## 1. Introduction

The analysis of strategic interactions affecting tax policy has received major attention in the literature on local public economics in recent decades. Since the seminal contribution by Tiebout (1956), a number of research vectors has been followed. One of the most relevant concerns the existence of imitation mechanisms affecting municipal tax choices, including the tax mimicking hypothesis and the yardstick competition scenarios (Salmon, 1987; Besley and Case, 1995). Updated reviews of this empirical research vector are provided by Costa-Font, De-Albuquerque and Doucouliagos (2014),[1] and Delgado, Lago-Peñas and Mayor (2015).

Of course, benchmarking requires references. The idea that politicians, voters and other stakeholders look at neighbour municipalities as a shortcut seems reasonable. But how neighbourhood should be understood? This issue is crucial for developing theoretical mechanisms to explain interactions but also for empirical research.

The neighbourhood weight matrix is usually based on geographic proximity. In particular, jurisdictions sharing borders, distance or k-nearest jurisdictions. But it can also relies upon different socioeconomic characteristics. Some previous studies focus on per capita income to define the neighbourhood (e.g. Schaltegger and Küttel, 2002), but income is just one of the dimensions of wellbeing and, hence, it may be a partial and limited measure. To the best of our knowledge, this paper is the first attempt to incorporate differences in quality of life as a driver of strategic tax interactionsnthe major contribution of this research.

The motivation is straightforward. Jurisdictions may choose municipalities to be mimicked according not just to proximity in distance terms, but also to their rankings in indicators on social welfare and quality of life. Thus we are assuming that quality of life is key to understand the complex process affecting location decisions[2] by individuals and businesses, and in consequence the tax choices made by the incumbents. This standpoint

[1] Through a meta-regression analysis and regarding inter-jurisdictional fiscal interactions at the local level of government, they conclude that horizontal tax competition exists although it is weaker that in the county, state or nation level. Another interesting conclusion of this paper is that authors find little evidence of time variation in the magnitude of the interactions.

[2] See Lockwood and Rohlin (2014) for a recent study on interrelations between location-based tax incentives and quality of life and business environment.

presumes the existence of more sophisticated agents aware of differences in quality of life across municipalities. Agents would take them into account when they look for benchmarks to evaluate local tax policies.

In contrast with previous studies including all municipalities above a relatively small threshold in a certain territory, this research focuses on the largest municipalities. Specifically, the database includes Spanish municipalities over 50,000 inhabitants, considering that the tax imitation processes can be more feasible among neighbour jurisdictions of similar size. Nowadays this case has not been analysed in Spain, and only Dubois and Paty (2010) have paid attention to the biggest municipalities to date, concretely in France, where the definition of the neighbourhood cannot be based on the contiguity and hence socio-economic variables can be employed to that aim. Concretely, they consider neighbouring cities that are similar in terms of demographic characteristics, specifically the population size.

Finally, this paper focuses on the main local tax in Spain, the property tax, estimating different spatial models and comparing the results come out using economic and non-economic spatial weights matrices.

## 2. Theoretical background and empirical strategy

Following Brueckner (2003), the theoretical models underlying most of the empirical studies in the field of the strategic interaction among governments can be grouped into two categories: spillover models and resource-flow models, although lead to similar empirical specifications. The former include environmental models (Fredriksson and Millimet, 2002) and yardstick competition models, and the latter tax competition[3] and welfare competition models. In all these models a reaction function shows how the choices made by one jurisdiction depend on the choices of the other jurisdictions.

Our empirical strategy to analyse interactions among jurisdictions also relies on a tax reaction function estimated through spatial econometric models. The definition of the weight matrix (W) capturing potential linkages between the neighbouring is a first and key step. We assume that tax choices are based not only on the own municipal

[3] Wilson (1986) and Zodrow and Mieszkowski (1986). See Wilson (1999) for a review of theories of tax competition.

characteristics, but also on tax choices made by neighbouring jurisdictions, and inter-municipal differentials in the quality of life.

To configure matrix W ,we consider previous works in the literature. Its translation to the present case is straightforward. Case, Hines and Rosen (1993) suggest the construction of weights based on economic distance in a way that a bigger spatial weight is assigned to two territories where the similarity among them is as bigger. This is the simply expression to compute these weights:

$$w_{ij} = \frac{1}{|y_i - y_j|} \qquad [1]$$

Boarnet (1998) follows this proposal and normalize these weights such that the sum of the weights for any territory is 1 according to the expression:

$$w_{ij} = \frac{1/|y_i - y_j|}{\sum_j 1/|y_i - y_j|} \qquad [2]$$

In both cases, the weights are the result of comparisons, that is, they use distance measures or similarity indicators.

However, it is widely known that the construction of the W matrix is an open and debatable question to date. There are several possible specifications and few agreements regarding the criterions, depending on the specific study, available data, and so on. The use of definitions that include parameters may be troublesome in the estimation and inference procedures, and it leads us to a specification based on a binary matrix when the problem relies on the model errors. However, as the perspective is the modeling of spatial data, the weights structure that condition the covariance structure should be based on the spatial interaction theory and, hence, get some distance measure.

Corrado and Fingleton (2012) claim for a major research and justification in the elaboration of the weight matrix by using economic variables. More recently, Halleck Vega and Elhorst (2015) assert that “the basic identification problem in spatial econometrics is the difficulty to distinguish different models and different specifications of W from each other without reference to specific economic theories”.Liu and Martínez-Vázquez (2014) empirically address this issue in the context of the analysis of tax interactions. They follow the recommendation by Case, Hines and Rosen (1993) arguing that “neighbourliness does not necessarily connote geographic proximity”. Municipalities may consider as neighbours other municipalities that are similar to them economically, i.e. “spatial interactions do not have to be restricted” to their geographic neighbourhood, but can occur over longer distances if jurisdictions are similar in an economic sense” (Janeba and Osterloh, 2013). Liu and Martínez-Vázquez (2014) propose a different spatial weight matrix using a combination between physical distance and economic similarity using per capita GDP . Moreover, Hauptmeier, Mittermaier and Rincke (2012) propose a spatial weight matrix taking into account both the physical distance between municipalities and their different size in terms of population.

In our opinion, if economic and social issues matter for defining benchmarking peers, the weight matrix should be based on complex quality of life indexes to be able to capture the dimensions potentially relevant. Fortunately, Gonzalez, Carcaba and Ventura (2011) provide recent and complete estimates for the Spanish municipalities. Their index is based on a Value Efficiency Analysis (VEA)[4] and cover aspects related to consumption, social services, housing, transport, environment, labour market, health, culture and leisure, education and security, representing eight of the nine dimensions outlined by Stiglitz, Sen and Fitoussi (2009). Hence our main weight matrix will combine distance with the index produced by Gonzalez, Carcaba, and Ventura (2011) in the following way.

First, we consider that municipalities’ tax choices may affect and be influenced by other tax choices in municipalities located in their catchment area. This catchment area could be defined using a geographic criterion (distance) or considering the similarity between municipalities (economic distance). In the first alternative, the spatial weights are $w_{ij}{}^{d} = 1$ if the distance between municipalities i and j are less than a certain cut-off distance. Otherwise, its value will be zero. Following the second criteria the spatial weights are obtained using eq (1) and considered the quality of life index as the socio-economic channel through which comparison between municipalities come out and tax interaction operate. Then, $w_{ij}{}^{Q} = \frac{1}{\left|Q_i - Q_j\right|}$ if $i \neq j$ . These two spatial weight matrices are combined using the Hadamar product: $W^{QD} = W^{Q} \circ W^{D}$ . Once this spatial weight matrix is row-normalized each spatial weight is calculated following this expression:

[4] VEA is a weights restriction method that allows incorporate qualitative information into the Data Envelopment Analysis (DEA) specification, a non-parametric frontier analysis method extended in the efficiency literature. For detailed information regarding VEA see Halme *et al.* (1999).

$$w_{ij}^{QD} = \begin{cases} {}^{1}\!\!\diagup\!{\left|q_i - q_j\right|} \Big/ \sum_j \frac{1}{\left|q_i - q_j\right|} & \text{if} \quad d_{ij} < d \\ 0 & \text{in other wise} \end{cases}$$

### 2.1. Endogeneity

As Kelejian and Piras (2014) state, “researchers rarely consider the possible endogeneity of their weighting matrix even when its endogeneity is evident, although this is sometimes suggested”. The endogeneity issue is not only limited to how the spatial weights have been built, but spatial lag of the control variables in a SDM or SLX may be considered also endogenous. This problem has been pointed out by Fingleton (2008) and more recently by Kelejian and Piras (2014), Arbués, Baños and Mayor (2015) and Kelejian (2016), among others.

In order to deal with this endogeneity, we start by discussing two alternative solutions based, in both cases, on instrumental variables estimators. First, Kelejian and Piras (2014) try to build instrument variables by regressing the spatial weights on exogenous variables and propose a two stage least squares (2SLS) estimation for a short panel data. Recently, this proposal has been applied by Kostov and LeGallo (2015) using the sum of bilateral distances and the sum of estimated bilateral trade costs for each pair of countries as instrumental variables for the endogenous spatial weights. However, one shortcoming of this procedure is the high level assumptions to obtain the asymptotic results (Qu and Lee, 2015).

On the basis of this criticism, Qu and Lee (2015) for a cross-sectional setting, and Qu, Wang and Lee (2016) for a spatial panel framework, propose three estimation methods for dealing with an endogenous spatial weight matrix: two-stage instrumental variable (2SIV) method, quasi-maximum likelihood estimation (QMLE) approach, and generalized method of moments (GMM). The main difference is how they manage the endogeneity issue derived from the introduction of “economic” spatial weights. First, Qu and Lee (2015) derived the asymptotic results based on basic regularity conditions. Secondly, they propose the control function approach to solve the endogeneity issue derived from the endogenous weights, i.e. the source of endogeneity is modelled explicitly. Then, two equations appear: one for the non-zero values of the spatial weight matrix and other for the spatial process followed by the dependent variable. The disturbances in both equations are allowed to be correlated so “the spatial weight matrix becomes endogenous, when their correlation coefficient is non-zero”.More interesting for our research is approach performed by Qu, Wang and Lee (2016) to give evidence about the need to consider and solve the endogeneity issues derived from an “economic” spatial weight matrix[5].

With regard to the estimation method, we apply maximum likelihood (ML) and instrumental variables (IV) to fit the spatial lag model for both property tax indicators using both matrices. In this empirical exercise, we follow the strategy developed by Qu and Lee (2015) and Hsieh and Lee (2016) where the endogeneity is addressed using an auxiliary function (as it was described above) so we compare the estimations derived from ML and IV methods with the results once the endogeneity is handled. This method is named in the tables as 2SIV.

In the first step, we estimate the quality of life using the following regression model:

$$q_{it} = f(q_{it-1}, z_t, z_{t-1}) + \vartheta_{it} \qquad [7]$$

where $q_{it}$ is the quality of life of municipality *i* and year *t*, $q_{it-1}$ is the quality of life in the previous period, and *z* collects some variables about municipalities characteristics. The estimated residuals $\hat{\upsilon}_{it}$ are included in the spatial lag model as another control variable in a second-step of the estimation process:

$$T = \rho WT + \beta X + \gamma\hat{\vartheta} + \varepsilon \qquad [8]$$

[5] In their empirical setting, they estimate a tax interaction function following the spatial weight proposed by Redoano (2007).