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TAX LIMITED REACTION FUNCTIONS

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SUMMARY

This paper models for the first time a spatial process in local tax policies in the presence of centrally imposed fiscal limitations. Focusing on the frequently encountered case of a tax rate cap, we evaluate three empirical approaches to the analysis of spatially dependent limited tax policies: 1) a Bayesian spatial approach for censored dependent variables; 2) a Tobit corner solution model augmented with a spatial lag; 3) a spatial discrete hazard model. The evidence arising from an investigation of severely state-constrained local vehicle taxes in Italy suggests that ignoring tax limitations can lead to substantial underestimation of inter-jurisdictional fiscal interaction.

Key words: tax limitations; tax reaction function; spatial auto-correlation.

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1 INTRODUCTION

Following early contributions in the 1990s (Case, 1993, Case *et al.*, 1993, Besley and Case, 1995), spatial econometrics methods pioneered by Cliff and Ord (1981) and popularized by Anselin (1988) have been extensively applied to the analysis of decentralized fiscal policy-making in the past two decades. Most of that research has focused on the investigation of spatial patterns in fiscal competition among local authorities (Brueckner, 2003, Revelli, 2005).

However, little attention has been devoted to the empirical modelling of spatially dependent fiscal policies in the presence of tax limitations imposed on local authorities by state (federal) governments. In fact, all of the existing empirical analyses of inter-jurisdictional fiscal competition rest on the often implausible assumption that local decision-makers are actually free to set their preferred tax policies.¹ Joumard and Kongsrud (2003) and Sutherland *et al.* (2005) document instead that most OECD country governments impose lower and/or upper limits on local tax rates, and forty-six of the US states place restrictions on local property taxes (Calabrese and Epple, 2010).² Overall, the examples of local tax limitations around the world are countless.³

This paper models for the first time a spatial process in local tax policies in the presence of centrally imposed fiscal limitations. Taking the conventional spatial lag specification that does not account for corner solutions at the tax limits as a benchmark, we evaluate three empirical approaches to the analysis of spatially dependent limited tax policies: 1) a Bayesian spatial approach for censored dependent variables; 2) a Tobit corner solution model augmented with

¹In an early study of property tax competition within the Boston metropolitan area, Brueckner and Saavedra (2001) indeed highlighted the link between local tax limitations and the intensity of tax competition. They pointed out that “reaction functions become flat once they encounter the levy-limit constraint” (Brueckner and Saavedra, 2001, p. 220), and acknowledged that “implementing this kind of double regime specification in a spatial lag context appears difficult” (Brueckner and Saavedra, 2001, p. 220).

²Local property tax rate limitations in the US states date back as early as the 1930s, and became widespread after California’s Proposition 13 in the late 1970s (Wolman *et al.*, 2008).

³Local tax limitations are in place in virtually all European countries, most frequently including local property taxes (for instance, the *Impuesto sobre los bienes inmuebles* in Spain and the *Grundsteuer* in Germany) and local business taxes (as the *Taxe professionnelle* in France and the *Imposta regionale sulle attività produttive* in Italy).

a spatial lag; 3) a spatial discrete hazard model focusing on the discrete corner solution outcome.

While in general, and similarly to standard multivariate analysis of limited dependent variables, the direction and size of the bias arising from ignoring tax limitations are unknown a priori (Pudney, 1991), intuition suggests that tax reaction functions become flat once authorities hit the tax limit, thereby leading to underestimation of the degree of inter-jurisdictional fiscal interaction when overlooking the constraint-induced corner solutions (Brueckner and Saavedra, 2001).

In order to verify if that intuition is correct and evaluate the performance of the above empirical approaches, we apply them to panel data over the years 2000 to 2006 on the vehicle registration tax policies of the one-hundred Italian provinces, where the state-wide tax rate cap was binding for about half of the authorities in the year 2000 and up to almost 90% of them in the year 2006. The results suggest that ignoring tax limitations can lead to substantial underestimation of inter-jurisdictional fiscal interaction. Explicitly allowing for the corner solutions generated by tax limitations provides significantly stronger evidence of spatial dependence than conventional models that ignore tax limits, calling for a rethinking of the existing empirical evidence on spatial correlation in local tax policies.

The paper devotes the next four sections to the illustration of each of the estimation approaches in turn, starting from the conventional spatial lag dependence model that ignores tax limitations in section **2**. Section **6** reports the estimation results on severely state-constrained local vehicle taxes in Italy, and discusses the relevance and applicability of those empirical approaches to other institutional contexts, focusing on their ability to capture the specific features of the tax limitations in force. Section **7** concludes by pointing to the need of explicitly considering top-down limitations when exploring the pattern of spatial dependence among decentralized policy-making units.

2 THE SPATIAL LAG DEPENDENCE MODEL

Scholars applying spatial econometric techniques to local government data have typically modelled the local tax rate determination process as a conventional spatial lag dependence specification:⁴

$$\tau_{it} = \rho\tau_{-it} + x'_{it}\beta + \varepsilon_{it} \quad (1)$$

where τ_{it} is the tax rate set by jurisdiction i ($i = 1, \dots, N$) in year t ($t = 1, \dots, T$), x_{it} is a vector of local characteristics (“internal” determinants of the local tax policy), and ρ (with $-1 < \rho < 1$ to ensure spatial stationarity) is the first-order spatial auto-regressive coefficient relating own tax rates to the spatially weighted average of other jurisdictions’ tax rates:

$$\tau_{-it} = \sum_{j=1}^N w_{ij}\tau_{jt} \quad (2)$$

where w_{ij} are non-stochastic weights that formalize the arrangement of jurisdictions in space. For instance, according to the conventional binary contiguity criterion and upon row-normalization, w_{ij} equals $\frac{1}{n_i}$ if jurisdiction j is adjacent to jurisdiction i , 0 otherwise, with n_i being the number of units sharing a border with unit i .⁵ Finally, ε_{it} is assumed to be independently and identically distributed across geographical units and over time.⁶

The spatial lag dependence model can be inverted and expressed in matrix form as:

$$\tau = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \varepsilon \quad (3)$$

⁴See the reviews in Brueckner (2003), Allers and Elhorst (2005) and Revelli (2005). More recent work (Elhorst, 2010a) calls for more general and encompassing spatial specifications that nonetheless ignore the external constraints (fiscal limitations) on local government policies.

⁵Clearly, alternative weighting criteria might be employed in order to reflect possibly more involved - and not necessarily of a geographical nature - interaction processes among local units (Revelli, 2005, 2008). However, the adoption of an adjacency-based criterion should suffice for the point to be made in this paper, and can be easily extended to any weighting criterion.

⁶In fact, residual spatial autocorrelation, i.e., the possibility of a spatial process in ε_{it} , ought to be tested for before estimating the spatial lag specification (1). See Elhorst (2010a) and section 6 below.

where I is the $(NT \times NT)$ identity matrix and $W = [I_T \otimes W_N]$ is the block-diagonal, row-standardized spatial weights matrix, with $W_N = \{w_{ij}\}$, $i, j = 1, \dots, N$, and $\sum_j w_{ij} = 1, \forall i$. Formulation (3) makes it clear that, with $\rho \neq 0$, a perturbation at any location will be transmitted to all other units. By assuming that $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$, the spatial lag dependence model can be estimated by maximum likelihood (ML) techniques (Anselin, 1988, Elhorst, 2010b).

However, local governments around the world are frequently subject to stringent regulations on their tax and spending decisions, making the ideal paradigm of intergovernmental competition sort of blurred in practice.⁷ A frequently encountered case is a cap ($\bar{\tau}$) on a local tax rate τ , meaning that $\tau \leq \bar{\tau}$ and ideally calling for a corner solution model accounting for clustering at the tax limit.

Overlooking the fact that a number of authorities might be tax-constrained at $\bar{\tau}$ is bound to lead to similar problems as the ones that are encountered in non-spatial econometric settings when the dependent variable is limited (Pudney, 1991). In particular, and most importantly for our purposes, the maximum likelihood estimate of the first-order spatial auto-regressive coefficient ρ measuring the degree of spatial dependence in (1) is biased. Intuitively, an authority hitting the tax limit $\tau_{it} = \bar{\tau}$ gives the impression of deliberately setting its tax policy independently of what happens in other jurisdictions ($\frac{\partial \tau_{it}}{\partial x_{jt}} = 0$ for $j \neq i$ in (3)), while being in reality constrained by state limitations to do so.

3 A BAYESIAN CENSORED DEPENDENT VARIABLE APPROACH

One possibility of empirically modelling a spatial process as (1)-(2) while allowing for the tax limitation $\tau_{it} \leq \bar{\tau}$ consists in following a latent variable approach (LeSage and Pace, 2009), and assuming that the observed tax rate τ_{it} in the

⁷The issue of capping on decentralized fiscal policies has attracted considerable interest in the theoretical and empirical public economics literature. Nechyba (1997), Cremer and Palfrey (2000), Vigdor (2004) and Calabrese and Epple (2010) investigate origins and political support for tax limitations. Wang (1999) and Konrad (2009) discuss the consequences of minimum tax rates in theoretical models of commodity and capital income tax competition respectively, while most of the empirical literature concerns the impact of tax and expenditure limitations on policy outcomes in the US states (Figlio, 1997, Downes *et al.*, 1998, Dye *et al.*, 2005).

presence of the tax limit is generated as:

$$\tau_{it} = \begin{cases} \bar{\tau} & \text{if } \tau_{it}^* \geq \bar{\tau} \\ \tau_{it}^* & \text{if } \tau_{it}^* < \bar{\tau} \end{cases} \quad (4)$$

where τ_{it}^* can be interpreted as the “desired” tax rate - i.e., the tax rate that would be set in the absence of tax limitations, but that might be unobserved due to capping - and is allowed to follow a spatial auto-regressive process:⁸

$$\tau_{it}^* = \rho\tau_{-it}^* + x'_{it}\beta + \varepsilon_{it} \quad (5)$$

$$\tau_{-it}^* = \sum_{j=1}^N w_{ij}\tau_{jt}^* \quad (6)$$

with w_{ij} playing a similar role as in (2) above. With $-1 < \rho < 1$, the matrix form of equation (5) can be inverted and expressed as:

$$\tau^* = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \varepsilon = (I - \rho W)^{-1} X\beta + u \quad (7)$$

where: $E(\varepsilon\varepsilon') = \sigma_\varepsilon^2 I$, and $u = (I - \rho W)^{-1} \varepsilon$, with variance-covariance matrix:

$$\Omega_u = (I - \rho W)^{-1} (I - \rho W)^{-1'} \sigma_\varepsilon^2 \quad (8)$$

The substantial difference of the latent variable model (7) with respect to a non-spatial specification ($\rho = 0$) is that the spatially correlated covariance structure (8) does not allow the simplification of the multivariate distribution into the product of univariate distributions. Moreover, the heteroscedasticity implied by the spatial covariance structure causes inconsistency of standard non-spatial limited dependent variable estimation methods (McMillen, 1992, Fleming, 2004).

A number of approaches have been recently proposed to consistently estimate variants of (7), particularly with reference to a binary dependent variable setting (spatial Probit), and where spatial dependence typically takes the form of a

⁸The argument that is being made here relies on the assumption that observations below the censoring point are unaffected by the existence of the tax cap. However, Konrad (2009) shows that this might not be the case in a theoretical framework of Stackelberg competition for mobile capital, due to the strategic effect of a non-binding tax limit.

first-order autoregressive process in the residuals (Pinkse and Slade, 1998):

$$\tau^* = X\beta + v \tag{9}$$

$$v = \lambda Wv + \varepsilon \tag{10}$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2 I) \tag{11}$$

where λ (with $-1 < \lambda < 1$) is the auto-regressive coefficient in the spatial error process and W is as defined above.⁹

The proposed estimation methods for the above models either focus on the heteroscedasticity induced by the spatial model structure and address it by making specific assumptions on the form of the spatial weights matrix (Case, 1992) and the variance-covariance structure (Pinkse and Slade, 1998), or make full use of the spatial information and rely on computationally complex techniques (the EM algorithm, simulation methods or Bayesian methods) to tackle the issue of multidimensional integration (Fleming, 2004).¹⁰

Within the latter class of models, the Bayesian spatial discrete choice method developed by LeSage (2000) overcomes some drawbacks that arise in the EM algorithm when estimating standard errors (McMillen, 1992), and has the advantage of allowing the errors to be heteroscedastic after controlling for spatial dependence. Moreover, it tends to be superior to simulation methods in terms of computational requirements and flexibility (Beron and Vijverberg, 2004), and seems the best suited to estimate a censored dependent variable model with simultaneous spatial dependence (Fleming, 2004). The Bayesian approach to limited dependent variables is based on the idea of treating the unobserved τ^* vector for corner solution observations as an additional set of parameters that are sampled sequentially from their conditional posterior distributions via an MCMC (Markov Chain Monte Carlo) sampling scheme. In particular, given N_c censored observations for which $\tau_{it} = \bar{\tau}$, and N_u uncensored observations

⁹Flores-Lagunes and Schnier (2011) develop a sample selection model with spatial error dependence both in the selection and in the main equation.

¹⁰Klier and McMillen (2008) propose a linearized logit version of Pinkse and Slade (1998) spatial GMM estimator that can be applied to a model with a spatially lagged latent dependent variable.

for which $\tau_{it} = \tau_{it}^* < \bar{\tau}$, the posterior distribution for the unobserved N_c vector is expressed as a multivariate truncated normal distribution, conditional on the N_u uncensored observations and model parameters (LeSage and Pace, 2009, p. 301). In practice, the latent variables τ^* for censored observations are obtained through Gibbs sampling with data augmentation, and the remaining model parameters are drawn sequentially from the same posterior distributions, conditional on τ^* , as in the continuous dependent variable case.¹¹

4 A TOBIT APPROACH

A potential drawback of the spatial latent variable specification (5)-(6) consists in the fact that it best applies to instances of true censoring - *i.e.*, non-observability of a variable above a given threshold, - while it is unlikely to capture the process that is at work in typical local public finance contexts, where tax limitations produce actual corner solution outcomes. In the presence of competition among local governments - say, to attract mobile business - each authority should be supposed to care about the actual policies enacted by its neighbors, not their (unobserved) desired ones. As a result, the empirical specification would require the “ideal” tax policy of each government (τ_{it}^*) to be affected by neighboring jurisdictions’ observed tax policies.

A feasible approach to modelling that sort of spatial spillover in the Tobit framework is based on the spatial discrete choice model developed by Dubin (1995) and implemented, among others, by Hautsch and Klotz (2003), Paez and Scott (2007) and Paez *et al.* (2008): it consists in allowing own latent attitudes towards taxation (τ_{it}^*) to be affected by neighbors’ time-lagged fiscal policies ($\tau_{jt-1}; j \neq i$) - *i.e.*, a space-time lagged specification.¹² Besides depicting a re-

¹¹The LeSage (2000) approach is extensively discussed in Fleming (2004) and LeSage and Pace (2009), and has been recently applied to a local public finance context by Fiva and Rattso (2007).

¹²On the other hand, a Tobit model where the optimal, unobserved tax policy of a government (τ_{it}^*) is allowed to be affected by neighboring jurisdictions’ contemporaneous observed tax policies ($\tau_{jt}; j \neq i$) is known to be algebraically inconsistent and cannot therefore be implemented empirically (Beron and Vijverberg, 2004, Klier and McMillen, 2007). In fact, postulating that the latent vector τ^* depends on the observed outcome vector τ via the spatial matrix W would imply that the probability of authority i ending up in a corner solution is af-

alistic process by which corner solutions arise as outcomes of fiscal externalities generated by the actual policies implemented in nearby localities (Case, 1992), a space-time lagged specification can be justified by the idea that the adjustment to neighboring authorities' policies does not take place instantly due to the sluggishness of the political process: upon observing the choices of their neighbors in year t , local governments react by selecting their own fiscal policies for the next period. This implies modelling the latent tax policy as:

$$\tau_{it}^* = x'_{it}\beta + \rho\tau_{-it-1} + \varepsilon_{it} \quad (12)$$

$$\tau_{-it-1} = \sum_{j=1}^N w_{ij}\tau_{jt-1} \quad (13)$$

According to (12), neighboring jurisdictions' tax policies in period $t - 1$ defined in (13) affect an authority's tax policy in the subsequent period t and, in the presence of the tax limitation $\tau_{it} \leq \bar{\tau}$, authority i might then end up in a corner solution outcome if $\tau_{it}^* > \bar{\tau}$. Moreover, an interesting feature of the space-time lagged model - as shown by LeSage and Pace (2009, p. 26) - is that the steady state equilibrium of a dynamic model where spatial units set their policies after observing decisions in neighboring units is approximately the same as that of a spatial autoregressive process as in equation (1). This can be proved by recursive substitution of τ_{-it-q} , $q = 1, \dots, T$, in (12) under the assumptions that $|\rho| < 1$, $x_{it} \approx x_i$, and W is row-normalized, leading to the reduced form $E(\tau) \approx (I - \rho W)^{-1} X\beta$.

Assuming that $\varepsilon \sim N(0, \sigma_\varepsilon^2 I)$ in (12), a space-time lagged corner solution Tobit model can be estimated, with $P(\tau_{it} = \bar{\tau} | x_{it}, \tau_{-it-1}) = \Phi\left(\frac{x'_{it}\beta + \rho\tau_{-it-1} - \bar{\tau}}{\sigma_\varepsilon}\right)$ for corner solution outcomes, and $f(\tau_{it} | x_{it}, \tau_{-it-1}) = \frac{1}{\sigma_\varepsilon} \phi\left(\frac{\tau_{it} - x'_{it}\beta - \rho\tau_{-it-1}}{\sigma_\varepsilon}\right)$ for observations below the tax limit. In order to obtain an estimate of the degree of inter-jurisdictional interaction that is comparable with the maximum likelihood estimate of the spatial lag dependence model that ignores the tax limitations, we will focus on the marginal effects based on the expected value of

pected, via the feedback from neighboring jurisdictions, by the observed outcome of authority i being against a tax limit.

the tax rate conditional on exogenous observable variables and neighbors' tax rates ($E(\tau_{it} | x_{it}, \tau_{-it-1})$).

5 A DISCRETE HAZARD APPROACH

Finally, the spatial latent variable specification (5)-(6) and the space-time lagged Tobit specification (12)-(13) rely on the conventional assumption that, in every period, a government elaborates its optimal tax rate by making marginal adjustments based on the realizations of the observables. Casual observation of local government taxing behavior as well as a look at the dataset illustrated in section 6, though, suggest that the above models might not be properly capturing two empirical features that are frequently observed in local government data. First, it is rarely the case in practice that a government hitting the upper bound (the tax cap) ever reverts from there in the future, giving the impression of experiencing an irreversible failure as the ones that are typically captured in hazard models (Jenkins, 1995). Second, local governments are often observed to adjust their policies infrequently, probably due to the political costs of a tax policy change: for instance, the event of a government “jumping” to the corner solution tax limit (or even from the lower to the upper limit) is not rare in the dataset described in section 6.

In order to embed those frequently encountered features in our empirical work, this section treats the occurrence of a government ending up in a corner solution as a discrete and irreversible event. We model the event of local government i hitting the threshold $\tau_{it} = \bar{\tau}$ at some point $t = 1, \dots, T$ as a discrete failure, and estimate the probability - or hazard - of exiting from the inner interval $(0, \bar{\tau})$ in period t conditional on having survived until then (Jenkins, 1995).

In particular, let $T_i \in t = \{1, 2, \dots, T\}$ denote the discrete survival time of local government i , i.e., the number of years that elapse before the government sets the maximum tax rate. The authorities surviving until the end of the period with $\tau_{it} < \bar{\tau}$ have a (censored) duration of $T_i = T$. The hazard function of T_i

is the probability that $T_i = t$, conditional on government i not having failed in previous periods and on a number of time-varying characteristics plus a set of time dummies capturing duration dependence. Define the index function y_{it} :

$$y_{it} = \begin{cases} 1 & \text{if } \tau_{it}^* \geq \bar{\tau} \\ 0 & \text{if } \tau_{it}^* < \bar{\tau} \end{cases} \quad (14)$$

Observations for which the event never occurs in the period considered take value 0 in all years; when the event occurs ($y_{it} = 1$), the local government exits the sample. In order to ascertain whether neighboring governments' fiscal choices affect the probability that a government hits the upper bound, it seems reasonable to follow the argument in section 4 above and allow τ_{it}^* to be defined as in (12)-(13). Under the assumption of ε_{it} being normally distributed, the hazard model can be estimated by standard Probit according to the index function (14). Clearly, the estimated coefficients from the discrete hazard model - in particular, the change in the probability of hitting the tax limit following a change in the τ_{jt-1} variable - will only be qualitatively comparable with the ones from the previous models.

6 EMPIRICAL ANALYSIS

6.1 The provincial vehicle tax in Italy

While almost entirely neglected in the empirical public economics literature, vehicle taxation is widely employed at the decentralized level in both developed and developing countries, and might generate spatial auto-correlation for two reasons.¹³ First, as long as the tax base (motor vehicles) is mobile across jurisdictions, local vehicle taxation might give rise to competition to attract tax base and induce correlation across neighboring authorities' fiscal policies. Second, due to the high visibility of vehicle taxes and the widespread ownership of motor vehicles, vehicle taxation can work as a signal of a government's quality, and could therefore foster accountability and yardstick competition between decentralized governments (Besley and Case, 1995).

¹³Empirical analyses of decentralized vehicle taxation are Mahadi *et al.* (1993), Suter and Walter (2001), and Solé Ollé (2003).

The provincial vehicle registration tax was introduced in Italy in the year 2000 in order to reduce reliance on external funding of provincial expenditures. Given that vehicle tax revenues amount to around 60% of own tax revenues and are partly used for the maintenance of roads, the introduction of the vehicle tax was meant to enhance the accountability of local administrators to their electorates.¹⁴ All motor vehicles are liable to the payment of the tax the first time they are registered under a given owner's name in the archive of one of the 100 Italian provinces. The total tax due is made of a lump-sum amount plus a variable component that is related to the size, power and destination of the vehicle. Central government establishes a lower and an upper bound on the vehicle tax parameters, with the upper bound corresponding to a 20% higher tax burden than the one corresponding to the lower bound. Consequently, the decision of each province basically consists in determining autonomously the percentage tax spread (τ from here onwards, with $0 \leq \tau \leq 20$).

Table 1 reports the average τ along with the number of provinces setting the minimum ($\tau = \underline{\tau} = 0$) and maximum ($\tau = \bar{\tau} = 20$) tax spreads in each of the seven years following its introduction (2000-2006). The table shows that provinces steadily raised their tax spreads over time, with almost 90% of them hitting the upper bound by the year 2006. The nationwide growth in the provincial tax might have been caused by the increase in public spending responsibilities of provincial governments as a result of the process of devolution of administrative functions by upper levels of government (State and regions) during the 2000s. In fact, while the devolution of central and regional responsibilities to local governments was accompanied by growing grants to cope with the novel spending requirements, the financial inadequacy argument was forcefully put forward by provincial governments during the devolution process.¹⁵

¹⁴Italian provinces are responsible for maintenance of intermunicipal roads in non-metropolitan areas, while other roads are maintained by the State (national roads) or by the municipalities (municipal roads). This creates a complex overlapping of responsibilities that makes it hard to accurately measure the performance of provinces and renders the vehicle tax-public service provision nexus pretty loose in practice.

¹⁵In addition, during the years 2000s the Italian population rose from less than 57 to over 59 million and the total stock of vehicles expanded from less than 40 to over 46 million (data sources in Appendix). The tax cap was eventually raised to 30% in 2007.

A similar picture emerges from figure 1, where the evolution of the geographical pattern of the vehicle tax during the period under examination is depicted, and table 2, showing that the tax spread was raised by provincial governments 113 times between 2000 and 2006. Interestingly, the last column in table 2 shows that in only four of the 113 instances the tax rise occurred in a year when a provincial election was scheduled to take place, with the remaining 109 tax rises being decided in safer non-election years.¹⁶ Furthermore, while the chances of success of the incumbent in the overall sample exceed 75%, only 50% of the incumbents that raised the tax in election years managed to be re-elected, suggesting that electoral considerations play a role in vehicle tax setting, with provincial governments seeming to time tax increases in order to minimize their adverse popularity consequences.¹⁷

6.2 Estimation results

In order to verify if vehicle taxes across adjacent provinces are correlated, we start from the estimation of the spatial lag specification (1) that ignores statewide tax limits. In building the matrix of weights W , we employ the conventional border-sharing criterion - with $w_{ij} = 1$ if provinces i and j have a common border, 0 otherwise - and subsequently standardize W by row-sum division.¹⁸

The vector of time-varying explanatory variables x_{it} includes grants per capita, income (value added) per capita, the stock of vehicles registered in the

¹⁶Provincial elections take place every five years, with direct popular election of the president of the Province, typically out of four to five candidates, and the members of the provincial Council. $\frac{3}{4}$ of the 100 Provinces held an election around the middle of the period (2003-2004), while some Provinces had an election in the early 2000s and went again to the polls five years later.

¹⁷This evidence must of course be taken with caution due to the very few occurrences of tax rises in election years. In fact, the small number of observations precludes us from explicitly estimating a re-election equation.

¹⁸As far as the two islands are concerned, we maintain the strict border-sharing principle, in the sense that: a) provinces separated by sea are not considered neighbors; b) provinces located in the same island are considered neighbors only if they actually have a common border. This implies, for instance, that Sassari, the upper north province in Sardinia, is not taken to be a neighbor of the province of Cagliari, located in the deep south of the island; or that the province of Messina, on the extreme east of the island, is not a first-order neighbor of the province of Reggio Calabria, on the mainland, or Trapani, in the extreme west of Sicily.

province in the previous year, a dummy variable that equals 1 in election years, and a dummy variable that equals 1 if the government is right-wing. τ_{-it} is the weighted average of neighboring provinces' tax spreads defined in equation (2). Based on the fact that the (700×1) vector of average neighboring provinces' tax spreads equals $[I \otimes W] \tau$, where I is the (7×7) identity matrix and $W = \{w_{ij}\}$ is the (100×100) exogenous spatial weights matrix, the matrix form of equation (1) can be inverted as in (3) and estimated by maximum likelihood techniques.

The ML estimation results are reported in table 3. All specifications include fixed province (q_i) and time (z_t) effects. Column (a) reports the results of estimation of a non-spatial specification ($\rho = 0$); column (b) reports the ML estimates of a spatial lag specification including no covariates ($\beta = 0$); column (c) shows the corresponding ML results when all covariates are included; finally, column (d) contains the ML estimation results of a spatial error dependence model (Anselin, 1988), where $\rho = 0$ and nearby provinces are allowed to be hit by spatially auto-correlated shocks:

$$\tau_{it} = x'_{it}\beta + q_i + z_t + v_{it} \quad (15)$$

$$v_{it} = \lambda v_{-it} + \varepsilon_{it} \quad (16)$$

where, similarly to equation (2), v_{-it} is defined as:

$$v_{-it} = \sum_{j=1}^{100} w_{ij} v_{jt} \quad (17)$$

The tests for spatial auto-correlation in column (a) of table 3 point towards the presence of some positive spatial auto-correlation in the residuals of a non-spatial specification. The robust LM (Lagrange Multiplier) tests developed by Anselin *et al.* (1996) tend to favour the spatial lag dependence model over the spatial error dependence model.¹⁹

The parsimonious specification in column (b) of table 3 yields a significant ML estimate of the spatial auto-correlation coefficient ρ of about 0.12. After

¹⁹The Moran test is asymptotically distributed as a standard normal under the null hypothesis of absence of spatial auto-correlation, while the LM tests against the hypotheses of a spatial lag - model (1) - or a spatial error - model (15)-(16) - are both distributed as $\chi^2(1)$ (Anselin *et al.*, 1996).

controlling for a number of exogenous local characteristics, though, evidence of spatial dependence in τ dwindles. The ML estimate of ρ in column (c) is an admittedly not overwhelming and only marginally significant value of about 0.08. However, as argued above, this is what one could expect given the tax limitation on the dependent variable, and $\hat{\rho}_{ML}$ might be suffering from a downward bias. As for the other variables, right-wing ideology, proximity to elections, per capita income and grants from upper levels of government all tend to be associated with lower tax rates, and the stock of vehicles circulating in the province has a positive effect on the provincial tax rate.

Table 4 reports the direct and indirect marginal effects from the spatial lag specification in table 3, column (c), based on: $E(\tau) = S(\rho)X\beta = (I - \rho W)^{-1} X\beta$ (LeSage and Pace, 2009, p. 38). The direct effects of the x vector variables ($x_{irt}, r = 1, \dots, R$) on τ_{it} ($\partial\tau_{it}/\partial x_{irt} = S_{ii}(\rho)\beta_r$) depend on the diagonal elements of the $S(\rho)$ matrix, and capture the “feedback loops” from a change in x_{irt} on τ_{jt} ($j \neq i$) and back on τ_{it} , with $S_{ii}(\rho) \geq 1$ (Elhorst, 2010a). In practice, the magnitude of the direct effects depends on the position of units in space and on their degree of connectivity with other units as determined by W , and differs across units. Consequently, average direct effects based on the mean of the trace of matrix $S(\rho)$ are reported. Conversely, the indirect effects $\partial\tau_{it}/\partial x_{jrt} = S_{ij}(\rho)\beta_r$ ($j \neq i$) rely on the off-diagonal elements of matrix $S(\rho)$ and arise from the fact that a change in variable r in a single unit can potentially affect all other units. Average indirect effects are based on the mean of the row (or column) sums of matrix $S(\rho)$, and quantify the impact of a change in x_{jrt} in all other units on τ_{it} (or of a change in x_{irt} at a particular location on all other τ_{jt}).²⁰ None of the indirect effects in table 4, though, turns out to be statistically significant.

Table 5 reports the estimation results of the Bayesian spatial model.²¹ The

²⁰The average row sum (total impact *to* an observation) and the average column sum (total impact *from* an observation) are equal (LeSage and Pace, 2009, p. 37).

²¹Estimation is performed in Matlab based on the routines for a spatial auto-regressive censored dependent variable model (sart_g function) provided by James LeSage (www.spatial-econometrics.com).

estimate of the spatial auto-correlation coefficient is 0.15 and is highly significant in the basic specification with $\beta = 0$ (column (h)), while it is around 0.10 when the effect of the explanatory variables is accounted for (column (i)). Overall, the results from the Bayesian spatial model based on (5)-(6) provide a similar picture as the spatial lag specification that ignores censoring. The coefficient estimates on the other explanatory variables are similar in the two models: ideological, electoral and financial variables play a role in the provincial tax determination process, though income is estimated here to have a positive effect and vehicle stock a negative effect on the tax rate. Finally, the indirect marginal effects reported in column (k) are again hardly different from zero.

Table 6 reports the corner solution Tobit and discrete hazard estimates. Columns (m) and (n) refer to estimates from a Tobit model that only accounts for the upper bound on the tax rate, while columns (o) and (p) are based on a model that also accounts for the lower bound at 0. In all cases, the estimates of the Tobit partial effects computed at the sample mean $E(\tau_{it} | x_{it}, \tau_{-it-1})$ reveal an effect from neighbors' tax rates on the own tax rate that is highly significant and almost twice as large as the corresponding ML estimate of ρ from the previous models, suggesting that ignoring the corner solutions generated by tax limitations might lead to substantial underestimation of the local interaction process. On the other hand, the magnitude of the estimated coefficients on the other covariates declines. Accounting also for the corner solutions at the lower tax limits (for a total of 54 observations at the $\tau_{it} = 0$ corner solution, the 2000 cross-section being lost when taking one-year lags) further reinforces the evidence of an effect from previous period's tax policies in neighboring jurisdictions on own tax policies: as could be expected given that the corner solution tends to flatten the reaction function, the estimated coefficient on time-lagged neighbors' tax policies increases from 0.152 to 0.165 when the corner solution at zero is explicitly accounted for.²²

²²It could be argued that the rising number of capped authorities over time reduces the variability of the neighborhood variable, thereby making identification of ρ more heavily dependent on the information in the early sample years. When splitting the sample into two subsamples (2001-2003 and 2004-2006), and estimating the Tobit model on them separately, it

Finally, column (q) in table 6 reports the discrete hazard model results. Since the 2000 cross-section is lost in taking one-period lags of neighboring provinces' tax rates, and due to the fact that provinces leave the sample when hitting the upper bound, estimation is performed on an unbalanced panel data set of 150 observations, 32 of which reach the $\bar{\tau}$ limit over the years 2001 to 2006. Reported coefficients are partial probability effects computed at the sample means. Partial effects for dummy variables are computed as the change in probability when a dummy variable shifts from 0 to 1, so that, for instance, the probability that a right-wing government hits the upper threshold is estimated to be over ten percentage points lower than it is for a left-wing government. The coefficient on the election year dummy has a similar size, but is not statistically significant. As far as the effect of lagged neighboring provinces' tax policies is concerned, an increase by 2 percentage points in the average tax rate of neighboring provinces is estimated to raise the probability of a province hitting the upper bound $\bar{\tau}$ in the subsequent year by around 3 percentage points. This means that, for instance, an "average" left-wing government elected in the year 2000 has an around 20% probability of hitting the tax limit in 2001 (the second year in the sample) if neighboring authorities were setting a zero tax rate in 2000 ($\sum_{j=1}^N w_{ij}\tau_{jt-1} = 0$), while the probability remarkably jumps to about 50% if all adjacent provinces were upper-capped in 2000 ($\sum_{j=1}^N w_{ij}\tau_{jt-1} = 20$).

6.3 Discussion

Overall, the evidence reported in the above section suggests that tax limits play a non-negligible role and should be explicitly accounted for when modelling a spatial process in state-constrained local tax policies. In general, the performance of the modelling approaches that we have employed and their usefulness and applicability to other contexts than the one examined here will depend on their ability to capture the specific features of the institutional framework under consideration, namely the nature of the state-local government structure as well

turns out that the space-time lag coefficient estimate is similar in the two subsamples, though it is slightly bigger and more significant in the early sample years.

as the binding intensity of the tax limitations in force.

As far as the Bayesian censored dependent variable approach is concerned, its rationale and aims generally tend to make it more suited to true censoring applications - i.e., unobservability of a variable above (or below) a threshold - than to corner solutions arising as outcomes of fiscal externalities in the presence of imperative tax limits. The tax limited competition process seems in fact to be best captured by the more realistic - and computationally simpler - space-time lagged Tobit and hazard models, that allow for a sluggish response to neighboring authorities' policies and facilitate a reaction function interpretation of local governments' behavior.

As for the hazard model, its discrete nature makes it sort of problematic to directly compare its results with the ones emerging from the continuous dependent variable models, and would seem to jeopardize its general relevance in applied work. However, it is often the case in typical empirical applications that locally managed and centrally regulated policies - say, an explicit fiscal policy such as the choice of a local tax rate, or a labour market policy such as the size of a youth employment subsidy - can in fact be approximated by, or coded as, a binary choice. In practice, local decision-makers commonly face the choice of setting a standard fiscal effort that goes unnoticed to central regulators, or opting for a high intensity policy that is liable to capping. The closer the actual features of the local decision-making process to a binary choice, and the stronger the degree of irreversibility of that local choice (due, say, to an underlying trend pushing decision-makers towards the corner solutions), the more likely is the parsimonious and easy to implement discrete hazard model to be the most suitable approach for an investigation of the degree of dependence of a government policy on the policies of peer governments. On the other hand, if the discrete capping event is a rare and reversible event - with the realization of a corner solution outcome in a given period being likely to be followed by an internal solution in subsequent periods - and the variability of the observed governments' choices below (above) the upper (lower) limit is high, the space-

time lagged Tobit model seems preferable.

7 CONCLUDING REMARKS

This paper has explored for the first time the modelling of a spatial process in local tax policies in the presence of centrally imposed fiscal limitations. Spatial patterns in decentralized tax policies can in principle arise from a number of plausible sources - including competition to attract tax base and jobs, public expenditure spill-overs, or information externalities, - and have been the object of a sizeable empirical literature that has relied on the implicit and universal assumption that decentralized governments are free to set their tax policy instruments. However, local governments around the globe are commonly constrained by a number of top-down limitations on their fiscal policies, most frequently by the imposition of caps (or floors) on the tax rates they can set, making the ideal paradigm of open intergovernmental competition sort of blurred in practice.

While tax and expenditure limitation regimes vary considerably across countries, their common trait is the generation of corner solution outcomes for the authorities hitting the tax limits. By means of an empirical application to provincial vehicle taxation in Italy, and taking the conventional spatial lag specification that does not account for corner solutions as a benchmark, this paper has aimed at showing the working of different empirical approaches and pointing to the importance of the institutional set-up and data features in guiding the practitioner to select the most appropriate tool for the case under consideration. In particular, we have presented and implemented three empirical approaches to estimate the inter-jurisdictional spatial interaction coefficient in the frequently encountered case of central government exercising its command by imposing upper limits on local fiscal choices: 1) a Bayesian spatial approach for censored dependent variables; 2) a Tobit corner solution model augmented with a spatial lag; 3) a spatial discrete hazard model focusing on the discrete corner solution outcome.

It turns out that explicitly allowing for the corner solutions generated by tax

limitations unveils a significantly stronger spatial dependence process than when employing conventional approaches: the Tobit model yields an estimate of the spatial coefficient that is around twice as large as either the standard maximum likelihood estimate from the spatial lag dependence model that ignores tax limits (the baseline empirical model) or the Bayesian spatial censored model. Finally, the discrete hazard model that treats the occurrence of a government ending up in a corner solution as a discrete and irreversible event provides further corroborating evidence that the probability of an authority hitting the upper bound is strongly and significantly affected by the fiscal choices of neighboring authorities.

This paper represents just the first step into the empirical investigation of the impact of top-down fiscal limitations on horizontal competition processes, and the performance and usefulness of the modelling approaches that we have discussed need to be carefully evaluated in terms of their ability to capture the specific features of the institutional framework that is object of inquiry. However, explicit recognition of the fact that local governments are “creatures of state governments” (Calabrese and Epple, 2010) seems to require proper consideration of statewide tax limitation systems when exploring the pattern of spatial dependence in decentralized government policies.

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Table 1 The provincial vehicle registration tax: key statistics

	Average τ	$\tau_t = \underline{\tau}$	$\tau_t = \overline{\tau}$	$\tau_t = \overline{\tau} \mid \tau_{t-1} < \overline{\tau}$
2000	11.9	31	56	56
2001	14.5	19	68	12
2002	16.5	9	79	11
2003	16.7	8	80	1
2004	16.9	8	81	1
2005	17.6	6	86	5
2006	18	4	88	2
2000-2006	16.5			

Notes: 100 Provinces; τ is the provincial vehicle registration tax rate. $\underline{\tau}$ and $\overline{\tau}$ are the lower (0%) and upper (20%) bounds set by central government respectively.

Table 2 Vehicle tax policy and provincial elections

	$el = 1$	$\Delta\tau > 0$	$\Delta\tau > 0$ & $el = 1$
2000	6	69	2
2001	9	14	0
2002	10	15	1
2003	12	2	1
2004	63	3	0
2005	6	7	0
2006	13	3	0
2000-2006	119	113	4
% re-elected	76.5		50

Notes: 100 Provinces; $el = 1$ in year t if a provincial election is held in that year. $\Delta\tau = \tau_t - \tau_{t-1}$ is the change in the provincial vehicle registration tax rate τ from year $t - 1$ to year t . Setting a positive tax rate in year 2000 (the year of introduction of the provincial vehicle tax) is treated as a tax increase.

Table 3 Vehicle tax determination: spatial lag and error dependence

	(a)	(b)	(c)	(d)
	ML	ML	ML	ML
election dummy $_{it}$	-0.641 (0.443)		-0.608 (0.431)	-0.631 (0.440)
grants $_{it}$	-2.966*** (0.729)		-2.782*** (0.732)	-2.791*** (0.761)
income $_{it-1}$	-0.446* (0.244)		-0.430* (0.245)	-0.435* (0.248)
stock of vehicles $_{it-1}$	1.774** (0.718)		1.749** (0.715)	1.750** (0.716)
right-wing dummy $_{it-1}$	-0.575 (0.866)		-0.523 (0.851)	-0.503 (0.858)
ρ		0.117*** (0.008)	0.074* (0.040)	
λ				0.062 (0.054)
Observations	700	700	700	700
Moran test (p value)	1.882* (0.060)			
LM lag test (p value)	3.690* (0.055)			
LM error test (p value)	2.019 (0.155)			

Notes: dep. var. = provincial tax spread ($0 \leq \tau \leq 20$); standard errors in parentheses; *, **, *** (p-value < 0.10, 0.05, 0.01); fixed province and year effects included.

Table 4 Direct and indirect marginal effects: spatial lag dependence model

	(e)	(f)	(g)
	marginal effects (table 3, column (c))		
	direct	indirect	total
election dummy $_{it}$	-0.607 (0.431)	-0.048 (0.061)	-0.655 (0.466)
grants $_{it}$	-2.798*** (0.749)	-0.218 (0.192)	-3.016*** (0.789)
income $_{it-1}$	-0.430* (0.249)	-0.034 (0.038)	-0.464* (0.270)
stock of vehicles $_{it-1}$	1.748** (0.696)	0.145 (0.144)	1.893** (0.770)
right-wing dummy $_{it-1}$	-0.557 (0.866)	-0.039 (0.104)	-0.596 (0.940)

Table 5 Vehicle tax determination: Bayesian censored model

	(h)	(i)	(j)	(k)	(l)
	marginal effects				
			direct	indirect	total
election _{it}		-0.612 (0.824)	-0.614 (0.827)	-0.067 (0.112)	-0.681 (0.921)
grants _{it}		-1.252** (0.634)	-1.256** (0.636)	-0.136 (0.112)	-1.392** (0.712)
income _{it-1}		0.232*** (0.057)	0.233*** (0.057)	0.025 (0.016)	0.258*** (0.065)
vehicles _{it-1}		-0.649*** (0.067)	-0.651*** (0.067)	-0.071* (0.041)	-0.722*** (0.083)
right-wing _{it-1}		-2.615*** (0.554)	-2.623*** (0.556)	-0.287 (0.180)	-2.910*** (0.643)
ρ	0.153*** (0.051)	0.098* (0.050)			
Observations			700		
$\tau_{it} = \bar{\tau}$			538		

Notes: standard errors in parentheses; *, **, *** (p-value < 0.10, 0.05, 0.01); fixed year effects included.

Table 6 Vehicle tax determination: Tobit and hazard models

	(m)	(n)	(o)	(p)	(q)
	Tobit		Tobit		hazard
	(upper limit)		(lower and upper limits)		
election_{it}		-0.047 (0.551)		-0.032 (0.628)	-0.100 (0.078)
grants_{it}		0.002 (0.005)		0.001 (0.005)	-0.001 (0.001)
income_{it-1}		0.043 (0.038)		0.068 (0.044)	-0.017*** (0.006)
vehicles_{it-1}		-2.335*** (0.379)		-2.813*** (0.454)	-0.030 (0.051)
right-wing_{it-1}		-1.864*** (0.502)		-2.030*** (0.539)	-0.109* (0.070)
$\frac{\partial E(\tau_{it} x_{it},\tau_{-it-1})}{\partial \tau_{-it-1}}$	0.202*** (0.055)	0.152*** (0.047)	0.210*** (0.055)	0.165*** (0.053)	
$\frac{\partial P(\tau_{it}=\bar{\tau})}{\partial \tau_{-it-1}}$					0.015** (0.007)
observations	600	600	600	600	150
$\tau_{it} = 20$	482	482	482	482	32
$\tau_{it} = 0$	-	-	54	54	-

Notes: standard errors in parentheses; *, **, *** (p-value < 0.10, 0.05, 0.01); fixed year effects included.

Appendix

Table A1 Variables used in the analysis: descriptive statistics

	obs.	mean	s.d.	min	max
SPATIAL LAG DEPENDENCE, CENSORED, TOBIT MODELS					
Vehicle tax spread (%)	700	16.5	6.9	0	20
Stock of vehicles (,000)	700	426.9	486.1	57.1	3514.2
Income (value added per capita; ,000 €)	700	20.1	5.0	10.8	34.3
Current spending per capita (€)	700	155.4	50.8	55.6	327.3
Grants per capita (€)	700	93.8	49.0	3.5	243.2
Right-wing control (%)	700	36			
DISCRETE HAZARD MODEL					
Vehicle tax spread (%)	150	8.9	8.0	0	20
Stock of vehicles (,000)	150	704.5	822.0	59.5	3383.1
Income (value added per capita; ,000 €)	150	19.7	6.1	10.9	34.3
Current spending per capita (€)	150	136.0	40.8	69.7	251.3
Grants per capita (€)	150	79.9	44.8	11.9	196.7
Right-wing control (%)	150	55			

Table A2 Variables used in the analysis: data sources

	SOURCE	YEARS
Vehicle tax	Automobile Club Italy - Quattroruote	2000-2006
Stock of vehicles	Public Registry of Vehicles	1999-2006
Income	National Statistics Institute	1999-2005
Current spending	Italian Government, Home Office	2000-2006
Grants	Italian Government, Home Office	2000-2006
Right-wing control	Italian Government, Home Office	1999-2006

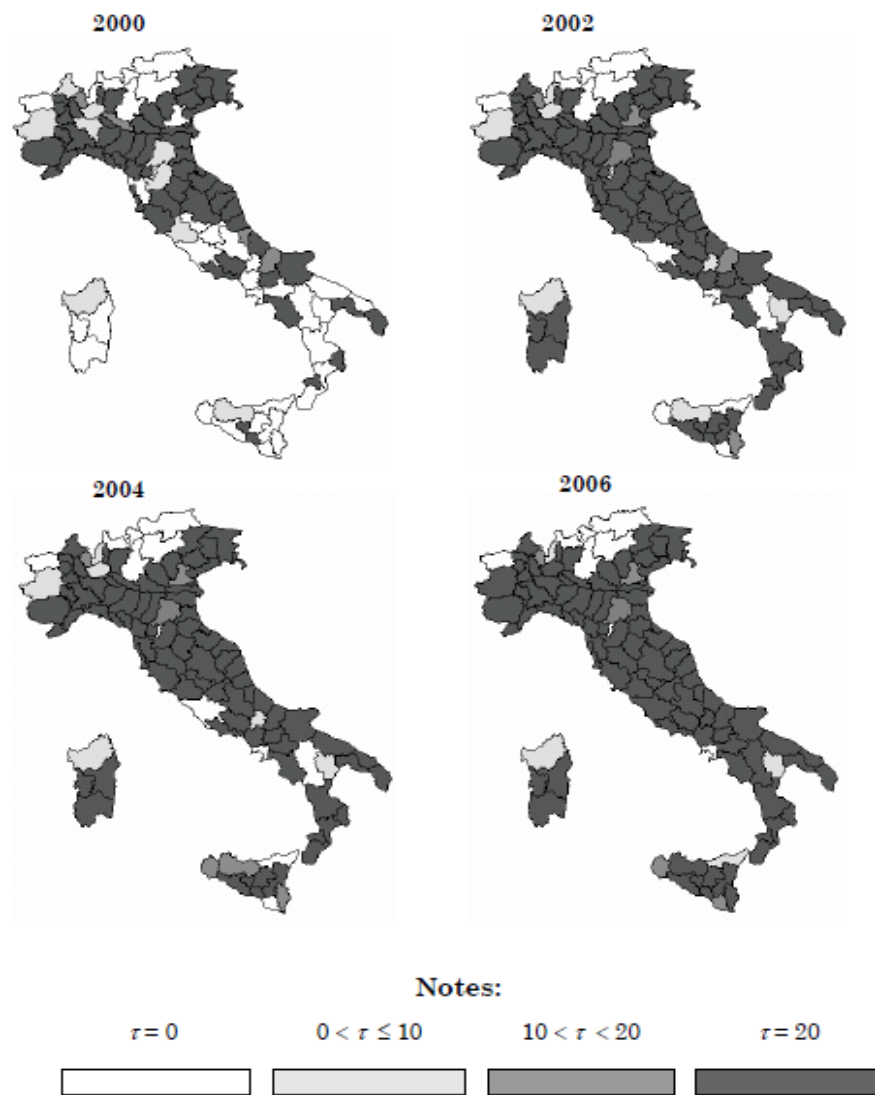


Figure 1: Vehicle tax spatial pattern