Spatial logit for large samples with local spatial lag and regional spatial random effects using linearized GMM: an application to land use models

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Spatial logit for large samples with local spatial lag and regional spatial random effects using linearized GMM: an application to land use models

Following Klier and McMillen (2008), we propose a linearized spatial logit GMM (LGMM) estimator for particular SAR models combining 2 spatial parameters and two spatial weights matrices. This model, a double spatial filter, is particularly suitable for modeling spatial binary choices where land use choices are influenced both by close neighbors and by neighboring municipalities' urban policies, and/or by urban public policy at a higher level (county, region). We show that under realistic empirical conditions, the estimators of full GMM are consistent and asymptotically normal. Moreover, using MC experiments with various forms of spatial weights matrix including spatially aggregated locations, we show that the proposed LGMM estimators accurately identify the presence of spatial effects for large sample sizes and provide accurate estimates of the unknown parameters when the average number of neighbors of the two spatial weights matrices is reasonable. Finally, we use the estimation techniques developed for the proposed double SAR model to analyze urban sprawl and urban policy spillover, investigating a huge sample for land use change at parcel level in France.

1 Introduction

The role of spatial dependence in location choice for residential and economic activities is currently a hot topic in regional and urban economics Irwin (2010). Land and house prices and location choice for housing and economic activities are often correlated to neighboring areas prices and location choices. This interdependence complicates the estimation, but spatial econometrics provides a large range of models, tests and estimators that deal with spatial autocorrelation and spatial heterogeneity (Anselin, 1988; LeSage, 1999). In the case of continuous dependent variables, with spatial autocorrelation and heteroscedastic error terms, consistent procedures have been proposed by Ord (1975), Kelejian and Prucha (1999), Lee and Liu (2009), Anselin (1988), and these estimators are now widely used in the land/house price hedonic literature. However, despite the fact that the spatial dependence structure implies inconsistent logit estimates, binary discrete choice and other limited dependent variable models have in the past received less attention in the spatial autocorrelation literature (McMillen, 1992; Pinkse and Slade, 1998). This recent and growing branch of research (Pinkse and Slade, 2010) should enrich the empirical approach to urban sprawl and land use pattern modeling.

In land use pattern modeling, which involves discrete choice modeling in an econometric framework, spatial micro-economic models offer a promising way to improve empirical models by integrating the key dimensions of constrained decision-making that other disciplines do not take into account (Irwin, 2010). GIS (geography information system) databases on land use, ownership and land sales, land use zoning and land development are now often available to researchers both for separate individuals/plots and over large areas. This provides huge samples, together with numerous decisional variables at the right scale. However, although micro-economic models enable interactions between land/house prices, local amenities and zoning policy to be analyzed, one of the main drawbacks of spatial econometrics models is sample size. The relatively limited use of spatial econometrics models in empirical land use pattern modeling is largely due to the fact that estimation of unknown parameters in cross-sectional spatial regression models is not feasible for large sample sizes, since it requires the inversion of the $n \times n$ matrix or involves n integrals, where n is the sample size. For binomial discrete-choice models, several estimators were proposed by Pinkse and Slade (1998), McMillen (1992), Case (1992) , LeSage (1997) and Beron and Vijverberg (2005). All these estimating approaches provide consistent and asymptotically normal estimators, but are limited to small samples if computing time is to be kept under control. Calabrese and Elkink (2014) provide a comparison of accuracy and of computing time performance of these estimators, from which it appears that only the linearized version of the generalized method of moments (GMM) estimator proposed by Klier and McMillen (2008) can be used for very large samples.

The main objective of our article is to propose a feasible estimator for spatial discrete-choice models on large samples, as an extension of Klier and McMillen (2008). This proposed estimator is a linearized version of the generalized method of moments (GMM) estimator to be fitted in a spatial discrete-choice model containing two spatial parameters for the spatial lag latent dependent variable. Using MC experiments with various patterns of spatial weights matrices including spatially aggregated locations, we show that our linearized GMM estimator accurately identifies the presence of spatial effects and it is able to produce accurate estimates of marginal effects, as in Klier and McMillen (2008) in the classic SAR case. Monte Carlo (MC) experiments also suggest that when the average number of neighbors increases, the variance of the spatial coefficient estimator in the GMM framework is also increasing. This is an important limitation for land use data for which the aggregated location of parcels leads to numerous neighbors in the urban core. The need to use large samples to reduce variability in estimates of the spatial coefficient when there are numerous neighbors makes classic GMM estimation less attractive for SAR/SEM/SARAR models, and highlights the importance of a linearized version of GMM. Finally, we point out the attractive features of the proposed approach for analusis of urban sprawl and urban policy spillover, using a huge sample on land use change at parcel level in France.

The organization of the paper is as follows. In Section 2, we describe our GMM estimator. The consistency and asymptotic normality of the estimator are established under certain conditions. In Section 3, we examine the properties of our estimator by performing a set of Monte Carlo experiments. Different forms of weight matrix for different mean numbers of neighbors are tested. Section 4 describes the empirical analysis and gives the estimation results, and Section 5 concludes. All proofs are relegated to the Appendix.

2 GMM and linearized version of GMM estimation of spatial logit models

We consider spatial binary discrete-choice models with double spatial filter (SAR models, Anselin 1980, 1988) that could be written in matrix form as:

$$(I - \rho M)(I - \lambda W)y^* = X\beta + \epsilon \tag{1}$$

$$y = \begin{cases} 1 & \text{if} \quad y^* \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

where y is the vector of the dependent binary variable, $y^* = (y_1^*, ..., y_n^*)'$ is the vector of the underlying latent variable, ρ is the scalar autoregressive parameter that captures the spatial autocorrelation of the dependent variable at upper level (country,region), λ is the scalar autoregressive parameter that captures simultaneous spatial dependence of the dependent variable at spatial unit level, W and M are $n \times n$ spatial weights matrices, $X = (X_1, ..., X_n)'$ a matrix of explanatory variables with X_i being a $k \times 1$ vector, β is the $k \times 1$ vector of coefficients and ϵ is a vector of innovations.

The use of a double spatial filter instead of a single weight matrix that captures both close and inter-municipality spatial interactions allows the significance of each kind of spatial interaction to be test separately. The LGMM approach uses the same gradients for models with a spatial filter based on $(I - \rho M)(I - \lambda W)$ or based on $(I - \rho M - \lambda W)$. Thus, the reasons for our choice of model (1) are the following: 1) this form is more generic, 2) LGMM may face more complications in estimating spatial parameters with this form of spatial filter.

We apply the following assumptions to this model:

1. The innovations are independently and identically distributed, with $\mathbb{E}(\epsilon_i) = 0$, and $\mathbb{E}\left(\epsilon_i^2\right) = \sigma_\epsilon^2 < \infty$.
2. All diagonal elements of the spatial weighting matrices W and M are zero.
3. The row and column sums of the matrices W and M are bounded uniformly in absolute value; i.e $max \sum_{i=1}^{N} |w_{i,j}| \leq c_W$ and $max \sum_{j=1}^{N} |w_{i,j}| \leq c_W$; $max \sum_{i=1}^{N} |m_{i,j}| \leq c_M$ and $max \sum_{j=1}^{N} |m_{i,j}| \leq c_M$
4. The $(I - \lambda W)$ and $(I - \rho M)$ are nonsingular with $|\lambda| < 1$ and $|\rho| < 1$.
5. The row and column sums of the matrices $(I - \lambda W)^{-1}$ and $(I - \rho M)^{-1}$ are bounded uniformly in absolute value.
6. The covariable matrix X has full column rank (for large enough n).

Under these assumptions, the spatial latent model (1) can be rewritten as:

$$y^* = (I - \lambda W)^{-1}(I - \rho M)^{-1}X\beta + (I - \lambda W)^{-1}(I - \rho M)^{-1}\epsilon \tag{2}$$

For simplicity of notation, we set $X^* = (I - \lambda W)^{-1}(I - \rho M)^{-1}X$, and $\nu = (I - \lambda W)^{-1}(I - \rho M)^{-1}\epsilon$, then:

$$y^* = X^*\beta + \nu$$

We obtain, $\mathbb{E}(\nu_i) = 0$ and the variance-covariance matrix is given by:

$$\mathbb{E}[\nu\nu'] = (I - \lambda W)^{-1}(I - \rho M)^{-1}((I - \rho M)^{-1})'((I - \lambda W)^{-1})'\sigma_\epsilon^2 = V$$

Let us denote $\sigma_V^2(\lambda, \rho) = diag(V) = (\sigma_1^2(\lambda, \rho), \sigma_2^2(\lambda, \rho), ..., \sigma_N^2(\lambda, \rho))'$. Thus the probability is given by :

$$\begin{aligned} P(y_i = 1) &= P(\nu_i \geq -X_i^*\beta) \\ &= P\left(\frac{-\nu_i}{\sigma_i} \leq \frac{X_i^*\beta}{\sigma_i}\right) \end{aligned} \tag{3}$$

Since the error terms are heteroscedastic, the standard probit estimation is inconsistent Poirier and Ruud (1988). Like Pinkse and Slade (1998), we use GMM estimation for ease when estimating this kind of model with spatial dependence[1]. The GMM approach requires a valid set of instrument variables for the criteria function Q: like Kelejian and Prucha (1999), we choose a matrix of instruments based on cross product between the spatial weights matrix and covariates X denoted $Z = \Big[X, WX, W^2X, ..., MX, M^2X, ..., WMX, W^2MX, ...]$.

Let us denote $\theta = [\beta, \rho, \lambda] \in \Theta$, where Θ is the open space of parameters. The parameter vector is estimated by minimizing the function:

$$Q(\theta) = S_N{}'(\theta)\Sigma_N S_N(\theta)$$

[1]The maximum-likelihood estimation is more efficient than the other estimating approaches, but it is unfeasible on large sample sizes.

where $S_N(\theta) = \frac{1}{N} Z'\tilde{u}$, Σ_N is some positive definite matrix and $\tilde{u}$ a generalized logit error defined as $\tilde{u}_i = y_i - P(y_i = 1)$ (Cox and Snell (1968); Gourieroux et al. (1987)).

The parameter vector is estimated by:

$$\theta_0 = \underset{\theta \in \Theta}{\text{argmin}}\ Q(\theta)$$

The properties of normality and consistence are given in Appendix page 35. However, inverting the $n \times n$ matrix limits GMM estimation to small or moderate sample sizes. Thus, we resort to linearization of the GMM estimation, as in Klier and McMillen (2008). The benefit of linearization is that no matrix will need to be inverted in order to estimate the spatial parameters ρ and λ.

2.1 Linearized version of GMM estimation of logit model

We provide a linearized version of a GMM estimator with a general adjusting coefficient in order to extend the techniques developed in Klier and McMillen (2008) for the other spatial models. For SEM and SARAR(1,1) models, Klier and McMillen (2008) showed that linearization was not feasible. The gradient term of the generalized error logit for ρ equals zero for all the observations when $\rho = 0$ ($\lambda = 0$). In our model we show that the gradient of each unknown parameter is not equal to zero, and this allows linearization.

When we have both W and M in our model as in expression 1 , we need the following additional condition for the linearized version : the covariable matrix (X, WX, MX) needs to have full column rank (for large enough n).

In our case, the ith generalized logit error is given by:

$$\tilde{u}_i = y_i - p_i \qquad p_i = \frac{exp\Big(X_i^* \beta\Big)}{1 + exp\Big(X_i^* \beta\Big)}$$

where $X^* = \dfrac{(I-\lambda W)^{-1}(I-\rho M)^{-1}X}{\sigma_V(\lambda,\rho)}$.

The gradient terms for the vector of unknown parameters $\theta = [\beta, \rho, \lambda]$ are given by :

$$
\begin{aligned}
G_{\beta_i} &= P_i(1-P_i)X^* & (4)\\
G_{\lambda_i} &= P_i(1-P_i)\Big[H_\lambda\beta - \frac{X^*\beta\Lambda^{\lambda}_{ii}}{\sigma^2_v}\Big] & (5)\\
G_{\rho_i} &= P_i(1-P_i)\Big[H_\rho\beta - \frac{X^*\beta\Lambda^{\rho}_{ii}}{\sigma^2_V}\Big] & (6)
\end{aligned}
$$

Where

$$
\begin{aligned}
H_\lambda &= \frac{(I-\lambda W)^{-1}W(I-\lambda W)^{-1}(I-\rho M)^{-1}X}{\sigma_V(\lambda,\rho)}\\
H_\rho &= \frac{(I-\lambda W)^{-1}(I-\rho M)^{-1}M(I-\rho M)^{-1}X}{\sigma_V(\lambda,\rho)}\\
\Lambda^{\lambda}_{ii} &= diag\Big[(I-\lambda W)^{-1}W(I-\lambda W)^{-1}(I-\rho M)^{-1}(I-\rho M)^{-1'}(I-\lambda W)^{-1'}\Big]\\
\Lambda^{\rho}_{ii} &= diag\Big[(I-\lambda W)^{-1}(I-\rho M)^{-1}M(I-\rho M)^{-1}(I-\rho M)^{-1'}(I-\lambda W)^{-1'}\Big]
\end{aligned}
$$

The generalized error term $\tilde{u}_i(\beta,\lambda,\rho) = y_i - p_i(\beta,\lambda,\rho)$ is a function of (β,ρ,λ). To linearize the generalized error term, we use a Taylor approximation. Let us denote $\theta_0 = (\beta_{logit}, \lambda = 0, \rho = 0)$. Then we have:

$$\tilde{u}_i(\beta,\lambda,\rho) - \tilde{u}_i(\beta_{logit},\lambda=0,\rho=0) = G(\theta-\theta_0) \tag{7}$$

where $G(\cdot)$ is a gradient term:

$$\tilde{u}_i(\beta,\lambda,\rho) = G(\theta-\theta_0) + \tilde{u}_i(\beta_{logit},\lambda=0,\rho=0) \tag{8}$$

The estimation algorithm is derived from a **two-time-two-step procedure** detailed in the following:

- Part 1:

Step1 In the first part of the procedure, estimate β_{logit} by standard logit (probit) with $\rho = \lambda = 0$[2], compute $u_{(\beta_{logit},0,0)}$ and the gradient terms as follows:

$$\begin{aligned} G_{\beta_i}(\beta_{logit}, \lambda = 0, \rho = 0) &= P_i(1 - P_i)X & (9) \\ G_{\lambda_i}(\beta_{logit}, \lambda = 0, \rho = 0) &= P_i(1 - P_i)WX\beta_{logit} & (10) \\ G_{\rho_i}(\beta_{logit}, \lambda = 0, \rho = 0) &= P_i(1 - P_i)MX\beta_{logit} \end{aligned}$$

Step2 Regress G_β, G_λ and G_ρ on Z. The predicted values are $\hat{G}_\beta$, $\hat{G}_\lambda$ and $\hat{G}_\rho$. Finally regress $u_{(\beta_{logit},0,0)} + G'_\beta \beta_{logit}$ on $\hat{G}_\beta$, $\hat{G}_\lambda$ and $\hat{G}_\rho$. The coefficients of this last regression provide the estimated values of β, λ and ρ. In the next step, we use only the estimate of $\hat{\rho}$ which is consistent at this stage when W and M have numerous common positive weights.

- Part 2:

Step1 In the second part of the procedure, estimate $\tilde{\beta}_{logit}$ by standard logit (probit) with $\rho = \hat{\rho}$ and $\lambda = 0$, and compute $\tilde{u}_{(\tilde{\beta}_{logit},0,\hat{\rho})}$ and the gradient terms as follows :

$$\begin{aligned} G_{\beta_i}(\tilde{\beta}_{logit}, \lambda = 0, \hat{\rho}) &= \tilde{P}_i(1 - \tilde{P}_i)\tilde{X}^* & (11) \\ G_{\lambda_i}(\tilde{\beta}_{logit}, \lambda = 0, \hat{\rho}) &= \tilde{P}_i(1 - \tilde{P}_i)\frac{W(I - \hat{\rho}M)^{-1}\tilde{X}^*\tilde{\beta}_{logit}}{\sigma_v(0, \hat{\rho})} & (12) \end{aligned}$$

where $\tilde{X}^* = \dfrac{(I - \hat{\rho}M)^{-1}X}{\sigma_V(0, \hat{\rho})}$, $\tilde{P}_i = \dfrac{exp\left(\tilde{X}_i^*\tilde{\beta}\right)}{1 + exp\left(\tilde{X}_i^*\tilde{\beta}\right)}$

Step2 Regress G_β and G_ρ on Z. The predicted values are $\hat{G}_\beta$ and $\hat{G}_\rho$. Finally regress

[2] Spatial autocorrelation and heteroscedasticity are ignored.

$\tilde{u}_{(\tilde{\beta}_{logit},\hat{\lambda},0)} + G'_{\beta}\tilde{\beta}_{logit}$ on $\hat{G}_{\beta}$ and $\hat{G}_{\rho}$. The coefficients of this last regression provide the estimated values of β and ρ.

This algorithm provides accurate estimators of λ and ρ, and an estimator of β with downward bias. It should be noted that this algorithm only requires inverting $(I - \lambda M)$ and $(I - \rho M)$ once, which makes it more practical than the full GMM estimation with large samples.

The probability p is a function of λ and ρ, while the index value is given by $X^*\beta = \dfrac{(I-\lambda W)^{-1}(I-\rho M)^{-1}X}{\sigma_V(\lambda,\rho)}\beta$. The linearized spatial binary logit estimate provides estimates of $\frac{\partial X^*\beta}{\partial X}$. Thus to correct the downward bias in β, we need to compute the marginal effects [3]. The general coefficient to adjust the downward bias in β is given by:

$$\frac{Tr(\sigma_V(\lambda,\rho))}{Tr((I-\lambda W)^{-1}(I-\rho M)^{-1})}$$

The covariance matrix of LGMM estimators The estimator of the covariance matrix is given by:

$$var(\hat{\beta}) = (\hat{G}'_{\beta}\hat{G}_{\beta})^{-1}\left[\sum_{i=1}^{n}\tilde{u}_{0i}^2\hat{G}'_{\beta_i}\hat{G}_{\beta_i}\right](\hat{G}'_{\beta}\hat{G}_{\beta})^{-1}$$

$$var(\hat{\rho}) = (\hat{G}'_{\rho}\hat{G}_{\rho})^{-1}\left[\sum_{i=1}^{n}\tilde{u}_{0i}^2\hat{G}'_{\rho_i}\hat{G}_{\rho_i}\right](\hat{G}'_{\rho}\hat{G}_{\rho})^{-1}$$

$$var(\hat{\lambda}) = (\hat{G}'_{\lambda}\hat{G}_{\lambda})^{-1}\left[\sum_{i=1}^{n}\tilde{u}_{0i}^2\hat{G}'_{\lambda_i}\hat{G}_{\lambda_i}\right](\hat{G}'_{\lambda}\hat{G}_{\lambda})^{-1}$$

It should be noted that $var(\hat{\beta})$ and $var(\hat{\lambda})$ use values from the second step and $var(\hat{\rho})$ uses values from the first step of the proposed two-steps procedure. We denote this estimator ALGMM, for Adjusted Linearized GMM.

[3] See appendix for more details.

3 Monte Carlo Analysis

In this section we present the results of Monte Carlo analysis to assess the bias of the linearized logit GMM estimator for the double spatial filter model.

3.1 Experimental design

The design of our Monte Carlo experiment is based on Klier and McMillen (2008) for the SAR case, but uses a greater variety of ways of simulating the weight matrix, particularly by varying the mean number of neighbors. Previous Monte Carlo studies, using a standard first-order contiguity matrices with two neighbors (sparse banded matrix), showed that standard logit estimation of β leads to underestimated values of β with a bias that increases with λ (and ρ) and conclude that GMM and LGMM estimations lead to a real improvement in estimating the parameter β. In our experiments, we consider five different ways of simulating the binary row normalized weight matrix, with different types of spatial locations and average numbers of neighbors varying between to 2 and 60.

Type A The first type of weight matrix (A) is similar to Klier and McMillen (2008), and uses a deterministic weight matrix composed of a diagonal band of k neighbors. For this weight matrix, we can directly choose the mean number of neighbors. For other cases that use random coordinates, we choose a neighboring distance that leads to the desired mean number of neighbors k.

Type B The second kind of weight matrix (B) is based on two uniform distributions $U(0,1)$ giving coordinates of observations (x, y).

Type C In the third type (C), we draw coordinates between $[0,1]$ from a normal distribution with a mean of 0.5 and a standard deviation of 0.2, redrawing if the coordinate is outside $[0,1]$. This makes it possible to draw coordinates aggregated around a point, with a spatial distribution similar to house locations in an urban monocentric framework.

Type D The fourth type (D) is polycentric (with 4 centers), and here we use a combination of normal distributions with a mean of 0.6 or 0.3 for x or y coordinates.

Type E The last type (E) uses random sampling from real location data (80 000 parcel centroids in ten contiguous municipalities in the Vaucluse region of southern France). Figure 1 shows 1000 simulated coordinates for the four last cases. Every weight matrix proposed here verifies assumptions 2, 3 and 4 at page 5.

Each experiment is based on :

1. different ways of simulating coordinates,

2. different mean numbers of neighbors for W and M in the SARAR case, with less neighbors for W than for M, and

3. different values for ρ, λ and n.

The explanatory variable X is drawn once from a $U(-1, 1)$ distribution. Like Klier and McMillen (2008), we use an approximation of inverse matrix for $(I - \rho M)^{-1}$ and $(I - \lambda W)^{-1}$ with a third-order expansion: $(I - \lambda W)^{-1} \equiv I + \lambda W + \lambda^2 W2 + \lambda^3 W3$, both to draw the endogenous variable and to estimate the vector of unknown parameters. Each experiment is based on 1000 replications and provides mean and standard deviation or RMSE of the unknown parameters.

3.1.1 Experimental design for the SAR case

In the SAR case, for each coordinate matrix simulated via one of the five above methods, we used different mean numbers of neighbors $k \in \{2, 4, 10, 20, 60\}$ to draw a row normalized weight matrix W. The parameter λ varies from 0 to 0.8 by intervals of 0.2, thus $\lambda \in \{0, 0.2, 0.4, 0.6, 0.8\}$. We estimate the vector of unknown parameters (β, λ) by full GMM logit as in (Pinkse and Slade, 1998).

We limit the Monte Carlo analysis to $n = 1000$ because this SAR case only serves to show the effects of increased k on λ variance, even in the logit GMM estimation for various types of weight matrix. This question does not appear to have been sufficiently addressed in previous studies; moreover, it guided us in designing the Monte Carlo experiment for the linearized GMM estimator.

GMM results for SAR DGP : Table 1 shows the results of MC for standard logit (SL) estimation of β and GMM estimation of (β, λ). If we consider the weight matrix of type A with two neighbors, our results are similar to those of Klier and McMillen (2008): logit estimates of β parameter are downwardly biased when λ increases and GMM provides quite accurate estimates of β and λ. We obtain the same results for all other weight matrix types with two neighbors. Random location sampling (type B) with two neighbors provides results very close to those of the deterministic weight matrix (A). For the other types of matrix, we note higher variance and bias at $\lambda \geq 0.6$.

When k the average number of neighbors increases, we found that in most cases bias and variance of λ increase. For example, for the weight matrix of type A used in previous studies, the variance of λ becomes very high at 10 neighbors. In fact, when k increases, whatever the weight matrix type, there is first an upward bias in λ at low values of λ and then a downward bias in λ above a threshold value of k. Take for example a random location sampling (type B): for $\lambda = 0.8$, we have accurate estimators when $k \in (4, 10, 20)$, an upward bias when $k = 2$ and a downward bias when $k = 60$.

When k increases, the standard deviation of the spatial parameter increases linearly for λ below 0.6. For $\lambda \geq 0.6$ variance decreases, and it increases above a threshold value of k. For example, for type E weight matrices, variance is decreasing when k increases for $k < 4$ and

$\lambda = 0.6$, and for $k < 10$ and $\lambda = 0.8$.

This empirical analysis points to the importance of choosing the right structure for the weight matrix when using GMM estimation of spatial logit models, and consequently when using LGMM estimation of spatial logit models. Thus, in a real case study, an appropriate mean number of neighbors should be chosen (relevant to the observed spatial dependence) according to sample size. For example, for $n = 1000$, $\lambda = 0.6$ and $k = 4$; $\lambda = 0.8$ and $k = 10$, we obtain accurate estimates and minimal standard deviation for all weight matrix types. This also highlights the importance of using larger samples and the value of the linearized version of GMM estimation proposed by Klier and McMillen (2008).

3.1.2 Experimental design for the double SAR model

In this section we compare the properties of three estimators by Monte Carlo simulations in order to shed light on how the properties of these estimators vary according to the number of observations, and to highlight the importance of the adjusting coefficient when a downward bias of the coefficient estimators is observed.

We consider different numbers of observations ranging from 1000 to 100000 : $n \in \{1000, 5000, 20000, 100000\}$. For $n = 1000$, which is the central case, we use three pairs of mean numbers of neighbors $k \in \{(2,4), (2,10), (4,10)\}$ and we use paired combinations of the vector $\{0, 0.2, 0.4, 0.6, 0.8\}$, with $\rho \in \{0, 0.2, 0.4, 0.6, 0.8\}$ and $\lambda \in \{0, 0.2, 0.4, 0.6, 0.8\}$, that respect the condition $\rho + \lambda \leq 0.8$. For $n \in \{5000, 20000, 100000\}$, we limit the number of configurations to two values for spatial parameters $\rho \in \{0, 0.4\}$ and $\lambda \in \{0, 0.4\}$, two pairs of mean numbers of neighbors $k \in \{(2,4), (4,10)\}$.

LGMM results for the double SAR DGP: Tables 2 and 3 show the results for the double SAR model using standard logit, the linearized GMM spatial and the adjusted LGMM estimators. We limit our comparison to weight matrices of type A, as in Klier and McMillen (2008) (See appendix for other cases).

For small spatial autocorrelation, all the estimators perform well. When the sum of the two spatial parameters is greater than 0.4, both the standard logit and LGMM estimators begin to provide biased β with RMSE larger than 0.1. The downward bias for the standard logit estimate of β becomes large when the mean number of neighbors increases or when spatial autocorrelation increases. Larger sample sizes do not lead to correction of this bias, as illustrated in table 3. For all cases in table 2, LGMM estimates of β are better than standard logit estimates, and ALGMM coefficient estimates are more accurate than LGMM in nearly all cases. The single case for which LGMM provides more accurate estimates of β is when $\lambda = 0$ and $\rho = 0.8$: however this case is unrealistic when matrix W and matrix M are identical and share a lot of common neighbors. When the true spatial parameters are smaller than 0.2, both LGMM and ALGMM estimators perform well. Under true ρ ranging from 0.4 to 0.8, LGMM tends to overestimate one of the two spatial parameters.

Two other noteworthy points arise from our MC experiments in which W and M are almost identical and share a lot of common neighbors. First, when matrix W has a higher mean number of neighbors than matrix M in a double SAR model as defined in 1, this increases the bias of λ estimates, and consequently of β estimates. If there is no reason not to, it is preferable to reverse the order of spatial filter in this case. Second, when the sum of the two spatial parameters is high and with a large difference in value between the two parameters, as when $\lambda = 0.2$ and $\rho = 0.6$, the ALGMM provides biased estimates of the spatial parameters and moderately biased estimates of the sum of the two parameters. This means that an acceptable RMSE can be maintained for β because an accurate estimates of the global spatial filter $(I - \rho M)^{-1}(I - \lambda W)^{-1}$ is achievable when matrix W and matrix M are almost identical and share a lot of common neighbors. When matrix W and matrix M have fewer common neighbors, we obtain accurate estimates of all coefficients even in these extreme cases.

Large sample sizes significantly reduce the RMSE for one spatial parameters for the LGMM estimator and for all spatial parameters for the ALGGM estimator. The standard logit remains biased for high values of spatial parameters even for large samples. Thus ALGMM estimator performs well as the sample size increases and as the difference between the W and M matrices increases. When samples contain more than 20000 observations, for all cases except $\lambda = 0$ and $\rho = 0.8$, the ALGMM estimators provide estimates for all coefficients with an RMSE under 0.05, 3 times less than for LGMM and standard logit. For the unrealistic extreme case $\lambda = 0$ and $\rho = 0.8$, ALGMM estimators provide estimates for all coefficients with a RMSE under 0.09 and probably reach the threshold of 0.5 for 200000 observations.

These promising results could also be improved by making W and M which are more independent and giving them fewer common neighbors, as in the case of our empirical example presented in the next section.

4 Empirical application

We turn now to an illustrative application of the proposed estimator to modeling land use change at parcel level in a data-rich environment. The works on LGMM estimator done for this article belongs to the URBANSIMUL project which aims to develop an urban-sprawl simulator at parcel scale for the region PACA (Provence-Alpes-CŹte dÕAzur) in southern France. A part of this project is devoted to evaluate the presence and the magnitude of urban spillover between municipalities that can impact land development. These issues lead us to the empirical application developed here.

By choosing the extent and the modalities of its urban development for the medium term through a land use plan (LUP) and related density requirements, each municipality will affect future urbanization of nearby municipalities (Cho and Linneman, 1993). For example, a municipality's low stock of developable land can divert demand to nearby municipalities; a high stock of developable land can have the reverse effect if the regional developable land market is not undersupplied. Depending on the extent and the nature of its urban development, which may affect local amenities and/or public services, a municipality can also modify the attractiveness of a region, with consequences for the future urbanization of nearby municipalities.

This question has been addressed mainly through the analysis of spillover effects on land and house prices, for example in Pollakowski and Wachter (1990) and more recently in Ihlanfeldt (2007) or through the analysis of spillover effects on housing production at aggregated scale - county or region - for example Levine (1999) or Chakraborty et al. (2010). To our knowledge, however, no econometric study of the spillover effects from the urban zoning/urban policy of neighboring/adjacent counties on land use change at parcel level has ever been attempted. The logit double SAR model proposed in this paper can be used to test the presence and the magnitude of spatial spillover between municipalities, while modeling the spatial urbanization process at fine scale.

The study area is composed of 57 municipalities which belong to 3 "SCOT" (*Schéma de cohérence territoriale*) an inter-municipality urban master plan. A "SCOT" is a planning instrument at supra-municipal level that defines overall medium-term objectives for urban development and is intended to coordinate all municipal LUPs. The study area can be qualified as polycentric, with several medium-dense towns and numerous peri-urban and rural municipalities. The area is also popular for holidays, with numerous isolated small villages lacking public services but with beautiful landscapes and numerous protected areas. Thus, land/house prices can be high, despite the distance from the Central Business District (CBD). Moreover, there is high demand for low-density development in the study area and, in general, an insufficient supply of developable land to meet this demand. As a result, municipal choices on land use zoning and on level of development in these holiday areas with an undersupplied developable land market can have spillover effects.

In the study area, we focus on the urban densification process inside the developable zones under the LUP between 2000 and 2009. The sample (see Appendix page 35 for a brief description of the data sources) for the 57 municipalities contains $n_0 = 161.232$ contiguous parcels aggregated by land title (hereafter CPLT)[4], with 55.796 observations built before the year 2000. Of the 105.436 remaining observations, 21.145 are developable and unbuilt as of the year 2000. So, the size of the sample used for estimation is $n = 21.145$. We consider the following double SAR model:

$$(I - \rho M^{\star})(I - \lambda W)y_{t0-9} = \tilde{\lambda}\tilde{W}y_{tm0} + X\beta + \epsilon \tag{13}$$

where y_{t0-9} is a binary variable for CPLT built or unbuilt between 2000 and 2009 in developable zones of LUPs, considering only CPLT unbuilt at the beginning of 2000. W is the $n \times n$ spatial weight matrix for the spatial lag term. y_{tm0} represents the parcels built before 2000, and then $\tilde{W}y_{tm0}$ represents a neighboring density at the beginning of 2000 that can be considered an exogenous variable. Note that $\tilde{W}$ is a $n \times n_0$ spatial weight matrix with more columns than rows. M is a $n \times n$ spatial weight matrix for measuring spillover effects which is based on neighboring municipalities.

Municipal spillovers relative to land use regulation can be driven by different kinds of relationships (Brueckner, 2003), including :

- Space. Closer municipalities may have higher spillovers;
- Size. Municipalities with larger populations or larger in size may act as leaders: other municipalities will basically react to the policies of the leader;
- Common membership of a higher-level jurisdiction. The higher jurisdiction generally

[4] Availability of micro-data on land ownership allows us to consider contiguous parcels belonging to the same land title (same owner) as a single unit (CPLT). Outside the urban core of towns, it is common in France to find two or three parcels of land for a single developed property (31.22% have a single parcel, 18.30% two parcels, 11.30% three parcels, and 90 % less than 10 parcels). For the purposes of studying low density urbanization, aggregating parcels of land by ownership yields a clearer spatial pattern between built and unbuilt spatial units.

forces all municipalities to coordinate local policies, so spillovers are essentially confined to municipalities that are members of the same jurisdiction level.

In our study area, due to the presence of the inter-municipal urban master plan jurisdiction (SCOT), we propose and test four specifications for M in order to take into account likely municipal spillovers:

$M1$ if $CPLT$ of municipality i and $CPLT$ of municipality j belong to the same inter-municipal urban master plan, they are neighbors.

$M2$ if $CPLT$ of municipality i and $CPLT$ of municipality j belong to the same inter-municipal urban master plan and municipality i and municipality j are contiguous, they are neighbors.

$M3$ if $CPLT$ of municipality i and $CPLT$ of municipality j belong to the same inter-municipal urban master plan and population of municipality j is higher than the population of municipality i, then $CPLT_j$ is a neighbor of $CPLT_i$.

$M4$ if $CPLT$ of municipality i and $CPLT$ of municipality j belong to the same inter-municipal urban master plan and population of municipality j is the highest of the inter-municipal urban master plan, $CPLT_j$ is a neighbor of $CPLT_i$.

Since we define neighboring at municipal scale for the M, we can reduce the dimension of M to $m \times m$ - where m is the number of municipalities - during some steps in the computation. Moreover, because we consider only municipal spillovers within one inter-municipal urban master plan, M is a block diagonal matrix with 3 blocks that facilitates the inversion of the spatial multiplier.

As mentioned in the last section, we need a reasonable average number of neighbors in order to obtain accurate estimates of the spatial parameters. Because we are interested in municipal spillover, this means that all the observations of neighboring municipalities will be neighbors.

Thus, the average number of neighbors for all M matrices will be far from reasonable. To obtain accurate estimates of the spatial parameters, we will therefore consider only a small proportion of the neighbors from the initial M matrices: we select only neighboring CPLTs with similar characteristics. To do so, we use a matching procedure to select the neighbors that are more likely to show spatial interaction, assuming that more similar observations will have more intense spatial interactions. The idea of mixing spatial and economic criteria to build spatial weight matrices is not new Case et al. (1993) and follows several recent recommendations in the spatial econometrics literature, for example Corrado and Fingleton (2012). A nice example of selecting neighbors using both spatial contiguity and intensity of economic relationship can be found in Franzese and Hays (2007). However, the use of economic distance to construct spatial weights matrices is still under debate in spatial econometrics. While it may be appropriate to numerous empirical contexts, it can also introduce endogeneity problems. Qu and Lee (2015) recently propose an elegant solution to reduce this problem. In our case, the Monte Carlo experiments based on the empirical data allow us both to define an optimal number of neighbors and to show the absence of bias due to potential endogeneity of W.

To identify the most similar observations among the initial neighbors of M matrices, we estimate a measure of similarity between CPLTs based on 5 characteristics. For 3 of these characteristics (area, distance from secondary road and orientation) we use Mahalanobis distance and we use exact matching for 2 of these characteristics (type of land owner and type of zoning). Then, the matching procedure selects from the initial neighbors set those neighbors that have the same type of owner and the same type of zoning, and that are as similar as possible in terms of area, distance from secondary road and orientation. In order to determine how many neighbors need to be selected for each observation, i.e. the number required for accurate estimates of spatial parameters, we run MC experiments with our empirical weight matrices W, $M1 : M4$ and empirical X, and simulate e and Y as in the MC experiment in section 3. In these experiments (details available on request), we first estimate the similarity index between CPLTs that are neighbors in the initial $M1 : M4$ matrices and test different subsets of neighbors using different numbers of k first neighbors for this similarity index. As soon as we have less than 30 neighbors, we obtain RMSE for λ and ρ under 0.1. We then choose for the application example 10 neighbors, denoted $M1\star : M4\star$, which allows us to obtain, in our MC experiments, an RMSE smaller than 0.05 for all cases. Note that because these 5 characteristics vary widely in each municipality, even with a threshold of 10 most similar neighbors, the matching procedure allows between 81 to 99% (depending on the M matrix) of initial neighbors from two municipalities to be selected at least once as neighbor.

Table 4 contains descriptive statistics of the exogenous variables X selected for this model among a large set of covariates ("distance to" variables, land and owner characteristics, slope, orientation, ...) using a stepwise procedure for the standard logit version of (1), i.e considering $\lambda = \rho = 0$. We choose $\tilde{W}$ using different neighboring distance radii in order to obtain the most significant coefficient $\tilde{\lambda}$ for the standard logit version of (1). As soon as the final set of covariates X was identified, we estimated Moran statistics for a spatial discrete model (Pinkse and Slade, 1998; Amaral et al. 2012) appropriate to the binomial logit case in order to test for spatial autocorrelation in residuals for all weight matrices W and M. We then have choose the neighboring distance radius for W that minimizes the residuals of ALGMM estimation of the single SAR version of (13), i.e considering $\rho = 0$. Finally we estimated the model (13) using the four specifications for M in order to identify municipal spillovers when the ALGMM estimation is used for the double SAR model.

4.1 Results

We perform spatial auto-correlation tests based on an adaptation of LM Moran test for binomial data (Pinkse and Slade 1998) using standard logit estimates of the residuals. For each test, we consider one of the 4 W matrices or 4 M matrices, because, as far as we known, there is no bidirectional test for spatial autocorrelation for binomial case. For any spatial weight matrix, we find strong spatial autocorrelation in standard logit residuals (details available on demand).

Table 5 shows the results of the standard logit estimation and the LGMM estimation of model (13) using W3 weight matrix (300 meters neighboring) combined with each "reduced" $M^\star$ matrices. The 300 meters neighboring for matrix W minimizes the residuals sum of square whatever is the $M^\star$ matrix. The coefficients associated to the characteristics of parcels, land owners and distance to urban services and land use zoning have expected signs and significance levels: they are not discussed here as our focus is on the spatial parameters $\tilde{\lambda}$, λ and ρ.

Compared to the standard logit, the ALGMM estimation improves the model adjustment with lower residuals sum of square for all models and better prediction of discrete choices. Changes in coefficient estimates for β between Standard Logit and LGMM have a maximum ratio of 2, but the coefficients remains quite comparable with no sign reversal, and no change for significance at 5 %, except for the distance to secondary road which is no more significant when spatial autocorrelation is taken into account. Coefficient estimates of β are almost identical between ALGMM models.

We found that both λ and $\tilde{\lambda}$ positive and highly significant, which means that the urbanization appears in proximity to CPLT already built or in proximity to CPLT with high probability to be built. This result is known and widely documented in the literature. However, we can note that contemporary spatial dependence of residential development is twice the past spatial dependence. This indicates that, in this region, urban planners may currently favor the densification of new residential development more than in the past. This result is coherent with the actual trend of land use policy in France that aim to limit low density urbanization since 2000[5]. If we also consider that the total amount of developable

[5]The law called SRU (*Solidarité et Renouvellement Urbain*) promotes densification for new and existing developable zones for future urbanization, forbids the use of minimum lot size and limits leap frog development.

area is constant during the period, we can provide two other explanations to this phenomena: as developable zones become more dense, 1) new urbanization become complex and only coordinated operations and "professional" urban projects are feasible, 2) we can face to a specialization of some undeveloped areas that becomes urban parks or parking.

The spatial coefficient ρ is significant for half of $M^{\star}$ matrices. We found a high positive spatial spillover between municipalities belonging to the same urban master plan ($M1^{\star}$). This spatial spillover becomes lower and less significant when we consider only contiguous municipalities belonging to the same urban master plan ($M2^{\star}$). When we consider only as neighbors municipalities of the same urban master plan with higher population ($M3^{\star}$) or when we consider only as neighbors the municipality of the same urban master plan with the highest population ($M4^{\star}$), ρ is no more significant. This indicates that the spatial spillover between municipalities is mainly related to the belonging to the same master plan : the interaction between municipality master plan act at the intercommunal scale in which the urban master plan is elaborated, whatever is the size of the municipality.

5 Concluding remarks

The objective of this paper is to develop a feasible LGMM estimator for spatial autoregressive logit models that involve both a double spatial lag latent dependent variable. The proposed ALGMM estimator is computationally attractive on large samples because it avoids evaluating complex likelihood functions containing n-dimensional integration, the determinant of the $n \times n$ matrix and inversion of large matrices in each iteration. Under empirically reasonable conditions, the estimator is consistent and asymptotically normal. Monte Carlo experiments suggest that the ALGMM model accurately identifies spatial effects for large samples. With reasonable mean number of neighbors, the validity of our estimator is confirmed. Consequently, when sample size is sufficiently large relative to the mean number of neighbors, it can easily be used to test for spatial effects (spatial lag and/or spatial disturbance) without biasing the results toward rejection of the null both for unidirectional and bidirectional tests.

We apply our LGMM estimator to analyze urban sprawl and urban policy spillover at parcel level in France. The empirical results indicate that the probability of development is higher in very close neighboring of already built parcels, and this phenomena is more important than in the past in our study area: urban planners favor the densification of new residential development. It also indicates a positive spillover effect between municipalities belonging to the same master plan, and a negative spillover (competition) between the largest municipalities and all other municipalities of the same master plan.

Two major issues are extending this approach to the spatiotemporal case to allow the use of longitudinal spatial data and to the multinomial case (Irwin, 2010; Pinkse and Slade, 2010). Carrion-Flores et al. (2009) and Li et al. (2013) have proposed a straightforward extension of the LGMM SAR to multinomial case, but without studying the finite properties of the estimator for the various configurations of weight matrix types, of mean number of neighbors and of observed distributions of possible discrete choices. More work needs to be done in this direction. Incorporating the temporal dimension is more difficult because it leads to a parameter identification problem. A possible way to solve this problem would be to incorporate the temporal dimension in the spatial autoregressive error term: with some additional assumptions (to be identified in future works), the estimation of the dynamic panel data spatial logit model might be feasible. Another possibility we intend to explore is to study the dynamics of the spatial discrete choice to conceive empirical land use forecasting model is to use rank by rank estimation (year by year) of the estimator proposed here.

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6 Tables

n=1000		Weight matrix type (A)					Weight matrix type (B)					Weight matrix type (C)					Weight matrix type (D)					Weight matrix type (E)				
		Standard Logit		GMM			Standard Logit		GMM			Standard Logit		GMM			Standard Logit		GMM			Standard Logit		GMM		
λ_0	$\sharp W$	β_0	β_1	β_0	β_1	λ	β_0	β_1	β_0	β_1	λ	β_0	β_1	β_0	β_1	λ	β_0	β_1	β_0	β_1	λ	β_0	β_1	β_0	β_1	λ
0	2	0.002 *(0.07)*	1.006 *(0.11)*	0.002 *(0.07)*	1.013 *(0.11)*	0.001 *(0.16)*	0 *(0.07)*	1.012 *(0.12)*	0.001 *(0.07)*	1.02 *(0.12)*	-0.006 *(0.16)*	-0.001 *(0.07)*	1.006 *(0.12)*	-0.001 *(0.07)*	1.013 *(0.12)*	-0.013 *(0.18)*	0.003 *(0.06)*	0.998 *(0.12)*	0.004 *(0.07)*	1.006 *(0.12)*	-0.009 *(0.2)*	0.001 *(0.06)*	1.002 *(0.12)*	0.001 *(0.07)*	1.009 *(0.12)*	-0.018 *(0.2)*
0	4	-0.001 *(0.07)*	1.004 *(0.12)*	0.001 *(0.07)*	1.013 *(0.12)*	-0.026 *(0.25)*	-0.002 *(0.06)*	1.001 *(0.12)*	-0.001 *(0.07)*	1.01 *(0.12)*	-0.008 *(0.21)*	0.003 *(0.07)*	1 *(0.12)*	0.004 *(0.07)*	1.008 *(0.12)*	-0.014 *(0.22)*	-0.004 *(0.06)*	1.006 *(0.12)*	-0.004 *(0.07)*	1.013 *(0.12)*	-0.024 *(0.21)*	0 *(0.07)*	1.002 *(0.12)*	0.001 *(0.07)*	1.01 *(0.12)*	-0.007 *(0.2)*
0	10	0.003 *(0.07)*	1.005 *(0.12)*	0.022 *(0.24)*	1.013 *(0.12)*	-0.081 *(0.4)*	0.001 *(0.07)*	1.001 *(0.12)*	0.006 *(0.2)*	1.011 *(0.12)*	-0.051 *(0.38)*	0.001 *(0.07)*	0.998 *(0.12)*	0.002 *(0.15)*	1.006 *(0.12)*	-0.016 *(0.3)*	0 *(0.07)*	0.996 *(0.12)*	0.002 *(0.07)*	1.004 *(0.12)*	0.004 *(0.28)*	0.002 *(0.06)*	0.999 *(0.12)*	0.004 *(0.11)*	1.007 *(0.12)*	-0.002 *(0.26)*
0	20	0.001 *(0.07)*	1.003 *(0.11)*	0.003 *(0.32)*	1.011 *(0.11)*	-0.073 *(0.47)*	-0.004 *(0.06)*	1.007 *(0.12)*	0 *(0.3)*	1.016 *(0.12)*	-0.065 *(0.47)*	-0.001 *(0.06)*	1.009 *(0.12)*	-0.014 *(0.27)*	1.018 *(0.12)*	-0.035 *(0.39)*	0.001 *(0.07)*	1.006 *(0.12)*	0.013 *(0.28)*	1.013 *(0.12)*	-0.046 *(0.37)*	0.002 *(0.06)*	1.001 *(0.12)*	0.007 *(0.3)*	1.009 *(0.12)*	-0.049 *(0.39)*
0	60	0 *(0.07)*	1.002 *(0.12)*	0.004 *(0.22)*	1.008 *(0.12)*	-0.043 *(0.55)*	0 *(0.06)*	1.005 *(0.12)*	0.005 *(0.2)*	1.014 *(0.12)*	-0.051 *(0.66)*	0.002 *(0.07)*	1.012 *(0.12)*	0.013 *(0.18)*	1.024 *(0.12)*	-0.054 *(0.58)*	0.003 *(0.06)*	0.999 *(0.12)*	-0.001 *(0.31)*	1.005 *(0.12)*	-0.095 *(0.53)*	0.002 *(0.06)*	1.006 *(0.12)*	0.013 *(0.13)*	1.014 *(0.12)*	-0.068 *(0.58)*
0.2	2	0.01 *(0.07)*	0.99 *(0.12)*	0.004 *(0.06)*	1.013 *(0.12)*	0.2 *(0.16)*	0.002 *(0.07)*	1.007 *(0.12)*	-0.002 *(0.06)*	1.011 *(0.12)*	0.193 *(0.16)*	0.003 *(0.06)*	0.992 *(0.12)*	0 *(0.06)*	1.013 *(0.12)*	0.193 *(0.19)*	0.001 *(0.06)*	0.998 *(0.12)*	-0.001 *(0.06)*	1.01 *(0.12)*	0.193 *(0.18)*	0.004 *(0.06)*	0.985 *(0.12)*	0.001 *(0.06)*	1.014 *(0.12)*	0.2 *(0.17)*
0.2	4	0.004 *(0.07)*	0.998 *(0.12)*	0 *(0.06)*	1.014 *(0.12)*	0.18 *(0.21)*	0.005 *(0.07)*	0.984 *(0.11)*	0 *(0.06)*	1.008 *(0.11)*	0.185 *(0.2)*	0.008 *(0.07)*	0.994 *(0.12)*	0.003 *(0.06)*	1.012 *(0.12)*	0.209 *(0.2)*	0.009 *(0.06)*	0.992 *(0.12)*	0.003 *(0.06)*	1.014 *(0.12)*	0.193 *(0.21)*	0 *(0.07)*	0.994 *(0.12)*	-0.001 *(0.06)*	1.013 *(0.12)*	0.203 *(0.18)*
0.2	10	0.008 *(0.07)*	1 *(0.12)*	-0.002 *(0.19)*	1.015 *(0.12)*	0.148 *(0.33)*	0.007 *(0.07)*	1.003 *(0.12)*	0.006 *(0.11)*	1.017 *(0.12)*	0.153 *(0.32)*	0.006 *(0.06)*	0.998 *(0.12)*	0.002 *(0.06)*	1.013 *(0.12)*	0.189 *(0.26)*	0.006 *(0.07)*	1.004 *(0.12)*	0.001 *(0.06)*	1.011 *(0.12)*	0.199 *(0.26)*	0.003 *(0.06)*	0.992 *(0.12)*	0 *(0.06)*	1.009 *(0.12)*	0.173 *(0.23)*
0.2	20	0.006 *(0.07)*	1.003 *(0.12)*	0.013 *(0.22)*	1.014 *(0.12)*	0.098 *(0.44)*	0.007 *(0.06)*	1.004 *(0.12)*	0.005 *(0.19)*	1.014 *(0.12)*	0.136 *(0.42)*	0.004 *(0.07)*	0.995 *(0.12)*	-0.015 *(0.28)*	1.016 *(0.13)*	0.15 *(0.37)*	0.002 *(0.07)*	1 *(0.12)*	-0.006 *(0.14)*	1.01 *(0.12)*	0.159 *(0.34)*	0.005 *(0.06)*	1.001 *(0.12)*	0.007 *(0.14)*	1.012 *(0.12)*	0.16 *(0.34)*
0.2	60	0.006 *(0.07)*	0.999 *(0.12)*	0.012 *(0.16)*	1.006 *(0.12)*	0.079 *(0.55)*	0.007 *(0.06)*	0.996 *(0.12)*	-0.001 *(0.29)*	1.008 *(0.12)*	0.061 *(0.66)*	0.006 *(0.07)*	1.008 *(0.12)*	0.002 *(0.23)*	1.022 *(0.12)*	0.098 *(0.55)*	0.012 *(0.07)*	1.002 *(0.12)*	0.006 *(0.27)*	1.009 *(0.12)*	0.127 *(0.49)*	0.008 *(0.06)*	1 *(0.12)*	0.007 *(0.18)*	1.011 *(0.12)*	0.078 *(0.58)*
0.4	2	0.013 *(0.07)*	0.947 *(0.12)*	0.001 *(0.05)*	1.011 *(0.12)*	0.407 *(0.15)*	0.005 *(0.07)*	0.984 *(0.12)*	-0.002 *(0.05)*	1.013 *(0.12)*	0.408 *(0.16)*	0.003 *(0.07)*	0.955 *(0.12)*	-0.001 *(0.05)*	1.009 *(0.12)*	0.405 *(0.17)*	0.001 *(0.07)*	0.978 *(0.12)*	-0.002 *(0.05)*	1.018 *(0.12)*	0.409 *(0.19)*	0.002 *(0.06)*	0.946 *(0.12)*	-0.004 *(0.05)*	1.014 *(0.12)*	0.395 *(0.19)*
0.4	4	0.01 *(0.07)*	0.961 *(0.12)*	-0.002 *(0.05)*	1.006 *(0.12)*	0.396 *(0.19)*	0.014 *(0.06)*	0.952 *(0.12)*	0 *(0.05)*	1.013 *(0.13)*	0.397 *(0.18)*	0.011 *(0.06)*	0.97 *(0.12)*	0 *(0.05)*	1.014 *(0.12)*	0.405 *(0.2)*	0.013 *(0.07)*	0.969 *(0.12)*	0.001 *(0.05)*	1.02 *(0.12)*	0.401 *(0.19)*	0.005 *(0.06)*	0.963 *(0.12)*	0.002 *(0.05)*	1.014 *(0.12)*	0.402 *(0.18)*
0.4	10	0.015 *(0.06)*	0.98 *(0.11)*	0.001 *(0.06)*	1.012 *(0.12)*	0.353 *(0.27)*	0.01 *(0.06)*	0.979 *(0.12)*	-0.004 *(0.12)*	1.008 *(0.12)*	0.356 *(0.28)*	0.012 *(0.06)*	0.982 *(0.12)*	-0.001 *(0.05)*	1.016 *(0.12)*	0.392 *(0.25)*	0.013 *(0.06)*	0.993 *(0.12)*	0.001 *(0.05)*	1.009 *(0.12)*	0.39 *(0.23)*	0.013 *(0.07)*	0.968 *(0.11)*	0.001 *(0.05)*	1.012 *(0.12)*	0.391 *(0.2)*
0.4	20	0.01 *(0.07)*	0.99 *(0.12)*	0 *(0.06)*	1.011 *(0.12)*	0.336 *(0.36)*	0.01 *(0.07)*	0.989 *(0.12)*	-0.001 *(0.12)*	1.007 *(0.12)*	0.353 *(0.36)*	0.02 *(0.06)*	0.981 *(0.12)*	0.003 *(0.09)*	1.021 *(0.12)*	0.372 *(0.3)*	0.016 *(0.07)*	0.985 *(0.12)*	-0.001 *(0.12)*	1.007 *(0.12)*	0.381 *(0.29)*	0.009 *(0.07)*	1.001 *(0.12)*	-0.003 *(0.11)*	1.021 *(0.12)*	0.357 *(0.29)*
0.4	60	0.015 *(0.07)*	1.002 *(0.12)*	-0.001 *(0.23)*	1.012 *(0.12)*	0.256 *(0.5)*	0.016 *(0.07)*	0.996 *(0.12)*	0.012 *(0.11)*	1.013 *(0.13)*	0.269 *(0.63)*	0.014 *(0.07)*	0.997 *(0.12)*	0.008 *(0.09)*	1.02 *(0.12)*	0.307 *(0.53)*	0.022 *(0.07)*	0.996 *(0.12)*	-0.002 *(0.25)*	1.007 *(0.12)*	0.311 *(0.46)*	0.015 *(0.07)*	0.992 *(0.12)*	0.007 *(0.22)*	1.006 *(0.12)*	0.274 *(0.53)*
0.6	2	0.019 *(0.07)*	0.882 *(0.11)*	0 *(0.04)*	1.008 *(0.11)*	0.605 *(0.15)*	0.013 *(0.07)*	0.937 *(0.12)*	0.001 *(0.04)*	1.013 *(0.11)*	0.607 *(0.17)*	0.012 *(0.06)*	0.9 *(0.12)*	0.003 *(0.04)*	1.013 *(0.12)*	0.628 *(0.22)*	0.006 *(0.07)*	0.924 *(0.12)*	0 *(0.05)*	1.009 *(0.12)*	0.618 *(0.22)*	0.012 *(0.06)*	0.882 *(0.12)*	0.001 *(0.05)*	1.014 *(0.12)*	0.626 *(0.21)*
0.6	4	0.024 *(0.06)*	0.914 *(0.11)*	0.001 *(0.04)*	1.011 *(0.12)*	0.607 *(0.17)*	0.029 *(0.06)*	0.887 *(0.12)*	0.003 *(0.04)*	1.006 *(0.12)*	0.601 *(0.18)*	0.014 *(0.07)*	0.919 *(0.11)*	0 *(0.04)*	1.01 *(0.12)*	0.611 *(0.2)*	0.019 *(0.06)*	0.914 *(0.12)*	0 *(0.04)*	1.014 *(0.13)*	0.602 *(0.2)*	0.005 *(0.07)*	0.91 *(0.11)*	0.001 *(0.04)*	1.015 *(0.12)*	0.612 *(0.19)*
0.6	10	0.026 *(0.07)*	0.942 *(0.11)*	0 *(0.04)*	1.012 *(0.12)*	0.592 *(0.2)*	0.027 *(0.06)*	0.946 *(0.12)*	0.003 *(0.04)*	1.012 *(0.12)*	0.594 *(0.23)*	0.026 *(0.06)*	0.945 *(0.12)*	0 *(0.04)*	1.013 *(0.12)*	0.599 *(0.21)*	0.02 *(0.06)*	0.973 *(0.12)*	-0.001 *(0.04)*	1.019 *(0.12)*	0.599 *(0.23)*	0.021 *(0.07)*	0.923 *(0.12)*	0.002 *(0.04)*	1.01 *(0.12)*	0.588 *(0.18)*
0.6	20	0.03 *(0.07)*	0.969 *(0.12)*	0.003 *(0.17)*	1.008 *(0.12)*	0.545 *(0.29)*	0.02 *(0.07)*	0.973 *(0.12)*	0.003 *(0.05)*	1.005 *(0.12)*	0.554 *(0.29)*	0.028 *(0.06)*	0.943 *(0.11)*	-0.003 *(0.14)*	1.016 *(0.12)*	0.579 *(0.27)*	0.029 *(0.07)*	0.964 *(0.12)*	0.005 *(0.04)*	1.009 *(0.12)*	0.58 *(0.26)*	0.017 *(0.06)*	0.968 *(0.12)*	0.001 *(0.04)*	1.011 *(0.12)*	0.573 *(0.24)*
0.6	60	0.03 *(0.07)*	0.999 *(0.12)*	0.006 *(0.06)*	1.016 *(0.12)*	0.541 *(0.38)*	0.032 *(0.07)*	0.988 *(0.12)*	0.016 *(0.09)*	1.013 *(0.12)*	0.498 *(0.53)*	0.025 *(0.07)*	0.981 *(0.12)*	0.013 *(0.1)*	1.017 *(0.12)*	0.516 *(0.48)*	0.039 *(0.07)*	0.997 *(0.12)*	0.003 *(0.12)*	1.016 *(0.12)*	0.551 *(0.38)*	0.023 *(0.07)*	0.983 *(0.12)*	0.005 *(0.06)*	1.007 *(0.12)*	0.505 *(0.45)*
0.8	2	0.026 *(0.06)*	0.805 *(0.11)*	-0.001 *(0.04)*	1.015 *(0.12)*	0.816 *(0.19)*	0.015 *(0.06)*	0.873 *(0.11)*	0 *(0.04)*	1.018 *(0.11)*	0.821 *(0.2)*	0.011 *(0.06)*	0.844 *(0.12)*	0 *(0.04)*	1.016 *(0.13)*	0.826 *(0.26)*	0.011 *(0.06)*	0.869 *(0.11)*	0.002 *(0.04)*	1.01 *(0.12)*	0.824 *(0.26)*	0.018 *(0.06)*	0.818 *(0.11)*	0.003 *(0.04)*	1.01 *(0.13)*	0.849 *(0.31)*
0.8	4	0.029 *(0.06)*	0.844 *(0.11)*	-0.002 *(0.03)*	1.015 *(0.12)*	0.818 *(0.18)*	0.032 *(0.07)*	0.814 *(0.12)*	-0.001 *(0.04)*	1.014 *(0.13)*	0.813 *(0.2)*	0.025 *(0.06)*	0.86 *(0.11)*	0.003 *(0.04)*	1.013 *(0.12)*	0.81 *(0.22)*	0.029 *(0.06)*	0.844 *(0.11)*	0 *(0.04)*	1.011 *(0.13)*	0.817 *(0.23)*	0.004 *(0.06)*	0.843 *(0.12)*	0.001 *(0.04)*	1.023 *(0.12)*	0.846 *(0.32)*
0.8	10	0.044 *(0.07)*	0.883 *(0.11)*	0.002 *(0.03)*	1.009 *(0.12)*	0.796 *(0.17)*	0.033 *(0.06)*	0.899 *(0.12)*	0.001 *(0.03)*	1.014 *(0.12)*	0.789 *(0.2)*	0.039 *(0.07)*	0.9 *(0.12)*	0 *(0.03)*	1.017 *(0.12)*	0.796 *(0.23)*	0.031 *(0.06)*	0.93 *(0.12)*	0 *(0.03)*	1.021 *(0.12)*	0.797 *(0.22)*	0.022 *(0.06)*	0.855 *(0.12)*	-0.002 *(0.03)*	1.01 *(0.12)*	0.814 *(0.19)*
0.8	20	0.046 *(0.06)*	0.926 *(0.12)*	0.002 *(0.03)*	1.003 *(0.12)*	0.783 *(0.19)*	0.033 *(0.07)*	0.949 *(0.12)*	0.002 *(0.03)*	1.013 *(0.12)*	0.771 *(0.25)*	0.047 *(0.06)*	0.895 *(0.12)*	0.001 *(0.03)*	1.015 *(0.13)*	0.792 *(0.27)*	0.034 *(0.06)*	0.928 *(0.11)*	0 *(0.03)*	1.01 *(0.12)*	0.789 *(0.24)*	0.028 *(0.07)*	0.927 *(0.12)*	0.001 *(0.03)*	1.015 *(0.12)*	0.799 *(0.22)*
0.8	60	0.054 *(0.06)*	0.972 *(0.12)*	0.008 *(0.05)*	1.004 *(0.12)*	0.739 *(0.32)*	0.05 *(0.07)*	0.974 *(0.12)*	-0.007 *(0.32)*	1.012 *(0.12)*	0.672 *(0.51)*	0.039 *(0.07)*	0.967 *(0.12)*	0.004 *(0.05)*	1.027 *(0.12)*	0.758 *(0.41)*	0.061 *(0.07)*	0.98 *(0.12)*	-0.002 *(0.16)*	1.014 *(0.12)*	0.765 *(0.33)*	0.036 *(0.07)*	0.977 *(0.12)*	0.004 *(0.04)*	1.017 *(0.12)*	0.724 *(0.37)*

Table 1: Results of Monte Carlo experiment with 1000 replications, SAR Model.

Table 2: Mean and RMSE from Monte Carlo simulations - Type A weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	2	4	0.001	1.007	-1.003	0.002	1.010	-1.006	-0.004	0.004	0.002	1.010	-1.006	-0.004	0.004
		RMSE			0.072	0.089	0.088	0.073	0.090	0.088	0.106	0.150	0.073	0.090	0.088	0.106	0.152
1000	0	0.2	2	4	0.001	0.997	-0.999	0.000	1.009	-1.011	0.011	0.201	0.000	1.009	-1.011	0.011	0.199
		RMSE			0.074	0.087	0.088	0.059	0.088	0.089	0.112	0.150	0.059	0.088	0.089	0.112	0.157
1000	0.2	0.2	2	4	-0.001	0.958	-0.954	0.000	1.004	-1.001	0.188	0.274	0.000	0.995	-0.992	0.188	0.226
		RMSE			0.077	0.096	0.099	0.046	0.087	0.088	0.109	0.171	0.046	0.087	0.088	0.109	0.163
1000	0	0.4	2	4	0.002	0.949	-0.953	0.002	1.007	-1.012	0.022	0.461	0.001	0.999	-1.004	0.022	0.441
		RMSE			0.073	0.100	0.100	0.041	0.096	0.099	0.111	0.162	0.041	0.091	0.094	0.111	0.158
1000	0.2	0.4	2	4	0.001	0.889	-0.888	0.000	1.044	-1.044	0.192	0.551	0.000	0.976	-0.976	0.192	0.445
		RMSE			0.084	0.140	0.142	0.036	0.152	0.160	0.115	0.226	0.033	0.090	0.093	0.115	0.159
1000	0.4	0.4	2	4	-0.002	0.801	-0.805	0.002	1.267	-1.275	0.319	0.733	0.001	0.927	-0.932	0.319	0.475
		RMSE			0.086	0.215	0.211	0.084	0.512	0.521	0.148	0.374	0.050	0.116	0.109	0.148	0.158
1000	0	0.6	2	4	-0.000	0.865	-0.860	0.004	1.373	-1.367	0.043	0.789	0.002	0.988	-0.983	0.043	0.635
		RMSE			0.083	0.159	0.161	0.059	0.644	0.643	0.124	0.241	0.035	0.106	0.099	0.124	0.105
1000	0.2	0.6	2	4	-0.002	0.780	-0.781	-0.001	1.657	-1.664	0.206	0.874	-0.001	0.917	-0.919	0.206	0.590
		RMSE			0.089	0.234	0.233	0.128	0.890	0.900	0.125	0.302	0.062	0.142	0.130	0.125	0.098
1000	0	0.8	2	4	-0.002	0.677	-0.677	0.003	2.091	-2.094	0.083	0.986	0.002	0.970	-0.972	0.083	0.756
		RMSE			0.104	0.332	0.332	0.276	1.124	1.127	0.162	0.188	0.144	0.327	0.331	0.162	0.138
1000	0	0	4	2	0.001	1.007	-1.005	0.001	1.010	-1.008	-0.004	0.005	0.001	1.010	-1.008	-0.004	0.005
		RMSE			0.074	0.091	0.088	0.075	0.092	0.089	0.155	0.107	0.075	0.092	0.089	0.157	0.107
1000	0	0.2	4	2	0.000	0.987	-0.989	0.000	1.001	-1.004	0.043	0.180	0.000	1.000	-1.002	0.019	0.180
		RMSE			0.074	0.091	0.089	0.058	0.090	0.089	0.158	0.113	0.058	0.090	0.089	0.161	0.113
1000	0.2	0.2	4	2	-0.000	0.957	-0.953	-0.001	1.002	-0.997	0.269	0.188	-0.001	0.993	-0.989	0.222	0.188
		RMSE			0.077	0.095	0.098	0.043	0.086	0.087	0.173	0.114	0.043	0.086	0.088	0.169	0.114
1000	0	0.4	4	2	-0.004	0.936	-0.931	-0.002	0.996	-0.991	0.171	0.337	-0.002	0.979	-0.974	0.075	0.337
		RMSE			0.074	0.109	0.111	0.041	0.088	0.086	0.230	0.126	0.040	0.090	0.089	0.190	0.126
1000	0.2	0.4	4	2	0.001	0.882	-0.878	-0.001	1.011	-1.008	0.435	0.325	-0.001	0.961	-0.958	0.295	0.325
		RMSE			0.079	0.145	0.149	0.036	0.093	0.097	0.285	0.136	0.033	0.092	0.095	0.196	0.136
1000	0.4	0.4	4	2	0.002	0.804	-0.797	-0.000	1.247	-1.240	0.724	0.325	-0.000	0.928	-0.922	0.469	0.325
		RMSE			0.082	0.212	0.220	0.081	0.482	0.487	0.364	0.146	0.049	0.111	0.119	0.152	0.146
1000	0	0.6	4	2	0.003	0.828	-0.832	-0.000	1.005	-1.009	0.445	0.445	-0.000	0.924	-0.929	0.223	0.445
		RMSE			0.078	0.190	0.187	0.041	0.094	0.098	0.475	0.195	0.037	0.111	0.111	0.300	0.195
1000	0.2	0.6	4	2	-0.002	0.769	-0.766	0.004	1.237	-1.234	0.719	0.429	0.003	0.901	-0.898	0.394	0.429
		RMSE			0.080	0.244	0.247	0.090	0.459	0.460	0.545	0.215	0.057	0.130	0.132	0.256	0.215
1000	0	0.8	4	2	0.001	0.670	-0.673	0.004	1.756	-1.756	0.911	0.504	0.001	0.834	-0.835	0.424	0.504
		RMSE			0.089	0.339	0.336	0.246	0.913	0.910	0.919	0.330	0.104	0.188	0.188	0.477	0.330

Table 3: Mean and RMSE from Monte Carlo simulations - Type A weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
5000	0	0	2	4	0.002	1.001	-1.001	0.002	1.002	-1.001	-0.001	0.003	0.002	1.002	-1.001	-0.001	0.003
		RMSE			0.032	0.038	0.039	0.032	0.038	0.039	0.047	0.066	0.032	0.038	0.039	0.047	0.066
5000	0	0.4	2	4	-0.001	0.951	-0.951	-0.000	0.992	-0.991	0.021	0.454	-0.000	0.989	-0.988	0.021	0.439
		RMSE			0.034	0.063	0.062	0.018	0.040	0.039	0.052	0.087	0.018	0.041	0.040	0.052	0.081
5000	0.4	0.4	2	4	0.000	0.805	-0.804	-0.000	0.999	-0.998	0.333	0.693	-0.000	0.928	-0.927	0.333	0.502
		RMSE			0.036	0.198	0.200	0.023	0.039	0.040	0.088	0.304	0.021	0.081	0.082	0.088	0.126
5000	0	0.8	2	4	-0.002	0.793	-0.792	0.002	1.007	-1.007	0.067	0.974	0.001	0.959	-0.959	0.067	0.864
		RMSE			0.038	0.210	0.211	0.026	0.044	0.044	0.086	0.177	0.025	0.057	0.057	0.086	0.100
5000	0	0	4	10	0.000	1.001	-0.999	0.000	1.001	-1.000	0.001	-0.003	0.000	1.001	-1.000	0.001	-0.003
		RMSE			0.033	0.040	0.040	0.034	0.040	0.040	0.061	0.096	0.034	0.040	0.040	0.061	0.096
5000	0	0.4	4	10	-0.000	0.977	-0.977	0.000	1.006	-1.006	0.016	0.505	0.000	1.004	-1.004	0.016	0.491
		RMSE			0.034	0.045	0.045	0.017	0.040	0.040	0.064	0.144	0.017	0.040	0.040	0.064	0.142
5000	0.4	0.4	4	10	-0.001	0.863	-0.864	0.001	1.125	-1.126	0.430	0.825	0.001	0.958	-0.958	0.430	0.422
		RMSE			0.040	0.142	0.141	0.038	0.136	0.137	0.076	0.438	0.032	0.057	0.056	0.076	0.110
5000	0	0.8	4	10	0.001	0.859	-0.858	0.000	1.034	-1.032	0.070	0.990	0.000	1.027	-1.025	0.070	0.974
		RMSE			0.042	0.145	0.147	0.044	0.060	0.058	0.095	0.190	0.044	0.052	0.051	0.095	0.179
20000	0	0	2	4	-0.000	1.001	-1.001	-0.000	1.001	-1.001	-0.001	0.000	-0.000	1.001	-1.001	-0.001	0.000
		RMSE			0.016	0.020	0.020	0.016	0.020	0.020	0.023	0.033	0.016	0.020	0.020	0.023	0.033
20000	0	0.4	2	4	0.000	0.952	-0.953	0.000	0.993	-0.993	0.020	0.454	0.000	0.990	-0.990	0.020	0.440
		RMSE			0.017	0.052	0.051	0.009	0.021	0.020	0.031	0.064	0.009	0.023	0.022	0.031	0.054
20000	0.4	0.4	2	4	0.001	0.805	-0.804	-0.000	0.997	-0.996	0.337	0.689	-0.000	0.926	-0.925	0.337	0.498
		RMSE			0.018	0.196	0.197	0.011	0.020	0.020	0.069	0.291	0.010	0.076	0.077	0.069	0.105
20000	0	0.8	2	4	-0.000	0.792	-0.791	0.001	1.012	-1.011	0.067	0.987	0.001	0.959	-0.958	0.067	0.867
		RMSE			0.019	0.209	0.210	0.012	0.025	0.026	0.072	0.187	0.012	0.045	0.046	0.072	0.079
20000	0	0	4	10	0.000	1.001	-1.001	0.000	1.001	-1.001	-0.001	0.000	0.000	1.001	-1.001	-0.001	0.000
		RMSE			0.017	0.019	0.019	0.017	0.019	0.019	0.028	0.046	0.017	0.019	0.019	0.028	0.046
20000	0	0.4	4	10	0.000	0.975	-0.977	0.000	1.003	-1.004	0.015	0.507	0.000	1.001	-1.002	0.015	0.494
		RMSE			0.018	0.031	0.031	0.009	0.019	0.020	0.034	0.117	0.009	0.019	0.020	0.034	0.108
20000	0.4	0.4	4	10	-0.000	0.862	-0.862	-0.000	1.122	-1.123	0.433	0.823	-0.000	0.954	-0.954	0.433	0.415
		RMSE			0.019	0.139	0.139	0.019	0.125	0.126	0.047	0.426	0.016	0.049	0.050	0.047	0.053
20000	0	0.8	4	10	0.000	0.858	-0.858	-0.000	1.033	-1.033	0.072	0.990	-0.001	1.032	-1.032	0.072	0.988
		RMSE			0.022	0.143	0.143	0.021	0.041	0.041	0.080	0.190	0.021	0.040	0.040	0.080	0.188
100000	0	0	2	4	0.000	1.000	-1.000	0.000	1.000	-1.000	0.000	0.000	0.000	1.000	-1.000	0.000	0.000
		RMSE			0.007	0.009	0.009	0.007	0.009	0.009	0.011	0.015	0.007	0.009	0.009	0.011	0.015
100000	0	0.4	2	4	0.000	0.951	-0.951	0.000	0.991	-0.991	0.019	0.455	0.000	0.989	-0.989	0.019	0.440
		RMSE			0.008	0.049	0.049	0.004	0.012	0.012	0.022	0.056	0.004	0.014	0.014	0.022	0.043
100000	0.4	0.4	2	4	0.000	0.805	-0.805	-0.000	0.997	-0.997	0.336	0.689	-0.000	0.926	-0.926	0.336	0.499
		RMSE			0.008	0.196	0.196	0.005	0.009	0.009	0.065	0.289	0.004	0.074	0.074	0.065	0.100
100000	0	0.8	2	4	-0.000	0.791	-0.791	0.000	1.012	-1.012	0.066	0.990	0.000	0.958	-0.958	0.066	0.867
		RMSE			0.009	0.209	0.209	0.006	0.016	0.016	0.067	0.190	0.005	0.043	0.043	0.067	0.070
100000	0	0	4	10	-0.000	1.000	-1.000	-0.000	1.000	-1.000	0.000	-0.001	-0.000	1.000	-1.000	0.000	-0.001
		RMSE			0.007	0.009	0.009	0.007	0.009	0.009	0.013	0.021	0.007	0.009	0.009	0.013	0.021
100000	0	0.4	4	10	0.000	0.976	-0.976	0.000	1.003	-1.003	0.018	0.506	0.000	1.001	-1.001	0.018	0.492
		RMSE			0.008	0.026	0.026	0.004	0.009	0.009	0.022	0.108	0.004	0.009	0.009	0.022	0.095
100000	0.4	0.4	4	10	0.000	0.863	-0.862	-0.000	1.123	-1.122	0.433	0.823	-0.000	0.955	-0.954	0.433	0.416
		RMSE			0.009	0.138	0.138	0.008	0.123	0.123	0.036	0.424	0.007	0.046	0.047	0.036	0.028
100000	0	0.8	4	10	0.000	0.859	-0.858	-0.000	1.032	-1.032	0.071	0.990	-0.000	1.032	-1.032	0.071	0.990
		RMSE			0.009	0.142	0.142	0.010	0.034	0.034	0.073	0.190	0.010	0.034	0.034	0.073	0.190

Name	Label	Mean or freq.
y_{t0-9}	1 = developed 0= undeveloped (between 2000-2009)	16629/4516
$\tilde{W}1y_{tm0}$	housing density at 100 meters in 2000	0.8446
$\tilde{W}3y_{tm0}$	housing density at 300 meters in 2000	0.8441
$\tilde{W}5y_{tm0}$	housing density at 500 meters in 2000	0.8279
area CPLT	area of contiguous parcels aggregated by land title (CPLT) in m^2	2312
owner age	Age of the principal owner	62.23
dist main road	distance in meter to main road	2972.9
dist secondary road	distance in meter to secondary road	12.46
dist small road	distance in meter to small road	7.41
dist cbd	distance in meter to CBD	10983
local owner	owner inhabitants of the municipality (yes/no)	13845/7300
zoning	*3 developable zoning classes*	
	urban dense (ref)	13734
	urban under development	4684
	low density	4256
type of owner	*5 types of owner*	
	Individual/private (ref)	15898
	Society	2180
	Municipality	1724
	Co-owners	995
	Other public administrations	348

Table 4: Covariables

Variables / Weight matrix	**Standard Logit**	**ALGMM** $W3$ $M1^{\star}$	$W3$ $M2^{\star}$	$W3$ $M3^{\star}$	$W3$ $M4^{\star}$
(Intercept)	-2.45 *(0)*	-1.411 *(0)*	-1.448 *(0)*	-1.842 *(0)*	-1.711 *(0)*
local owner	0.9964 *(0)*	0.9393 *(0)*	0.9466 *(0)*	0.9504 *(0)*	0.957 *(0)*
owner age	-0.06892 *(0)*	-0.06634 *(0)*	-0.06715 *(0)*	-0.06677 *(0)*	-0.06666 *(0)*
Owner type *(ref=Municipality)*					
Owner type=Co-owners	3.003 *(0)*	2.712 *(0)*	2.687 *(0)*	2.778 *(0)*	2.608 *(0)*
Owner type=Other public	2.057 *(1.389e-10)*	1.77 *(0)*	1.682 *(0)*	1.724 *(0)*	1.608 *(0)*
Owner type=Society	2.291 *(1.537e-24)*	2.043 *(0)*	2.006 *(0)*	2.077 *(0)*	1.916 *(0)*
Owner type=Private	3.222 *(0)*	2.8 *(0)*	2.832 *(0)*	3.054 *(0)*	2.907 *(0)*
zoning *(ref=high density)*					
zoning=under develop.	-0.3535 *(3.34e-09)*	-0.2698 *(4.112e-08)*	-0.2568 *(3.776e-07)*	-0.2718 *(2.826e-07)*	-0.275 *(2.849e-07)*
zoning=low density	-0.2238 *(3.185e-05)*	-0.1278 *(0.003047)*	-0.1237 *(0.005612)*	-0.158 *(0.000788)*	-0.166 *(0.0005003)*
log(areaCPLT)	0.331 *(2.895e-128)*	0.3006 *(0)*	0.3017 *(0)*	0.307 *(0)*	0.3023 *(0)*
slope	-0.05845 *(0)*	-0.02241 *(2.526e-08)*	-0.02324 *(1.536e-08)*	-0.0278 *(4.841e-11)*	-0.02609 *(5.292e-10)*
dist small road = 0TRUE	-0.528 *(0)*	-0.5248 *(0)*	-0.5402 *(0)*	-0.5309 *(0)*	-0.538 *(0)*
dist small road	-0.004865 *(0.01305)*	-0.002299 *(0.1542)*	-0.001858 *(0.2937)*	-0.001794 *(0.3062)*	-0.00254 *(0.134)*
dist secondary road	-0.01074 *(4.134e-15)*	-0.01289 *(0)*	-0.01512 *(0)*	-0.01362 *(0)*	-0.01272 *(0)*
dist to major city	-8.553e-06 *(0.0008458)*	-4.704e-06 *(0.02099)*	-4.536e-06 *(0.02956)*	-4.654e-06 *(0.03771)*	-4.236e-06 *(0.0618)*
$\tilde{\lambda}(W3y_{tm0})$		0.1578 *(1.64e-08)*	0.1545 *(2.922e-08)*	0.1755 *(1.915e-08)*	0.1797 *(5.785e-09)*
λ		0.3822 *(0)*	0.3758 *(0)*	0.3829 *(0)*	0.393 *(0)*
ρ		0.1205 *(0.0001202)*	0.08115 *(0.01012)*	-0.01433 *(0.6254)*	-0.05274 *(0.08318)*
RSS	2550.841	2537.598	2524.342	2504.513	2501.16
% TRUE 1	57.8388	59.27812	59.30027	59.23384	59.30027
% TRUE 0	88.5381	88.94101	88.93499	88.92297	88.94702

Table 5: Standard logit and ALGMM estimation results, using spatial weight matrix W3

7 Figures

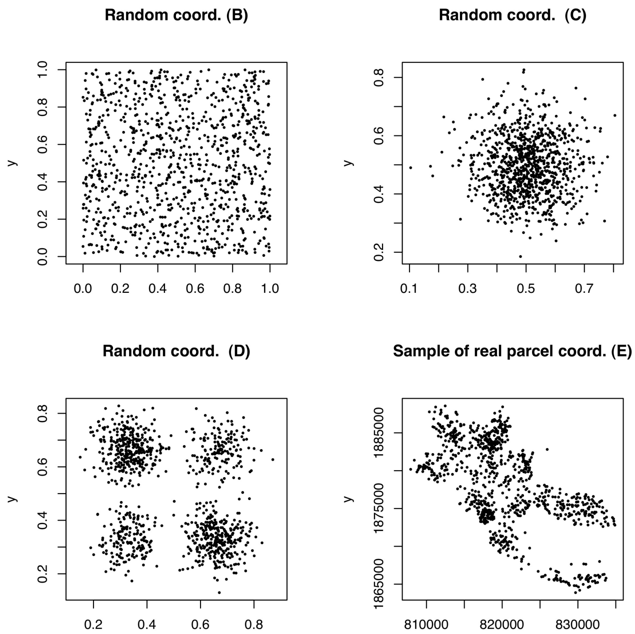

Figure 1: Class of simulated coordinates (Random cases, $n = 1000$)

Appendices

A Database Sources

A digital geodatabase on land parcel borders (PCI - *plan cadastral informatisé*, available for more then 80 % of the Provence region) and a fiscal database on land ownership at individual level (MAJIC database, whole region) were provided by the regional government for the year 2010. Access to these two major databases with around 6 million observations was granted to the INRA team under a pilot secondment agreement with local government for econometric analysis of land use change. For each parcel, this gave us the date of the sale, whether the land is developed, the nature of the development (all land and building characteristics used for tax calculations by the French administration), their intended use (housing, professional, commercial), the date of construction, the owners and any other land/property they own. The Land Use Plan Geodatabase was obtained from the nationally administered regional environmental agencies (DREAL - *Direction Régionale de l'Environnement, de l'Aménagement et du Logement*), which are in charge of the legal control of town and county planning policy. They produce a digitalized land-use plan for each municipality, harmonized for comparative use: the resulting regional geodatabase is called "Generalized LUP" and is updated every two years. Several other GIS databases on public infrastructure and road networks (BD TOPO® - *IGN Institut de Géographique National*) and environmental/risk zoning (DREAL, *carmen, cartorisque*) were used to create spatial candidate regressors (legal and physical constraints to development and minimum distance from attractive or undesirable features).

B Asymptotic properties

The GMM logit estimator of $\theta = [\beta, \rho, \lambda] \in \Theta$, $\theta^* = [\beta^*, \rho^*, \lambda^*] \in \Theta$, where Θ is the parameters open space, is the argmin of

$$Q(\theta) = S_N{}'(\theta)\Sigma_N S_N(\theta) = \left[\frac{1}{N}\sum_{i=1}^{N} g(\tilde{u}_i,\theta)\right]' \Sigma_N \left[\frac{1}{N}\sum_{i=1}^{N} g(\tilde{u}_i,\theta)\right]$$

Where Q is the objective function, $S_N(\theta) = \frac{1}{N}Z'\tilde{u} = \frac{1}{N}\sum_{i=1}^{N} g(\tilde{u}_i,\theta)$ and Σ_N some positive definite matrix.

B.1 Spatial Mixing Condition

Let $(X_s, s \in S \subseteq \boldsymbol{Z}^2)$ be a random field observed on the lattice S and defined on a given probability space $(\Omega, \mathcal{F}, \boldsymbol{P})$. Let $(\Gamma_k, k \in \boldsymbol{N})$ be a fixed sequence of finite subsets of $\boldsymbol{Z}^2$. Let $\mathcal{B}_{s_k} \subset \mathcal{F}$ be the σ-algebra generated by the random field $(X_s, s \in \Gamma_k)$. Let $d_\infty(\Gamma_1, \Gamma_2) = inf(d_\infty(s^1, s^2), s^k \in \Gamma_k)$ denote the minimum infinity distance from an element of Γ_1 to an element of Γ_2. The mixing coefficient as Bolthausen (2010) is defined as follows, if k and $l \in \boldsymbol{N} \cup \{\infty\}$

$$\alpha_{k,l}(n) = sup\{|P(A \cap B) - P(A)P(B)|\}, A \in \mathcal{B}_{s_p}, B \in \mathcal{B}_{s_q}$$

and

$$|\Gamma_p| \leq k, |\Gamma_q| \leq l, d(\Gamma_p, \Gamma_q) \geq n$$

We say $(X_s, s \in S \subseteq \boldsymbol{Z}^2)$ is a strong mixing random field or α-mixing random field if

$$\lim_{n\to\infty} \alpha_{k,l}(n) \to 0$$

B.2 Asymptotic properties of θ

Consistency: We suppose $(\tilde{u}_i, i \in D_N \subset \boldsymbol{Z}^2)$. A set of sufficient conditions for consistency is needing

A1. D_N grows uniformly in two non-opposing directions as $N \to \infty$.

A2. $\Sigma_N \to \Sigma$ a.s, where Σ is a positive-definite matrix.

A3. $(\tilde{u}_i \in D_N \subset \boldsymbol{Z}^2)$ is a strong mixing

A4. Z is uniformly bounded.

A5. $\sum_{d=1}^{\infty} d\alpha_{1,1}(d) < \infty$

Proposition 1 Given conditions A1-A5

$\theta^* \to \theta$, as $N \to \infty$, a.s.

Proof.

The first-order conditions from minimizing Eq. (1) are

$$\left[\frac{1}{N}\sum_{i=1}^{N} Dg(\tilde{u}_i, \theta)\right]' \Sigma_N \left[\frac{1}{N}\sum_{i=1}^{N} g(\tilde{u}_i, \theta)\right] = 0$$

where $Dg(,)$ denotes the derivative of g with respect to θ. The mean value theorem implies that

$$g(\tilde{u}_i, \theta^*) = g(\tilde{u}_i, \theta) + Dg(\tilde{u}_i, \bar{\theta})(\theta^* - \theta)$$

where $\bar{\theta} \in \{c\theta^* + (1-c)\theta, c \in (0,1)\}$. By combining Eq.(2) and (3), we obtain the familiar expression,

$$
\begin{aligned}
\sqrt{N}(\theta^* - \theta) &= -\left\{\left[\frac{1}{N}\sum_{i=1}^{N} Dg(\tilde{u}_i, \theta^*)\right]' \Sigma_N \left[\frac{1}{N}\sum_{i=1}^{N} Dg(\tilde{u}_i, \bar{\theta})\right]\right\}^{-1} \\
&\qquad \times \left[\frac{1}{N}\sum_{i=1}^{N} Dg(\tilde{u}_i, \theta^*)\right]' \Sigma_N \frac{1}{\sqrt{N}} \sum_{i=1}^{N} g(\tilde{u}_i, \theta)
\end{aligned}
$$

For the consistent estimation, we need a law of large numbers for strong mixing random fields. For this see Diallo (2011).

B.3 Asymptotic normality

To establish the asymptotic normality, we utilize Diallo (2011) or Jenish and Prucha (2009) central limit theorem for non-stationary strong mixing random fields. Using the theorem requires additional conditions:

A5. $\sum_{d=1}^{\infty} d\alpha_{1,1}(d) < \infty$

A6. $\alpha_{1,\infty}(d) = o(d^{-2})$

Proposition 2: Given the conditions of proposition 1 and the additional conditions,

$$
\sqrt{N}(\theta^* - \theta) \longrightarrow N(0, DVD')
$$

where $V = \mathbb{E}(g(\tilde{u}_i, \theta)g'(\tilde{u}_i, \theta))$ is a positive-definite matrix,

$$
D = \left\{\left[\frac{1}{N}\sum_{i=1}^{N} Dg(\tilde{u}_i, \theta)\right]' \Sigma_N \left[\frac{1}{N}\sum_{i=1}^{N} Dg(\tilde{u}_i, \theta)\right]\right\}^{-1} \left[\frac{1}{N}\sum_{i=1}^{N} Dg(\tilde{u}_i, \theta)\right]' \Sigma_N
$$

Saw E.q (4), all that is needed to establish asymptotic normality is to use a central limit theorem for no-stationary strong mixing random fields (see Diallo (2011) or Jenish and Prucha (2009)).

C General adjusting coefficient

We shall now provide the general term of the adjusting coefficient for all weight matrix to adjust the linearized logit estimate of β. For this, some manipulations of linear algebra are needed. To illustrate how to identify the expression of these marginal effects, we use an approximation of $(I-\lambda W)^{-1}(I-\rho M)^{-1}$ as follows :

$$(I-\lambda W)^{-1}(I-\rho M)^{-1} = I + \rho M + \lambda W + \lambda^2 W^2 + \rho^2 M^2 + \rho\lambda MW$$

Without loss of generality we limit our approximation to second order multiplier.

$$
\begin{aligned}
X^*\beta &= (I + \rho M + \lambda W + \lambda^2 W^2 + \rho^2 M^2 + \rho\lambda MW + ...)X\beta/\sigma_v(\lambda,\rho) \\
&= \begin{pmatrix} X_1 \frac{\beta}{\sigma_{v,1}} \\ X_2 \frac{\beta}{\sigma_{v,2}} \\ . \\ . \\ X_i \frac{\beta}{\sigma_{v,i}} \\ . \\ . \\ X_n \frac{\beta}{\sigma_{v,n}} \end{pmatrix} + \rho \begin{pmatrix} \sum_{j=1}^n m_{1,j} X_j \frac{\beta}{\sigma_{v,1}} \\ \sum_{j=1}^n m_{2,j} X_j \frac{\beta}{\sigma_{v,2}} \\ . \\ . \\ \sum_{j=1}^n m_{i,j} X_j \frac{\beta}{\sigma_{v,i}} \\ . \\ . \\ \sum_{j=1}^n m_{n,j} X_j \frac{\beta}{\sigma_{v,n}} \end{pmatrix} + \lambda \begin{pmatrix} \sum_{j=1}^n w_{1,j} X_j \frac{\beta}{\sigma_{v,1}} \\ \sum_{j=1}^n w_{2,j} X_j \frac{\beta}{\sigma_{v,2}} \\ . \\ . \\ \sum_{j=1}^n w_{i,j} X_j \frac{\beta}{\sigma_{v,i}} \\ . \\ . \\ \sum_{j=1}^n w_{n,j} X_j \frac{\beta}{\sigma_{v,n}} \end{pmatrix} \\
&+ \lambda^2 \begin{pmatrix} \sum_{k=1}^n (\sum_{j=1}^n w_{1,j} w_{j,k}) X_k \frac{\beta}{\sigma_{v,1}} \\ \sum_{k=1}^n (\sum_{j=1}^n w_{2,j} w_{j,k}) X_k \frac{\beta}{\sigma_{v,2}} \\ . \\ . \\ \sum_{k=1}^n (\sum_{j=1}^n w_{i,j} w_{j,k}) X_k \frac{\beta}{\sigma_{v,i}} \\ . \\ . \\ \sum_{k=1}^n (\sum_{j=1}^n w_{n,j} w_{j,k}) X_k \frac{\beta}{\sigma_{v,n}} \end{pmatrix} + \rho\lambda \begin{pmatrix} \sum_{k=1}^n (\sum_{j=1}^n m_{1,j} w_{j,k}) X_k \frac{\beta}{\sigma_{v,1}} \\ \sum_{k=1}^n (\sum_{j=1}^n m_{2,j} w_{j,k}) X_k \frac{\beta}{\sigma_{v,2}} \\ . \\ . \\ \sum_{k=1}^n (\sum_{j=1}^n m_{i,j} w_{j,k}) X_k \frac{\beta}{\sigma_{v,i}} \\ . \\ . \\ \sum_{k=1}^n (\sum_{j=1}^n m_{n,j} w_{j,k}) X_k \frac{\beta}{\sigma_{v,n}} \end{pmatrix} \\
&+ \rho^2 \begin{pmatrix} \sum_{k=1}^n (\sum_{j=1}^n m_{1,j} m_{j,k}) X_k \frac{\beta}{\sigma_{v,1}} \\ \sum_{k=1}^n (\sum_{j=1}^n m_{2,j} m_{j,k}) X_k \frac{\beta}{\sigma_{v,2}} \\ . \\ . \\ \sum_{k=1}^n (\sum_{j=1}^n m_{i,j} m_{j,k}) X_k \frac{\beta}{\sigma_{v,i}} \\ . \\ . \\ \sum_{k=1}^n (\sum_{j=1}^n m_{n,j} m_{j,k}) X_k \frac{\beta}{\sigma_{v,n}} \end{pmatrix}
\end{aligned} \tag{14}
$$

According to the previous term, the partial derivative for each observation is:

$$\frac{\partial X_i^*}{\partial X_i} = \frac{1}{\sigma_i}(1 + \lambda w_{ii} + \rho m_{ii} + \lambda^2 \sum_{j=1}^n w_{ij} w_{ji} + \rho^2 \sum_{j=1}^n w_{ij} w_{ji} + ...)$$

The fact that X varies across individuals implies the following adjusting coefficient:

$$AC = \frac{1}{1/n \sum_{i=1}^n \frac{1}{\sigma_i}(1 + \lambda w_{ii} + \lambda^2 \sum_{j=1}^n w_{ij} w_{ji} + ...)}$$

Finally, we obtain:

$$AC = \frac{1}{1/n \sum_{i=1}^{n} \frac{w_{ii}^*}{\sigma_i}}$$

where w_{ii}^* are the diagonal elements of the matirix $(I - \lambda W)^{-1}(I - \rho M)^{-1}$. It is interesting to note that

$$Tr[(I - \lambda W)^{-1}(I - \rho M)^{-1}] = \sum_{i=1}^{n}(1 + \lambda w_{ii} + \rho m_{ii} + \lambda^2 \sum_{j=1}^{n} w_{ij} w_{ji} + \rho^2 \sum_{j=1}^{n} m_{ij} m_{ji} + ...)$$

In a particular case where $\sigma_i = 1/n \sum_{k=1}^{n} \sigma_k$, we obtain a more compact term of the adjusting coefficient

$$AC = \frac{Tr((\sigma_V(\lambda))}{Tr[(I - \lambda W)^{-1}(I - \rho M)^{-1}]}$$

where Tr is the trace operator of matrix.

D Estimate results for the other matrices types

Table 6: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type B weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	4	2	-0.000	1.008	-1.007	-0.000	1.011	-1.010	-0.003	0.004	-0.000	1.011	-1.010	-0.003	0.004
		RMSE			0.075	0.087	0.090	0.076	0.087	0.090	0.122	0.094	0.076	0.087	0.090	0.123	0.094
1000	0	0.2	4	2	-0.002	0.987	-0.985	-0.002	1.002	-1.000	0.010	0.204	-0.002	1.001	-0.999	-0.004	0.204
		RMSE			0.074	0.090	0.090	0.062	0.089	0.090	0.122	0.094	0.062	0.089	0.090	0.125	0.094
1000	0.2	0.2	4	2	-0.005	0.958	-0.957	-0.003	0.998	-0.996	0.226	0.208	-0.003	0.993	-0.991	0.197	0.208
		RMSE			0.080	0.098	0.094	0.050	0.089	0.085	0.129	0.103	0.050	0.089	0.085	0.129	0.103
1000	0	0.4	4	2	-0.001	0.921	-0.924	-0.000	0.981	-0.984	0.054	0.412	-0.000	0.971	-0.974	-0.019	0.412
		RMSE			0.075	0.116	0.111	0.047	0.087	0.083	0.138	0.108	0.046	0.089	0.085	0.148	0.108
1000	0.2	0.4	4	2	0.002	0.875	-0.877	0.000	0.976	-0.979	0.283	0.404	0.000	0.954	-0.958	0.198	0.404
		RMSE			0.082	0.151	0.149	0.037	0.089	0.088	0.154	0.108	0.036	0.096	0.095	0.141	0.108
1000	0.4	0.4	4	2	0.000	0.795	-0.794	0.002	1.003	-1.002	0.539	0.413	0.002	0.931	-0.930	0.409	0.413
		RMSE			0.086	0.221	0.222	0.043	0.114	0.121	0.201	0.118	0.039	0.107	0.109	0.132	0.118
1000	0	0.6	4	2	0.004	0.815	-0.816	0.001	0.994	-0.995	0.140	0.640	0.001	0.952	-0.953	-0.076	0.640
		RMSE			0.080	0.204	0.201	0.038	0.101	0.098	0.200	0.126	0.036	0.112	0.108	0.221	0.126
1000	0.2	0.6	4	2	-0.002	0.767	-0.760	0.001	0.999	-0.989	0.376	0.616	0.001	0.933	-0.925	0.186	0.616
		RMSE			0.083	0.247	0.253	0.045	0.106	0.107	0.224	0.123	0.041	0.120	0.127	0.177	0.123
1000	0	0.8	4	2	-0.002	0.665	-0.663	0.004	1.241	-1.237	0.300	0.885	0.003	1.148	-1.144	-0.169	0.885
		RMSE			0.087	0.344	0.346	0.093	0.347	0.345	0.341	0.138	0.085	0.324	0.322	0.287	0.138

Table 7: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type B weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	10	2	0.007	1.005	-1.005	0.007	1.009	-1.008	-0.000	0.000	0.007	1.009	-1.008	0.000	0.000
		RMSE			0.075	0.091	0.087	0.077	0.092	0.088	0.183	0.085	0.077	0.092	0.088	0.183	0.085
1000	0	0.2	10	2	0.001	0.985	-0.980	0.001	1.002	-0.997	0.018	0.206	0.001	1.001	-0.995	-0.003	0.206
		RMSE			0.073	0.089	0.088	0.061	0.089	0.087	0.176	0.081	0.061	0.089	0.087	0.161	0.081
1000	0.2	0.2	10	2	0.005	0.976	-0.975	0.002	1.009	-1.008	0.271	0.203	0.002	1.003	-1.001	0.222	0.203
		RMSE			0.078	0.091	0.093	0.048	0.089	0.089	0.189	0.087	0.047	0.088	0.089	0.164	0.087
1000	0	0.4	10	2	0.001	0.924	-0.926	0.001	0.983	-0.985	0.065	0.420	0.001	0.976	-0.978	-0.027	0.420
		RMSE			0.077	0.114	0.116	0.048	0.088	0.091	0.188	0.090	0.048	0.089	0.092	0.160	0.090
1000	0.2	0.4	10	2	0.003	0.903	-0.896	-0.000	1.013	-1.005	0.359	0.423	-0.000	0.977	-0.969	0.201	0.423
		RMSE			0.082	0.129	0.133	0.041	0.101	0.103	0.240	0.093	0.039	0.089	0.090	0.152	0.093
1000	0.4	0.4	10	2	0.002	0.853	-0.852	-0.002	1.377	-1.379	0.711	0.428	-0.000	0.959	-0.959	0.411	0.428
		RMSE			0.086	0.168	0.169	0.119	0.760	0.773	0.361	0.099	0.059	0.094	0.095	0.122	0.099
1000	0	0.6	10	2	0.002	0.818	-0.818	-0.001	1.011	-1.011	0.203	0.662	-0.001	0.966	-0.966	-0.090	0.662
		RMSE			0.077	0.198	0.199	0.043	0.107	0.101	0.282	0.117	0.040	0.105	0.097	0.201	0.117
1000	0.2	0.6	10	2	-0.000	0.790	-0.790	-0.001	1.163	-1.159	0.529	0.650	-0.000	0.946	-0.945	0.138	0.650
		RMSE			0.085	0.225	0.227	0.094	0.429	0.408	0.389	0.111	0.061	0.104	0.108	0.183	0.111
1000	0	0.8	10	2	0.002	0.668	-0.668	-0.014	1.455	-1.452	0.455	0.919	-0.009	1.246	-1.244	-0.223	0.919
		RMSE			0.087	0.341	0.341	0.178	0.588	0.579	0.510	0.145	0.132	0.394	0.390	0.306	0.145

Table 8: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type B weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	10	4	-0.000	1.005	-1.004	-0.000	1.008	-1.007	0.002	-0.002	-0.000	1.008	-1.007	0.001	-0.002
		RMSE			0.075	0.090	0.088	0.077	0.091	0.089	0.193	0.114	0.077	0.091	0.089	0.194	0.114
1000	0	0.2	10	4	0.001	0.995	-0.988	0.000	1.008	-1.002	0.032	0.204	0.000	1.006	-1.000	-0.003	0.204
		RMSE			0.076	0.088	0.086	0.061	0.089	0.086	0.198	0.113	0.061	0.089	0.086	0.195	0.113
1000	0.2	0.2	10	4	-0.001	0.976	-0.972	-0.001	1.012	-1.008	0.273	0.212	-0.001	1.002	-0.998	0.205	0.212
		RMSE			0.074	0.087	0.093	0.043	0.092	0.093	0.208	0.121	0.042	0.086	0.089	0.199	0.121
1000	0	0.4	10	4	-0.001	0.944	-0.946	-0.002	1.006	-1.009	0.110	0.432	-0.002	0.987	-0.990	-0.052	0.432
		RMSE			0.076	0.103	0.101	0.042	0.088	0.090	0.226	0.126	0.041	0.087	0.087	0.221	0.126
1000	0.2	0.4	10	4	-0.002	0.916	-0.912	0.001	1.039	-1.035	0.377	0.431	0.001	0.979	-0.974	0.150	0.431
		RMSE			0.082	0.120	0.123	0.042	0.146	0.154	0.268	0.124	0.037	0.088	0.090	0.220	0.124
1000	0.4	0.4	10	4	-0.002	0.855	-0.858	0.001	1.455	-1.461	0.714	0.443	0.001	0.953	-0.956	0.333	0.443
		RMSE			0.089	0.169	0.163	0.140	0.836	0.847	0.370	0.134	0.065	0.106	0.101	0.213	0.134
1000	0	0.6	10	4	-0.002	0.848	-0.842	0.001	1.130	-1.123	0.338	0.671	0.000	0.985	-0.979	-0.185	0.671
		RMSE			0.087	0.173	0.178	0.066	0.235	0.241	0.398	0.142	0.051	0.124	0.131	0.356	0.142
1000	0.2	0.6	10	4	-0.006	0.799	-0.804	0.009	1.515	-1.523	0.635	0.693	0.006	0.989	-0.993	-0.057	0.693
		RMSE			0.094	0.216	0.213	0.172	0.817	0.830	0.485	0.170	0.092	0.199	0.195	0.433	0.170
1000	0	0.8	10	4	-0.001	0.664	-0.663	0.008	2.799	-2.800	0.772	0.941	0.001	1.496	-1.498	-0.695	0.941
		RMSE			0.104	0.345	0.345	0.663	2.028	2.034	0.800	0.163	0.319	0.649	0.658	0.796	0.163

Table 9: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type C weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	4	2	-0.002	1.006	-1.004	-0.003	1.009	-1.007	0.003	-0.000	-0.003	1.009	-1.007	0.002	-0.000
		RMSE			0.077	0.091	0.089	0.077	0.091	0.090	0.122	0.104	0.077	0.091	0.090	0.123	0.104
1000	0	0.2	4	2	-0.003	0.991	-0.990	-0.003	1.004	-1.002	0.006	0.207	-0.003	1.003	-1.001	-0.006	0.207
		RMSE			0.075	0.087	0.086	0.064	0.087	0.086	0.120	0.103	0.064	0.087	0.086	0.122	0.103
1000	0.2	0.2	4	2	0.002	0.957	-0.957	0.002	0.991	-0.990	0.222	0.203	0.002	0.988	-0.988	0.205	0.203
		RMSE			0.078	0.093	0.096	0.052	0.084	0.086	0.125	0.107	0.052	0.084	0.086	0.123	0.107
1000	0	0.4	4	2	0.002	0.942	-0.942	0.000	0.989	-0.989	0.026	0.410	0.000	0.985	-0.984	-0.019	0.410
		RMSE			0.076	0.106	0.105	0.054	0.090	0.088	0.130	0.116	0.053	0.090	0.088	0.143	0.116
1000	0.2	0.4	4	2	-0.001	0.899	-0.899	-0.001	0.979	-0.977	0.248	0.403	-0.001	0.968	-0.967	0.198	0.403
		RMSE			0.078	0.130	0.131	0.041	0.086	0.086	0.131	0.108	0.041	0.088	0.088	0.126	0.108
1000	0.4	0.4	4	2	-0.002	0.832	-0.831	0.000	0.984	-0.985	0.506	0.405	0.000	0.945	-0.946	0.417	0.405
		RMSE			0.081	0.187	0.187	0.037	0.096	0.094	0.176	0.112	0.035	0.099	0.097	0.127	0.112
1000	0	0.6	4	2	0.000	0.856	-0.854	0.001	0.991	-0.990	0.083	0.645	0.001	0.972	-0.971	-0.061	0.645
		RMSE			0.080	0.166	0.168	0.041	0.097	0.098	0.155	0.126	0.040	0.101	0.102	0.184	0.126
1000	0.2	0.6	4	2	-0.005	0.799	-0.798	-0.001	0.978	-0.977	0.332	0.618	-0.001	0.938	-0.937	0.193	0.618
		RMSE			0.081	0.216	0.217	0.038	0.095	0.097	0.193	0.124	0.036	0.105	0.107	0.160	0.124
1000	0	0.8	4	2	-0.000	0.710	-0.710	-0.000	1.092	-1.089	0.184	0.880	-0.000	1.058	-1.056	-0.109	0.880
		RMSE			0.083	0.300	0.300	0.046	0.195	0.194	0.235	0.132	0.045	0.203	0.205	0.217	0.132

Table 10: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type C weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	10	2	-0.004	1.007	-1.008	-0.004	1.010	-1.012	0.008	-0.004	-0.004	1.010	-1.012	0.008	-0.004
		RMSE			0.076	0.091	0.090	0.078	0.091	0.091	0.133	0.086	0.078	0.091	0.091	0.133	0.086
1000	0	0.2	10	2	0.003	0.987	-0.987	0.003	1.000	-1.000	0.008	0.205	0.003	0.999	-1.000	-0.002	0.205
		RMSE			0.075	0.090	0.087	0.064	0.090	0.086	0.137	0.090	0.064	0.090	0.086	0.130	0.090
1000	0.2	0.2	10	2	-0.001	0.972	-0.972	-0.002	0.998	-0.997	0.232	0.208	-0.002	0.995	-0.995	0.210	0.208
		RMSE			0.076	0.093	0.092	0.050	0.089	0.087	0.139	0.088	0.049	0.089	0.087	0.130	0.088
1000	0	0.4	10	2	0.001	0.943	-0.942	0.002	0.989	-0.989	0.021	0.421	0.002	0.987	-0.986	-0.019	0.421
		RMSE			0.077	0.104	0.105	0.054	0.088	0.087	0.142	0.094	0.054	0.088	0.088	0.131	0.094
1000	0.2	0.4	10	2	-0.003	0.915	-0.917	-0.001	0.989	-0.991	0.262	0.422	-0.001	0.978	-0.981	0.195	0.422
		RMSE			0.081	0.119	0.122	0.040	0.087	0.089	0.156	0.098	0.040	0.088	0.090	0.131	0.098
1000	0.4	0.4	10	2	-0.000	0.869	-0.868	-0.001	1.018	-1.016	0.530	0.427	-0.001	0.967	-0.965	0.421	0.427
		RMSE			0.084	0.155	0.158	0.040	0.135	0.133	0.200	0.103	0.036	0.090	0.093	0.124	0.103
1000	0	0.6	10	2	0.003	0.855	-0.852	0.001	0.988	-0.986	0.064	0.664	0.001	0.979	-0.977	-0.047	0.664
		RMSE			0.078	0.168	0.171	0.040	0.094	0.095	0.152	0.124	0.039	0.096	0.097	0.140	0.124
1000	0.2	0.6	10	2	-0.004	0.825	-0.825	0.001	1.005	-1.004	0.358	0.643	0.001	0.961	-0.961	0.196	0.643
		RMSE			0.082	0.192	0.193	0.039	0.103	0.099	0.219	0.115	0.037	0.097	0.095	0.140	0.115
1000	0	0.8	10	2	-0.004	0.704	-0.703	-0.001	1.204	-1.203	0.224	0.914	-0.001	1.153	-1.152	-0.133	0.914
		RMSE			0.083	0.307	0.307	0.069	0.299	0.300	0.290	0.142	0.062	0.277	0.277	0.212	0.142

Table 11: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type C weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	10	4	-0.001	1.010	-1.006	-0.001	1.013	-1.009	0.008	-0.003	-0.001	1.013	-1.009	0.006	-0.003
		RMSE			0.074	0.092	0.088	0.075	0.092	0.089	0.160	0.123	0.075	0.092	0.089	0.163	0.123
1000	0	0.2	10	4	-0.003	0.997	-0.992	-0.003	1.009	-1.004	0.004	0.212	-0.003	1.008	-1.003	-0.014	0.212
		RMSE			0.076	0.087	0.087	0.063	0.088	0.088	0.150	0.121	0.063	0.088	0.088	0.155	0.121
1000	0.2	0.2	10	4	-0.001	0.972	-0.971	0.000	1.001	-1.001	0.227	0.215	0.000	0.997	-0.997	0.194	0.215
		RMSE			0.080	0.091	0.094	0.049	0.086	0.089	0.155	0.115	0.049	0.086	0.089	0.157	0.115
1000	0	0.4	10	4	-0.001	0.957	-0.956	-0.000	1.003	-1.002	0.040	0.422	-0.000	0.996	-0.995	-0.040	0.422
		RMSE			0.080	0.097	0.098	0.049	0.089	0.089	0.161	0.122	0.049	0.088	0.088	0.182	0.122
1000	0.2	0.4	10	4	0.003	0.911	-0.914	0.000	0.992	-0.996	0.274	0.429	0.000	0.971	-0.975	0.160	0.429
		RMSE			0.081	0.125	0.120	0.036	0.090	0.087	0.182	0.130	0.035	0.092	0.087	0.194	0.130
1000	0.4	0.4	10	4	-0.001	0.854	-0.860	0.003	1.043	-1.049	0.550	0.446	0.003	0.953	-0.959	0.373	0.446
		RMSE			0.091	0.166	0.161	0.051	0.184	0.182	0.225	0.133	0.042	0.094	0.089	0.169	0.133
1000	0	0.6	10	4	-0.002	0.867	-0.871	-0.001	1.043	-1.047	0.129	0.676	-0.001	0.999	-1.003	-0.143	0.676
		RMSE			0.082	0.158	0.157	0.038	0.161	0.165	0.210	0.152	0.036	0.147	0.150	0.296	0.152
1000	0.2	0.6	10	4	-0.003	0.817	-0.820	0.001	1.115	-1.119	0.444	0.671	0.001	0.976	-0.979	0.054	0.671
		RMSE			0.092	0.200	0.198	0.069	0.242	0.245	0.305	0.156	0.055	0.143	0.144	0.319	0.156
1000	0	0.8	10	4	0.006	0.708	-0.708	-0.011	1.656	-1.655	0.391	0.932	-0.008	1.381	-1.380	-0.474	0.932
		RMSE			0.098	0.302	0.303	0.176	0.767	0.764	0.443	0.159	0.140	0.526	0.522	0.584	0.159

Table 12: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type D weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	4	2	0.003	1.005	-1.004	0.003	1.008	-1.006	-0.001	0.001	0.003	1.008	-1.006	-0.002	0.001
		RMSE			0.072	0.090	0.090	0.073	0.091	0.091	0.124	0.108	0.073	0.091	0.091	0.125	0.108
1000	0	0.2	4	2	0.004	0.991	-0.989	0.004	1.004	-1.001	0.011	0.197	0.004	1.003	-1.000	0.000	0.197
		RMSE			0.074	0.090	0.088	0.063	0.090	0.088	0.130	0.117	0.063	0.090	0.088	0.135	0.117
1000	0.2	0.2	4	2	-0.002	0.960	-0.962	-0.001	0.994	-0.995	0.216	0.204	-0.001	0.991	-0.992	0.200	0.204
		RMSE			0.074	0.096	0.096	0.049	0.088	0.087	0.118	0.113	0.048	0.088	0.088	0.119	0.113
1000	0	0.4	4	2	-0.001	0.947	-0.946	-0.001	0.992	-0.990	0.029	0.409	-0.001	0.987	-0.985	-0.015	0.409
		RMSE			0.075	0.101	0.101	0.053	0.087	0.086	0.134	0.117	0.052	0.087	0.087	0.152	0.117
1000	0.2	0.4	4	2	-0.001	0.890	-0.888	-0.001	0.971	-0.969	0.245	0.402	-0.001	0.961	-0.959	0.194	0.402
		RMSE			0.078	0.138	0.141	0.041	0.091	0.091	0.146	0.123	0.040	0.094	0.094	0.153	0.123
1000	0.4	0.4	4	2	-0.003	0.822	-0.822	-0.000	0.962	-0.962	0.474	0.393	-0.000	0.935	-0.935	0.409	0.393
		RMSE			0.082	0.196	0.195	0.035	0.096	0.096	0.162	0.127	0.034	0.105	0.104	0.134	0.127
1000	0	0.6	4	2	0.005	0.856	-0.850	0.002	0.996	-0.990	0.072	0.648	0.002	0.976	-0.971	-0.074	0.648
		RMSE			0.080	0.168	0.172	0.041	0.102	0.110	0.150	0.133	0.040	0.107	0.115	0.195	0.133
1000	0.2	0.6	4	2	0.002	0.813	-0.812	-0.000	0.980	-0.979	0.298	0.622	-0.000	0.950	-0.948	0.181	0.622
		RMSE			0.081	0.205	0.204	0.036	0.104	0.102	0.173	0.141	0.034	0.111	0.109	0.174	0.141
1000	0	0.8	4	2	-0.002	0.719	-0.723	-0.004	1.109	-1.116	0.197	0.873	-0.004	1.075	-1.081	-0.152	0.873
		RMSE			0.085	0.292	0.288	0.049	0.220	0.224	0.252	0.137	0.048	0.232	0.236	0.290	0.137

Table 13: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type D weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	10	2	-0.001	1.012	-1.007	-0.001	1.015	-1.009	0.006	0.001	-0.001	1.015	-1.009	0.005	0.001
		RMSE			0.075	0.089	0.089	0.075	0.091	0.089	0.125	0.091	0.075	0.091	0.089	0.125	0.091
1000	0	0.2	10	2	-0.003	0.990	-0.988	-0.001	1.004	-1.001	0.014	0.205	-0.001	1.003	-1.000	0.002	0.205
		RMSE			0.077	0.089	0.090	0.064	0.088	0.089	0.144	0.090	0.064	0.088	0.089	0.136	0.090
1000	0.2	0.2	10	2	0.001	0.974	-0.971	0.002	1.002	-0.998	0.237	0.210	0.002	0.999	-0.995	0.211	0.210
		RMSE			0.078	0.092	0.092	0.049	0.089	0.088	0.140	0.090	0.049	0.088	0.088	0.129	0.090
1000	0	0.4	10	2	-0.001	0.940	-0.943	0.000	0.987	-0.991	0.024	0.423	0.000	0.985	-0.988	-0.014	0.423
		RMSE			0.076	0.101	0.105	0.053	0.082	0.090	0.144	0.097	0.053	0.082	0.091	0.134	0.097
1000	0.2	0.4	10	2	0.000	0.914	-0.918	-0.000	0.986	-0.991	0.273	0.426	-0.000	0.974	-0.979	0.199	0.426
		RMSE			0.081	0.121	0.119	0.038	0.088	0.088	0.158	0.097	0.037	0.090	0.089	0.129	0.097
1000	0.4	0.4	10	2	-0.001	0.864	-0.875	-0.000	1.010	-1.023	0.537	0.434	-0.000	0.962	-0.974	0.422	0.434
		RMSE			0.091	0.159	0.148	0.041	0.119	0.121	0.193	0.105	0.038	0.094	0.087	0.112	0.105
1000	0	0.6	10	2	-0.002	0.858	-0.858	-0.001	0.998	-0.997	0.080	0.662	-0.001	0.985	-0.984	-0.061	0.662
		RMSE			0.078	0.163	0.164	0.042	0.096	0.092	0.171	0.123	0.041	0.101	0.097	0.162	0.123
1000	0.2	0.6	10	2	-0.007	0.824	-0.823	-0.002	1.025	-1.023	0.381	0.653	-0.002	0.962	-0.961	0.172	0.653
		RMSE			0.085	0.193	0.194	0.045	0.117	0.119	0.247	0.121	0.040	0.099	0.100	0.158	0.121
1000	0	0.8	10	2	-0.001	0.720	-0.716	-0.001	1.229	-1.223	0.181	0.918	-0.001	1.200	-1.194	-0.142	0.918
		RMSE			0.083	0.291	0.294	0.062	0.338	0.327	0.241	0.146	0.059	0.334	0.324	0.215	0.146

Table 14: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type D weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	10	4	-0.004	1.007	-1.012	-0.005	1.010	-1.014	0.002	-0.005	-0.005	1.010	-1.014	0.001	-0.005
		RMSE			0.072	0.087	0.087	0.074	0.088	0.088	0.154	0.115	0.074	0.088	0.088	0.155	0.115
1000	0	0.2	10	4	0.003	0.992	-0.990	0.002	1.004	-1.002	0.014	0.203	0.002	1.003	-1.001	-0.004	0.203
		RMSE			0.077	0.090	0.089	0.064	0.090	0.089	0.143	0.112	0.063	0.090	0.089	0.145	0.112
1000	0.2	0.2	10	4	0.003	0.975	-0.974	0.002	1.002	-1.001	0.230	0.212	0.002	0.998	-0.997	0.199	0.212
		RMSE			0.078	0.089	0.089	0.048	0.087	0.087	0.155	0.110	0.048	0.086	0.086	0.156	0.110
1000	0	0.4	10	4	0.000	0.956	-0.954	-0.000	1.003	-1.001	0.046	0.424	-0.000	0.995	-0.994	-0.039	0.424
		RMSE			0.076	0.097	0.096	0.047	0.086	0.084	0.156	0.127	0.047	0.085	0.084	0.173	0.127
1000	0.2	0.4	10	4	-0.001	0.916	-0.918	-0.000	0.997	-0.999	0.281	0.426	-0.000	0.977	-0.979	0.174	0.426
		RMSE			0.080	0.118	0.119	0.036	0.085	0.089	0.171	0.118	0.035	0.086	0.089	0.162	0.118
1000	0.4	0.4	10	4	-0.003	0.861	-0.864	0.001	1.036	-1.040	0.536	0.436	0.001	0.960	-0.964	0.384	0.436
		RMSE			0.091	0.162	0.158	0.046	0.169	0.160	0.216	0.128	0.040	0.096	0.091	0.158	0.128
1000	0	0.6	10	4	0.003	0.865	-0.868	0.000	1.052	-1.055	0.134	0.679	0.000	1.006	-1.009	-0.155	0.679
		RMSE			0.086	0.159	0.156	0.041	0.167	0.176	0.215	0.153	0.039	0.148	0.157	0.304	0.153
1000	0.2	0.6	10	4	0.002	0.825	-0.824	0.000	1.082	-1.080	0.389	0.676	0.000	0.984	-0.981	0.088	0.676
		RMSE			0.089	0.192	0.194	0.056	0.193	0.201	0.251	0.150	0.049	0.139	0.147	0.255	0.150
1000	0	0.8	10	4	-0.004	0.708	-0.706	0.006	1.564	-1.564	0.318	0.932	0.005	1.389	-1.389	-0.358	0.932
		RMSE			0.102	0.303	0.303	0.153	0.672	0.675	0.375	0.156	0.127	0.531	0.533	0.447	0.156

Table 15: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type E weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	4	2	0.001	1.006	-1.010	0.001	1.009	-1.013	-0.002	-0.001	0.001	1.009	-1.013	-0.002	-0.001
		RMSE			0.076	0.090	0.095	0.078	0.091	0.097	0.115	0.108	0.078	0.091	0.097	0.116	0.108
1000	0	0.2	4	2	0.002	0.995	-0.988	0.002	1.008	-1.001	0.011	0.200	0.002	1.007	-1.001	0.002	0.200
		RMSE			0.077	0.083	0.088	0.066	0.085	0.088	0.112	0.104	0.066	0.084	0.088	0.116	0.104
1000	0.2	0.2	4	2	0.000	0.959	-0.957	-0.000	0.992	-0.990	0.210	0.202	-0.000	0.990	-0.988	0.197	0.202
		RMSE			0.078	0.095	0.098	0.053	0.087	0.090	0.118	0.107	0.053	0.087	0.090	0.118	0.107
1000	0	0.4	4	2	0.003	0.943	-0.941	0.003	0.988	-0.986	0.022	0.406	0.003	0.984	-0.982	-0.013	0.406
		RMSE			0.078	0.101	0.104	0.055	0.085	0.085	0.120	0.116	0.055	0.086	0.086	0.132	0.116
1000	0.2	0.4	4	2	-0.000	0.892	-0.893	-0.000	0.967	-0.968	0.248	0.394	-0.000	0.959	-0.960	0.211	0.394
		RMSE			0.075	0.139	0.137	0.042	0.092	0.089	0.135	0.118	0.041	0.095	0.093	0.132	0.118
1000	0.4	0.4	4	2	-0.000	0.829	-0.828	-0.001	0.968	-0.968	0.488	0.386	-0.001	0.941	-0.941	0.426	0.386
		RMSE			0.079	0.189	0.191	0.035	0.092	0.099	0.163	0.129	0.034	0.099	0.104	0.128	0.129
1000	0	0.6	4	2	-0.001	0.853	-0.855	-0.002	0.974	-0.976	0.064	0.623	-0.002	0.961	-0.963	-0.036	0.623
		RMSE			0.074	0.169	0.169	0.042	0.096	0.102	0.141	0.125	0.041	0.101	0.106	0.164	0.125
1000	0.2	0.6	4	2	-0.001	0.802	-0.800	-0.001	0.964	-0.961	0.294	0.608	-0.001	0.939	-0.937	0.203	0.608
		RMSE			0.083	0.214	0.215	0.035	0.102	0.101	0.161	0.131	0.035	0.111	0.110	0.154	0.131
1000	0	0.8	4	2	-0.000	0.726	-0.721	0.002	1.075	-1.070	0.147	0.870	0.002	1.058	-1.053	-0.096	0.870
		RMSE			0.085	0.285	0.289	0.044	0.185	0.185	0.210	0.132	0.044	0.210	0.209	0.222	0.132

Table 16: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type E weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	10	2	0.002	1.003	-1.004	0.001	1.006	-1.007	-0.004	0.002	0.001	1.006	-1.007	-0.004	0.002
		RMSE			0.077	0.090	0.088	0.078	0.091	0.089	0.128	0.088	0.078	0.091	0.089	0.128	0.088
1000	0	0.2	10	2	-0.002	0.991	-0.985	-0.001	1.004	-0.999	0.006	0.203	-0.001	1.003	-0.998	-0.001	0.203
		RMSE			0.075	0.087	0.089	0.065	0.086	0.088	0.127	0.084	0.065	0.086	0.088	0.122	0.084
1000	0.2	0.2	10	2	-0.001	0.970	-0.965	-0.001	0.999	-0.994	0.230	0.211	-0.001	0.996	-0.991	0.205	0.211
		RMSE			0.076	0.094	0.094	0.049	0.091	0.088	0.136	0.094	0.049	0.091	0.088	0.127	0.094
1000	0	0.4	10	2	0.002	0.942	-0.943	0.002	0.989	-0.990	0.023	0.416	0.002	0.986	-0.988	-0.013	0.416
		RMSE			0.077	0.104	0.104	0.054	0.086	0.088	0.128	0.094	0.054	0.087	0.088	0.120	0.094
1000	0.2	0.4	10	2	0.001	0.914	-0.908	0.001	0.989	-0.982	0.267	0.418	0.001	0.977	-0.970	0.205	0.418
		RMSE			0.079	0.121	0.125	0.039	0.089	0.088	0.156	0.100	0.038	0.089	0.089	0.129	0.100
1000	0.4	0.4	10	2	-0.001	0.865	-0.862	0.001	1.051	-1.048	0.568	0.410	0.001	0.972	-0.970	0.445	0.410
		RMSE			0.085	0.159	0.162	0.044	0.173	0.164	0.222	0.097	0.038	0.090	0.093	0.117	0.097
1000	0	0.6	10	2	-0.005	0.861	-0.867	-0.001	0.980	-0.988	0.058	0.647	-0.001	0.973	-0.980	-0.037	0.647
		RMSE			0.077	0.163	0.157	0.044	0.096	0.092	0.153	0.118	0.044	0.100	0.097	0.145	0.118
1000	0.2	0.6	10	2	-0.000	0.819	-0.822	-0.001	1.006	-1.008	0.353	0.637	-0.001	0.956	-0.958	0.213	0.637
		RMSE			0.083	0.197	0.197	0.042	0.107	0.107	0.214	0.114	0.038	0.099	0.100	0.129	0.114
1000	0	0.8	10	2	-0.001	0.719	-0.717	-0.001	1.190	-1.188	0.159	0.908	-0.002	1.164	-1.161	-0.107	0.908
		RMSE			0.084	0.291	0.294	0.059	0.304	0.306	0.227	0.140	0.055	0.304	0.301	0.183	0.140

Table 17: The Mean and the RMSE of the estimators of the coefficient and autocorrelation parameters obtained from Monte Carlo simulations - Type E weight matrices

					Standard Logit			LGMM					ALGMM				
Sample size	λ_0	ρ_0	W	M	b_1	b_2	b_3	b_1	b_2	b_3	λ	ρ	b_1	b_2	b_3	λ	ρ
1000	0	0	10	4	-0.001	1.008	-1.011	-0.001	1.010	-1.013	-0.003	-0.001	-0.001	1.010	-1.013	-0.003	-0.001
		RMSE			0.073	0.088	0.086	0.074	0.088	0.087	0.137	0.102	0.074	0.088	0.087	0.138	0.102
1000	0	0.2	10	4	-0.003	0.991	-0.993	-0.002	1.005	-1.007	0.010	0.205	-0.002	1.004	-1.006	-0.007	0.205
		RMSE			0.075	0.087	0.086	0.061	0.088	0.087	0.148	0.102	0.061	0.088	0.087	0.147	0.102
1000	0.2	0.2	10	4	0.001	0.967	-0.970	0.000	1.000	-1.003	0.245	0.205	0.000	0.995	-0.998	0.213	0.205
		RMSE			0.074	0.095	0.089	0.044	0.090	0.085	0.151	0.104	0.044	0.089	0.084	0.145	0.104
1000	0	0.4	10	4	-0.003	0.941	-0.941	-0.002	0.994	-0.993	0.057	0.422	-0.002	0.986	-0.984	-0.023	0.422
		RMSE			0.077	0.102	0.104	0.047	0.085	0.085	0.163	0.114	0.046	0.086	0.086	0.163	0.114
1000	0.2	0.4	10	4	-0.002	0.904	-0.902	-0.002	0.994	-0.992	0.292	0.425	-0.002	0.971	-0.968	0.178	0.425
		RMSE			0.079	0.128	0.130	0.036	0.087	0.089	0.179	0.118	0.035	0.089	0.092	0.167	0.118
1000	0.4	0.4	10	4	0.004	0.840	-0.837	0.000	1.073	-1.069	0.587	0.431	-0.000	0.952	-0.949	0.394	0.431
		RMSE			0.090	0.180	0.183	0.056	0.207	0.203	0.242	0.123	0.045	0.097	0.098	0.141	0.123
1000	0	0.6	10	4	0.001	0.850	-0.855	-0.000	1.022	-1.028	0.133	0.664	-0.000	0.984	-0.990	-0.103	0.664
		RMSE			0.084	0.171	0.167	0.038	0.127	0.132	0.204	0.138	0.037	0.122	0.127	0.235	0.138
1000	0.2	0.6	10	4	0.002	0.805	-0.806	-0.002	1.083	-1.086	0.413	0.659	-0.002	0.971	-0.974	0.110	0.659
		RMSE			0.088	0.210	0.210	0.058	0.194	0.194	0.267	0.144	0.050	0.151	0.149	0.242	0.144
1000	0	0.8	10	4	0.000	0.691	-0.694	0.000	1.456	-1.463	0.305	0.922	0.000	1.332	-1.338	-0.288	0.922
		RMSE			0.096	0.318	0.315	0.118	0.566	0.571	0.352	0.151	0.105	0.490	0.496	0.378	0.151