2 equal to unity.

An observed spatial pattern in property taxation is not necessarily due to competition among local governments. Also common shocks and unobserved correlates will appear as spatial auto-correlation. In empirical work it is a challenge to separate the spatial auto-regressive probit model from the spatial error probit model. With spatially correlated omitted variables, we have a pattern of spatial error of the form:

$$\mathbf{u} = \boldsymbol{\lambda}\mathbf{M}\mathbf{u} + \boldsymbol{\varepsilon}, \tag{7}$$

where ε is a well behaved error term and M is a neighbor matrix. Estimating the spatial autoregressive probit model can in principle lead to a false conclusion of yardstick competition (ρ>0) when ρ=0 holds in the true model. The ability to separate spatial lag from spatial error depends on the quality of the other explanatory variables in equation(2).[7] Bordignon et al. (2003) argue that yardstick competition is likely to show up as spatial error because the spatial lag model implicitly assumes that tax rates are spatially correlated *independently* of the levels of the other covariates, while the spatial error model tests for correlation of the tax rates which cannot be explained by the other covariates. In section 5 we estimate both the spatial lag and the spatial error model and compare them with respect to model fit and predictive ability.

5. The Discrete Choice of Having Property Taxes

Our main results are reported in Table 1. We start out with a benchmark formulation of the fiscal demand model ignoring the spatial dimension in model A. The extended formulation taking into account strategic interaction among neighboring governments are shown in models B and C. Model B is a straightforward probit estimation where the observed decisions of neighbors' represent the strategic interaction and simultaneity is ignored (more on this below). Model C is based on the Markov Chain Monte Carlo technique outlined in section 4 where spatial interaction in the latent variable is estimated. Model D assumes spatial error.

The estimated coefficients reported in Table 1 show the effect of a one-unit increase in each explanatory variable on the latent dependent variable. Since this effect is hard to interpret, we follow the common practice and express the marginal impact of a change in each explanatory variable j on the probability that the dependent variable equals 1, i.e.

$$\frac{d\,\Pr[dptax_i = 1 \mid \mathbf{X}_i]}{dX_{ij}} = \hat{\beta}_j\,\phi(\mathbf{X}_i\,\hat{\beta}), \tag{8}$$

where ϕ is the standard normal probability density function and '^' indicates parameter estimate. Since this measure differs for each observation i we compute the marginal impact for each observation and average over this set of values. Finally, for ease of interpretation we provide the marginal effect of a one standard deviation (s.d.) increase in each explanatory variable.

In the presence of spatial interdependence, the usual expression for computing marginal effects, given by equation (8), is no longer valid. Since other observations are endogenously responding to changes in any explanatory variable one needs to take into account the so called 'spatial multiplier' when calculating marginal effects. For a complete description of how the marginal effects are calculated in models C and D, we refer the reader to Beron and Vijverberg (2004: 173-175).

Table 1 about here.

The positive and statistically significant spatial lag parameter in Model C suggests that if a given municipality's neighbors propensity to levy property taxation increases, this increases the original municipality's probability of levying property taxation. The result implies that fiscal competition matters when local governments make tax decisions. With limited mobility of the tax base and politically highly visible decisions, we interpret the spatial interdependence found to be driven by yardstick competition rather than competition for a mobile tax base. Existing empirical studies of relevance typically also point to yardstick competition as the most likely source of strategic interaction (Allers and Elhorst, 2005, provide an overview).

Equation (2) implies that it is the neighbor's latent variable (Wdptax*) that matters for local government i, and not neighbors' observed decisions (Wdptax). The estimate of ρ in model C captures strategic interaction in "underlying" propensities to levy property taxation. The alternative model B assumes that the propensity to levy property taxation depends on the observed decision of neighbors ($\mathbf{dptax^*} = \rho\mathbf{Wdptax} + \mathbf{x\beta} + \mathbf{u}$), which is the formulation most in line with the intuition of yardstick competition. Only the latent variable model C represents algebraically consistent handling of the endogeneity problem (Beron and Vijverberg, 2004, Klier and McMillen, 2007). Model B is included for comparison and to calculate the interaction effect comparable to other studies.

The estimate of strategic interaction is assumed to be upward biased when simultaneity is not taken into account. The marginal effect with upward bias in model B is calculated to 0.4. The size of the effect is similar to studies of property tax competition in continuous tax revenue. Allers and Elhorst (2005), Bordignon et al. (2003) and Sollé-Ollé (2003) all find reaction coefficients of 0.3-0.4 studying property tax decisions in a continuous setting in the Netherlands, Italy and Spain respectively.

As an alternative to the spatial lag model, we also estimate the spatial error probit model with the MCMC approach, reported as model D in Table 1. Again we find evidence of a geographic pattern in the property taxation decisions. The spatial error probit yields a Pseudo-R^2 and a spatial effect (λ) of the same magnitudes as in model C. We cannot rule out that omitted spatially correlated variables are an important part of the spatial auto-correlation, but our set of control variables do include the factors shown to be of importance in other studies of local taxation in Norway. The estimated spatial lag parameter is generally not sensitive to what control variables that are included in our probit models. Since the interaction effect, ρ, does not change much as additional covariates are included in the regression it is less likely to change if we were able to add some of the potentially missing omitted variables. The spatial error parameter, λ, is somewhat more sensitive to which control variables that are included.

The geographical distribution of the use of residential property taxation as a local tax shows a clear pattern. An interesting observation is that none of the municipalities in the counties Vestfold and Akershus levy residential property taxation. The counties are close to Oslo and most of the local governments have a high private income level. Our interpretation is that yardstick competition holds them all away from property taxation.

Apart from yardstick competition, several other municipality characteristics affect the discrete choice decision whether to levy property taxation. The fiscal demand variables included are private income level and central government grants. The likelihood of having property tax decreases with the level of private income. The effect is statistically significant and quantitatively important. A one standard deviation increase in private income reduces (on average) the probability of levying property tax with approximately 16 percentage points. Since private income represents both a demand effect and is an indicator of the local tax base, the negative coefficient shows that the tax base effect dominates. In the demand framework, higher private income is expected to lead to higher demand for local public services and having property tax is a way of arranging additional revenue to finance services. Central government grants have no statistically significant effect. This result is consistent with the flypaper effect.

In accordance with many other demand studies of local governments in Norway, ideology and fragmentation are shown to be important for the choice of property taxation. The share of socialists in the local council is an important predictor of property taxation. More socialists increase the likelihood of having property taxation. The size of the effect is quite large, a one standard deviation increase in the share of socialists increases the likelihood of having property taxation by 15 percentage points, on average. The result is consistent with the results of Borge and Rattsø (2004), who study the socialist influence in a model focused on the role of income distribution for the tax structure. Petterson-Lidbom (2004) has shown a similar effect of socialist orientation on the tax level in a Swedish study using the discontinuity method to compare local governments close to 50 percent socialists.

Political fragmentation (measured by the Herfindahl index, HERF) is shown to contribute to property taxation. Higher value of the index means less party fragmentation of the local council. The negative coefficient implies that increased party fragmentation is associated with higher likelihood of having property taxation. The quantitative effect is of political importance. A one standard deviation increase in party fragmentation increases the likelihood of having property tax by about 5 percentage points. The positive relationship between political fragmentation and likelihood of having property taxation is consistent with the Roubini and Sachs (1989) view that political fragmentation is a source of fiscal inefficiency. Perotti and Kontopoulos (2002) argue that political fragmentation may lead to excessive government and consequently a high tax level. In the Norwegian context, Kalseth and Rattsø (1998) show that political fragmentation in local governments has economic effects, in their data they found excessive administrative spending in fragmented councils. Borge (1995) find that political fragmentation is associated with higher level of user charges. In this understanding our relationship between fragmentation and property taxation may reflect 'political strength'. A strong political leadership may be better able to hold down the tax (and spending) level. An alternative interpretation says that political fragmentation motivates property taxation. The party fragmentation of the local council may motivate the introduction of property taxation to improve the incentives of the officials of the local government. We cannot discriminate between the two interpretations here.

Ignoring spatial dependence generally leads non-spatial models to attribute spatial autocorrelation in the dependent variable to explanatory variables rather than assign this variation to spatial dependence. This can potentially yield seriously biased effects in non-spatial models. We find that this is not the case for the discrete choice of property taxation. Comparing model A to model C we find that all marginal effects are only slightly underestimated in the non-spatial probit model.

The predictive ability of the models is described in Table 2. The upper panel shows the relationship between actual and predicted existence of residential property taxation. The prediction rule is such that dptax is predicted to equal unity if $\Pr[dptax_i = 1 \mid X_i, W] > 0.5$, and zero otherwise. All models correctly predict 226-229 of the 301 local governments in the sample or about 75 percent of the observations. Apparently the spatial probit models do not outperform the non-spatial probit model. However, as illustrated in the lower panel of Table 2, a closer comparison of the spatial vs. non-spatial probit reveals that Models C and D clearly predict better than model A. For most local governments that actually levies property taxation $\Pr[dptax_i = 1 \mid X_i, W]$ increases in the spatial probit models, while for most local governments without property taxation $\Pr[dptax_i = 1 \mid X_i, W]$ decreases. In aggregate, the spatial probit models have a better prediction for around 73 percent of the observations in comparison to the non-spatial probit model. We see this as another confirmation of the importance of the yardstick competition mechanism. Comparing the spatial lag probit to the spatial error probit we find that the former predict better local governments that levy property taxation, while the latter predict better local governments that do not levy property taxation.

Table 2 about here.

6. Concluding Remarks

Local governments in Norway can choose to have residential property tax. In this positive analysis of taxation we have shown that the chosen tax structure is affected by yardstick competition. The main econometric challenge addressed concerns spatial models with discrete dependent variables. The yardstick competition generates a distinct geographic pattern in local taxation. It is a challenge for future research to discriminate between alternative econometric representations of fiscal competition with discrete dependent variables.

The analysis also addresses broader determinants of the choice of having property taxation. Grants have no effect on the propensity to have property taxation, consistent with the flypaper effect. Political factors are important. More socialists in the local council increase the likelihood of having property taxation. As expected, socialist oriented politicians contribute to higher taxation. More party fragmentation of the local council is associated with higher propensity to have property taxation. The conventional interpretation is in terms of 'political strength', that only a 'strong' council is able to hold back the spending pressure and hold down the tax level.

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Notes

[1] The cut off at 2.500 inhabitants seems to work well as a general criterion and only 3 local governments with property taxation are excluded. The capital Oslo is excluded and data for two local governments are missing.

[2] Other studies which pursue different versions of the spatial latent variable approach include Case (1992), McMillen (1992), Pinkse and Slade (1998), Holloway et al. (2002) and Klier and McMillen (2007).

[3] Local governments that are too small to be allowed to levy property taxation are unlikely to be used as yardsticks for voters and we consequently exclude local governments with population size less than 2500 also from the spatially lagged dependent variable.

[4] The analysis is carried out using James Lesage's spatial econometric toolbox in the Matlab environment and Tim Thomas' corrected scripts (downloaded from respectively http://www.spatial-econometrics.com/ and http://www.timthomas.net/, August 2005).

[5] A general introduction to the Gibbs sampler can be found in Casella and George (1992).

[6] We have also experimented with 20 000, 30 000 and 50 000 draws. The parameter estimates are basically unaltered.

[7] Anselin et al. (1996) have proposed some LM tests to separate spatial error from spatial lag, but these are not implementable in the discrete dependent variable case.

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Table 1. Probit estimates of the discrete choice of having property taxation.

	Model A				Model B				Model C				Model D			
Variable	Coeff.	t-prob.	Marginal effect	Marginal effect*s.d.	Coeff.	t-prob.	Marginal effect	Marginal effect*s.d.	Coeff.	p-value	Marginal effect	Marginal effect*s.d.	Coeff.	p-value	Marginal effect	Marginal effect*s.d.
SPATIAL LAG (ρ)					1.72	0.00	0.40	0.12	0.21	0.00						
SPATIAL ERROR (λ)													0.32	0.00		
$\overline{y}$	-0.03	0.00	-0.01	-0.16	-0.02	0.01	0.00	-0.10	-0.03	0.00	-0.01	-0.15	-0.03	0.00	-0.01	-0.16
G	0.05	0.19	0.01	0.04	0.00	0.91	0.00	0.00	0.04	0.14	0.01	0.03	0.03	0.28	0.01	0.02
SOC	4.34	0.00	1.11	0.15	3.78	0.00	0.88	0.12	5.13	0.00	1.11	0.15	5.36	0.00	1.13	0.15
HERF	-2.93	0.10	-0.75	-0.05	-2.98	0.11	-0.70	-0.04	-3.65	0.04	-0.79	-0.05	-4.32	0.04	-0.91	-0.06
$\frac{y_m}{\overline{y}}$	-2.70	0.39	-0.69	-0.03	-2.47	0.46	-0.58	-0.02	-3.27	0.21	-0.71	-0.03	-2.70	0.27	-0.57	-0.02
POPULATION	0.01	0.22	0.00	0.05	0.01	0.29	0.00	0.03	0.01	0.06	0.00	0.05	0.01	0.05	0.00	0.06
CHILDREN	24.94	0.10	6.40	0.06	38.49	0.02	9.00	0.09	37.06	0.02	8.05	0.08	30.25	0.06	6.39	0.06
YOUNG	-12.78	0.24	-3.28	-0.05	-17.34	0.12	-4.06	-0.06	-15.79	0.13	-3.43	-0.05	-17.85	0.12	-3.77	-0.05
ELDERLY	6.56	0.23	1.68	0.05	9.38	0.10	2.19	0.07	11.23	0.05	2.44	0.08	6.79	0.21	1.44	0.05
RURAL	-3.47	0.00	-0.89	-0.21	-3.85	0.00	-0.90	-0.21	-4.47	0.00	-0.97	-0.23	-4.69	0.00	-0.99	-0.23
Constant	5.65	0.21			3.77	0.42			6.01	0.13			7.83	0.11		
McFadden R^2	0.29				0.35											
Pseudo R^2									0.66				0.66			
Log likelihood	-138.13				-126.41											
Estimation method	ML				ML (exogenous spatial lag)				MCMC				MCMC			
Number of observations	301				301				301				301			

Table 2. Predictive ability of the models.

		Model A		Model B		Model C		Model D	
		Predicted decisions		Predicted decisions		Predicted decisions		Predicted decisions	
		dptax=0	dptax=1	dptax=0	dptax=1	dptax=0	dptax=1	dptax=0	dptax=1
Actual decisions	dptax=0	165	31	162	34	160	36	167	29
	dptax=1	42	63	38	67	38	67	46	59
	Correctly predicted	228		229		227		226	

		Model C vs. Model A		Model D vs. Model A		Model D vs. Model C	
		Increase in $\Pr[dptax_i = 1 \mid X_i, W]$	Reduction in $\Pr[dptax_i = 1 \mid X_i, W]$	Increase in $\Pr[dptax_i = 1 \mid X_i, W]$	Reduction in $\Pr[dptax_i = 1 \mid X_i, W]$	Increase in $\Pr[dptax_i = 1 \mid X_i, W]$	Reduction in $\Pr[dptax_i = 1 \mid X_i, W]$
Actual decisions	dptax=0	56	140	30	166	16	180
	dptax=1	77	28	54	51	15	90
Share of observations with better prediction		0.72		0.73		0.65	

Appendix Table 1. Data description and descriptive statistics

Variable	Description	Full sample (n=301)		Local governments with property taxation (n=105)		Local governments without property taxation (n=196)	
		Mean	**St.dev.**	**Mean**	**St.dev.**	**Mean**	**St.dev.**
dptax	Dummy taking the value 1 for local governments levying residential property tax	0.35	0.48				
W*dptax	Spatially lagged value of dptax, interpreted as the share of neighbors with residential property taxation.	0.26	0.22	0.35	0.22	0.21	0.21
$\overline{y}$	Average before tax income for every person 17 years and older, measured in NOK 1000.	224.26	24.14	220.41	18.01	226.33	26.67
G	The sum of lump-sum grants from the central government and regulated income and wealth taxes, measured in NOK 1000 per capita.	23.88	3.32	23.74	3.03	23.95	3.47
SOC	The share of socialist representatives in the local council. A socialist is defined as a representative belonging to one of the following parties: NKP, RV, SV and AP.	0.37	0.13	0.44	0.12	0.33	0.12
HERF	Herfindahl-index measuring political fragmentation of the local council.	0.24	0.06	0.25	0.07	0.23	0.05
$\frac{y_m}{\overline{y}}$	Income distribution measured as the ratio of median to mean income, based on before tax income.	0.90	0.04	0.91	0.03	0.89	0.04
POPULATION	Total population in thousands (1st of January).	12.56	20.19	18.17	29.90	9.55	11.14
CHILDREN	The share of the population 0-5 years (1st of January).	0.08	0.01	0.08	0.01	0.08	0.01
YOUNG	The share of the population 6-15 years (1st of January).	0.14	0.01	0.13	0.01	0.14	0.01
ELDERLY	The share of the population 67 years and above (1st of January).	0.14	0.03	0.15	0.03	0.14	0.03
RURAL	The share of the population living in rural areas (3rd of November)	0.41	0.23	0.32	0.20	0.46	0.24

Note. The data on residential property taxation is collected in a survey carried out in 2001. The other data are provided by Norwegian Social Science Data Services and Statistics Norway. Neither of these institutions are responsible for the analyses conducted or for the conclusions drawn.