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ABSTRACT

Forecasting with Spatial Panel Data^{*}

This paper compares various forecasts using panel data with spatial error correlation. The true data generating process is assumed to be a simple error component regression model with spatial remainder disturbances of the autoregressive or moving average type. The best linear unbiased predictor is compared with other forecasts ignoring spatial correlation, or ignoring heterogeneity due to the individual effects, using Monte Carlo experiments. In addition, we check the performance of these forecasts under misspecification of the spatial error process, various spatial weight matrices, and heterogeneous rather than homogeneous panel data models.

JEL Classification: C33

Keywords: forecasting, BLUP, panel data, spatial dependence, heterogeneity

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1 Introduction

The literature on forecasting is rich with time series applications, but this is not the case for spatial panel data applications. Exceptions are Baltagi and Li (2004, 2006) with applications to forecasting sales of cigarettes and liquor per capita for U.S. states over time.¹ Best linear unbiased prediction (BLUP) in panel data using an error component model have been considered by Taub (1979), Baltagi and Li (1992), and Baillie and Baltagi (1999) to mention a few. Applications include Baltagi and Griffin (1997), Hsiao and Tahmiscioglu (1997), Schmalensee, Stoker and Judson (1998), Baltagi, Griffin and Xiong (2000), Hoogstrate, Palm and Pfann (2000), Baltagi, Bresson and Pirotte (2002, 2004), Frees and Miller (2004), Rapach and Wohar (2004), and Brucker and Siliverstovs (2006), see Baltagi (2008) for a recent survey. However, these panel forecasting applications do not deal with spatial dependence across the panel units. Spatial dependence models — popular in regional science and urban economics — deal with spatial interaction and spatial heterogeneity (see Anselin (1988) and Anselin and Bera (1998)). The structure of the dependence can be related to location and distance, both in a geographic space as well as a more general economic or social network space. Some commonly used spatial error processes include the spatial autoregressive (SAR) and the spatial moving average (SMA) error processes. Two different variants of these models for spatial panels are considered, one discussed in Anselin (1988) and another in Kapoor, Kelejian and Prucha (2007) and Fingleton (2007). The best linear unbiased predictors for the Anselin type model was derived by Baltagi and Li (2004). This paper derives the best linear unbiased predictors for the Kapoor, Kelejian and Prucha (2007) and Fingleton (2007) variants. More importantly, it compares the performance of sixteen various forecasts of the spatial panel data using Monte Carlo experiments. These include homogeneous as well as heterogeneous estimators of the spatial panel model and their corresponding forecasts. The true data generating process is assumed to be a simple error component regression model with spatial remainder disturbances of the autoregressive or moving average

¹In order to explain how spatial autocorrelation may arise in the demand for cigarettes, we note that cigarette prices vary among states primarily due to variation in state taxes on cigarettes. Border effect purchases not included in the cigarette demand equation can cause spatial autocorrelation among the disturbances. In forecasting sales of cigarettes, the spatial autocorrelation due to neighboring states and the individual heterogeneity across states is taken explicitly into account.

type. The best linear unbiased predictor is compared with other forecasts ignoring spatial correlation, or ignoring heterogeneity due to the individual effects. In addition, we check the performance of these forecasts under misspecification of the spatial error process, different spatial weight matrices, and various sample sizes. Section 2 introduces the error component model with spatially autocorrelated residuals of the SAR and SMA type. Section 3 describes the forecasts using the estimators considered in Section 2, while Section 4 gives the Monte Carlo design. Section 5 reports the results of the Monte Carlo simulations and Section 6 gives our summary and conclusion.

2 The Error Component Model with Spatially Autocorrelated Residuals

Consider a linear panel data regression model:

$$y_{it} = X_{it}\beta + \varepsilon_{it}, \quad i = 1, \dots, N; \quad t = 1, \dots, T \quad (1)$$

where the disturbance term follows an error component model with spatially autocorrelated residuals. The disturbance vector for time t is given by:

$$\varepsilon_t = \mu + \phi_t \quad (2)$$

where $\varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{Nt})'$, $\mu = (\mu_1, \dots, \mu_N)'$ denotes the vector of specific effects assumed to be *iid* $(0, \sigma_\mu^2)$ and $\phi_t = (\phi_{1t}, \dots, \phi_{Nt})'$ are the remainder disturbances which are independent of μ . We let the ϕ_t 's follow a spatial autoregressive (SAR) or a spatial moving average (SMA) error model. The SAR process is known to transmit the shocks globally while the SMA process transmits these shocks locally, see Anselin, Le Gallo and Jayet (2008).

The SAR specification for the $(N \times 1)$ error vector ϕ_t at time t can be expressed as:

$$\phi_t = \rho W_N \phi_t + v_t = (I_N - \rho W_N)^{-1} v_t = B_N^{-1} v_t \quad (3)$$

where W_N is an $(N \times N)$ known spatial weights matrix², ρ is the spatial autoregressive parameter and v_t is an $(N \times 1)$ error vector assumed to be dis-

²In the simplest case, the weights matrix is binary, with $w_{ij} = 1$ when i and j are neighbors and $w_{ij} = 0$ when they are not. By convention, diagonal elements are null: $w_{ii} = 0$ and the weights are almost always standardized such that the elements of each row sum to 1.

tributed independently across cross-sectional dimension with constant variance $\sigma_v^2 I_N$. $B_N = (I_N - \rho W_N)$ and is assumed to be non-singular. The error covariance matrix for the cross-section at time t becomes:

$$\Omega_t = E[\varepsilon_t \varepsilon_t'] = \sigma_\mu^2 I_N + \sigma_v^2 (B_N' B_N)^{-1} \quad (4)$$

For the full $(NT \times 1)$ vector of disturbances:

$$\varepsilon = (\iota_T \otimes I_N) \mu + (I_T \otimes B_N^{-1}) v \quad (5)$$

the corresponding $(NT \times NT)$ covariance matrix is given by:

$$\Omega = \sigma_\mu^2 (J_T \otimes I_N) + \sigma_v^2 [I_T \otimes (B_N' B_N)^{-1}] \quad (6)$$

where ι_T is a $(T \times 1)$ vector of ones and $J_T = \iota_T \iota_T'$ is a $(T \times T)$ matrix of ones.

The spatial moving average (SMA) specification for the $(N \times 1)$ error vector ϕ_t at time t can be expressed as:

$$\phi_t = \lambda W_N v_t + v_t = (I_N + \lambda W_N) v_t = D_N v_t \quad (7)$$

where $D_N = (I_N + \lambda W_N)$. The error covariance matrix for the cross-section at time t becomes:

$$\Omega_t = E[\varepsilon_t \varepsilon_t'] = \sigma_\mu^2 I_N + \sigma_v^2 (D_N D_N') \quad (8)$$

For the full $(NT \times 1)$ vector of disturbances:

$$\varepsilon = (\iota_T \otimes I_N) \mu + (I_T \otimes D_N) v \quad (9)$$

the corresponding $(NT \times NT)$ covariance matrix is given by:

$$\Omega = \sigma_\mu^2 (J_T \otimes I_N) + \sigma_v^2 [I_T \otimes (D_N D_N')] \quad (10)$$

MLE under normality of the disturbances using these error component models with spatial autocorrelation have been derived by Anselin (1988). The log-likelihood is given by:

$$L \propto -\frac{NT}{2} \ln(2\pi\sigma_v^2) - \frac{1}{2} \ln|\Sigma| - \frac{1}{2\sigma_v^2} \varepsilon' \Sigma^{-1} \varepsilon \quad (11)$$

where

$$\begin{aligned}
\varepsilon &= y - X\beta, \Omega = \sigma_v^2 \Sigma \\
\Sigma &= \begin{cases} (J_T \otimes \theta I_N) + [I_T \otimes (B'_N B_N)^{-1}] & \text{for SAR} \\ (J_T \otimes \theta I_N) + [I_T \otimes (D_N D'_N)] & \text{for SMA} \end{cases} \quad (12) \\
\text{with } \theta &= \sigma_\mu^2 / \sigma_v^2.
\end{aligned}$$

Regression models containing spatially correlated disturbance terms based on the SAR or SMA models are typically estimated using MLE, where the likelihood function corresponds to the normal distribution. However, this can be computationally demanding for large N . Kelejian and Prucha (1999) suggested a generalized moments (GM) estimation method for the SAR model in a cross-section setting, and Fingleton (2007) extended this generalized moments estimator to the SMA model. Kapoor, Kelejian and Prucha (2007) generalized this GM procedure from cross-section to panel data and derived its large sample properties when T is fixed and $N \rightarrow \infty$. However, their SAR random effects model (SAR-RE) differs from that described in (2) which we will call (RE-SAR). In fact, in their specification, the disturbance term ε_t itself follows a SAR process and the remainder term follows an error component structure. This allows the individual effects, i.e., the μ 's themselves to be spatially correlated but with the same ρ . In particular, the disturbance vector for time t is given by:

$$\varepsilon_t = \rho W_N \varepsilon_t + u_t \quad (13)$$

where u_t follows an error component structure :

$$u_t = \mu + v_t \quad (14)$$

The SAR-RE specification for the $(N \times 1)$ error vector ε_t at time t can be expressed as:

$$\varepsilon_t = (I_N - \rho W_N)^{-1} u_t = B_N^{-1} u_t \quad (15)$$

where $B_N = (I_N - \rho W_N)$. For the full $(NT \times 1)$ vector of disturbances:

$$\varepsilon = (\iota_T \otimes B_N^{-1}) \mu + (I_T \otimes B_N^{-1}) v \quad (16)$$

and the corresponding $(NT \times NT)$ covariance matrix is given by:

$$\Omega = \sigma_\mu^2 \left(J_T \otimes (B'_N B_N)^{-1} \right) + \sigma_v^2 \left[I_T \otimes (B'_N B_N)^{-1} \right] \quad (17)$$

Kapoor, et al. (2007) proposed three generalized moments (GM) estimators of ρ , σ_v^2 and $\sigma_1^2 (= \sigma_v^2 + T\sigma_\mu^2)$ based on the following six moment conditions:

$$E \begin{bmatrix} \frac{1}{N(T-1)} u_N' Q_{0,N} u_N \\ \frac{1}{N(T-1)} \bar{u}_N' Q_{0,N} \bar{u}_N \\ \frac{1}{N(T-1)} \bar{u}_N' Q_{0,N} u_N \\ \frac{1}{N} u_N' Q_{1,N} u_N \\ \frac{1}{N} \bar{u}_N' Q_{1,N} \bar{u}_N \\ \frac{1}{N} \bar{u}_N' Q_{1,N} u_N \end{bmatrix} = \begin{bmatrix} \sigma_v^2 \\ \sigma_v^2 \frac{1}{N} \text{tr}(W_N' W_N) \\ 0 \\ \sigma_1^2 \\ \sigma_1^2 \frac{1}{N} \text{tr}(W_N' W_N) \\ 0 \end{bmatrix} \quad (18)$$

where

$$u_N = \varepsilon_N - \rho \bar{\varepsilon}_N \quad (19)$$

$$\bar{u}_N = \bar{\varepsilon}_N - \rho \bar{\bar{\varepsilon}}_N \quad (20)$$

$$\bar{\varepsilon}_N = (I_T \otimes W_N) \varepsilon_N \quad (21)$$

$$\bar{\bar{\varepsilon}}_N = (I_T \otimes W_N) \bar{\varepsilon}_N \quad (22)$$

$$Q_{0,N} = \left(I_T - \frac{J_T}{T} \right) \otimes I_N \quad (23)$$

$$Q_{1,N} = \frac{J_T}{T} \otimes I_N \quad (24)$$

Under the random effects specification considered, the OLS estimator of β is consistent. Using $\hat{\beta}_{OLS}$ one gets a consistent estimator of the disturbances $\hat{\varepsilon} = y - X\hat{\beta}_{OLS}$. The GM estimators of σ_1^2 , σ_v^2 and ρ are the solution of the sample counterpart of the six equations given above. Kapoor, et al. (2007) suggest three GM estimators. The first involves only the first three moments which do not involve σ_1^2 and yield estimates of ρ and σ_v^2 . The fourth moment condition is then used to solve for σ_1^2 given estimates of ρ and σ_v^2 . The second GM estimator is based upon weighing the moment equations by the inverse of a properly normalized variance-covariance matrix of the sample moments evaluated at the true parameter values. A simple version of this weighting matrix is derived under normality of the disturbances. The third GM estimator is motivated by computational considerations and replaces a component of the weighting matrix for the second GM estimator by an identity matrix. Kapoor, et al. (2007) perform Monte Carlo experiments comparing MLE and these three GM estimation methods. They find that on average, the RMSE of MLE and their weighted GM estimators are quite

similar. The feasible GLS estimator of β is then obtained by replacing ρ , σ_v^2 and σ_1^2 by their GM estimators.³

Recently, Fingleton (2007) extended this GM estimator for the SMA panel data model with random effects. We call this SMA-RE to distinguish it from the RE-SMA procedure described in Anselin, et al. (2008). In fact, for the Fingleton (2007) SMA-RE, the disturbance term ε_t in (2) follows a SMA process and the remainder term follows an error component structure. Unlike the Anselin, et al. (2008) RE-SMA, the individual effects, i.e., the μ 's themselves are allowed to be spatially correlated but with the same λ . In particular, the disturbance vector for time t is given by:

$$\varepsilon_t = (I_N + \lambda W_N) u_t = D_N u_t \quad (25)$$

where $D_N = (I_N + \lambda W_N)$, and u_t follows an error component structure (14). So, the full SMA-RE ($NT \times 1$) vector of disturbances is given by:

$$\varepsilon = (\iota_T \otimes D_N) \mu + (I_T \otimes D_N) v \quad (26)$$

and the corresponding ($NT \times NT$) covariance matrix is given by:

$$\Omega = \sigma_\mu^2 (J_T \otimes (D_N D_N')) + \sigma_v^2 [I_T \otimes (D_N D_N')] \quad (27)$$

The moment conditions for SMA-RE are similar to those derived by Kapoor, et al. (2007), see Fingleton (2007).

3 Prediction

Goldberger (1962) has shown that, for a given Ω , the best linear unbiased predictor (BLUP) for the i th individual at a future period $T + \tau$ is given by:

$$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{GLS} + \omega' \Omega^{-1} \hat{\varepsilon}_{GLS} \quad (28)$$

where $\omega = E[\varepsilon_{i,T+\tau} \varepsilon]$ is the covariance between the future disturbance $\varepsilon_{i,T+\tau}$ and the sample disturbances ε . $\hat{\beta}_{GLS}$ is the GLS estimator of β from equation (1) based on Ω and $\hat{\varepsilon}_{GLS}$ denotes the corresponding GLS residual vector.

³Later, in our Monte Carlo experiments, we computed the predictors for all three GM estimators suggested by Kapoor, et al. (2007). However, the differences in root mean squared error performance were minor. To save space, we only report the second GM estimator, called weighted GM estimator by Kapoor, et al. (2007).

For the error component without spatial autocorrelation ($\lambda = 0$), this BLUP reduces to:

$$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{GLS} + \frac{\sigma_\mu^2}{\sigma_1^2} (\iota'_T \otimes l'_i) \hat{\varepsilon}_{GLS} \quad (29)$$

where $\sigma_1^2 = T\sigma_\mu^2 + \sigma_v^2$ and l_i is the i th column of I_N . This predictor was considered by Wansbeek and Kapteyn (1978), Lee and Griffiths (1979) and Taub (1979). The typical element of the last term of equation (29) is $(T\sigma_\mu^2/\sigma_1^2) \bar{\varepsilon}_{i,GLS}$ where $\bar{\varepsilon}_{i,GLS} = \sum_{t=1}^T \hat{\varepsilon}_{ti,GLS}/T$. Therefore, the BLUP of $y_{i,T+\tau}$ for the RE model modifies the usual GLS forecasts by adding a fraction of the mean of the GLS residuals corresponding to the i th individual. In order to make this forecast operational, $\hat{\beta}_{GLS}$ is replaced by its feasible GLS estimate and the variance components are replaced by their feasible estimates.

Baltagi and Li (2004, 2006) derived the BLUP correction term when both error components and spatial autocorrelation are present and ϕ_t follows a SAR process. So, the predictors for the SAR and the SMA are given by:

$$\hat{y}_{i,T+\tau} = \begin{cases} X_{i,T+\tau} \hat{\beta}_{MLE} + \theta (\iota'_T \otimes l'_i C_1^{-1}) \hat{\varepsilon}_{MLE} \\ = X_{i,T+\tau} \hat{\beta}_{MLE} + T\theta \sum_{j=1}^N c_{1,j} \bar{\varepsilon}_{j,MLE} & \text{for SAR} \\ X_{i,T+\tau} \hat{\beta}_{MLE} + \theta (\iota'_T \otimes l'_i C_2^{-1}) \hat{\varepsilon}_{MLE} \\ = X_{i,T+\tau} \hat{\beta}_{MLE} + T\theta \sum_{j=1}^N c_{2,j} \bar{\varepsilon}_{j,MLE} & \text{for SMA} \end{cases} \quad (30)$$

where c_{1j} (resp. $c_{2,j}$) is the j th element of the i th row of C_1^{-1} (resp. C_2^{-1}) with $C_1 = [T\theta I_N + (B'_N B_N)^{-1}]$ (resp. $C_2 = [T\theta I_N + (D_N D'_N)]$) and $\bar{\varepsilon}_{j,MLE} = \sum_{t=1}^T \hat{\varepsilon}_{tj,MLE}/T$. In other words, the BLUP of $y_{i,T+\tau}$ adds to $X_{i,T+\tau} \hat{\beta}_{MLE}$ a weighted average of the MLE residuals for the N individuals averaged over time. The weights depend upon the spatial matrix W_N and the spatial autoregressive (or moving average) coefficients ρ and λ . To make these predictors operational, we replace θ, ρ and λ by their estimates from the RE-spatial MLE with SAR or SMA. When there are no random individual effects, so that $\sigma_\mu^2 = 0$, then $\theta = 0$ and the BLUP prediction terms drop out completely from equation (30). In these cases, Ω in equation (12) reduces to $\sigma_v^2 [I_T \otimes (B'_N B_N)^{-1}]$ for SAR and $\sigma_v^2 [I_T \otimes (D_N D'_N)]$ for SMA, and the corresponding MLE for these models yield the pooled spatial MLE with SAR or SMA remainder disturbances.

For the Kapoor, et al. (2007) model, the BLUP of $y_{i,T+\tau}$ for the SAR-RE also modifies the usual GLS forecasts by adding a fraction of the mean of the GLS residuals corresponding to the i th individual. More specifically, the predictor is given by:

$$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{GLS} + \left(\frac{\sigma_{\mu}^2}{\sigma_1^2} \right) b_i (\iota'_T \otimes B_N) \hat{\varepsilon}_{GLS} \quad (31)$$

where b_i is the i th row of the matrix B_N^{-1} . This is derived in the Appendix of this paper which also shows the resulting predictor has the same form as that of the RE model (29). This proof applies to both the Kapoor, et al. (2007) SAR-RE specification and the Fingleton (2007) SMA-RE specification. Therefore, the BLUP of $y_{i,T+\tau}$ for the SAR-RE and the SMA-RE, like the usual RE model with no spatial effects, modifies the usual GLS forecasts by adding a fraction of the mean of the GLS residuals corresponding to the i th individual. While the predictor formula is the same, the MLEs for these specifications yield different estimates which in turn yield different residuals and hence different forecasts.

4 Monte Carlo Design

In this section, we consider the small sample performance of several predictors for an error component model with spatially autocorrelated residuals. The data generating process (DGP) consider two specifications on the remainder errors, namely SAR and SMA:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \varepsilon_{it}, \varepsilon_{it} = \mu_i + \phi_{it}, i = 1, \dots, N; t = 1, \dots, T \quad (32)$$

where⁴

$$x_{it} = \delta_i + \xi_{it}$$

with

$$\begin{aligned} \mu_i &\sim iid.N(0, \sigma_{\mu}^2), \delta_i \sim iid.U(-7.5, 7.5), \\ \xi_{it} &\sim iid.U(-5, 5), \beta_0 = 5, \beta_1 = 0.5 \end{aligned}$$

⁴In the spirit of Nerlove (1971), we have tried another DGP for x_{it} . We obtain the same ranking as those which appear in the reported tables. The only difference is that the gap between the average heterogeneous estimators and the homogeneous estimators widens with a Nerlove (1971) type design. In other words, the forecast performance of the heterogeneous estimators becomes worse.

$$\phi_t = \begin{cases} \rho W_N \phi_t + v_t & \text{for SAR} \\ \lambda W_N v_t + v_t & \text{for SMA} \end{cases} \quad \text{with } \rho, \lambda = \begin{cases} 0.8 \\ 0.4 \end{cases} \quad (33)$$

and

$$v_{it} \sim iid.N(0, \sigma_v^2) \quad (34)$$

We consider the simple regressions (32) and (33) with $N = (50, 100)$, $T = (10, 20)$ and two cases for the residuals variances:

$$\begin{cases} \sigma_\mu^2 = 4, & \sigma_v^2 = 16 \\ \sigma_\mu^2 = 16, & \sigma_v^2 = 4 \end{cases} \quad (35)$$

Following Kelejian and Prucha (1999), we use two weight matrices which essentially differ in their degree of sparseness. The weight matrices are labelled as “ j ahead and j behind” with the non-zero elements being $1/2j$, $j = 1$ and 5. Even with this modest design we have 64 experiments.

For each experiment, we obtain the following 16 estimators:

1. Pooled OLS which ignores the individual heterogeneity and the spatial autocorrelation.
2. The average heterogeneous OLS which estimates the cross-sectional equation using OLS for each time period and averages these heterogeneous estimates to obtain a pooled estimator, see Pesaran and Smith (1995).
3. The fixed-effects (FE) estimator which accounts for fixed individual effects but does not take into account the spatial autocorrelation.
4. The random effects (RE) estimator which assumes that the μ_i 's are $iid(0, \sigma_\mu^2)$, and independent of the remainder disturbances ϕ_{it} 's. This estimator accounts for random individual effects but does not take into account the spatial autocorrelation.
5. The RE-spatial MLE assuming a SAR specification (RE-SAR) on the remainder disturbances. In this case, the μ_i 's are $iid(0, \sigma_\mu^2)$ and are independent of the ϕ_{it} 's which follow a SAR process, see Anselin, et al. (2008).

6. The RE-spatial MLE assuming a SMA specification (RE-SMA) on the remainder disturbances. In this case, the μ_i 's are $iid(0, \sigma_\mu^2)$ and are independent of the ϕ_{it} 's which follow a SMA process, see Anselin, et al. (2008).
7. The pooled spatial MLE assuming a SAR specification (Pooled SAR) on the remainder disturbances. This estimator ignores the individual heterogeneity but takes into account the spatial autocorrelation of the SAR type.
8. The pooled spatial MLE assuming a SMA specification (Pooled SMA) on the remainder disturbances. This estimator ignores the individual heterogeneity but takes into account the spatial autocorrelation of the SMA type.
9. The average heterogeneous spatial MLE assuming a SAR specification on the remainder disturbances. This estimates cross-sectional MLE with SAR disturbances for each time period and averages the estimates over time.
10. The average heterogeneous spatial GM estimator assuming a SAR specification on the remainder disturbances proposed by Kelejian and Prucha (1999). This estimates cross-sectional GM estimator with SAR disturbances for each time period and averages the estimates over time.
11. The average heterogeneous spatial MLE assuming a SMA specification on the remainder disturbances. This estimates cross-sectional MLE with SMA disturbances for each time period and averages the estimates over time.
12. The average heterogeneous spatial GM estimator assuming a SMA specification on the remainder disturbances proposed by Fingleton (2007). This estimates cross-sectional GM estimator with SMA disturbances for each time period and averages the estimates over time.
13. The FE-spatial MLE assuming a SAR specification (FE-SAR) on the remainder disturbances.
14. The FE-spatial MLE assuming a SMA specification (FE-SMA) on the remainder disturbances.

15. The (SAR-RE) model following Kapoor, et al. (2007). This utilizes a panel data GM estimator where the disturbance term itself follows a SAR process and the remainder term follows an error component structure.
16. The (SMA-RE) model following Fingleton (2007). This utilizes a panel data GM estimator where the disturbance term itself follows a SMA process and the remainder term follows an error component structure.

Next, we compute the following predictors for the i th individual at a future period $T + \tau$ for $\tau = 1, 2, \dots, 5$:

OLS	$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{OLS}$
Average hetero. OLS	$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{av.OLS}$
FE ⁵	$\begin{cases} \hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{FE} + \hat{\mu}_i \\ \text{with } \hat{\mu}_i = \bar{y}_i - \bar{X}_i \hat{\beta}_{FE}, \bar{y}_i = \sum_{t=1}^T y_{it}/T \end{cases}$
RE	$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{RE} + \frac{\sigma_\mu^2}{\sigma_1^2} (\iota'_T \otimes \iota'_i) \hat{\varepsilon}_{RE}$
RE-SAR	$\begin{cases} \hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{MLE,RE-SAR} + \theta (\iota'_T \otimes \iota'_i C_1^{-1}) \hat{\varepsilon}_{MLE,RE-SAR} \\ \text{with } C_1 = [T\theta I_N + (B'_N B_N)^{-1}] \text{ and } \theta = \sigma_\mu^2 / \sigma_v^2 \end{cases}$
RE-SMA	$\begin{cases} \hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{MLE,RE-SMA} + \theta (\iota'_T \otimes \iota'_i C_2^{-1}) \hat{\varepsilon}_{MLE,RE-SMA} \\ \text{with } C_2 = [T\theta I_N + (D'_N D'_N)] \text{ and } \theta = \sigma_\mu^2 / \sigma_v^2 \end{cases}$
Pooled SAR	$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{MLE,SAR}$
Pooled SMA	$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{MLE,SMA}$
Average hetero. SAR	$\hat{y}_{i,T+\tau} = \begin{cases} X_{i,T+\tau} \hat{\beta}_{av.MLE,SAR} \\ X_{i,T+\tau} \hat{\beta}_{av.GM,SAR} \end{cases}$
Average hetero. SMA	$\hat{y}_{i,T+\tau} = \begin{cases} X_{i,T+\tau} \hat{\beta}_{av.MLE,SMA} \\ X_{i,T+\tau} \hat{\beta}_{av.GM,SMA} \end{cases}$
FE-SAR	$\begin{cases} \hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{MLE,FE-SAR} + \hat{\mu}_i \\ \text{with } \hat{\mu}_i = \bar{y}_i - \bar{X}_i \hat{\beta}_{MLE,FE-SAR}, \bar{y}_i = \sum_{t=1}^T y_{it}/T \end{cases}$
FE-SMA	$\begin{cases} \hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{MLE,FE-SMA} + \hat{\mu}_i \\ \text{with } \hat{\mu}_i = \bar{y}_i - \bar{X}_i \hat{\beta}_{MLE,FE-SMA}, \bar{y}_i = \sum_{t=1}^T y_{it}/T \end{cases}$
SAR-RE	$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{MLE,SAR-RE} + \left(\frac{\sigma_\mu^2}{\sigma_1^2} \right) (\iota'_T \otimes \iota'_i) \hat{\varepsilon}_{MLE,SAR-RE}$
SMA-RE	$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{MLE,SMA-RE} + \left(\frac{\sigma_\mu^2}{\sigma_1^2} \right) (\iota'_T \otimes \iota'_i) \hat{\varepsilon}_{MLE,SMA-RE}$

For all experiments, 1000 replications are performed and the RMSE for one step to five step ahead forecasts are reported.

5 Monte Carlo Results

5.1 The Spatial Dependence Specification Effect

Table 1 gives the RMSE for the one year, two year,..., and five year ahead forecasts along with the average RMSE for all 5 years. These are out of sample forecasts when the true DGP is a RE panel model with SAR remainder disturbances. The sample size is $N = 50$ and $T = 10$, the weight matrix is $W(1,1)$, i.e., one neighbor behind and one neighbor ahead. In general, for $\rho = 0.4, 0.8$ and $\sigma_\mu^2 = 4, 16$, the lowest RMSE is that of RE-SAR. This is followed closely by SAR-RE and SMA-RE. It confirms the findings of Kapoor, et al. (2007) that, on average, RMSE of MLE and their GM estimators are quite similar. It also seems like misspecifying the SAR by an SMA in an error component model does not affect the forecast performance as long as it is taken into account. As the spatial autoregressive parameter ρ doubles from 0.4 to 0.8, the RMSE also doubles. The RMSE improves as σ_μ^2 gets large, i.e., 16 rather than 4, for estimators that take heterogeneity into account. Pooled OLS, average heterogeneous OLS, pooled SAR, pooled SMA, average heterogeneous SAR (MLE and GM) and average heterogeneous SMA (MLE and GM) perform worse in terms of RMSE than spatial/panel homogeneous estimators. This forecast comparison is robust whether we are predicting one period, two periods or 5 periods ahead and is also reflected in the average over the five years. The gain in forecast performance is substantial once we account for RE or FE and is only slightly improved by additionally accounting for spatial autocorrelation, i.e., FE-SAR or RE-SAR, FE-SMA, or RE-SMA.

Table 2 gives the RMSE results when the true DGP is a RE panel model with SMA remainder disturbances. The sample size is still $N = 50, T = 10$, and the weight matrix is $W(1,1)$. In general, for $\rho = 0.4, 0.8$ and $\sigma_\mu^2 = 4, 16$, the lowest RMSE is that of RE-SMA. This is followed closely by RE-SAR.

⁵See Baillie and Baltagi (1998).

Misspecifying the SMA by an SAR in an error component model does not seem to affect the forecast performance as long as it is taken into account. However, the magnitudes of the RMSE in Table 2 (where the true DGP is a RE-SMA process) are much lower than those in Table 1 (where the true DGP is a RE-SAR process). Once again, the forecast RMSE of based on MLE and their GM counterparts are quite similar, compare SAR-RE and SMA-RE with RE-SAR and RE-SMA. The RMSE improves as σ_μ^2 gets large, i.e., 16 rather than 4, for estimators that take heterogeneity into account. As the spatial autoregressive parameter λ increases from 0.4 to 0.8, the RMSE also increases but not as much as it did for the SAR process in Table 1. Pooled OLS, average heterogeneous OLS, pooled SAR, pooled SMA, average heterogeneous SAR (MLE and GM) and average heterogeneous SMA (MLE and GM) perform worse in terms of RMSE than spatial/panel homogeneous estimators. This forecast performance is robust whether we are predicting one period, two periods or 5 periods ahead and is also reflected in the average over the five years. Once again, the gain in forecast performance is substantial once we account for RE or FE and is only slightly improved by additionally accounting for spatial autocorrelation, i.e., FE-SMA, or RE-SMA, FE-SAR or RE-SAR.

5.2 Sensitivity Analysis

5.2.1 The Spatial Weight Matrix effect

Tables 3 and 4 report the RMSE results as Tables 1 and 2 except that the weight matrix is changed from a $W(1, 1)$ to $W(5, 5)$, i.e., five neighbors behind and five neighbors ahead. Except for the magnitudes of the RMSE, the same rankings in terms of RMSE performance are exhibited as before.

Tables 5 and 6 report the RMSE results as Tables 1 and 2 except that T is now doubled from 10 to 20 holding N fixed at 50. Except for the magnitudes of the RMSE, the same rankings in terms of RMSE performance are exhibited as before.

Table 7 reports the RMSE results when $\rho = \lambda = 0.8$, the weight matrix is $W(1, 1)$, and N is doubled from 50 to 100 holding T fixed at 10. While Table 8 reports the RMSE results as Table 7 except that the weight matrix is $W(5, 5)$. Except for the magnitudes of the RMSE, the same rankings in terms of RMSE performance are exhibited as before.⁶

⁶Other Tables for $W(5, 5)$ and $(N, T) = (100, 20)$ show the same rankings in terms of

5.2.2 Sensitivity to Irregular Lattice Structures

The spatial weights matrices considered in the paper are regular lattice structures. Using real irregular lattices structures, as in Anselin and Moreno (2003) and in Kelejian and Prucha (1999), does not change the conclusions of the Monte Carlo study. We used real-world matrices by taking spatial groupings of French administrative communes for dimension $N = 50$.⁷ Those spatial matrices have been used by Baltagi, Bresson and Pirotte (2007). Spatial weight matrices may represent high-order contiguity relationships. We use a k -order contiguity matrix containing $N - 1$ potential neighborhoods in French municipalities. We have patterns of 0 and 1 values in an $(N - 1)$ by $(N - 1)$ grid for the k -nearest neighborhoods and we use the 1-nearest neighborhood ($k = 1$) and the 5-nearest neighborhoods ($k = 5$).⁸ Results of Tables 9 to 12 are very similar to those of Tables 1 to 4. Using irregular lattice structures do not change the main conclusions in terms of the RMSE forecast performance of the various estimators considered. These are similar to the rankings obtained when regular lattice structures are used, only the magnitudes of the RMSE differ.

5.2.3 Robustness to Non-Normality

So far, we have been assuming that the error components have been generated by the normal distribution. In this section, we check the sensitivity of our results to non-normal disturbances. In particular, we generate the μ_i 's from a χ^2 distribution and we let the remainder disturbances follow the normal distribution. Tables 13 and 14 give similar results as those of Tables 1 and 2 (when the individual effects follow a normal distribution). So, the results seem to be robust to non-normality of the disturbances of the χ^2 type.

RMSE forecast performance and are not shown here to save space. These are available upon request from the authors.

⁷Other Tables for $N = 100$ are available upon request from the authors.

⁸Note that a non-zero entry in row i , column j denotes that neighborhoods i and j have borders that touch and are therefore considered "neighbors". For $N = 50$ and for $k = 5$, and for the 2401 possible elements in the 49 by 49 matrix, there are only 250 non-zero elements. So, the sparseness value is 10% ($= 250/2500$). These non-zero entries reflect the contiguity relations between the 5-nearest neighborhoods.

6 Summary and Conclusion

Our Monte Carlo study finds that when the true DGP is RE with a SAR or SMA remainder disturbances, estimators that ignore heterogeneity/spatial correlation perform badly in RMSE forecasts. For our experiments, accounting for heterogeneity improves the forecast performance by a big margin and accounting for spatial correlation improves the forecast but by a smaller margin. Ignoring both leads to the worst forecasting performance. Heterogeneous estimators based on averaging perform worse than homogeneous estimators in forecasting performance. This performance improves with a larger sample size and seems robust to the type of spatial error structure imposed on the remainder disturbances. These Monte Carlo experiments confirm earlier empirical studies that report similar findings.

7 Appendix

This appendix first derives the BLUP for the KKP model which we are calling the (SAR-RE) model described in (13) and (14). The variance-covariance matrix Ω is given in (17). The inverse of Ω is given by:

$$\Omega^{-1} = \frac{1}{\sigma_v^2} \left[\left(I_T - \frac{T\sigma_\mu^2}{\sigma_1^2} \bar{J}_T \right) \otimes (B'_N B_N) \right]$$

where $\bar{J}_T = J_T/T$ and $\sigma_1^2 = T\sigma_\mu^2 + \sigma_v^2$ and $B_N = (I_N - \rho W_N)$. From (13) and (14), we have :

$$\varepsilon_{T+\tau} = B_N^{-1} u_{T+\tau} = B_N^{-1} (\mu + v_{T+\tau})$$

so that,

$$\begin{aligned} E \left[\varepsilon_{T+\tau} \varepsilon' \right] &= E \left[B_N^{-1} (\mu + v_{T+\tau}) \left((\iota_T \otimes B_N^{-1}) \mu + (I_T \otimes B_N^{-1}) v \right)' \right] \\ &= \sigma_\mu^2 B_N^{-1} \left(\iota_T' \otimes B_N^{-1'} \right) \\ \omega' &= E \left[\varepsilon_{i,T+\tau} \varepsilon' \right] = \sigma_\mu^2 b_i \left(\iota_T' \otimes B_N^{-1'} \right) \end{aligned}$$

where b_i is the i th row of the matrix B_N^{-1} . In this case,

$$\omega' \Omega^{-1} = \frac{\sigma_\mu^2}{\sigma_v^2} b_i \left(\iota_T' \otimes B_N^{-1'} \right) \left[\left(I_T - \frac{T\sigma_\mu^2}{\sigma_1^2} \bar{J}_T \right) \otimes (B'_N B_N) \right]$$

$$\begin{aligned}
&= \frac{\sigma_\mu^2}{\sigma_v^2} b_i \left[\left(\iota'_T \otimes B_N \right) - \frac{T\sigma_\mu^2}{\sigma_1^2} \left(\iota'_T \otimes B_N \right) \right] \\
&= \frac{\sigma_\mu^2}{\sigma_1^2} b_i \left(\iota'_T \otimes B_N \right)
\end{aligned}$$

But $b_i (\iota'_T \otimes B_N) = (1 \otimes b_i) (\iota'_T \otimes B_N) = (\iota'_T \otimes l'_i)$, where l'_i is the i th row of I_N . This holds because $B_N^{-1} B_N = I_N$ and therefore $b_i B_N = l'_i$. This means that the predictor of the KKP model from (28) is given by:

$$\hat{y}_{i,T+\tau} = X_{i,T+\tau} \hat{\beta}_{GLS} + \frac{\sigma_\mu^2}{\sigma_1^2} (\iota'_T \otimes l'_i) \hat{\varepsilon}_{GLS} \quad (36)$$

which is the same as that of the RE model with no spatial correlation. While the predictor formula is the same, the MLEs for these specifications yield different estimates which in turn yield different residuals and hence different forecasts.

The proof is the similar for the Fingleton (2007) specification which we are calling the (SMA-RE) model described in (25) and (14). The variance-covariance matrix Ω is given in (27). The inverse of Ω is given by:

$$\Omega^{-1} = \frac{1}{\sigma_v^2} \left[\left(I_T - \frac{T\sigma_\mu^2}{\sigma_1^2} \bar{J}_T \right) \otimes (D_N D'_N)^{-1} \right]$$

where $D_N = (I_N + \lambda W_N)$. From (25) and (14), we have :

$$\varepsilon_{T+\tau} = D_N u_{T+\tau} = D_N (\mu + v_{T+\tau})$$

so that,

$$\begin{aligned}
E[\varepsilon_{T+\tau} \varepsilon'] &= E[D_N (\mu + v_{T+\tau}) ((\iota'_T \otimes D_N) \mu + (I_T \otimes D_N) v)'] \\
&= \sigma_\mu^2 D_N (\iota'_T \otimes D'_N) \\
\omega' &= E[\varepsilon_{i,T+\tau} \varepsilon'] = \sigma_\mu^2 d_i (\iota'_T \otimes D'_N)
\end{aligned}$$

where d_i is the i th row of the matrix D_N . In this case,

$$\begin{aligned}
\omega' \Omega^{-1} &= \frac{\sigma_\mu^2}{\sigma_v^2} d_i (\iota'_T \otimes D'_N) \left[\left(I_T - \frac{T\sigma_\mu^2}{\sigma_1^2} \bar{J}_T \right) \otimes (D_N D'_N)^{-1} \right] \\
&= \frac{\sigma_\mu^2}{\sigma_v^2} d_i \left[\left(\iota'_T \otimes D_N^{-1} \right) - \frac{T\sigma_\mu^2}{\sigma_1^2} \left(\iota'_T \otimes D_N^{-1} \right) \right] \\
&= \frac{\sigma_\mu^2}{\sigma_1^2} d_i (\iota'_T \otimes D_N^{-1})
\end{aligned}$$

But $d_i (\iota'_T \otimes D_N^{-1}) = (1 \otimes d_i) (\iota'_T \otimes D_N^{-1}) = (\iota'_T \otimes l'_i)$, where l'_i is the i th row of I_N . This holds because $D_N D_N^{-1} = I_N$ and therefore $d_i D_N^{-1} = l'_i$. This means that the predictor of the Fingleton (2007) model is again the same as that of the RE model with no spatial correlation. While the predictor formula is the same, the MLEs for these specifications yield different estimates which in turn yield different residuals and hence different forecasts.

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Table 1 - Forecasts RMSE - (N,T)=(50,10), SAR data generating process for ϕ , W(1,1), 1000 replications

			Estimators															
			Pooled	Av. hetero.	FE	RE	Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
	ρ	σ_{μ}^2	OLS	OLS			MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.9781	3.9782	3.8102	3.7645	3.9781	3.9781	3.9606	3.8093	3.7558	3.9782	3.9782	3.9464	3.8093	3.7558	3.7610	3.7765
		16	3.6289	3.6290	1.9019	1.8989	3.6300	3.6299	3.6522	1.9007	1.8971	3.6301	3.6300	3.6569	1.9007	1.8973	1.8978	1.9134
	0.8	4	7.0556	7.0552	7.1957	7.0218	7.0529	7.0389	7.0558	7.1917	6.9564	7.0541	7.0403	7.0796	7.1917	6.9668	7.0187	7.0382
		16	4.6529	4.6533	3.5908	3.5764	4.6584	4.6569	4.6697	3.5863	3.5518	4.6589	4.6576	4.6644	3.5867	3.5603	3.6047	3.5908
2nd year	0.4	4	4.4164	4.4165	4.2360	4.1840	4.4162	4.4162	4.3423	4.2354	4.1763	4.4164	4.4164	4.3721	4.2353	4.1755	4.1808	4.1739
		16	3.8731	3.8733	2.1207	2.1175	3.8742	3.8743	3.8849	2.1194	2.1155	3.8742	3.8744	3.8918	2.1195	2.1156	2.1164	2.1216
	0.8	4	7.8106	7.8106	7.9469	7.7633	7.8066	7.7911	7.8100	7.9408	7.6956	7.8073	7.7920	7.8306	7.9407	7.7034	7.7832	7.8190
		16	5.1174	5.1177	4.0090	3.9942	5.1221	5.1209	5.1206	4.0039	3.9661	5.1225	5.1213	5.1084	4.0042	3.9754	3.9923	3.9833
3rd year	0.4	4	4.5807	4.5808	4.3992	4.3445	4.5805	4.5805	4.5627	4.3986	4.3364	4.5806	4.5807	4.5560	4.3985	4.3357	4.3414	4.3475
		16	3.9582	3.9585	2.2004	2.1972	3.9591	3.9592	3.9660	2.1992	2.1954	3.9591	3.9594	3.9682	2.1993	2.1956	2.1963	2.2023
	0.8	4	8.1467	8.1467	8.2921	8.1023	8.1424	8.1273	8.1458	8.2853	8.0289	8.1430	8.1279	8.1618	8.2854	8.0382	8.1016	8.1402
		16	5.2892	5.2894	4.1685	4.1529	5.2936	5.2923	5.2763	4.1636	4.1234	5.2940	5.2928	5.2674	4.1640	4.1337	4.1387	4.1450
4th year	0.4	4	4.6719	4.6720	4.4891	4.4335	4.6718	4.6717	4.6676	4.4882	4.4250	4.6719	4.6720	4.6583	4.4881	4.4245	4.4301	4.4332
		16	4.0024	4.0026	2.2471	2.2440	4.0031	4.0033	4.0117	2.2460	2.2423	4.0032	4.0034	4.0125	2.2461	2.2424	2.2432	2.2451
	0.8	4	8.3035	8.3035	8.4435	8.2560	8.2997	8.2836	8.3011	8.4367	8.1826	8.3005	8.2843	8.3225	8.4370	8.1922	8.3142	8.3214
		16	5.3799	5.3802	4.2531	4.2377	5.3838	5.3826	5.3662	4.2481	4.2085	5.3841	5.3829	5.3626	4.2485	4.2183	4.2296	4.2143
5th year	0.4	4	4.7238	4.7239	4.5443	4.4870	4.7238	4.7238	4.7274	4.5432	4.4778	4.7239	4.7240	4.7199	4.5432	4.4775	4.4836	4.4906
		16	4.0283	4.0285	2.2727	2.2698	4.0288	4.0290	4.0362	2.2716	2.2681	4.0289	4.0291	4.0374	2.2716	2.2682	2.2689	2.2718
	0.8	4	8.4195	8.4197	8.5680	8.3756	8.4158	8.3995	8.4173	8.5606	8.2997	8.4164	8.4001	8.4331	8.5608	8.3100	8.4299	8.4256
		16	5.4280	5.4282	4.2962	4.2812	5.4313	5.4301	5.4156	4.2911	4.2526	5.4317	5.4305	5.4125	4.2914	4.2618	4.2808	4.2710
Average	0.4	4	4.4742	4.4743	4.2957	4.2427	4.4741	4.4740	4.4601	4.2949	4.2343	4.4742	4.4743	4.4505	4.2949	4.2338	4.2394	4.2444
		16	3.8982	3.8984	2.1486	2.1455	3.8990	3.8992	3.9102	2.1474	2.1437	3.8991	3.8993	3.9133	2.1474	2.1438	2.1445	2.1509
	0.8	4	7.9472	7.9471	8.0892	7.9038	7.9435	7.9281	7.9460	8.0830	7.8326	7.9443	7.9289	7.9655	8.0831	7.8421	7.9295	7.9489
		16	5.1735	5.1738	4.0635	4.0485	5.1778	5.1766	5.1697	4.0586	4.0205	5.1782	5.1770	5.1631	4.0589	4.0299	4.0492	4.0409

Table 2 - Forecasts RMSE - (N,T)=(50,10), SMA data generating process for ϕ , W(1,1), 1000 replications

	Estimators																	
			Pooled	Av. hetero.			Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
	λ	σ^2_{μ}	OLS	OLS	FE	RE	MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.6702	3.6703	3.4717	3.4261	3.6704	3.6701	3.6706	3.4707	3.4193	3.6705	3.6702	3.6669	3.4707	3.4187	3.4330	3.4375
		16	3.5582	3.5582	1.7481	1.7455	3.5583	3.5584	3.5606	1.7478	1.7450	3.5584	3.5585	3.5569	1.7479	1.7449	1.7444	1.7323
	0.8	4	3.9870	3.9873	3.8507	3.7906	3.9857	3.9856	3.9878	3.8481	3.7653	3.9858	3.9859	3.9770	3.8480	3.7635	3.7915	3.8213
		16	3.6364	3.6364	1.9117	1.9095	3.6381	3.6377	3.6235	1.9098	1.9068	3.6380	3.6376	3.6316	1.9097	1.9062	1.9270	1.9078
2nd year	0.4	4	4.0793	4.0793	3.8608	3.8133	4.0794	4.0792	4.0796	3.8600	3.8060	4.0795	4.0793	4.0816	3.8600	3.8056	3.8269	3.8097
		16	3.7747	3.7748	1.9380	1.9354	3.7751	3.7754	3.7756	1.9375	1.9346	3.7752	3.7755	3.7759	1.9376	1.9345	1.9282	1.9255
	0.8	4	4.4390	4.4391	4.2819	4.2224	4.4388	4.4386	4.4209	4.2783	4.1971	4.4396	4.4396	4.4105	4.2777	4.1952	4.2168	4.2313
		16	3.8696	3.8697	2.1223	2.1191	3.8716	3.8714	3.8791	2.1201	2.1157	3.8718	3.8717	3.8821	2.1199	2.1149	2.1374	2.1270
3rd year	0.4	4	4.2357	4.2358	4.0121	3.9644	4.2358	4.2358	4.2367	4.0111	3.9563	4.2360	4.2359	4.2393	4.0111	3.9560	3.9785	3.9661
		16	3.8526	3.8527	2.0109	2.0084	3.8531	3.8534	3.8521	2.0104	2.0074	3.8531	3.8535	3.8537	2.0104	2.0074	2.0076	2.0047
	0.8	4	4.6176	4.6177	4.4527	4.3926	4.6176	4.6175	4.5966	4.4490	4.3684	4.6184	4.6184	4.5887	4.4483	4.3652	4.3835	4.3981
		16	3.9613	3.9614	2.2116	2.2084	3.9636	3.9634	3.9673	2.2095	2.2054	3.9638	3.9636	3.9692	2.2094	2.2045	2.2194	2.2168
4th year	0.4	4	4.3113	4.3114	4.0834	4.0354	4.3110	4.3111	4.3131	4.0823	4.0263	4.3112	4.3112	4.3161	4.0823	4.0263	4.0608	4.0475
		16	3.8901	3.8902	2.0500	2.0474	3.8905	3.8908	3.8901	2.0494	2.0464	3.8906	3.8909	3.8917	2.0494	2.0463	2.0465	2.0482
	0.8	4	4.7133	4.7133	4.5470	4.4856	4.7135	4.7134	4.6870	4.5433	4.4613	4.7146	4.7144	4.6837	4.5428	4.4581	4.4617	4.4901
		16	4.0100	4.0101	2.2659	2.2627	4.0122	4.0121	4.0134	2.2642	2.2598	4.0123	4.0122	4.0152	2.2639	2.2590	2.2619	2.2631
5th year	0.4	4	4.3637	4.3638	4.1367	4.0876	4.3635	4.3635	4.3653	4.1357	4.0786	4.3637	4.3637	4.3695	4.1357	4.0786	4.1094	4.0975
		16	3.9122	3.9124	2.0748	2.0722	3.9126	3.9129	3.9147	2.0743	2.0712	3.9127	3.9131	3.9147	2.0742	2.0711	2.0729	2.0752
	0.8	4	4.7697	4.7698	4.6004	4.5394	4.7702	4.7700	4.7457	4.5967	4.5160	4.7713	4.7712	4.7428	4.5963	4.5125	4.5223	4.5371
		16	4.0405	4.0405	2.2956	2.2926	4.0426	4.0425	4.0396	2.2937	2.2898	4.0428	4.0427	4.0411	2.2934	2.2889	2.2890	2.2901
Average	0.4	4	4.1321	4.1321	3.9129	3.8653	4.1320	4.1319	4.1331	3.9120	3.8573	4.1322	4.1320	4.1347	3.9120	3.8570	3.8817	3.8717
		16	3.7976	3.7977	1.9644	1.9618	3.7979	3.7982	3.7986	1.9639	1.9609	3.7980	3.7983	3.7986	1.9639	1.9608	1.9599	1.9572
	0.8	4	4.5053	4.5054	4.3466	4.2861	4.5051	4.5050	4.4876	4.3431	4.2616	4.5059	4.5059	4.4805	4.3426	4.2589	4.2752	4.2956
		16	3.9036	3.9036	2.1614	2.1584	3.9056	3.9054	3.9046	2.1594	2.1555	3.9058	3.9055	3.9079	2.1592	2.1547	2.1669	2.1610

Table 3 - Forecasts RMSE - (N,T)=(50,10), SAR data generating process for ϕ , W(5,5), 1000 replications

			Estimators															
			Pooled	Av. hetero.	FE	RE	Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
	ρ	σ_μ^2	OLS	OLS			MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.6604	3.6604	3.4537	3.4118	3.6600	3.6601	3.6448	3.4535	3.4095	3.6602	3.6603	3.6338	3.4536	3.4095	3.4415	3.4417
		16	3.5736	3.5735	1.7414	1.7405	3.5737	3.5739	3.5697	1.7410	1.7402	3.5736	3.5739	3.5671	1.7411	1.7403	1.7351	1.7342
	0.8	4	4.9150	4.9149	4.8055	4.7733	4.9133	4.8926	4.8984	4.8040	4.7355	4.9135	4.8926	4.9076	4.8040	4.7365	4.7109	4.7822
		16	3.9279	3.9279	2.4155	2.4138	3.9283	3.9272	3.8975	2.4131	2.4063	3.9284	3.9270	3.9042	2.4133	2.4080	2.3947	2.3975
2nd year	0.4	4	4.0515	4.0516	3.8391	3.7896	4.0515	4.0515	4.0529	3.8386	3.7868	4.0515	4.0516	4.0498	3.8386	3.7868	3.8221	3.8177
		16	3.7783	3.7784	1.9310	1.9294	3.7785	3.7786	3.7817	1.9307	1.9290	3.7786	3.7790	3.7805	1.9307	1.9291	1.9233	1.9236
	0.8	4	5.4516	5.4517	5.3368	5.2966	5.4509	5.4281	5.4571	5.3352	5.2602	5.4510	5.4283	5.4597	5.3351	5.2595	5.2384	5.3148
		16	4.2189	4.2188	2.6745	2.6715	4.2195	4.2180	4.2021	2.6725	2.6625	4.2198	4.2181	4.1977	2.6725	2.6652	2.6551	2.6764
3rd year	0.4	4	4.2132	4.2133	3.9946	3.9444	4.2133	4.2134	4.2197	3.9941	3.9419	4.2133	4.2135	4.2203	3.9942	3.9419	3.9698	3.9781
		16	3.8499	3.8500	2.0047	2.0029	3.8500	3.8503	3.8582	2.0045	2.0025	3.8501	3.8506	3.8556	2.0045	2.0025	2.0018	1.9992
	0.8	4	5.6484	5.6484	5.5355	5.4903	5.6473	5.6280	5.6924	5.5331	5.4516	5.6475	5.6282	5.6855	5.5331	5.4521	5.4781	5.5263
		16	4.3224	4.3224	2.7734	2.7701	4.3232	4.3219	4.3141	2.7716	2.7613	4.3235	4.3221	4.3130	2.7717	2.7640	2.7746	2.7792
4th year	0.4	4	4.3083	4.3083	4.0871	4.0372	4.3086	4.3085	4.3133	4.0867	4.0341	4.3085	4.3087	4.3118	4.0867	4.0342	4.0471	4.0522
		16	3.8902	3.8902	2.0461	2.0442	3.8903	3.8904	3.8991	2.0458	2.0437	3.8904	3.8908	3.8944	2.0458	2.0437	2.0420	2.0440
	0.8	4	5.7632	5.7632	5.6516	5.6042	5.7617	5.7412	5.7872	5.6492	5.5624	5.7619	5.7413	5.7905	5.6492	5.5644	5.5835	5.6212
		16	4.3837	4.3836	2.8346	2.8315	4.3844	4.3831	4.3727	2.8325	2.8224	4.3847	4.3833	4.3731	2.8326	2.8250	2.8343	2.8335
5th year	0.4	4	4.3621	4.3621	4.1403	4.0901	4.3623	4.3622	4.3606	4.1399	4.0869	4.3622	4.3624	4.3587	4.1399	4.0870	4.0913	4.1018
		16	3.9133	3.9134	2.0714	2.0695	3.9135	3.9137	3.9247	2.0712	2.0691	3.9136	3.9141	3.9197	2.0712	2.0691	2.0665	2.0674
	0.8	4	5.8382	5.8382	5.7313	5.6808	5.8371	5.8162	5.8620	5.7293	5.6378	5.8372	5.8164	5.8640	5.7292	5.6407	5.6510	5.7074
		16	4.4187	4.4186	2.8668	2.8640	4.4195	4.4182	4.4019	2.8648	2.8551	4.4198	4.4184	4.3993	2.8649	2.8576	2.8702	2.8755
Average	0.4	4	4.1191	4.1191	3.9030	3.8546	4.1191	4.1191	4.1182	3.9025	3.8518	4.1191	4.1193	4.1149	3.9026	3.8519	3.8744	3.8783
		16	3.8010	3.8011	1.9589	1.9573	3.8012	3.8014	3.8067	1.9586	1.9569	3.8012	3.8017	3.8035	1.9587	1.9569	1.9537	1.9537
	0.8	4	5.5233	5.5233	5.4121	5.3690	5.5221	5.5012	5.5394	5.4102	5.3295	5.5222	5.5014	5.5414	5.4101	5.3306	5.3324	5.3904
		16	4.2543	4.2542	2.7129	2.7102	4.2550	4.2537	4.2376	2.7109	2.7015	4.2552	4.2538	4.2375	2.7110	2.7040	2.7058	2.7124

Table 4 - Forecasts RMSE - (N,T)=(50,10), SMA data generating process for ϕ , W(5,5), 1000 replications

			Estimators															
	λ	σ_{μ}^2	Pooled	Av. hetero.			Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
			OLS	OLS	FE	RE	MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.5909	3.5909	3.3764	3.3363	3.5911	3.5912	3.5823	3.3759	3.3356	3.5911	3.5911	3.5859	3.3759	3.3354	3.3417	3.3338
		16	3.5114	3.5116	1.6868	1.6846	3.5115	3.5116	3.5249	1.6867	1.6843	3.5115	3.5121	3.5175	1.6867	1.6843	1.6906	1.6851
	0.8	4	3.6763	3.6763	3.4731	3.4312	3.6759	3.6761	3.6593	3.4724	3.4280	3.6760	3.6763	3.6546	3.4722	3.4275	3.4035	3.3943
		16	3.5299	3.5300	1.7293	1.7273	3.5300	3.5304	3.5553	1.7291	1.7269	3.5301	3.5306	3.5662	1.7290	1.7267	1.7231	1.7248
2nd year	0.4	4	3.9719	3.9720	3.7426	3.6993	3.9721	3.9724	3.9858	3.7424	3.6988	3.9721	3.9726	3.9829	3.7424	3.6985	3.7173	3.7026
		16	3.7285	3.7287	1.8800	1.8778	3.7289	3.7291	3.7246	1.8798	1.8774	3.7289	3.7295	3.7237	1.8798	1.8774	1.8757	1.8718
	0.8	4	4.0662	4.0662	3.8506	3.8034	4.0658	4.0659	4.0556	3.8497	3.7987	4.0659	4.0660	4.0490	3.8496	3.7984	3.7954	3.7802
		16	3.7328	3.7328	1.9132	1.9106	3.7330	3.7333	3.7692	1.9130	1.9100	3.7331	3.7335	3.7823	1.9129	1.9101	1.9116	1.9099
3rd year	0.4	4	4.1258	4.1258	3.8950	3.8495	4.1259	4.1262	4.1356	3.8946	3.8482	4.1259	4.1264	4.1315	3.8946	3.8480	3.8544	3.8491
		16	3.8057	3.8059	1.9534	1.9513	3.8059	3.8061	3.8035	1.9533	1.9510	3.8060	3.8065	3.8018	1.9533	1.9510	1.9528	1.9464
	0.8	4	4.2227	4.2227	3.9958	3.9493	4.2222	4.2224	4.2096	3.9949	3.9452	4.2223	4.2226	4.2038	3.9947	3.9447	3.9422	3.9333
		16	3.8127	3.8128	1.9925	1.9899	3.8129	3.8131	3.8410	1.9923	1.9896	3.8130	3.8134	3.8527	1.9923	1.9896	1.9869	1.9913
4th year	0.4	4	4.2050	4.2051	3.9729	3.9270	4.2050	4.2053	4.2140	3.9726	3.9258	4.2050	4.2055	4.2135	3.9726	3.9255	3.9288	3.9275
		16	3.8465	3.8466	1.9921	1.9902	3.8467	3.8469	3.8420	1.9919	1.9898	3.8467	3.8473	3.8395	1.9919	1.9899	1.9900	1.9894
	0.8	4	4.3004	4.3004	4.0741	4.0261	4.2999	4.3001	4.2914	4.0734	4.0214	4.3000	4.3002	4.2846	4.0732	4.0209	4.0191	4.0143
		16	3.8530	3.8531	2.0306	2.0282	3.8531	3.8533	3.8774	2.0304	2.0280	3.8532	3.8536	3.8810	2.0303	2.0279	2.0313	2.0293
5th year	0.4	4	4.2560	4.2561	4.0203	3.9746	4.2560	4.2562	4.2663	4.0200	3.9735	4.2560	4.2564	4.2663	4.0200	3.9733	3.9762	3.9787
		16	3.8694	3.8696	2.0158	2.0139	3.8697	3.8700	3.8634	2.0157	2.0136	3.8697	3.8704	3.8610	2.0157	2.0136	2.0141	2.0161
	0.8	4	4.3474	4.3474	4.1229	4.0736	4.3469	4.3472	4.3447	4.1222	4.0683	4.3470	4.3473	4.3401	4.1221	4.0678	4.0724	4.0629
		16	3.8766	3.8767	2.0576	2.0551	3.8767	3.8769	3.8999	2.0573	2.0548	3.8768	3.8771	3.9069	2.0572	2.0547	2.0545	2.0553
Average	0.4	4	4.0299	4.0300	3.8014	3.7573	4.0300	4.0303	4.0368	3.8011	3.7564	4.0300	4.0304	4.0360	3.8011	3.7562	3.7637	3.7583
		16	3.7523	3.7525	1.9056	1.9035	3.7525	3.7527	3.7517	1.9055	1.9032	3.7525	3.7532	3.7487	1.9055	1.9032	1.9046	1.9018
	0.8	4	4.1226	4.1226	3.9033	3.8567	4.1222	4.1223	4.1121	3.9025	3.8523	4.1222	4.1225	4.1064	3.9024	3.8519	3.8465	3.8370
		16	3.7610	3.7611	1.9446	1.9422	3.7611	3.7614	3.7885	1.9444	1.9419	3.7612	3.7616	3.7989	1.9444	1.9418	1.9415	1.9421

Table 5 - Forecasts RMSE - (N,T)=(50,20), SAR data generating process for ϕ , W(1,1), 1000 replications

	Estimators																	
			Pooled	Av. hetero.	FE	RE	Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
	ρ	σ _μ ²	OLS	OLS			MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.9511	3.9513	3.7364	3.7155	3.9516	3.9516	3.9631	3.7358	3.7105	3.9516	3.9517	3.9672	3.7358	3.7096	3.7289	3.7116
		16	3.6164	3.6164	1.8633	1.8625	3.6180	3.6180	3.6429	1.8629	1.8618	3.6182	3.6183	3.6441	1.8629	1.8618	1.8654	1.8654
	0.8	4	7.0636	7.0637	7.0399	6.9797	7.0634	7.0543	7.1286	7.0359	6.9436	7.0642	7.0551	7.1390	7.0356	6.9442	6.9870	6.9751
		16	4.6604	4.6608	3.5080	3.5046	4.6610	4.6607	4.7277	3.5066	3.4980	4.6604	4.6601	4.7194	3.5067	3.4997	3.4914	3.4981
2nd year	0.4	4	4.4075	4.4079	4.1572	4.1384	4.4081	4.4083	4.3916	4.1563	4.1335	4.4081	4.4084	4.3948	4.1563	4.1329	4.1372	4.1361
		16	3.8526	3.8526	2.0675	2.0667	3.8538	3.8539	3.8684	2.0672	2.0662	3.8539	3.8541	3.8755	2.0673	2.0663	2.0692	2.0659
	0.8	4	7.8524	7.8523	7.8121	7.7512	7.8511	7.8442	7.8893	7.8082	7.7158	7.8530	7.8459	7.9029	7.8083	7.7174	7.7551	7.7475
		16	5.1228	5.1230	3.9200	3.9160	5.1233	5.1228	5.1328	3.9180	3.9080	5.1233	5.1228	5.1272	3.9180	3.9100	3.8881	3.9055
3rd year	0.4	4	4.5841	4.5843	4.3239	4.3050	4.5846	4.5847	4.5668	4.3234	4.2998	4.5847	4.5849	4.5692	4.3234	4.2997	4.3076	4.3034
		16	3.9438	3.9438	2.1507	2.1500	3.9446	3.9447	3.9571	2.1504	2.1495	3.9447	3.9448	3.9611	2.1504	2.1495	2.1549	2.1467
	0.8	4	8.1797	8.1796	8.1425	8.0788	8.1789	8.1712	8.1870	8.1380	8.0444	8.1804	8.1727	8.1969	8.1380	8.0442	8.1139	8.0629
		16	5.2836	5.2838	4.0774	4.0722	5.2842	5.2837	5.3024	4.0753	4.0618	5.2844	5.2839	5.2963	4.0754	4.0656	4.0413	4.0582
4th year	0.4	4	4.6767	4.6769	4.4123	4.3931	4.6772	4.6773	4.6529	4.4118	4.3881	4.6773	4.6775	4.6563	4.4118	4.3879	4.3893	4.3832
		16	3.9904	3.9904	2.1964	2.1957	3.9916	3.9916	4.0038	2.1961	2.1953	3.9917	3.9918	4.0078	2.1961	2.1953	2.1976	2.1898
	0.8	4	8.3518	8.3519	8.3136	8.2480	8.3510	8.3435	8.3496	8.3097	8.2129	8.3527	8.3452	8.3546	8.3097	8.2123	8.2705	8.2339
		16	5.3737	5.3739	4.1635	4.1581	5.3748	5.3741	5.3871	4.1614	4.1466	5.3750	5.3743	5.3838	4.1615	4.1512	4.1180	4.1433
5th year	0.4	4	4.7296	4.7298	4.4640	4.4440	4.7300	4.7302	4.7138	4.4635	4.4388	4.7302	4.7303	4.7164	4.4635	4.4386	4.4428	4.4382
		16	4.0171	4.0171	2.2227	2.2221	4.0185	4.0185	4.0283	2.2224	2.2216	4.0186	4.0186	4.0318	2.2224	2.2216	2.2232	2.2189
	0.8	4	8.4459	8.4460	8.4041	8.3400	8.4451	8.4372	8.4425	8.4005	8.3036	8.4469	8.4390	8.4449	8.4006	8.3035	8.3642	8.3287
		16	5.4261	5.4263	4.2084	4.2034	5.4281	5.4273	5.4429	4.2062	4.1923	5.4284	5.4276	5.4431	4.2063	4.1964	4.1699	4.1907
Average	0.4	4	4.4698	4.4700	4.2188	4.1992	4.4703	4.4704	4.4576	4.2182	4.1941	4.4704	4.4706	4.4604	4.2182	4.1937	4.2012	4.1945
		16	3.8840	3.8841	2.1001	2.0994	3.8853	3.8853	3.9001	2.0998	2.0989	3.8854	3.8855	3.9041	2.0998	2.0989	2.1021	2.0974
	0.8	4	7.9787	7.9787	7.9424	7.8796	7.9779	7.9701	7.9994	7.9385	7.8441	7.9794	7.9716	8.0077	7.9384	7.8443	7.8981	7.8696
		16	5.1733	5.1736	3.9755	3.9709	5.1743	5.1737	5.1986	3.9735	3.9614	5.1743	5.1737	5.1940	3.9736	3.9646	3.9417	3.9592

Table 6 - Forecasts RMSE - (N,T)=(50,20), SMA data generating process for ϕ , W(1,1), 1000 replications

	Estimators																	
	λ σ_{μ}^2		Pooled	Av. hetero.	FE	RE	Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
			OLS	OLS			MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.6699	3.6698	3.3999	3.3863	3.6705	3.6704	3.6873	3.3994	3.3834	3.6706	3.6707	3.6803	3.3994	3.3828	3.3885	3.3517
		16	3.5573	3.5575	1.6920	1.6915	3.5575	3.5576	3.5501	1.6917	1.6911	3.5574	3.5575	3.5384	1.6917	1.6910	1.7044	1.6870
	0.8	4	3.9856	3.9856	3.7521	3.7370	3.9854	3.9854	3.9823	3.7505	3.7291	3.9860	3.9858	3.9883	3.7502	3.7282	3.7417	3.7272
		16	3.6376	3.6376	1.8802	1.8793	3.6387	3.6387	3.6182	1.8795	1.8778	3.6388	3.6389	3.6226	1.8794	1.8777	1.8990	1.8689
2nd year	0.4	4	4.0666	4.0666	3.7765	3.7606	4.0673	4.0673	4.0754	3.7760	3.7571	4.0675	4.0676	4.0721	3.7759	3.7564	3.7690	3.7332
		16	3.7723	3.7723	1.8861	1.8856	3.7721	3.7724	3.7691	1.8857	1.8851	3.7721	3.7724	3.7580	1.8857	1.8850	1.8916	1.8799
	0.8	4	4.4240	4.4241	4.1711	4.1538	4.4242	4.4242	4.4219	4.1698	4.1437	4.4251	4.4251	4.4266	4.1695	4.1428	4.1549	4.1537
		16	3.8756	3.8757	2.0870	2.0860	3.8777	3.8777	3.8650	2.0861	2.0845	3.8779	3.8779	3.8708	2.0860	2.0841	2.0938	2.0732
3rd year	0.4	4	4.2243	4.2243	3.9257	3.9098	4.2250	4.2250	4.2282	3.9252	3.9064	4.2252	4.2254	4.2223	3.9251	3.9058	3.9138	3.8949
		16	3.8441	3.8443	1.9592	1.9584	3.8440	3.8443	3.8485	1.9589	1.9579	3.8440	3.8443	3.8393	1.9589	1.9579	1.9619	1.9554
	0.8	4	4.5929	4.5929	4.3315	4.3135	4.5932	4.5932	4.5947	4.3300	4.3043	4.5945	4.5944	4.5975	4.3297	4.3027	4.3126	4.3234
		16	3.9644	3.9645	2.1704	2.1695	3.9665	3.9665	3.9558	2.1696	2.1682	3.9667	3.9667	3.9574	2.1695	2.1678	2.1776	2.1619
4th year	0.4	4	4.3108	4.3109	4.0036	3.9883	4.3114	4.3114	4.3064	4.0030	3.9852	4.3116	4.3117	4.3003	4.0030	3.9846	3.9869	3.9818
		16	3.8849	3.8850	2.0007	1.9999	3.8847	3.8850	3.8836	2.0005	1.9994	3.8848	3.8850	3.8752	2.0004	1.9994	2.0022	1.9994
	0.8	4	4.6780	4.6781	4.4134	4.3953	4.6789	4.6789	4.6829	4.4122	4.3857	4.6802	4.6801	4.6843	4.4120	4.3843	4.4054	4.4078
		16	4.0090	4.0091	2.2137	2.2129	4.0108	4.0108	4.0012	2.2129	2.2117	4.0110	4.0111	4.0032	2.2127	2.2113	2.2213	2.2041
5th year	0.4	4	4.3662	4.3663	4.0529	4.0382	4.3667	4.3666	4.3602	4.0524	4.0357	4.3669	4.3670	4.3537	4.0524	4.0351	4.0411	4.0360
		16	3.9107	3.9109	2.0252	2.0245	3.9107	3.9110	3.9069	2.0249	2.0240	3.9107	3.9110	3.8986	2.0249	2.0240	2.0274	2.0254
	0.8	4	4.7359	4.7359	4.4707	4.4520	4.7371	4.7370	4.7369	4.4692	4.4429	4.7385	4.7383	4.7396	4.4689	4.4412	4.4623	4.4588
		16	4.0418	4.0419	2.2428	2.2421	4.0434	4.0434	4.0313	2.2420	2.2412	4.0436	4.0436	4.0317	2.2418	2.2407	2.2496	2.2321
Average	0.4	4	4.1276	4.1276	3.8317	3.8167	4.1282	4.1282	4.1315	3.8312	3.8135	4.1283	4.1285	4.1257	3.8312	3.8129	3.8199	3.7995
		16	3.7939	3.7940	1.9127	1.9120	3.7938	3.7940	3.7916	1.9124	1.9115	3.7938	3.7940	3.7819	1.9123	1.9115	1.9175	1.9094
	0.8	4	4.4832	4.4833	4.2277	4.2103	4.4838	4.4837	4.4837	4.2263	4.2012	4.4849	4.4847	4.4873	4.2260	4.1998	4.2154	4.2142
		16	3.9057	3.9057	2.1188	2.1180	3.9074	3.9074	3.8943	2.1180	2.1167	3.9076	3.9076	3.8971	2.1179	2.1163	2.1282	2.1081

**Table 7 - Forecasts RMSE - (N,T)=(100,10), W(1,1), 1000 replications
 $\rho=\lambda=0.8$ for SAR and SMA data generating processes**

	Estimators																	
	true DGP	σ_{μ}^2	Pooled	Av. hetero.	FE	RE	Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
			OLS	OLS			MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	SAR	4	6.9985	6.9985	7.1226	6.9431	6.9975	6.9935	7.1114	7.1190	6.8901	6.9986	6.9947	7.0931	7.1193	6.8938	7.0744	7.0337
		16	4.6503	4.6503	3.5892	3.5704	4.6506	4.6505	4.6766	3.5874	3.5416	4.6506	4.6505	4.4448	3.5873	3.5529	3.5902	3.5771
	SMA	4	4.0103	4.0102	3.8592	3.8002	4.0100	4.0100	4.0062	3.8581	3.7799	4.0108	4.0107	3.9849	3.8580	3.7780	3.7920	3.7807
		16	3.6578	3.6578	1.9253	1.9221	3.6578	3.6578	3.6689	1.9242	1.9191	3.6578	3.6578	3.6573	1.9238	1.9182	1.9241	1.9189
2nd year	SAR	4	7.8090	7.8090	7.9482	7.7505	7.8072	7.8036	7.8799	7.9446	7.6914	7.8083	7.8048	7.8602	7.9449	7.6966	7.8694	7.7965
		16	5.1067	5.1067	4.0015	3.9818	5.1072	5.1071	5.1124	3.9998	3.9529	5.1072	5.1071	5.1245	3.9998	3.9641	4.0009	3.9824
	SMA	4	4.4542	4.4542	4.2866	4.2246	4.4542	4.4542	4.4428	4.2851	4.2039	4.4550	4.4550	4.4326	4.2849	4.2010	4.2212	4.2173
		16	3.9015	3.9015	2.1390	2.1358	3.9020	3.9020	3.9049	2.1379	2.1329	3.9019	3.9020	3.9004	2.1376	2.1321	2.1268	2.1282
3rd year	SAR	4	8.1109	8.1110	8.2604	8.0514	8.1097	8.1061	8.1691	8.2567	7.9908	8.1108	8.1074	8.1531	8.2570	7.9965	8.1481	8.1222
		16	5.2802	5.2802	4.1566	4.1380	5.2810	5.2808	5.2830	4.1548	4.1092	5.2811	5.2809	5.2993	4.1548	4.1202	4.1436	4.1359
	SMA	4	4.6117	4.6118	4.4413	4.3773	4.6119	4.6119	4.6106	4.4396	4.3562	4.6127	4.6127	4.5981	4.4394	4.3533	4.3891	4.3767
		16	3.9868	3.9869	2.2197	2.2165	3.9872	3.9873	3.9899	2.2187	2.2138	3.9872	3.9873	3.9852	2.2185	2.2129	2.2159	2.2105
4th year	SAR	4	8.2880	8.2881	8.4361	8.2247	8.2863	8.2825	8.3401	8.4323	8.1646	8.2872	8.2836	8.3265	8.4325	8.1699	8.3174	8.2757
		16	5.3754	5.3754	4.2379	4.2203	5.3764	5.3762	5.3696	4.2361	4.1923	5.3764	5.3763	5.3841	4.2362	4.2025	4.2274	4.2159
	SMA	4	4.7001	4.7001	4.5263	4.4619	4.7002	4.7002	4.6970	4.5246	4.4406	4.7011	4.7012	4.6862	4.5243	4.4375	4.4753	4.4638
		16	4.0305	4.0306	2.2643	2.2611	4.0310	4.0311	4.0350	2.2634	2.2584	4.0310	4.0310	4.0261	2.2632	2.2576	2.2595	2.2564
5th year	SAR	4	8.4030	8.4031	8.5526	8.3403	8.4015	8.3972	8.4337	8.5489	8.2779	8.4025	8.3984	8.4197	8.5491	8.2847	8.4158	8.3736
		16	5.4232	5.4232	4.2810	4.2636	5.4244	5.4242	5.4204	4.2791	4.2362	5.4243	5.4242	5.4327	4.2792	4.2459	4.2825	4.2742
	SMA	4	4.7576	4.7576	4.5825	4.5177	4.7578	4.7578	4.7505	4.5806	4.4958	4.7588	4.7588	4.7481	4.5804	4.4929	4.5331	4.5198
		16	4.0625	4.0625	2.2950	2.2919	4.0630	4.0630	4.0607	2.2940	2.2894	4.0629	4.0630	4.0515	2.2938	2.2886	2.2879	2.2826
Average	SAR	4	7.9219	7.9219	8.0640	7.8620	7.9204	7.9166	7.9868	8.0603	7.8029	7.9215	7.9178	7.9705	8.0606	7.8083	7.9650	7.9203
		16	5.1672	5.1672	4.0533	4.0348	5.1679	5.1678	5.1724	4.0514	4.0064	5.1679	5.1678	5.1815	4.0515	4.0171	4.0489	4.0371
	SMA	4	4.5068	4.5068	4.3392	4.2764	4.5068	4.5068	4.5014	4.3376	4.2553	4.5077	4.5077	4.4900	4.3374	4.2525	4.2822	4.2717
		16	3.9278	3.9278	2.1687	2.1655	3.9282	3.9282	3.9319	2.1677	2.1627	3.9282	3.9282	3.9241	2.1674	2.1619	2.1629	2.1593

Table 8 - Forecasts RMSE - (N,T)=(100,10), W(5,5), 1000 replications
 $\rho=\lambda=0.8$ for SAR and SMA data generating processes

	Estimators																	
	true DGP	σ_{μ}^2	Pooled	Av. hetero.	FE	RE	Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
			OLS	OLS			MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	SAR	4	4.8896	4.8896	4.8105	4.7424	4.8891	4.8842	4.8756	4.8090	4.7109	4.8891	4.8843	4.8631	4.8090	4.7104	4.7175	4.7375
		16	3.9142	3.9142	2.3915	2.3876	3.9141	3.9141	3.9341	2.3908	2.3731	3.9142	3.9142	3.9071	2.3907	2.3804	2.3936	2.3766
	SMA	4	3.6481	3.6481	3.4526	3.4061	3.6482	3.6481	3.6569	3.4522	3.3998	3.6482	3.6481	3.6532	3.4521	3.3997	3.3988	3.4030
		16	3.5641	3.5641	1.7221	1.7201	3.5641	3.5641	3.5640	1.7219	1.7193	3.5641	3.5641	3.5677	1.7219	1.7192	1.7239	1.7176
2nd year	SAR	4	5.4287	5.4286	5.3436	5.2695	5.4277	5.4231	5.4291	5.3420	5.2336	5.4277	5.4233	5.4096	5.3420	5.2341	5.2488	5.2694
		16	4.2142	4.2142	2.6762	2.6712	4.2141	4.2141	4.2449	2.6756	2.6548	4.2142	4.2141	4.2210	2.6755	2.6633	2.6632	2.6446
	SMA	4	4.0344	4.0344	3.8254	3.7736	4.0346	4.0345	4.0495	3.8250	3.7673	4.0347	4.0346	4.0555	3.8250	3.7669	3.7881	3.7818
		16	3.7822	3.7822	1.9174	1.9155	3.7823	3.7823	3.7733	1.9172	1.9148	3.7824	3.7824	3.7828	1.9172	1.9147	1.9158	1.9132
3rd year	SAR	4	5.6536	5.6534	5.5673	5.4915	5.6526	5.6479	5.6420	5.5659	5.4550	5.6526	5.6481	5.6318	5.5659	5.4552	5.4511	5.4916
		16	4.3316	4.3317	2.7876	2.7825	4.3317	4.3317	4.3494	2.7866	2.7673	4.3318	4.3318	4.3274	2.7866	2.7750	2.7642	2.7511
	SMA	4	4.1902	4.1902	3.9751	3.9225	4.1902	4.1902	4.2048	3.9747	3.9163	4.1903	4.1903	4.2137	3.9747	3.9160	3.9417	3.9364
		16	3.8599	3.8599	1.9944	1.9925	3.8600	3.8600	3.8512	1.9942	1.9919	3.8600	3.8600	3.8547	1.9942	1.9918	1.9915	1.9880
4th year	SAR	4	5.7652	5.7651	5.6767	5.6001	5.7643	5.7593	5.7521	5.6755	5.5624	5.7643	5.7593	5.7516	5.6754	5.5632	5.5707	5.6067
		16	4.3864	4.3865	2.8394	2.8342	4.3863	4.3863	4.4067	2.8383	2.8181	4.3864	4.3864	4.3796	2.8383	2.8263	2.8198	2.8078
	SMA	4	4.2767	4.2767	4.0579	4.0051	4.2768	4.2768	4.2908	4.0575	3.9988	4.2769	4.2769	4.3000	4.0575	3.9984	4.0228	4.0188
		16	3.8979	3.8979	2.0318	2.0300	3.8981	3.8981	3.8881	2.0316	2.0294	3.8981	3.8981	3.8923	2.0316	2.0293	2.0310	2.0292
5th year	SAR	4	5.8347	5.8346	5.7504	5.6716	5.8339	5.8290	5.8163	5.7492	5.6306	5.8338	5.8291	5.8164	5.7491	5.6329	5.6386	5.6769
		16	4.4237	4.4238	2.8759	2.8707	4.4238	4.4238	4.4366	2.8747	2.8544	4.4238	4.4238	4.4162	2.8748	2.8628	2.8540	2.8424
	SMA	4	4.3286	4.3287	4.1070	4.0542	4.3287	4.3287	4.3442	4.1066	4.0478	4.3288	4.3288	4.3505	4.1066	4.0474	4.0702	4.0662
		16	3.9212	3.9212	2.0574	2.0554	3.9213	3.9214	3.9125	2.0572	2.0547	3.9214	3.9214	3.9139	2.0572	2.0546	2.0560	2.0555
Average	SAR	4	5.5144	5.5142	5.4297	5.3550	5.5135	5.5087	5.5030	5.4283	5.3185	5.5135	5.5088	5.4945	5.4283	5.3192	5.3254	5.3564
		16	4.2540	4.2541	2.7141	2.7093	4.2540	4.2540	4.2743	2.7132	2.6935	4.2541	4.2541	4.2502	2.7132	2.7016	2.6990	2.6845
	SMA	4	4.0956	4.0956	3.8836	3.8323	4.0957	4.0957	4.1093	3.8832	3.8260	4.0958	4.0957	4.1146	3.8832	3.8257	3.8443	3.8412
		16	3.8051	3.8051	1.9446	1.9427	3.8052	3.8052	3.7978	1.9444	1.9420	3.8052	3.8052	3.8023	1.9444	1.9419	1.9436	1.9407

Table 9 - Forecasts RMSE - (N,T)=(50,10), SAR data generating process for ϕ , W(1,1) asymmetric weight matrix of French administrative communes, 1000 replications

			Estimators															
			Pooled	Av. hetero.	FE	RE	Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
	ρ	σ_{μ}^2	OLS	OLS			MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	4.1551	4.1552	4.0358	3.9706	4.1563	4.1564	4.2084	4.0338	3.9550	4.1561	4.1562	4.1772	4.0341	3.9588	3.9718	4.0408
		16	3.6742	3.6743	2.0307	2.0268	3.6747	3.6746	3.7101	2.0297	2.0240	3.6742	3.6745	3.6869	2.0297	2.0251	2.0188	1.7766
	0.8	4	9.9810	9.9856	9.3815	9.9337	10.0933	10.1004	9.5173	9.3512	9.9918	10.0797	10.0493	11.0071	9.3561	9.5768	14.1056	11.9221
		16	6.0600	6.0600	5.4403	5.3955	6.0623	6.0588	6.0347	5.4324	5.3177	6.0619	6.0607	5.9938	5.4322	5.3498	5.3437	5.9137
2nd year	0.4	4	4.6207	4.6208	4.4863	4.4181	4.6216	4.6217	4.6514	4.4840	4.4016	4.6212	4.6213	4.6323	4.4842	4.4058	4.4093	4.5255
		16	3.9151	3.9152	2.2464	2.2423	3.9160	3.9158	3.9599	2.2455	2.2397	3.9155	3.9157	3.9448	2.2456	2.2411	2.2401	2.0398
	0.8	4	11.1618	11.1681	11.4312	11.1342	11.1617	11.1559	10.6685	11.3428	11.4194	11.1554	11.1523	13.2402	11.3491	11.0807	14.8653	12.0044
		16	6.6797	6.6797	5.9939	5.9463	6.6853	6.6811	6.6860	5.9864	5.8707	6.6823	6.6810	6.6818	5.9864	5.9005	5.9473	6.9897
3rd year	0.4	4	4.8019	4.8020	4.6608	4.5919	4.8022	4.8024	4.8187	4.6587	4.5759	4.8019	4.8020	4.8093	4.6589	4.5792	4.5873	4.6235
		16	4.0085	4.0086	2.3379	2.3335	4.0098	4.0096	4.0529	2.3368	2.3305	4.0094	4.0095	4.0385	2.3368	2.3322	2.3302	2.2916
	0.8	4	12.5896	12.5954	13.0581	12.5818	12.6034	12.6015	11.1090	13.0022	12.8293	12.5959	12.5869	13.5612	13.0067	12.6192	14.0236	11.8049
		16	6.9318	6.9319	6.2300	6.1842	6.9396	6.9351	6.9420	6.2227	6.1073	6.9354	6.9344	6.9338	6.2228	6.1366	6.2060	6.5267
4th year	0.4	4	4.9024	4.9025	4.7604	4.6903	4.9028	4.9029	4.9106	4.7582	4.6746	4.9027	4.9029	4.9074	4.7585	4.6782	4.6926	4.8674
		16	4.0589	4.0591	2.3835	2.3794	4.0601	4.0599	4.0965	2.3825	2.3767	4.0597	4.0598	4.0885	2.3825	2.3782	2.3710	2.4283
	0.8	4	13.0269	13.0318	13.3271	13.0157	13.0225	13.0203	12.1625	13.3052	13.1667	13.0220	13.0217	13.7779	13.3076	12.9671	14.0499	12.3835
		16	7.0667	7.0667	6.3577	6.3117	7.0745	7.0700	7.0763	6.3503	6.2328	7.0698	7.0689	7.0685	6.3505	6.2637	6.3310	6.3103
5th year	0.4	4	4.9614	4.9616	4.8170	4.7469	4.9618	4.9620	4.9720	4.8148	4.7308	4.9617	4.9619	4.9667	4.8151	4.7346	4.7497	4.8157
		16	4.0865	4.0866	2.4125	2.4084	4.0876	4.0875	4.1232	2.4114	2.4058	4.0872	4.0874	4.1151	2.4114	2.4071	2.4017	2.5225
	0.8	4	13.4890	13.4947	13.7509	13.4767	13.4764	13.4771	13.2666	13.7220	13.5829	13.4730	13.4675	14.1849	13.7242	13.4160	13.9525	12.2767
		16	7.1538	7.1538	6.4418	6.3950	7.1625	7.1581	7.1581	6.4340	6.3148	7.1575	7.1566	7.1510	6.4342	6.3459	6.4185	6.3724
Average	0.4	4	4.6883	4.6884	4.5521	4.4836	4.6889	4.6891	4.7122	4.5499	4.4676	4.6887	4.6889	4.6986	4.5502	4.4713	4.4821	4.5746
		16	3.9486	3.9488	2.2822	2.2781	3.9496	3.9495	3.9885	2.2812	2.2753	3.9492	3.9494	3.9748	2.2812	2.2768	2.2724	2.2118
	0.8	4	12.0497	12.0551	12.1897	12.0284	12.0715	12.0710	11.3448	12.1447	12.1980	12.0652	12.0556	13.1542	12.1487	11.9319	14.1994	12.0783
		16	6.7784	6.7784	6.0928	6.0465	6.7848	6.7806	6.7794	6.0851	5.9687	6.7814	6.7803	6.7658	6.0852	5.9993	6.0493	6.4226

Table 10 - Forecasts RMSE - (N,T)=(50,10), SMA data generating process for ϕ , $W(1,1)$ asymmetric weight matrix of French administrative communes, 1000 replications

	Estimators																	
			Pooled	Av. hetero.			Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
	λ	σ^2_{μ}	OLS	OLS	FE	RE	MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.7809	3.7808	3.5814	3.5379	3.7822	3.7821	3.8043	3.5791	3.5262	3.7831	3.7829	3.7746	3.5791	3.5277	3.5663	3.5515
		16	3.5887	3.5886	1.8019	1.8003	3.5895	3.5894	3.6027	1.8010	1.7993	3.5901	3.5897	3.5790	1.8010	1.7993	1.8095	1.8088
	0.8	4	4.3674	4.3676	4.2789	4.1978	4.3665	4.3666	4.3992	4.2743	4.1715	4.3663	4.3664	4.3773	4.2727	4.1660	4.2319	4.2213
		16	3.7471	3.7470	2.1479	2.1440	3.7489	3.7487	3.7494	2.1466	2.1407	3.7492	3.7484	3.7325	2.1463	2.1395	2.1355	2.1329
2nd year	0.4	4	4.1973	4.1973	3.9972	3.9465	4.1982	4.1985	4.2122	3.9952	3.9346	4.1988	4.1989	4.1837	3.9952	3.9355	3.9610	3.9549
		16	3.8053	3.8053	1.9898	1.9884	3.8064	3.8065	3.8219	1.9892	1.9874	3.8072	3.8066	3.8084	1.9892	1.9874	2.0021	2.0062
	0.8	4	4.8689	4.8690	4.7680	4.6864	4.8694	4.8693	4.8883	4.7639	4.6591	4.8690	4.8690	4.8525	4.7622	4.6534	4.7003	4.6877
		16	4.0193	4.0193	2.3854	2.3817	4.0204	4.0204	4.0244	2.3835	2.3781	4.0206	4.0201	4.0001	2.3832	2.3770	2.3821	2.3708
3rd year	0.4	4	4.3641	4.3642	4.1645	4.1114	4.3649	4.3653	4.3629	4.1625	4.0999	4.3657	4.3657	4.3599	4.1624	4.1003	4.1042	4.1069
		16	3.8871	3.8872	2.0752	2.0738	3.8877	3.8879	3.8996	2.0745	2.0727	3.8884	3.8880	3.8903	2.0744	2.0725	2.0785	2.0819
	0.8	4	5.0644	5.0644	4.9605	4.8799	5.0650	5.0649	5.0699	4.9569	4.8509	5.0647	5.0647	5.0435	4.9556	4.8451	4.8845	4.8738
		16	4.1141	4.1141	2.4801	2.4761	4.1157	4.1156	4.1222	2.4781	2.4720	4.1159	4.1155	4.0955	2.4777	2.4708	2.4713	2.4660
4th year	0.4	4	4.4458	4.4459	4.2439	4.1899	4.4471	4.4474	4.4539	4.2419	4.1787	4.4478	4.4477	4.4435	4.2418	4.1791	4.1901	4.1942
		16	3.9249	3.9250	2.1216	2.1196	3.9255	3.9258	3.9445	2.1209	2.1183	3.9262	3.9259	3.9344	2.1208	2.1182	2.1195	2.1222
	0.8	4	5.1625	5.1626	5.0576	4.9749	5.1629	5.1628	5.1742	5.0533	4.9453	5.1631	5.1631	5.1466	5.0519	4.9399	4.9794	4.9755
		16	4.1643	4.1644	2.5301	2.5259	4.1661	4.1661	4.1721	2.5278	2.5212	4.1664	4.1660	4.1469	2.5272	2.5200	2.5214	2.5224
5th year	0.4	4	4.4976	4.4977	4.2964	4.2411	4.4986	4.4989	4.5052	4.2943	4.2302	4.4992	4.4992	4.5008	4.2943	4.2305	4.2456	4.2445
		16	3.9472	3.9473	2.1446	2.1425	3.9478	3.9480	3.9653	2.1438	2.1411	3.9484	3.9481	3.9564	2.1438	2.1411	2.1458	2.1490
	0.8	4	5.2171	5.2172	5.1101	5.0272	5.2179	5.2177	5.2409	5.1059	4.9979	5.2184	5.2184	5.2129	5.1047	4.9916	5.0386	5.0420
		16	4.1913	4.1913	2.5593	2.5551	4.1929	4.1929	4.2007	2.5570	2.5505	4.1932	4.1928	4.1792	2.5565	2.5493	2.5579	2.5532
Average	0.4	4	4.2571	4.2572	4.0567	4.0053	4.2582	4.2584	4.2677	4.0546	3.9939	4.2589	4.2589	4.2525	4.0546	3.9946	4.0135	4.0104
		16	3.8307	3.8307	2.0266	2.0249	3.8314	3.8315	3.8468	2.0259	2.0238	3.8321	3.8317	3.8337	2.0258	2.0237	2.0311	2.0336
	0.8	4	4.9361	4.9362	4.8350	4.7532	4.9363	4.9362	4.9545	4.8309	4.7249	4.9363	4.9363	4.9266	4.8294	4.7192	4.7669	4.7601
		16	4.0472	4.0472	2.4206	2.4166	4.0488	4.0488	4.0538	2.4186	2.4125	4.0491	4.0486	4.0308	2.4182	2.4113	2.4137	2.4090

Table 11 - Forecasts RMSE - (N,T)=(50,10), SAR data generating process for ϕ , W(5,5) asymmetric weight matrix of French administrative communes, 1000 replications

	Estimators																	
			Pooled	Av. hetero.	FE	RE	Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
	ρ	σ_μ^2	OLS	OLS			MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.7378	3.7381	3.5505	3.5077	3.7375	3.7376	3.7345	3.5494	3.5024	3.7375	3.7377	3.7351	3.5494	3.5008	3.5002	3.7998
		16	3.5580	3.5581	1.7728	1.7699	3.5603	3.5595	3.5726	1.7726	1.7690	3.5589	3.5593	3.5620	1.7726	1.7692	1.7776	1.9072
	0.8	4	5.7212	5.7210	5.6986	5.6317	5.7122	5.6908	5.7728	5.6943	5.6694	5.7170	5.7194	5.6710	5.6944	5.5835	5.7257	6.5819
		16	4.1824	4.1824	2.8355	2.8319	4.1857	4.1826	4.1996	2.8337	2.8071	4.1829	4.1819	4.2006	2.8338	2.8200	2.8318	3.3513
2nd year	0.4	4	4.1233	4.1237	3.9270	3.8750	4.1234	4.1239	4.1296	3.9263	3.8712	4.1232	4.1236	4.1446	3.9264	3.8691	3.8801	3.9050
		16	3.7876	3.7877	1.9771	1.9748	3.7894	3.7887	3.7993	1.9769	1.9741	3.7883	3.7887	3.7848	1.9769	1.9745	1.9719	2.0943
	0.8	4	6.3676	6.3677	6.3403	6.2672	6.3531	6.3335	6.3887	6.3362	6.3238	6.3609	6.3589	6.3212	6.3364	6.2137	6.3270	5.7960
		16	4.5451	4.5452	3.1584	3.1544	4.5496	4.5451	4.5415	3.1565	3.1296	4.5461	4.5448	4.5448	3.1566	3.1418	3.1552	3.6714
3rd year	0.4	4	4.2904	4.2906	4.0876	4.0360	4.2905	4.2908	4.2843	4.0868	4.0321	4.2904	4.2905	4.3064	4.0869	4.0301	4.0363	4.1751
		16	3.8611	3.8612	2.0518	2.0494	3.8630	3.8622	3.8770	2.0516	2.0485	3.8618	3.8622	3.8666	2.0516	2.0490	2.0452	2.0835
	0.8	4	6.6165	6.6168	6.5966	6.5164	6.6021	6.5814	6.6730	6.5927	6.5671	6.6102	6.6083	6.5702	6.5928	6.4634	6.5194	6.3848
		16	4.6793	4.6792	3.2918	3.2870	4.6832	4.6791	4.6847	3.2897	3.2589	4.6803	4.6788	4.6760	3.2898	3.2735	3.2866	3.3368
4th year	0.4	4	4.3835	4.3838	4.1786	4.1261	4.3837	4.3840	4.3727	4.1777	4.1220	4.3836	4.3838	4.3891	4.1778	4.1205	4.1130	4.0951
		16	3.9001	3.9002	2.0885	2.0863	3.9021	3.9014	3.9155	2.0883	2.0854	3.9009	3.9014	3.9083	2.0883	2.0859	2.0873	2.2285
	0.8	4	6.7475	6.7479	6.7260	6.6453	6.7361	6.7144	6.7928	6.7211	6.6999	6.7415	6.7384	6.7232	6.7213	6.5918	6.6467	6.6437
		16	4.7503	4.7503	3.3568	3.3523	4.7549	4.7504	4.7473	3.3547	3.3262	4.7519	4.7503	4.7426	3.3548	3.3394	3.3510	3.2717
5th year	0.4	4	4.4334	4.4337	4.2277	4.1747	4.4336	4.4338	4.4326	4.2268	4.1704	4.4335	4.4336	4.4434	4.2268	4.1689	4.1664	4.2339
		16	3.9201	3.9203	2.1117	2.1092	3.9221	3.9214	3.9399	2.1115	2.1084	3.9210	3.9214	3.9338	2.1115	2.1089	2.1097	2.2687
	0.8	4	6.8084	6.8087	6.7852	6.7061	6.7956	6.7748	6.8683	6.7804	6.7546	6.8021	6.7968	6.8067	6.7807	6.6514	6.7120	6.7112
		16	4.7890	4.7889	3.3940	3.3894	4.7937	4.7892	4.7822	3.3921	3.3628	4.7907	4.7889	4.7875	3.3922	3.3763	3.3955	3.3104
Average	0.4	4	4.1937	4.1940	3.9942	3.9439	4.1937	4.1940	4.1907	3.9934	3.9396	4.1936	4.1938	4.2037	3.9934	3.9379	3.9392	4.0418
		16	3.8054	3.8055	2.0004	1.9979	3.8074	3.8066	3.8208	2.0002	1.9971	3.8062	3.8066	3.8111	2.0002	1.9975	1.9983	2.1165
	0.8	4	6.4522	6.4524	6.4293	6.3534	6.4398	6.4190	6.4991	6.4250	6.4030	6.4463	6.4444	6.4185	6.4251	6.3008	6.3862	6.4235
		16	4.5892	4.5892	3.2073	3.2030	4.5934	4.5893	4.5911	3.2053	3.1769	4.5904	4.5889	4.5903	3.2054	3.1902	3.2040	3.3883

Table 12 - Forecasts RMSE - (N,T)=(50,10), SMA data generating process for ϕ , W(5,5) asymmetric weight matrix of French administrative communes, 1000 replications

	Estimators																	
			Pooled	Av. hetero.			Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
	λ	σ_{μ}^2	OLS	OLS	FE	RE	MLE	ML	GM	MLE	MLE	MLE	ML	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.5992	3.5992	3.4169	3.3717	3.5997	3.5999	3.6059	3.4164	3.3749	3.5996	3.5996	3.6014	3.4164	3.3691	3.3497	3.4269
		16	3.5402	3.5402	1.6946	1.6936	3.5413	3.5414	3.5182	1.6944	1.6935	3.5413	3.5415	3.5471	1.6944	1.6943	1.7046	1.6667
	0.8	4	3.7404	3.7406	3.5619	3.5171	3.7423	3.7402	3.7387	3.5615	3.5079	3.7397	3.7395	3.7386	3.5614	3.5051	3.4983	3.7018
		16	3.5763	3.5763	1.7736	1.7724	3.5784	3.5768	3.5765	1.7733	1.7717	3.5761	3.5766	3.5518	1.7733	1.7719	1.7671	1.9863
2nd year	0.4	4	3.9882	3.9883	3.7807	3.7315	3.9886	3.9885	3.9929	3.7803	3.7346	3.9885	3.9885	3.9787	3.7804	3.7292	3.7141	3.7752
		16	3.7325	3.7326	1.8843	1.8820	3.7337	3.7335	3.7255	1.8841	1.8820	3.7333	3.7336	3.7482	1.8841	1.8824	1.8924	1.8990
	0.8	4	4.1487	4.1488	3.9466	3.8985	4.1508	4.1490	4.1595	3.9463	3.8911	4.1484	4.1482	4.1572	3.9463	3.8876	3.9060	4.0544
		16	3.7945	3.7945	1.9649	1.9636	3.7965	3.7950	3.7956	1.9645	1.9631	3.7946	3.7949	3.7681	1.9645	1.9632	1.9608	2.1374
3rd year	0.4	4	4.1439	4.1440	3.9258	3.8766	4.1441	4.1442	4.1404	3.9253	3.8806	4.1441	4.1442	4.1386	3.9253	3.8742	3.8689	3.9639
		16	3.8086	3.8087	1.9598	1.9574	3.8097	3.8094	3.8019	1.9596	1.9574	3.8092	3.8094	3.8260	1.9596	1.9580	1.9655	1.9680
	0.8	4	4.3099	4.3100	4.1039	4.0546	4.3127	4.3109	4.3117	4.1034	4.0469	4.3097	4.3096	4.3163	4.1034	4.0436	4.0568	4.0984
		16	3.8692	3.8693	2.0447	2.0431	3.8721	3.8702	3.8734	2.0443	2.0424	3.8699	3.8701	3.8470	2.0442	2.0425	2.0438	2.1830
4th year	0.4	4	4.2235	4.2236	3.9988	3.9501	4.2239	4.2240	4.2289	3.9984	3.9547	4.2238	4.2240	4.2267	3.9984	3.9480	3.9478	4.0507
		16	3.8489	3.8490	2.0028	2.0005	3.8499	3.8498	3.8420	2.0026	2.0006	3.8495	3.8498	3.8650	2.0026	2.0011	2.0032	1.9883
	0.8	4	4.3863	4.3865	4.1806	4.1298	4.3888	4.3869	4.3979	4.1799	4.1220	4.3861	4.3860	4.4070	4.1799	4.1188	4.1376	4.3898
		16	3.9086	3.9086	2.0920	2.0902	3.9114	3.9097	3.9116	2.0916	2.0894	3.9094	3.9096	3.8932	2.0916	2.0895	2.0859	2.1698
5th year	0.4	4	4.2738	4.2739	4.0483	3.9994	4.2743	4.2744	4.2805	4.0478	4.0040	4.2742	4.2744	4.2790	4.0478	3.9974	3.9973	4.0307
		16	3.8698	3.8699	2.0246	2.0222	3.8708	3.8706	3.8620	2.0244	2.0223	3.8704	3.8707	3.8878	2.0244	2.0228	2.0260	1.9919
	0.8	4	4.4411	4.4412	4.2345	4.1830	4.4432	4.4420	4.4491	4.2337	4.1754	4.4410	4.4410	4.4584	4.2337	4.1723	4.1896	4.3298
		16	3.9337	3.9338	2.1190	2.1171	3.9367	3.9350	3.9372	2.1186	2.1163	3.9347	3.9348	3.9176	2.1185	2.1163	2.1123	2.2562
Average	0.4	4	4.0457	4.0458	3.8341	3.7859	4.0461	4.0462	4.0497	3.8337	3.7898	4.0461	4.0461	4.0449	3.8337	3.7836	3.7756	3.8495
		16	3.7600	3.7601	1.9132	1.9112	3.7611	3.7609	3.7499	1.9130	1.9112	3.7607	3.7610	3.7748	1.9130	1.9117	1.9183	1.9028
	0.8	4	4.2053	4.2054	4.0055	3.9566	4.2076	4.2058	4.2114	4.0050	3.9486	4.2050	4.2049	4.2155	4.0050	3.9455	3.9577	4.1148
		16	3.8164	3.8165	1.9989	1.9973	3.8190	3.8174	3.8188	1.9984	1.9966	3.8169	3.8172	3.7955	1.9984	1.9967	1.9940	2.1465

Table 13 - Forecasts RMSE - (N,T)=(50,10), SAR data generating process for ϕ , W(1,1), 1000 replications under non-normality of individual effects

	Estimators																	
			Pooled	Av. hetero.	FE	RE	Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
	ρ	σ_{μ}^2	OLS	OLS			MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.9843	3.9843	3.8382	3.7875	3.9851	3.9851	3.9382	3.8371	3.7811	3.9858	3.9853	3.9646	3.8372	3.7793	3.7658	3.7748
		16	3.6053	3.6055	1.9078	1.9063	3.6062	3.6064	3.5985	1.9068	1.9047	3.6062	3.6064	3.5523	1.9068	1.9047	1.9053	1.8890
	0.8	4	7.1129	7.1136	7.2553	7.0794	7.1079	7.0996	7.0918	7.2510	7.0585	7.1095	7.1052	7.0710	7.2515	7.0284	7.0274	7.0651
		16	4.6280	4.6280	3.5936	3.5781	4.6288	4.6276	4.6144	3.5912	3.5555	4.6285	4.6285	4.6275	3.5912	3.5636	3.6072	3.5700
2nd year	0.4	4	4.3846	4.3848	4.2351	4.1769	4.3853	4.3854	4.3615	4.2332	4.1700	4.3862	4.3855	4.3940	4.2332	4.1694	4.1758	4.1855
		16	3.8386	3.8386	2.1195	2.1177	3.8400	3.8400	3.8379	2.1185	2.1161	3.8400	3.8401	3.7906	2.1186	2.1163	2.1200	2.1139
	0.8	4	7.8694	7.8698	8.0282	7.8327	7.8657	7.8516	7.8364	8.0208	7.8165	7.8670	7.8612	7.8633	8.0211	7.7782	7.8009	7.7973
		16	5.0879	5.0877	4.0125	3.9963	5.0906	5.0888	5.0560	4.0091	3.9693	5.0907	5.0902	5.0778	4.0092	3.9789	3.9965	3.9857
3rd year	0.4	4	4.5505	4.5506	4.4045	4.3422	4.5510	4.5512	4.5436	4.4023	4.3345	4.5518	4.5513	4.5538	4.4023	4.3349	4.3386	4.3471
		16	3.9260	3.9261	2.2016	2.1996	3.9269	3.9270	3.9281	2.2007	2.1984	3.9270	3.9272	3.8853	2.2008	2.1985	2.2016	2.1962
	0.8	4	8.1983	8.1986	8.3547	8.1578	8.1953	8.1803	8.1728	8.3467	8.1401	8.1968	8.1916	8.1733	8.3468	8.1020	8.1314	8.0947
		16	5.2566	5.2564	4.1800	4.1625	5.2589	5.2569	5.2433	4.1764	4.1337	5.2589	5.2583	5.2468	4.1765	4.1442	4.1660	4.1409
4th year	0.4	4	4.6440	4.6441	4.4982	4.4345	4.6446	4.6447	4.6292	4.4962	4.4266	4.6452	4.6449	4.6391	4.4963	4.4275	4.4165	4.4388
		16	3.9691	3.9692	2.2455	2.2435	3.9699	3.9700	3.9702	2.2447	2.2422	3.9700	3.9703	3.9296	2.2447	2.2423	2.2405	2.2421
	0.8	4	8.3769	8.3771	8.5328	8.3333	8.3737	8.3591	8.3368	8.5245	8.3186	8.3752	8.3709	8.3320	8.5247	8.2773	8.2932	8.2741
		16	5.3387	5.3386	4.2529	4.2362	5.3417	5.3396	5.3215	4.2493	4.2083	5.3417	5.3410	5.3354	4.2496	4.2180	4.2461	4.2309
5th year	0.4	4	4.6925	4.6926	4.5465	4.4825	4.6933	4.6933	4.6871	4.5444	4.4746	4.6940	4.6935	4.6986	4.5444	4.4754	4.4726	4.4953
		16	3.9955	3.9957	2.2725	2.2704	3.9963	3.9964	3.9971	2.2717	2.2692	3.9964	3.9966	3.9525	2.2718	2.2693	2.2666	2.2691
	0.8	4	8.4803	8.4805	8.6351	8.4361	8.4766	8.4619	8.4395	8.6269	8.4259	8.4780	8.4740	8.4222	8.6272	8.3795	8.4074	8.3813
		16	5.3877	5.3876	4.2969	4.2799	5.3903	5.3883	5.3718	4.2931	4.2520	5.3903	5.3897	5.3847	4.2933	4.2615	4.2954	4.2892
Average	0.4	4	4.4512	4.4513	4.3045	4.2447	4.4519	4.4519	4.4319	4.3026	4.2374	4.4526	4.4521	4.4500	4.3027	4.2373	4.2339	4.2483
		16	3.8669	3.8670	2.1494	2.1475	3.8679	3.8680	3.8664	2.1485	2.1461	3.8679	3.8681	3.8221	2.1485	2.1462	2.1468	2.1421
	0.8	4	8.0075	8.0079	8.1612	7.9679	8.0038	7.9905	7.9755	8.1540	7.9519	8.0053	8.0006	7.9723	8.1543	7.9131	7.9321	7.9225
		16	5.1398	5.1397	4.0672	4.0506	5.1421	5.1403	5.1214	4.0638	4.0237	5.1420	5.1415	5.1344	4.0640	4.0333	4.0622	4.0434

Table 14 - Forecasts RMSE - (N,T)=(50,10), SMA data generating process for ϕ , W(1,1), 1000 replications under non-normality of individual effects

			Estimators															
			Pooled	Av. hetero.			Pooled SAR	Av. hetero. SAR		FE-SAR	RE-SAR	Pooled SMA	Av. hetero. SMA		FE-SMA	RE-SMA	SAR-RE	SMA-RE
	ρ	σ^2_μ	OLS	OLS	FE	RE	MLE	MLE	GM	MLE	MLE	MLE	MLE	GM	MLE	MLE	GM	GM
1st year	0.4	4	3.6733	3.6734	3.4998	3.4549	3.6746	3.6745	3.6271	3.4987	3.4473	3.6748	3.6750	3.6574	3.4986	3.4485	3.4357	3.4539
		16	3.4929	3.4932	1.7556	1.7525	3.4940	3.4941	3.4804	1.7551	1.7510	3.4939	3.4940	3.4827	1.7550	1.7511	1.7336	1.7350
	0.8	4	3.9969	3.9972	3.8617	3.8078	3.9973	3.9966	3.9817	3.8584	3.7885	3.9997	3.9992	3.9887	3.8579	3.7860	3.7983	3.8020
		16	3.5497	3.5495	1.9274	1.9242	3.5524	3.5514	3.5657	1.9249	1.9203	3.5522	3.5516	3.5819	1.9244	1.9192	1.9219	1.9204
2nd year	0.4	4	4.0535	4.0534	3.8677	3.8189	4.0541	4.0540	4.0285	3.8663	3.8117	4.0545	4.0544	4.0544	3.8662	3.8127	3.8111	3.8231
		16	3.7113	3.7116	1.9382	1.9358	3.7119	3.7121	3.7025	1.9375	1.9344	3.7118	3.7121	3.7042	1.9375	1.9345	1.9271	1.9294
	0.8	4	4.4167	4.4168	4.2835	4.2212	4.4170	4.4164	4.3894	4.2799	4.1969	4.4194	4.4188	4.4118	4.2792	4.1940	4.2167	4.2318
		16	3.7920	3.7921	2.1416	2.1385	3.7944	3.7939	3.8054	2.1394	2.1354	3.7942	3.7940	3.8197	2.1391	2.1343	2.1341	2.1358
3rd year	0.4	4	4.2007	4.2007	4.0168	3.9653	4.2009	4.2010	4.1888	4.0154	3.9581	4.2012	4.2013	4.2063	4.0153	3.9594	3.9635	3.9718
		16	3.7873	3.7876	2.0075	2.0051	3.7879	3.7883	3.7774	2.0067	2.0037	3.7879	3.7883	3.7772	2.0067	2.0038	2.0066	2.0078
	0.8	4	4.5866	4.5866	4.4500	4.3852	4.5876	4.5866	4.5760	4.4459	4.3620	4.5895	4.5891	4.5831	4.4454	4.3584	4.3836	4.3842
		16	3.8824	3.8826	2.2276	2.2245	3.8841	3.8836	3.8915	2.2251	2.2213	3.8837	3.8838	3.9154	2.2249	2.2202	2.2155	2.2156
4th year	0.4	4	4.2871	4.2872	4.1026	4.0499	4.2877	4.2878	4.2745	4.1012	4.0429	4.2879	4.2881	4.2814	4.1010	4.0440	4.0378	4.0524
		16	3.8243	3.8246	2.0460	2.0434	3.8246	3.8249	3.8150	2.0452	2.0420	3.8246	3.8250	3.8178	2.0452	2.0421	2.0451	2.0480
	0.8	4	4.6830	4.6830	4.5438	4.4782	4.6831	4.6822	4.6643	4.5391	4.4548	4.6849	4.6846	4.6652	4.5384	4.4507	4.4714	4.4656
		16	3.9245	3.9247	2.2678	2.2647	3.9262	3.9258	3.9301	2.2654	2.2615	3.9258	3.9259	3.9626	2.2650	2.2602	2.2625	2.2616
5th year	0.4	4	4.3336	4.3337	4.1502	4.0964	4.3340	4.3341	4.3277	4.1489	4.0897	4.3343	4.3345	4.3378	4.1488	4.0908	4.0843	4.0988
		16	3.8487	3.8489	2.0716	2.0691	3.8490	3.8493	3.8374	2.0710	2.0677	3.8489	3.8493	3.8416	2.0710	2.0678	2.0739	2.0698
	0.8	4	4.7412	4.7413	4.6001	4.5343	4.7420	4.7408	4.7269	4.5957	4.5119	4.7436	4.7434	4.7220	4.5950	4.5073	4.5249	4.5125
		16	3.9535	3.9537	2.2953	2.2922	3.9548	3.9545	3.9573	2.2928	2.2887	3.9545	3.9546	3.9903	2.2923	2.2874	2.2895	2.2925
Average	0.4	4	4.1096	4.1097	3.9274	3.8771	4.1103	4.1103	4.0893	3.9261	3.8699	4.1106	4.1107	4.1075	3.9260	3.8711	3.8665	3.8800
		16	3.7329	3.7332	1.9638	1.9612	3.7335	3.7337	3.7225	1.9631	1.9597	3.7334	3.7338	3.7247	1.9631	1.9598	1.9572	1.9580
	0.8	4	4.4849	4.4850	4.3478	4.2853	4.4854	4.4845	4.4677	4.3438	4.2628	4.4874	4.4870	4.4742	4.3432	4.2593	4.2790	4.2792
		16	3.8204	3.8205	2.1719	2.1688	3.8224	3.8218	3.8300	2.1695	2.1654	3.8221	3.8220	3.8540	2.1692	2.1643	2.1647	2.1652