ESTIMATING SPATIAL MODELS BY GENERALIZED MAXIMUM ENTROPY
OR
HOW TO GET RID OF W

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ESTIMATING SPATIAL MODELS BY GENERALIZED MAXIMUM ENTROPY *or* HOW TO GET RID OF W

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ABSTRACT:

The classical approach to estimate spatial models uses a spatial weights matrix to measure spatial interaction between locations. The rule followed to choose this matrix is supposed to be the most similar to the "true" spatial effects. Literature shows clearly the negative effects of the choice of a wrong matrix. The main problem is the lack of knowledge about which is the true specification. Furthermore, a single parameter is estimated and it should be seen as an average spatial effect among locations. In this paper we propose the use of maximum entropy econometrics to estimate spatial models. This method allows the estimation of a specific spatial parameter for each pair of regions and, hence, the spatial lag matrix is not chosen but estimated. We compare by means of Monte Carlo simulations classical with maximum entropy estimators in several scenarios on the true spatial effect. The results show that maximum entropy estimates outperform the classical estimates when the specification of the weights matrix is not similar with the true.

Keywords: spatial econometrics, generalized maximum entropy econometrics, spatial spillovers, Monte Carlo simulations.

JEL codes: C21

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1. INTRODUCTION

Since the seminal papers by Cliff and Ord (1973), Paelinck and Klassen (1979) and Anselin (1988) empirical studies with cross-section and panel data have kept into account the spatial dependence among locations by means of spatial econometrics techniques. Generally speaking, spatial econometric methods measure spatial interaction and incorporate spatial structure into regression analysis. Literature shows several methodological suggestions for including spatial relationships in econometric regression models. As a result, the empirical applications to several fields of economic analysis have mushroomed lately including, among others, studies in demand analysis, international economics, labor economics, public economics and local public finance and agricultural and environmental economics, to name but a few.

Although there are other approaches to address the spatial interactions in an econometric model, the most common procedure followed in the literature is to specify a determined spatial structure by means of a spatial lag operator [Anselin (1988)]. This "classical" approach uses a matrix **W** which elements w_{ij}, play a very important role. Each cell w_{ij} of this matrix measures the spatial interaction between the locations i and j and can be interpreted as the influence that a variable located in region j has over other (or the same) variable located in region i. However, the values of these elements are not estimated. Lag spatial matrix **W** is fixed exogenously to the model following some rule according with the convictions of the researcher about the "true", but unknown, spatial interaction. In other words, the **W** matrix is imposed by the researcher somehow. Once the values w_{ij} are a priori imposed, they are employed together with the data of the variables to estimate the model.

The problem on this approach rises because estimates (and, therefore, the accuracy of the model) rely very much on the choice of spatial weights **W.** This issue can be considered as an important question for the estimation of the spatial econometric models. In Stetzer (1982), a numerical experiment by a series of Monte Carlo simulations is carried out to test the effects on the forecasting accuracy of misspecifying the elements of **W**. Florax and Rey (1995) and Griffith (1996) made a similar exercise examining the consequences of misspecifications. [1]

In a few words, all these papers show that a "wrong" specification of **W** is an important problem. But the question now is: When is it wrong and when is it right? This point can be seen as a drawback of the classical spatial models. As Anselin (2002) says, "the specification

[1] Other papers where the effects of misspecification are treated are Anselin (1985) or Anselin and Rey (1991). Other more recent works that study the impact of different specifications of the weight matrices are Bavaud (1998), where he introduces the possibility of using non-zero weights for the elements in the main diagonal; or Getis and Aldstadt (2004), where they search a **W** matrix that measures all the spatial dependence

of the weight matrix is a matter of some arbitrariness and is often cited as a major weakness of the lattice approach." Furthermore, Case *et al.* (1993) point out that "in principle, it would be desirable to estimate the elements of the **W** matrix along with the other parameters. In practice, such an approach is out of the question because of insufficient degrees of freedom". As we will see in the following sections, generalized maximum entropy (GME) econometrics is well suited to deal with this problem. GME econometrics allows to estimate models where is not necessary the specification of an exogenous spatial lag matrix **W**, because it is possible to estimate a spatial parameter for each pair of regions. We compare the performance of this estimator with the competing "classical" approach based on maximum likelihood estimators in models where spatial structure is assumed by means of a weights matrix **W**.

The structure of the paper is as follows. In section 2 we describe the classical approach to estimate spatial models, and show our proposed model to simulate. Section 3 gives an overview and some intuitions of the GME methodology. Section 4 compares the performance of GME estimators with the competing estimators based on maximum likelihood technique. A series of Monte Carlo simulations are computed to evaluate both techniques under several spatial structures. Section 5 shows a sensitivity analysis, in order to check if the results obtained in the previous section depend excessively on the choice of the priors for the application of the GME technique. Finally, section 6 concludes.

2. A (MORE) GENERAL APPROACH FOR THE ESTIMATION OF SPATIAL EFFECTS

Depending on the assumptions about the way the spatial correlation affects the dependent variable, the literature distinguishes several possibilities, being the so-called spatial autoregressive (SAR) structure perhaps the most commonly used. Formally, for a set of N cross-sectional data, a SAR model can be written as:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{1}$$

where $\mathbf{y}$ is the $(N \times 1)$ vector with the values of the dependent variable, $\mathbf{W}$ is the $(N \times N)$ matrix of spatial weights, $\mathbf{X}$ is a $(N \times K)$ matrix of exogenous variables, $\boldsymbol{\beta}$ is a $(K \times 1)$ vector of parameters to estimate and $\boldsymbol{\varepsilon}$ is a $(N \times 1)$ stochastic error. In addition, ρ is a spatial interaction parameter that measures how the endogenous variable y is spatially influenced.

The previous specification is a simple way to model the spatial interactions among regions, but it is possible to claim some weakness for estimate it. Firstly, the model (1) has a single parameter ρ.[2] Hence, it is necessary to see the spatial interaction as an effect "in average" among regions. Furthermore, the estimated parameter ρ depends on the rule followed by the researcher to define the matrix **W**, as the literature clearly shows. Various possibilities have been suggested to define **W**, although most generally they are based on some concept of geographical proximity. Following this approach, a very simple way to characterize the elements w_{ij} is by defining them as binary variables that take value 1 when locations i and j have a common border and 0 otherwise. This is simple, but sometimes it seems to be of an excessive simplicity, since excludes the spatial relationships among non common-border regions. The geographical distance between locations i and j can be used in a more direct way, defining w_{ij} as a negative function of distance. Other authors claim for using not physical but economic measures of distance, based on interregional trade flows, income differences, etc.[3]

The election of this matrix is always in some sense a question of subjectivity introduced in the estimation. As a result, the estimation of the effect of the spatial-lag variables is a mix between data and chosen values for **W**. In other words, the previous specification is in fact a rather rudimentary way to express a much more complex spatial structure, as it follows in matricial terms:

$$\mathbf{y} = \mathbf{\Omega y} + \mathbf{X\beta} + \boldsymbol{\varepsilon} \qquad (2)$$

Where $\mathbf{\Omega}$ is a $N \times N$ matrix with zeros in its main diagonal and elements ρ_{ij} elsewhere:

$$\mathbf{\Omega} = \begin{bmatrix} 0 & \rho_{12} & \cdots & \rho_{1N} \\ \rho_{21} & 0 & \cdots & \rho_{2N} \\ \cdot & \cdot & \cdot & \cdot \\ \rho_{N1} & \rho_{N2} & \cdots & 0 \end{bmatrix} \qquad (3)$$

The Model (2)-(3) includes a specific spatial parameter ρ_{ij} for each pair of regions. If this is the "real" spatial structure, the number of parameters to be estimated increases enormously. Model (1) requires the estimation of K+1 parameters from N observations. In contrast, in the spatial structure represented in (2) the number of parameters to be estimated is K+N(N-

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[2] Exceptions to this general spatial models are the so-called "spatial regime models". See Anselin (1990).

[3] Good examples of this other approach can be found in Case *et al.* (1993), and López-Bazo *et al.* (2004). These papers define the spatial weights based on commercial relationships, while in Boarnet (1998) the weights increase with the similarity between the investigated regions. Molho (1995) and Fingleton (2001) propose a hybrid spatial weight based on economic variable and decreasing interaction force with distance.

1), which obviously is implausible by means of classical econometrics (ordinary least squares or maximum likelihood, for example) given the negative number of degrees of freedom. Technically, this problem is labeled as an "ill-posed" econometric problem. If the number of observations *N* increases, this does not solve the problem but makes it worse, since the number of spatial parameters ρ_{ij} to estimate also grows. When several observations of the variables are available along *T* periods of time, the cross-section model can be transformed into a panel data model, although usually the length of the time series is not large enough to achieve efficient estimates. Even if the number of time periods was sufficient, and the problem became "not-ill-posed", most probably it would be "ill-conditioned" given the high degree of multicollinearity between the variables y_{it}.

These problems are circumvented estimating spatial models like (1): just one spatial parameter ρ is estimated and interpreted as the average spatial effect. In such a situation, the spatial spillover from a region *j* to other location *i* (the element ρ_{ij}), could be obtained as the product ρw_{ij}, but then the estimated spillover is a mix between data and (exogenous) values of **W**. The choice of the spatial weight matrix is a key step in the spatial econometric modelling and nowadays there is not a unique rule to select an appropriate specification of this matrix. In fact, this problem is suggested for future research by Anselin *et al.* (2004) and Paelink *et al.* (2004) among others. Note that if the spatial weights w_{ij} are based on a measure of simply geographical distance, then the spillover from location *i* to location *j* will be exactly the same as the spillover from *j* to *i*.[4] This could turn into a strong simplification of the spatial relationships in an economy. Furthermore, if the **W** matrix is constructed as a contiguity matrix, then the spatial structure imposed is even simpler: between every pair of contiguous locations the spatial spillover is always the same and equal to ρ. The use of spatial weights based on some type of economic variables (instead of or besides geographical distance) could avoid the imposition of these symmetric relationships, but some problems of endogenity can emerge. Cohen and Morrison (2004) and Case *et al.* (1993) analyzed this problem and modified the weights in order to guarantee the ortogonality between the weights and the explanatory variables.

[4] The row standardization of the **W** matrix implies that becomes asymmetric even though the original matrix may nave been symmetric. Bhattacharjee and Jensen-Butler (2005) propose the estimation of the spatial weight matrix which is consistent with a given or estimated spatial autocovariance without the non-negativity constraint on the off-diagonal elements.

As a summary, it seems to be clear the interest to recover models like (2)-(3) for the estimation of spatial effects. GME econometrics appears as a useful procedure to estimate those ill-posed or ill-conditioning models, and to gather empirical evidence of the spatial relationships of the economy.

3. GENERALIZED MAXIMUM ENTROPY ECONOMETRICS: AN OVERVIEW[5]

Let us assume that a discrete random event can take K possible outcomes $E_1, E_2, \ldots E_K$ with the respective distribution of probabilities $\mathbf{p} = p_1, p_2, ..., p_K$ such that $\sum_{k=1}^{K} p_k = 1$. Following the formulation proposed by Shannon (1948), the entropy of this distribution $\mathbf{p}$ is:

$$H(\mathbf{p}) = -\sum_{k=1}^{K} p_k \ln p_k \qquad (4)$$

The entropy function H measures the 'uncertainty' of the outcomes of the event. This function reaches its maximum when $\mathbf{p}$ is a uniform distribution: $p_k = \frac{1}{K}, \forall \mathrm{k}$. On the other hand, this function takes a value zero (no uncertainty) when the probability of one of the outcomes goes to one. If some information about the variable (*i.e.*, observations) is available, it can be used to estimate an unknown distribution of probabilities for a random variable x which can get values $\{x_1, ..., x_K\}$. Suppose that there are N observations $\{y_1, y_2, ..., y_N\}$ available such that:

$$\sum_{k=1}^{K} p_k f_i(x_k) = y_i,\ 1 \leq \mathrm{i} \leq \mathrm{N} \qquad (5)$$

where $\{f_1(x), f_2(x), ..., f_N(x)\}$ is a set of known functions representing the relationships between the random variable x and the observed data $\{y_1, y_2, ..., y_N\}$. In such a case, the ME principle can be applied to recover the unknown probabilities. This principle is based on the selection of the probability distribution that maximizes equation (4) among all of the possible probability distributions that fulfil (5). In other words, the ME principle chooses the "most uniform" distribution that agrees with the information. The following constrained maximization problem is posed:

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[5] This section summarizes the process to estimate the parameters of a linear model. See Golan, Judge and Miller (1996) and Kapur and Kesavan (1992) for further details.

$$\underset{\mathbf{p}}{Max}\, H(\mathbf{p}) = -\sum_{k=1}^{K} p_k \ln p_k \tag{6a}$$

subject to:

$$\sum_{k=1}^{K} p_k f_i(x_k) = y_i;\ i = 1,...,N \tag{6b}$$

$$\sum_{k=1}^{K} p_k = 1 \tag{6c}$$

In this problem, the last restriction is just a normalization constraint that guarantees the estimated probabilities add-up to one, while the first N restrictions guarantee that the recovered distribution of probabilities is compatible with the data for all N observations. It is important to note that even for N=1 (a situation with only one observation), the ME approach yields an estimate of the probabilities. Hence, in situations in which the number of observations is not large enough to apply classical econometrics, this approach can be used to obtain robust estimates of unknown parameters.

For our current purposes, it is important to note that the above-sketched procedure can be generalized and extended to the estimation of unknown parameters for traditional linear models. Let us suppose that the problem at hand is the estimation of a linear model where a variable y depends on K explanatory variables x_i:

$$\mathbf{y} = \mathbf{X\beta} + \mathbf{e} \tag{7}$$

where $\mathbf{y}$ is a $(N \times 1)$ vector of observations for y, $\mathbf{X}$ is a $(N \times K)$ matrix of observations for the x_k variables, $\boldsymbol{\beta}$ is the $(K \times 1)$ vector of unknown parameters $\boldsymbol{\beta}' = (\beta_1,...,\beta_K)$ to be estimated, and $\mathbf{e}$ is a $(N \times 1)$ vector reflecting the random term of the linear model. For each β_k, this methodology assumes that there is some information about its likely $M \geq 2$ possible realizations. This information is included for the estimation by means of a 'support' vector $\mathbf{b'} = (b_1,...,b^*,...,b_M)$, which elements are symmetrically distanced around a central value $\beta_k = b^*$ (the prior expected value of the parameter), with corresponding probabilities $\mathbf{p}'_k = (p_{k1},..., p_{kM})$. This vector $\mathbf{b}$ is based on the researcher's prior knowledge (or beliefs) about the likely values of the parameter.[6] Now, vector $\boldsymbol{\beta}$ can be written as:

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[6] Golan *et al.* (1996, chapter 8) pay attention to the consequences of choices concerning the elements of the vector **b**. For the sake of convenient exposition, it will be assumed that the M values are the same for every parameter, although this assumption can easily be relaxed.

$$\boldsymbol{\beta}=\begin{bmatrix}\beta_1\\ \beta_2\\ \cdots\\ \beta_K\end{bmatrix}=\mathbf{Bp}=\begin{bmatrix}\mathbf{b'} & \mathbf{0} & . & \mathbf{0}\\ \mathbf{0} & \mathbf{b'} & . & \mathbf{0}\\ . & . & . & .\\ \mathbf{0} & \mathbf{0} & . & \mathbf{b'}\end{bmatrix}\begin{bmatrix}\mathbf{p_1}\\ \mathbf{p_2}\\ \cdots\\ \mathbf{p}_K\end{bmatrix} \tag{8}$$

where **B** and **p** have dimensions ($K\times KM$) and ($KM\times 1$), respectively. The value for each parameter is then given by:

$$\beta_k=\mathbf{b'p}_k=\sum_{m=1}^{M} b_m p_{km};\quad k=1,...,K \tag{9}$$

For the random term, a similar approach is followed. To express the lack of information about the actual values contained in **e**, we assume a distribution for each e_i, with a set of $R\geq 2$ values $\mathbf{v'}=(v_1,...,v_R)$ with respective probabilities $\mathbf{q}_i'=(q_{i1},q_{i2},...,q_{iR})$.[7] Hence, we can write:

$$\mathbf{e}=\begin{bmatrix}e_1\\ e_2\\ \cdots\\ e_N\end{bmatrix}=\mathbf{Vq}=\begin{bmatrix}\mathbf{v'} & \mathbf{0} & . & \mathbf{0}\\ \mathbf{0} & \mathbf{v'} & . & \mathbf{0}\\ . & . & . & .\\ \mathbf{0} & \mathbf{0} & . & \mathbf{v'}\end{bmatrix}\begin{bmatrix}\mathbf{q_1}\\ \mathbf{q_2}\\ \cdots\\ \mathbf{q}_N\end{bmatrix} \tag{10}$$

and the value of the random term for an observation *i* equals

$$e_i=\mathbf{v'q}_i=\sum_{r=1}^{R} v_r q_{ir};\quad i=1,...,N \tag{11}$$

And, consequently, model (7) can be transformed into:

$$\mathbf{y}=\mathbf{XBp}+\mathbf{Vq} \tag{12}$$

Now, the estimation problem for the unknown vector of parameters $\boldsymbol{\beta}$ is reduced to the estimation of $N+K$ probability distributions of the support vectors, and the following maximization problem (adapted from problem (6)) can be solved to obtain these estimates:

$$\underset{\mathbf{p},\mathbf{q}}{Max}\, H(\mathbf{p},\mathbf{q})=-\sum_{k=1}^{K}\sum_{m=1}^{M} p_{km}\ln p_{km}-\sum_{i=1}^{N}\sum_{r=1}^{R} q_{ir}\ln q_{ir} \tag{13a}$$

subject to:

$$\sum_{k=1}^{K}\sum_{m=1}^{M} x_{ki} b_m p_{km}+\sum_{r=1}^{R} v_r q_{ir}=y_i;\ i=1,...,N \tag{13b}$$

[7] Usually, the distribution for the errors is assumed symmetric and centered about 0, therefore $\mathrm{v}_1=-\mathrm{v}_R$.

$$\sum_{m=1}^{M} p_{km} = 1;\ k = 1,...,K \tag{13c}$$

$$\sum_{r=1}^{R} q_{ir} = 1;\ i = 1,...,N \tag{13d}$$

By solving this GME program, we recover the estimated probabilities that allow us to obtain estimates for the unknown parameters.[8] The estimated value of β_k will be:

$$\hat{\beta}_k = \sum_{m=1}^{M} \hat{p}_{km} b_m\ ; k = 1,...,K \tag{14}$$

Note that the solution of the constrained maximization problem (13) without additional information yields estimates equal to the expected value b^* of the prior distribution, since in such a situation the recovered distribution would be uniform.

For the GME estimation of model (2), it is necessary estimate 3 groups of elements: parameters β_k, errors e_i and the spatial effects ρ_{ij} in matrix $\mathbf{\Omega}$. The GME procedure for the β_k parameters and the e_i error terms is the same as explained previously. Following the same procedure, for each ρ_{ij} it will be assumed that there are $L \geq 2$ possible realizations (assumed the same for all ρ_{ij}) that appear in a support vector $\mathbf{z}' = (z_1,...,z_L)$, with corresponding probabilities $\mathbf{s}'_{ij} = (s_{ij1},...,s_{ijL})$. Therefore, the matrix $\mathbf{\Omega}$ with elements ρ_{ij} will be expressed as:

$$\mathbf{\Omega} = \begin{bmatrix} 0 & \rho_{12} & \cdots & \rho_{1N} \\ \rho_{21} & 0 & \cdots & \rho_{2N} \\ \bullet & \bullet & \bullet & \bullet \\ \rho_{N1} & \rho_{N2} & \cdots & 0 \end{bmatrix} = \mathbf{z}' \otimes \mathbf{S} = \mathbf{z}' \otimes \begin{bmatrix} 0 & \mathbf{s_{12}} & \bullet & \mathbf{s_{1N}} \\ \mathbf{s_{21}} & 0 & \bullet & \mathbf{s_{2N}} \\ \bullet & \bullet & \bullet & \bullet \\ \mathbf{s_{N1}} & \mathbf{s_{N2}} & \bullet & 0 \end{bmatrix} \tag{15}$$

Where $\otimes$ denotes the Kronecker product. Consequently, equation (2) can be rewritten as:

$$\mathbf{y} = \mathbf{z}' \otimes \mathbf{Sy} + \mathbf{XBp} + \mathbf{Vq} \tag{16}$$

Now, the GME program for the unknown set of parameters $\boldsymbol{\beta}$ and $\mathbf{\Omega}$ is turned into the estimation of K+N(N-1)+N probability distributions, in the following terms:

$$\underset{\mathbf{p,s,q}}{Max}\, H(\mathbf{p},\mathbf{q},\mathbf{s}) = -\sum_{k=1}^{K}\sum_{m=1}^{M} p_{km} \ln p_{km} - \sum_{i \neq j}^{N}\sum_{j \neq i}^{N}\sum_{l=1}^{L} s_{ijl} \ln s_{ijl} - \sum_{i=1}^{N}\sum_{r=1}^{R} q_{ir} \ln q_{ir} \tag{17a}$$

[8] Golan *et al.* (1996, Chapter 6) show that these estimators are consistent and asymptotically normal. In Golan *et al.* (1996, Chapter 7) the finite sample behaviour of the GME estimators is numerically compared to traditional least squares and maximum likelihood estimators. In experimental samples with limited data, the ME estimators are found to be superior.

subject to:

$$\sum_{j\neq i}^{N}\sum_{l=1}^{L} y_j z_l s_{ijl} + \sum_{k=1}^{K}\sum_{m=1}^{M} x_{ki} b_m p_{km} + \sum_{r=1}^{R} v_r q_{ir} = y_i;\ i = 1,\ldots,N \tag{17b}$$

$$\sum_{m=1}^{M} p_{km} = 1;\ k = 1,\ldots,K \tag{17c}$$

$$\sum_{r=1}^{R} q_{ir} = 1;\ i = 1,\ldots,N \tag{17d}$$

$$\sum_{l=1}^{L} s_{ijl} = 1;\ i = 1,\ldots,N;\ j = 1,\ldots,N;\ \forall \mathrm{i} \neq \mathrm{j} \tag{17e}$$

By solving this GME program, we recover the estimated probabilities that allow us to obtain estimates for the unknown parameters. The estimated value of the spatial spillovers will be:

$$\hat{\rho}_{ij} = \sum_{l=1}^{L} \hat{s}_{ijl} z_l\ ;\ \forall i \neq j \tag{18}$$

4. MONTE CARLO SIMULATIONS

The model to be simulated for a grid of $N = 15$ artificially generated locations was shown in (2): $\mathbf{y} = \boldsymbol{\Omega}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$. The values for simulation are:

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} 1.5 \\ 0.5 \end{bmatrix} \tag{19a}$$

$$\varepsilon_i \approx \mathbf{N}[0,1];\ i = 1,\ldots,N \tag{19b}$$

$$x_i \approx \mathbf{U}[0,10];\ i = 1,\ldots,N \tag{19c}$$

which are kept constant along the simulations.

For simulating several spatial structures, the elements ρ_{ij} of matrix $\boldsymbol{\Omega}$ have been generated in different scenarios. In the first case the spatial spillovers are generated uniformly and constrained to take only positive values not greater than 1, with two possibilities: 1) Only some cells of the matrix (out of its trace) are allowed to be non-zero. This happens when the regions are neighbors. In order to decide when two locations *i* and *j* can be considered as neighbors, a rook criterion has been applied to our grid of 15 simulated locations.[9] Hence, the spatial effect can be:

$$\begin{cases} \rho_{ij} \approx \mathbf{U}[0,1] & \text{if } i \text{ and } j \text{ have a common border} \\ \rho_{ij} = 0 & \text{otherwise} \end{cases} \tag{20}$$

This matrix of spatial parameters will be labeled as $\mathbf{\Omega^{R1}}$, where subscript denotes that this matrix follows a rook criterion; 2) All the off-diagonal elements of the matrix are allowed to be not zero:

$$\rho_{ij} \approx \mathbf{U}[0,1];\ \forall i \neq j \tag{21}$$

This means that there are spatial relationships among all regions and, obviously, it is a more general spatial structure. We will denote the matrix as $\mathbf{\Omega^{F1}}$, where here the superscript F is used to call the attention to the point that the matrix is completely "filled".

For the second case to be considered, the spatial parameters can take negative or positive values either, with the limit of 0.5 in absolute value. We considerer the same two previous alternatives:

$$\begin{cases} \rho_{ij} \approx \mathbf{U}[-0.5,0.5] & \text{if } i \text{ and } j \text{ have a common border} \\ \rho_{ij} = 0 & \text{otherwise} \end{cases} \tag{22}$$

$$\rho_{ij} \approx \mathbf{U}[-0.5,0.5];\ \forall i \neq j \tag{23}$$

The spillovers matrices simulated for cases (22) and (23) are labeled as $\mathbf{\Omega^{R2}}$ and $\mathbf{\Omega^{F2}}$, respectively. Clearly, the spatial processes generated by matrices $\mathbf{\Omega^{F1}}$ and $\mathbf{\Omega^{F2}}$ are more complex than those produced by $\mathbf{\Omega^{R1}}$ and $\mathbf{\Omega^{R2}}$, in the sense that the number of spatial relationships among the locations is greater in the former cases.

Under these four scenarios, equation (2) with spatial structures (20), (21), (22) or (23), we will compare the performance of GME estimation with other more classical proposals that will be taken as a benchmark. The classical approach consists in the estimation of models like (1), which uses a spatial weights matrix (**W**) chosen by the research. This model will be estimated using the classical maximum likelihood (ML) estimator and, furthermore, the GME estimator proposed in Marshall and Mittelhammer (2004), hereafter GME-MM.[10] In

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[9] If a contiguity matrix is specified, two cells of the regular grid are contiguous if they have a common border of non-zero length, but the common border may be defined in different ways. The rook criterion considers as *common border* the common edge. Following a queen criterion, the common border would be a common vertex.

[10] It is important to note that Marshall and Mittelhammer (2004) use a version of GME estimator for the estimation of the parameters of model (1), i.e., to estimate a single spatial parameter using a spatial weight

order to estimate model (1), it is necessary to define a matrix of spatial weights $\mathbf{W}$ for the grid of 15 locations. We consider two very simple and popular binary configurations for this matrix, being both of them based on a contiguity criterion: one is defined following a rook criterion and another following a queen criterion, labeled respectively as $\mathbf{W}^{\mathbf{R}}$ and $\mathbf{W}^{\mathbf{Q}}$.[11]

The competing alternative to model (1) will be the estimation of model (2) by GME econometrics. We estimate three versions of model (2). In the two first, the estimated matrix $\mathbf{\Omega}$ is not full-filled, but some of its off-diagonal elements are zero following a rook or a queen criterion. We will define these estimates with $\mathbf{\Omega}^{\mathbf{R}}$ and $\mathbf{\Omega}^{\mathbf{Q}}$, respectively. The third model to estimate by GME is the most general, where all the off-diagonals elements are not zero and, hence, matrix is full-filled: $\mathbf{\Omega}^{\mathbf{F}}$.

Following the GME procedure, it will be necessary to specify some support for the set of parameters to estimate and for the errors. For all the GME estimations we have chosen the following support vectors: $\mathbf{b}=[0,1,2]$ will be the discrete common support for β_0 and β_1; $\mathbf{z}=[-1,0,1]$ will be the discrete common support for every ρ_{ij}*;* and finally the support $\mathbf{v}$ for the error will be generated as a three-point vector centered about 0 following the 3-sigma rule of variable *y* in each trial of the simulation, which is the most common practice.

Tables 1-4 summarize the results of compare the 3 groups of estimators under the 4 true scenarios proposed. To make the comparison we have computed along the 100 simulations the mean of the bias when estimating β_0 and β_1 and the squared forecasting error (MSFE).

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matrix. Our aim is to extent the use of GME estimators for more complex spatial structures, like those shown in (2).

[11] As we will see, a key point of our exercise is the different consequences of chose a wrong or a right matrix W in the estimation by maximum likelihood, comparing with the GME estimates proposed in this paper.

Table 1. Estimates under model (2) and (20), true matrix is Ω^{R1}

Average results	$\hat{\beta}_0$	Bias $\hat{\beta}_0$	$\hat{\beta}_1$	Bias $\hat{\beta}_1$	MSE β_0	MSE β_1	MSFE
ML with W^R	-1.956	-3.456	0.908	0.407	12.210	0.181	1169.431
ML with W^Q	-5.656	-7.156	0.893	0.393	54.936	0.216	732.333
GME-MM with W^R	0.894	-0.606	0.606	0.106	0.368	0.015	612.916
GME-MM with W^Q	0.871	-0.629	0.561	0.061	0.396	0.008	730.154
GME Ω^R	0.907	-0.593	0.396	-0.104	0.352	0.013	682.534
GME Ω^Q	0.915	-0.585	0.460	-0.040	0.342	0.003	900.810
GME Ω^F	0.950	-0.550	0.778	0.278	0.303	0.008	272.706

Table 2. Estimates under model (2) and (21), true matrix is Ω^{F1}

Average results	$\hat{\beta}_0$	Bias $\hat{\beta}_0$	$\hat{\beta}_1$	Bias $\hat{\beta}_1$	MSE β_0	MSE β_1	MSFE
ML with W^R	-4.311	-5.811	0.827	0.327	34.959	0.169	41.187
ML with W^Q	-4.191	-5.691	0.802	0.302	32.233	0.154	39.178
GME-MM with W^R	0.343	-1.157	0.003	-0.497	1.354	0.250	87.437
GME-MM with W^Q	0.456	-1.044	0.011	-0.489	1.098	0.240	43.757
GME Ω^R	0.443	-1.057	0.024	-0.476	1.122	0.227	35.655
GME Ω^Q	0.505	-0.995	0.023	-0.477	0.992	0.228	22.588
GME Ω^F	0.760	-0.740	0.103	-0.397	0.549	0.158	21.246

Table 3. Estimates under model (2) and (22), true matrix is Ω^{R2}

Average results	$\hat{\beta}_0$	Bias $\hat{\beta}_0$	$\hat{\beta}_1$	Bias $\hat{\beta}_1$	MSE β_0	MSE β_1	MSFE
ML with W^R	2.104	0.604	0.483	-0.017	1.296	0.026	60.129
ML with W^Q	-0.428	-1.928	0.511	0.011	18.709	0.086	98.179
GME-MM with W^R	1.112	-0.388	0.478	-0.022	0.152	0.006	39.186
GME-MM with W^Q	1.061	-0.439	0.447	-0.053	0.195	0.007	39.661
GME Ω^R	0.970	-0.530	0.474	-0.026	0.282	0.002	9.089
GME Ω^Q	0.922	-0.578	0.610	0.110	0.334	0.014	5.228
GME Ω^F	0.959	-0.541	0.677	0.177	0.293	0.074	1.908

Table 4. Comparison of the estimators in scenario (28d), true matrix is Ω^{F2}

Average results	$\hat{\beta}_0$	Bias $\hat{\beta}_0$	$\hat{\beta}_1$	Bias $\hat{\beta}_1$	MSE β_0	MSE β_1	MSFE
ML with W^R	5.841	4.341	-2.160	-2.660	65.287	18.198	7718.992
ML with W^Q	8.730	7.230	-2.705	-3.205	78.772	18.488	10361.023
GME-MM with W^R	0.946	-0.554	0.754	0.254	0.307	0.069	648.593
GME-MM with W^Q	0.975	-0.525	0.897	0.397	0.276	0.163	338.425
GME Ω^R	0.896	-0.604	0.484	-0.016	0.365	0.004	202.635
GME Ω^Q	0.936	-0.564	0.664	0.164	0.319	0.030	182.675
GME Ω^F	0.958	-0.542	0.743	0.243	0.295	0.060	136.584

First table refers to the scenario where the spatial spillovers are non-negative and the $\mathbf{\Omega}$ matrix was generated following a rook criterion. Consequently, a rational feeling would be that the models that include the belief that the $\mathbf{W}$ matrix is like $\mathbf{W}^{\mathbf{R}}$ are going to yield lower measures of error than those that impose a spatial structure derived from a $\mathbf{W}^{\mathbf{Q}}$ matrix or those that do not use at all any configuration of the spillovers as a priori information, i.e., a fully "filled" matrix. If we examine the results of the simulation, it can be observed how the imposition of the right spatial configuration has special transcendence when we use a ML estimator. Table 1 shows that if we specify correctly the configuration of $\mathbf{W}$ (the true matrix of spatial interactions is similar to the structure we are imposing) there is not a clear gain of using the GME technique proposed, taking as reference the GME-MM estimators.[12] Only models like (2) with a fully filled $\mathbf{\Omega}$, which implies a considerable increase in the computational complexity, improve the forecasting accuracy of the GME-MM model, but they do not yield unquestionably better estimates for the β parameters. If we make a wrong choice in the design of the $\mathbf{W}$ matrix (imposing, for example, a queen criterion in this first scenario), the consequences over our ML estimates of the model can be serious.[13] Note that in contrast, the magnitude of the choice of $\mathbf{W}$ is not so important if we use some of the GME based models (even the GME-MM proposal). This can be seen as an advantage of using these techniques instead of more classical ML estimators since it seems that the gravity of a misspecification in $\mathbf{W}$ is reduced.

The question now is: what happen if the actual spatial structure is much more complex than the configuration of the $\mathbf{W}$ matrix we are specifying for our model? Table 2 can give some clues about the answer. This Table refers to a scenario where there are (non-negative) spatial interactions between every pair of locations. We would expect that the GME estimators that do not include the structure contained in the $\mathbf{W}$ matrices somehow outperformed the ML and GME-MM estimators (since these impose a spatial structure derived from a rook or queen $\mathbf{W}$ matrix). Note that GME models estimated using a matrix of spatial spillovers $\mathbf{\Omega}^{\mathbf{F1}}$ assume spatial structures with a higher number of correlations among locations than those considered when we use the rook or queen criterion. In other words, models that use a rook or queen $\mathbf{W}$ matrix both include "wrong" prior information, which forces the model to estimate a much more simple spatial structure than the actual

12 Although there are clear gains by using GME-MM instead ML, the performance of models GME-MM are very similar to the GME models proposed in this paper.
13 This numerical result agrees with the conclusions of some previously mentioned papers, like Stetzer (1982) or Florax and Rey (1995).

one. The results of our Monte Carlo simulations do not disagree with this idea: in general terms the results of the MSE for the parameters and the MSFE measure present the lowest values for the GME models proposed in this paper. The figures of Table 2 show clear improvements in the estimate of the β parameters and in the forecasting errors with respect to the ML estimators. Taking as benchmark the GME-MM proposal the improvements are much more modest but still remarkable.

Finally, when the spatial structure is even more complex, i.e., the spatial parameters can take also negative values (Tables 3 and 4), GME estimates achieve a better performance comparing with the ML estimator, even when the choice of **W** is similar with the true structure imposed. All in all, the results of the simulation suggest that it may be better not imposing any spatial structure in the estimation than considering an excessively simple one. It is important to remark that this lack of a specific configuration of **W** is only possible using the GME estimators proposed in the paper, but the ML and GME-MM always need of a concrete definition of matrix **W**. The general idea, consequently, is that the GME procedure proposed could be used successfully when there is not a clear certainty about which is the right specification for matrix **W**.

5. A SENSITIVITY ANALYSIS

A potential drawback of the GME estimators is an excessively high dependence of the estimates on the support vectors specified. This is an important issue since when we compared the performance of GME with ML in the previous subsection we were not being completely "fair", since we gave supports **b** and **z** that were quite well specified given how we simulate the different scenarios. For example, the GME estimates of spatial spillovers β parameters should necessarily lay between 0 and 2, which limits the potential error that we can yield compared with ML technique (which does not restrict their values a priori). In order to check if the relatively good performance of the proposed GME estimators is just a consequence of this correct prior belief included in the supports, a sensitivity analysis is required.

To do that, we have taken the maximum and minimum estimates of β_0, β_1 and ρ obtained along the 100 simulations by the ML procedure. In the cases where the spillovers were generated between 0 and 1 these bounds were:

$\hat{\beta}_0$ max.	0.439	$\hat{\beta}_1$ max.	1.605	$\hat{\rho}$ max.	0.511
$\hat{\beta}_0$ min.	-11.326	$\hat{\beta}_1$ min.	0.297	$\hat{\rho}$ min.	-0.178

And when the spillovers were generated between -0.5 and 0.5:

$\hat{\beta}_0$ max.	25.535	$\hat{\beta}_1$ max.	6.467	$\hat{\rho}$ max.	0.452
$\hat{\beta}_0$ min.	-10.664	$\hat{\beta}_1$ min.	-13.215	$\hat{\rho}$ min.	-0.260

If we take these extreme estimates as the bounds for new support vectors **b'** and **z'** note that we will augment the wideness of these vectors and we will increase, therefore, the uncertainty about the plausible values of the parameters. More important, we are providing the GME programs with "bad" information since the central points of the new support are far from being the true values of the parameters; in contrast with the original supports chosen (this is especially clear for the case of the β parameters). Furthermore, note that the true β_0 parameters are out of the range of the maximum and minimum values specified in the first case.

Considering the same measures of error to evaluate all the rival estimating procedures we obtain the following results:[14]

Table 5. Sensitivity analysis. Estimates under model (2) and (20), true matrix is Ω^{R1}

Average results	$\hat{\boldsymbol{\beta}}_0$	Bias $\hat{\boldsymbol{\beta}}_0$	$\hat{\boldsymbol{\beta}}_1$	Bias $\hat{\boldsymbol{\beta}}_1$	MSE $\boldsymbol{\beta}_0$	MSE $\boldsymbol{\beta}_1$	MSFE
ML with W^R	-1.956	-3.456	0.908	0.407	12.210	0.181	1169.431
ML with W^Q	-5.656	-7.156	0.893	0.393	54.936	0.216	732.333
GME-MM with W^R	-4.934	-6.434	0.887	0.387	41.400	0.150	833.770
GME-MM with W^Q	-4.852	-6.352	0.753	0.253	40.473	0.068	1128.866
GME Ω^R	-4.944	-6.444	0.798	0.298	41.554	0.089	805.401
GME Ω^Q	-5.274	-6.774	0.830	0.330	45.910	0.110	1220.308
GME Ω	-2.345	-3.845	0.973	0.473	15.091	0.225	62.3409

[14] Obviously, the results obtained by ML estimators are identical to those obtained previously.

Table 6. Sensitivity analysis. Estimates under model (2) and (21), true matrix is Ω^{F1}

Average results	$\hat{\beta}_0$	Bias $\hat{\beta}_0$	$\hat{\beta}_1$	Bias $\hat{\beta}_1$	MSE β_0	MSE β_1	MSFE
ML with W^R	2.104	0.604	0.483	-0.017	1.296	0.026	60.129
ML with W^Q	-0.428	-1.928	0.511	0.011	18.709	0.086	98.179
GME-MM with W^R	1.701	0.201	0.290	-0.210	0.779	0.050	38.441
GME-MM with W^Q	2.068	0.568	0.322	-0.178	0.676	0.036	28.305
GME Ω^R	0.045	-1.455	0.533	0.033	2.272	0.008	28.150
GME Ω^Q	0.302	-1.198	0.307	-0.193	1.608	0.043	29.100
GME Ω	-2.699	-4.199	0.302	-0.198	18.084	0.055	10.914

Table 7. Sensitivity analysis. Estimates under model (2) and (22), true matrix is Ω^{R2}

Average results	$\hat{\beta}_0$	Bias $\hat{\beta}_0$	$\hat{\beta}_1$	Bias $\hat{\beta}_1$	MSE β_0	MSE β_1	MSFE
ML with W^R	-4.311	-5.811	0.827	0.327	34.959	0.169	41.187
ML with W^Q	-4.191	-5.691	0.802	0.302	32.233	0.154	39.178
GME-MM with W^R	-3.105	-4.605	0.329	-0.171	21.260	0.029	98.721
GME-MM with W^Q	-1.980	-3.480	0.305	-0.195	12.158	0.038	50.024
GME Ω^R	-2.341	-3.841	0.392	-0.108	14.826	0.014	42.114
GME Ω^Q	-2.131	-3.631	0.331	-0.169	13.251	0.029	52.947
GME Ω	-1.026	-2.526	0.443	-0.057	6.427	0.005	46.694

Table 8. Sensitivity analysis. Estimates under model (2) and (23), true matrix is Ω^{F2}

Average results	$\hat{\beta}_0$	Bias $\hat{\beta}_0$	$\hat{\beta}_1$	Bias $\hat{\beta}_1$	MSE β_0	MSE β_1	MSFE
ML with W^R	5.841	4.341	-2.160	-2.66	65.287	18.198	7718.992
ML with W^Q	8.730	7.223	-2.705	-3.2045	78.772	18.488	10361.023
GME-MM with W^R	-0.195	-1.695	0.582	0.082	3.186	0.011	667.669
GME-MM with W^Q	-0.518	-2.018	0.832	0.332	5.541	0.132	333.742
GME Ω^R	1.677	0.177	0.235	-0.265	0.672	0.048	452.720
GME Ω^Q	0.046	-1.454	0.218	-0.282	2.802	0.093	390.753
GME Ω	0.081	-1.419	-0.013	-0.513	2.200	0.276	203.191

Tables 5 to 8 show the behavior of the GME estimators under these new support vectors. Obviously, the measure errors for the β parameters increase and the forecasting errors are also larger almost in all the situations. Even so, the general proposal explained in the previous subsection still remains: from Tables 6 and 8 we can observe how the GME models that do not employ a **W** matrix still outperform competing estimators based on models that consider a wrong (too simple) configuration of the actual spatial structure.

When one wants to estimate a spatial econometric model it is necessary to assume some prior information. One possibility is using a classical approach and specifying a matrix **W** of spatial weights: this could imply important consequences for the accuracy of the estimates if this belief is not correct. Other possibility is using some of the GME estimators assuming that the support vectors that we have to define for the parameters really bound their actual values. One might think that, in most cases, for the researcher is easier to define plausible values of the economic parameters rather than giving an accurate description of spatial structure by means of defining a matrix **W**. The basic idea that suggest the results of this sensitivity analysis is that the performance of the spatial models are more vulnerable to wrong priors of the first type than to bad specifications of the vectors used as support by the GME estimators.

6. CONCLUDING REMARKS

Generalized maximum entropy econometrics is an attractive methodology to deal with estimation of "ill-posed" or "ill-conditioned" models. In this paper we propose the use of this technique to estimate complex spatial structures, which fit with these "ill-behaved" situations where the number of observations is not large enough to estimate the desired number of parameters. To compare the performance of the proposed technique to other more traditional estimation methodologies a series of Monte Carlo simulations are carried out under different scenarios. The outcomes of the simulations suggest that the proposed GME technique outperforms other competing estimators if the actual spatial structure is different from the assumptions specified in the **W** matrix, which is inevitably used by these other methodologies.

The most important advantages of the proposed GME procedure is that it does not require necessarily the assumption of an exogenously specified matrix of spatial weights **W**. On the other hand, it requires the specification of priors for the values of the parameters to be estimated. Consequently, the use of the GME procedure implies switching from assumptions about the underlying spatial structure to beliefs about the values of the parameters. However, our feeling is that for the researcher is generally easier to make more accurate assumptions about the plausible values of the parameters than about the structure of the spatial relationships among the locations studied. Nevertheless, this paper must be seen just as a first approximation to an approach that potentially can be very useful for the estimation of spatial models. However, much further research in this direction must be done with the GME technique proposed. Its performance has to be evaluated under more sophisticated definitions of **W,** different types of spatial correlation, sizes of sample, etc.

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