Spatial patterns of GP expenditures

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Abstract:

The study focuses on the variation in the utilisation of health care services in general practice (GP). A number of factors determining the use of GP services such as socio-demographic variables, availability of primary care services, labour marker, urbanisation structures, etc. are investigated. As GP utilisation is to a certain extent locally determined, spatial mechanisms may emerge. Competition and learning effects among spatially clustered municipalities may lead to spatial clustering of health care behaviour, i.e. endogenous spatial spillover may be in play. From an econometric point of view, the salient features of the case described above are that we have several correlative cross-sections of yearly data on GP services for the whole set of Danish municipalities. Moreover, the data show a clear spatial structure as well as strong time dynamics. This a panel database with several sources of dependence, which requires a specific methodological treatment. We will proceed specifying a seemingly unrelated regression, SUR, model in which we allow for interactions between the municipalities. Our objective is to obtain a specification capable of discriminating the impact of the properly exogenous factors in the determination of GP expenditures, from the spatial effects and the time effects related to the population and its spatial distribution.

1. Introduction

Variation in the utilization of health care services has been investigated in numerous studies focusing on e.g. the prevalence and incidence of diseases, mixed opinions of the effectiveness of surgery, practice style, health supply resource and differing patient preferences as possible determinants. Medical research has been interested in the study of small area variation (SAV) as an indicator of the effectiveness of a given level of service delivery (Wennberg and Gittelsohn 1973; Wennberg et al 1982). Economists have studied the same phenomena but have focused on supply factors, supplier induced demand (SID) and inadequate diffusion of medical information (Folland S et al 2004, Phelps CE 1995, 2000 Roemer MI 1961). Studies of the geographical variability of utilisation patterns have focused mostly on the determinants and the consequences of variation but little attention has been devoted to the geographical dynamics of the variation which means that a number of questions is yet to be explored e.g. is the geographical variation clustered in neighbouring geographical units.

This study focuses on the temporal dynamics of the factors that influence the utilisation of health care services in general practice (GP). One can think of a number of risk factors determining the use of GP services such as socio-demographic variables, morbidity and mortality, availability of primary care services, accessibility of hospitals etc. These determinants may, however, not be randomly distributed across the geographical units but may have an underlying spatial patterns. A non-random underlying spatial pattern may if ignored bias the significance of the determinants (Case et al 1993; Revelli F 2002) whereby inflated conclusions potentially occur.

Spatial mechanisms may emerge from several sources. Competition and learning effects among spatially clustered municipalities may lead to spatial clustering of health care behaviour, i.e. endogenous spatial spillover may be in play. Furthermore, exogenous spatial spillover may exist. Specifically, observed or unobserved determinants may affect the health care behaviour, not only in the municipality where they are observed, but also in a surrounding cluster of municipalities. Examples of such endogenous spillover readily occur. Provision of services at the regional level which partly induce or substitute GP utilisation may exert influence beyond the regional borderline. Likewise, GP utilisation may be affected by economic, demographic, social, labour market and urbanisation structures of the neighbouring regions. Neighbouring GPs may also influence each others. Finally, the very existence of spatial clustering of health care behaviour together with spatial clustering of observed as well as unobserved determinants may lead to spurious regression, in the sense that estimated relationships present themselves as stronger than they really are. At the extreme, variables which are unrelated apart from being independently spatially clustered may in such cases seem to be significantly related. Indeed, not accounting for spatial dynamics has been shown to potentially lead to biased and inefficient estimates of the parameters of an equation of public expenditure determination (Case et al 1993; Revelli F 2002). Few studies based on data from small-areas have explicitly studied the nature and implications of the spatial variation in medical practice, see e.g. Westert GP et al 2004 Joines et al 2003 Moscone et al 2005.

Yet another stream of studies applies panel data methods to account for potential unobservable differences in tastes and preferences in the health care expenditure function. Some evidence (DiMatteo and DiMatteo (1998), DiMatteo (2000) Gerdtham and Jönsson (2000), Giannoni and Hitiris (2002)) uses various forms of times series cross section analysis, including random or fixed effects specifications. However, none of these consider spatial interactions. Furthermore, the standard panel data methods applied are quite simplistic and thus fall into one of two caveats by being either heavily over-parameterized (e.g. fixed effects panel data specifications) or very parsimoniously parameterized (e.g. random effects panel data specifications). In-between forms allowing for time decay in intra-regional correlation (for example the seemingly unrelated regression approach) seldom find application. One aim of the present study is to integrate the seemingly unrelated regression approach with spatial spillover specifications in order to provide an investigation of the simultaneous importance of panel effects and spatial effects.

The seemingly unrelated regressions (SUR) equations is a traditional multivariate econometric formulation employed in very different fields included, obviously, the spatial analysis. The basis of the approach are very well-known since the initial works of Zellner (1962), Theil (1971), Malinvaud (1970), Schmidt (1976) and Dwivedi and Srivastava (1978).

SUR models are discussed in chapter 10 of the textbook of Anselin (1988a) as a special case of space-time models, in which there is a limited degree of dependence between the errors of the different equations. Anselin introduces the term of spatial SUR that '*consists of an equation for each time period which is estimated for a cross-section of spatial units'* (p. 141). In each of these equations, some spatial elements may be introduced in form of mechanisms of intra-equation spatial error autocorrelation, a spatially lagged dependent variable or both. Rey and Montouri (1999), Fingleton (2001, 2007), Egger and Pfaffermayr (2004), Moscone et al (2007), Lauridsen et al (2008) or LeGallo and Chasco (2008) use this technique in different applications. The main characteristics of this approach are the existence of a limited heterogeneity among the individuals (in fact, the regression coefficients are assumed to be the same for all of them) and a certain unbalance between the cross-section dimension (say R, the number of individuals in the sample) and the number of cross-sections (T is the time dimension). Typically, in the context of our paper, the former should be greater than the second (or the ratio T/N should go to zero).

To summarise, the purpose of this study is: (1) to explore the temporal dynamics of the determinants of the variation in the utilisation of GP services; (2) test for the presence of spatial effects in the SUR specification and to confront the question of identifying the type of spatial process (LAG vs ERR) more adequate to the data; (3) Test the instability of the spatial dependence.

The paper contains four sections. In the second section we apply the maximum-likelihood approach to testing for different types of spatial autocorrelation in a standard spatial SUR model and the temporal instability of the spatial effect. In the third section we use this methodology to explain the contents. Finally, the fifth section comments on the main conclusion reached in the paper.

2. Testing for Spatial Autocorrelation in SUR models.

The specification that we adopt contains one equation in which we identify an endogenous variable, called y, and a set of explanatory variables, $\{x_1, x_2, ..., x_k\}$. The sample information consists of R different individuals observed in T consecutive time cross-sections; so, there are TR observations.

The model described above corresponds to a SUR specification to which we add the existence of spatial effects. We first present the general case of a model with an autoregressive spatial structure both in the main equation and in the errors (known as a SARMA model); next, the Spatial Lag Model (SLM) contains an spatial autoregressive term only in the main equation, whereas this autoregression appears only in the equation of the errors in the case of the Spatial Error Model (SEM).

2.1 Testing Spatial effect in a SARMA model.

This is the most general specification which includes spatial effects both in the main equations of the model as well as in the equations of the errors. The reference equations are:

$$\left.\begin{array}{ll} y_t = \lambda_t \mathbf{W}_1 y_t + x_t\beta + u_t & \Rightarrow \mathbf{A}_t y_t = x_t\beta + u_t \\ u_t = \rho_t \mathbf{W}_2 u_t + \varepsilon_t & \Rightarrow \mathbf{B}_t u_t = \varepsilon_t \end{array}\right\} \qquad (1)$$

$$\mathbf{A}_t = I_R - \lambda_t \mathbf{W}_1 \quad \mathbf{B}_t = I_R - \rho_t \mathbf{W}_2$$

y_t, u_t and ε_t are vectors of order (Rx1), x_t is a matrix of order (Rxk), β is a vector of parameters of order (kx1), I_R is the identity matrix of order (RxR) and $\mathbf{W}_1$ and $\mathbf{W}_2$ are weighting matrices also of order (RxR). For simplicity's sake, in the following we will suppose that these two weighting matrices coincide ($\mathbf{W}_1$=$\mathbf{W}_2$=$\mathbf{W}$). The vector of parameters β may remain constant or it may vary among the different cross-sections. The same applies in relation to the parameters of dependence, ρ_t and λ_t. Initially, we allow for the parameters of spatial dependence to take different values in different cross-sections. Using a more compact notation:

$$\left.\begin{array}{l} \mathbf{A}y = X\beta + u \\ \mathbf{B}u = \varepsilon \\ \varepsilon \sim N(0,\Omega) \end{array}\right\}$$

$$\underset{TRx1}{y = \begin{bmatrix} y_1 \\ y_2 \\ \cdots \\ y_T \end{bmatrix}}; \quad \underset{TRXTk}{X = \begin{bmatrix} x_1 & 0 & \cdots & 0 \\ 0 & x_2 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & x_T \end{bmatrix}}; \quad \underset{TRx1}{u = \begin{bmatrix} u_1 \\ u_2 \\ \cdots \\ u_T \end{bmatrix}}; \quad \underset{TRx1}{\varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdots \\ \varepsilon_T \end{bmatrix}} \qquad (2)$$

where $\mathbf{A} = I_{TR} - \Lambda \otimes \mathbf{W}$ and $\mathbf{B} = I_{TR} - \Upsilon \otimes \mathbf{W}$; Λ (respectively Υ) is an R by R diagonal matrix containing the parameters λ_i (respectively ρ_i) and $\otimes$ is the Kronecker product. The temporal dependence, introduced through the SUR mechanism, leads us to the matrix $\Omega = \Sigma \otimes I_R$ where Σ is an RxR matrix with σ_{ij} as its elements. As usual, we assume normality in the error terms.

In order to test for the existence of spatial effects in the specification of (1), we will use an approach based on the Lagrange Multipliers. The null hypothesis of the absence of spatial effects in the SUR model of (1) implies that:

$$H_0: \lambda_t = \rho_t = 0 \ (\forall t) \quad \text{vs} \quad H_A: \text{ No } H_0 \qquad (3)$$

After a few calculi, whose details appear in Mur and López (2009), the final expression of the test is:

$$\mathbf{LM}_{SARMA}^{SUR} = \begin{bmatrix} g'_{(\lambda)_{|H_0}} & g'_{(\rho)_{|H_0}} \end{bmatrix} \begin{bmatrix} I_{\lambda\lambda} - I_{\lambda\beta}I_{\beta\beta}^{-1}I_{\beta\lambda} & I_{\lambda\rho} \\ I_{\rho\lambda} & I_{\rho\rho} \end{bmatrix}^{-1} \begin{bmatrix} g_{(\lambda)_{|H_0}} \\ g_{(\rho)_{|H_0}} \end{bmatrix} \underset{as}{\sim} \chi^2(2T) \quad (4)$$

with $g_{(\lambda)_{|H_0}} = \left[\mathbf{\Sigma}^{-1} \circ \left(\hat{U}'Y_L\right)\right]'\tau$ and $g_{(\rho)_{|H_0}} = \left[\mathbf{\Sigma}^{-1} \circ \left(\hat{U}'\hat{U}_L\right)\right]'\tau$ where, $\circ$, is the Hadamard product, τ is a (Tx1) vector of ones, and $\hat{U}$ is an (RxT) matrix whose columns contains the SUR residuals corresponding to the different cross-sections: $\hat{U} = \begin{bmatrix} \hat{u}_1 & \hat{u}_2 & \cdots & \hat{u}_T \end{bmatrix}$. $\hat{U}_L$ is the spatial lag of these collection of residual series $\hat{U}_L = \begin{bmatrix} \mathbf{W}\hat{u}_1 & \mathbf{W}\hat{u}_2 & \cdots & \mathbf{W}\hat{u}_T \end{bmatrix}$; Y_L is specified analogously. The terms of the information matrix appear in Mur and López (2009).

2.2 Testing Spatial effect in a SLM model.

The second model that we consider is a particular case of the last one:

$$\begin{aligned} y_t &= \lambda_t \mathbf{W} y_t + x_t\beta + \varepsilon_t \Rightarrow \mathbf{A}_t y_t = x_t\beta + \varepsilon_t \\ \mathbf{A}_t &= I_R - \lambda_t \mathbf{W} \end{aligned} \quad (5)$$

all the elements that intervene in this specification have been defined previously. Using a more compact matrix notation:

$$\left.\begin{aligned} \mathbf{A}y &= X\beta + \varepsilon \\ \varepsilon &\sim N(0,\Omega) \end{aligned}\right\} \quad (6)$$

where $\mathbf{A} = I_{TR} - \Lambda \otimes \mathbf{W}$ and Ω is the same matrix as that indicated in (2).

The null hypothesis is that the spatial lag of the endogenous variable included in the right-hand side of the SUR model of (6) is not relevant:

$$H_0 : \lambda_t = 0 \ (\forall t) \qquad \text{vs} \qquad H_A : \text{No } H_0 \quad (7)$$

The Lagrange Multiplier, emerges as:

$$\mathbf{LM}_{SLM}^{SUR} = g'_{(\lambda)_{|H_0}} \left[I_{\lambda\lambda} - I_{\lambda\beta}I_{\beta\beta}^{-1}I_{\beta\lambda} \right]^{-1} g_{(\lambda)_{|H_0}} \underset{as}{\sim} \chi^2(T) \quad (8)$$

The terms of the score associated with parameters λ can be expressed as: $g_{(\lambda)_{|H_0}} = \left[\mathbf{\Sigma}^{-1} \circ \left(\hat{U}'Y_L\right)\right]'\tau$ whereas the elements that intervene in the matrix $I_{\lambda\lambda} - I_{\lambda\beta}I_{\beta\beta}^{-1}I_{\beta\lambda}$ are defined in Mur and López (2009).

2.3 Testing spatial effect in a SEM model

The case of the SUR model with a structure of spatial dependence in the error term, SEM, is well known since the seminal work of Anselin (1988b). Nevertheless, in order to give a more complete view of the discussion, we include also this case. The model has a simple structure:

$$\left.\begin{array}{l} y_t = x_t\beta + u_t \\ u_t = \rho_t \mathbf{W} u_t + \varepsilon_t \quad \Rightarrow \mathbf{B}_t u_t = \varepsilon_t \end{array}\right\} \qquad \mathbf{B}_t = I_R - \rho_t \mathbf{W} \tag{9}$$

More concisely:

$$y = X\beta + u \; ; \mathbf{B}u = \varepsilon \quad \text{with} \quad \varepsilon \sim N(0, \Omega = \Sigma \otimes I_R) \quad \text{and} \quad \mathbf{B} = I_{TR} - \Upsilon \otimes \mathbf{W} \tag{10}$$

The null hypothesis is that there is no SEM structure in the error terms of the SUR, which means that:

$$H_0 : \rho_t = 0 \; (\forall t) \quad \text{vs} \quad H_A : \text{ No } H_0 \tag{11}$$

The obtaining of the corresponding Multiplier is straightforward Mur and López (2009)):

$$\mathbf{LM}_{\text{SEM}}^{\text{SUR}} = g'_{(\rho)_{|H_0}} \left[I_{\rho\rho} \right]^{-1} g_{(\rho)_{|H_0}} \underset{as}{\sim} \chi^2(T) \tag{12}$$

As in the previous cases, we can propose a more compact expression for the term of the score vector associated with the parameters ρ, $g_{(\rho)_{|H_0}} = \left[\mathbf{\Sigma}^{-1} \circ \left(\hat{U}'\hat{U}_L \right) \right]'\tau$ and $I_{\rho\rho} = tr(\mathbf{W}'\mathbf{W}) I_R + tr(\mathbf{W}\mathbf{W}) \mathbf{\Sigma}^{-1} \circ \mathbf{\Sigma}$.

2.4. The robust Multipliers

The tests of the second section may help to improve the specification of SUR models in situations in which the spatial dimension plays an important role. The problem is that, in general, the Lagrange Multipliers are not robust to specification errors in the alternative (Davidson, 2000). The difficulties created by this lack of robustness confer great importance to the work of Bera and Yoon (1993), which obtain the correction needed for the raw Multipliers in order to behave properly. In this section, we apply this arguments to the $\mathbf{LM}_{\text{SLM}}^{\text{SUR}}$ and $\mathbf{LM}_{\text{SEM}}^{\text{SUR}}$ tests, following Anselin et al (1996).

The likelihood function of the SARMA model discussed in Section 2.1, $L[\varphi;\lambda;\rho]$, depends on three groups of parameters: those associated to the basic SUR structure, $\varphi' = [\beta'; \sigma_{ij}]$, those linked to the spatial lag of the endogenous variable, $\lambda' = [\lambda_1; \cdots; \lambda_T]$, and those that introduce spatial dependence into the error terms, $\rho' = [\rho_1; \cdots; \rho_T]$. If, for example, vector ρ is zero, the likelihood function collapses in $L_1[\varphi; \lambda]$ and the unidirectional test, whose null hypothesis is that H_0: λ=0, leads to the $\mathbf{LM}_{SLM}^{SUR}$ statistic of (10), distributed as a centered chi-squared $\chi^2(T,0)$. Under alternative hypotheses of the type $H_A: \lambda = \xi/\sqrt{R}$, with $\xi \neq 0$, this distribution will have a non-centrality parameter, $\chi^2(T, \pi_1)$, equal to $\pi_1 = \xi' I_{\lambda\cdot\varphi}\xi$ with $I_{\lambda\cdot\varphi} = I_{\lambda\lambda} - I_{\lambda\varphi}I_{\varphi\varphi}^{-1}I_{\varphi\lambda}$. The presence of this parameter is what gives power to the test.

If we assume that the true likelihood function is $L_2[\varphi; \rho]$, where λ is zero and ρ is different from zero, the $\mathbf{LM}_{SLM}^{SUR}$ statistic will have a of non-centrality bias even if the null hypothesis, H_0: λ=0, holds. In particular, for alternatives of the type $H_A: \rho = \zeta/\sqrt{R}; \zeta \neq 0$, the asymptotic distribution of the test statistic is a $\chi^2(T, \pi_2)$, where $\pi_2 = \zeta' I_{\lambda\rho\cdot\varphi} I_{\lambda\cdot\varphi}^{-1} I_{\lambda\rho\cdot\varphi}\zeta$ being $I_{\lambda\rho\cdot\varphi} = I_{\rho\lambda} - I_{\lambda\varphi}I_{\varphi\varphi}^{-1}I_{\varphi\rho}$. This factor of non-centrality will be positive if the terms of the score associated with λ and ρ ($g(\lambda)_{|H_0}$ and $g(\rho)_{|H_0}$, respectively) are correlated. Under the composite hypothesis that the two sets of parameters are zero, we show in Mur and López (2009) that the matrix $I_{\lambda\rho}$ is of a diagonal type, but not null. Given that matrix $I_{\varphi\lambda}$ is also different from zero but $I_{\varphi\rho}$=0, we obtain that $I_{\lambda\rho\cdot\varphi} = I_{\rho\lambda} \geq 0$. The consequence is that the parameter of no centrality π_2 will be positive and the $\mathbf{LM}_{SLM}^{SUR}$ statistic will unduly reject the hypothesis that the vector of parameters λ is zero when the data have been generated by a SUR with a SEM structure.

The discussion for the $\mathbf{LM}_{SEM}^{SUR}$ statistic of (15), under the assumption that the data have been generated by $L_1[\varphi; \lambda]$, is analogous. To be precise, under alternatives of the type $H_A: \lambda = \zeta/\sqrt{R}; \zeta \neq 0$, the asymptotic distribution of this statistic is a $\chi^2(T, \pi_3)$, where $\pi_3 = \zeta' I_{\lambda\rho\cdot\varphi} I_{\rho\cdot\varphi}^{-1} I_{\lambda\rho\cdot\varphi}\zeta$ with $I_{\rho\cdot\varphi} = I_{\rho\rho} - I_{\rho\varphi}I_{\varphi\varphi}^{-1}I_{\varphi\rho}$. For the same reasons as before, it will be true that $I_{\lambda\rho\cdot\varphi} = I_{\rho\lambda} \geq 0$ and π_3>0. This result induces to the

$\mathbf{LM}_{\text{SEM}}^{\text{SUR}}$ statistic to wrongly reject the hypothesis that the vector of parameters ρ is zero when the data have been generated by a SUR with a SLM structure.

The proposal of Bera and Yoon (1993, p. 652) '*is to construct a size-resistant test ... where we adapt the statistic for the nuisance parameters*'. The correction consists in adjusting the bias that affects both the score and the covariance matrix that intervene in the raw Lagrange Multiplier. In our case:

$$\left.\begin{array}{l} H_0 : \lambda_t = 0 \\ H_A : \text{No} \quad H_0 \end{array}\right\}$$

$$\mathbf{LM}^{*}{}_{\text{SLM}}^{\text{SUR}} = \left[g_{(\lambda)_{|H0}} - I_{\lambda\rho\cdot\varphi} I_{\rho\cdot\varphi}^{-1} g_{(\rho)_{|H0}} \right]' \left[I_{\lambda\cdot\varphi} - I_{\lambda\rho\cdot\varphi} I_{\rho\cdot\varphi}^{-1} I_{\lambda\rho\cdot\varphi} \right]^{-1} \left[g_{(\lambda)_{|H0}} - I_{\lambda\rho\cdot\varphi} I_{\rho\cdot\varphi}^{-1} g_{(\rho)_{|H0}} \right] \underset{as}{\sim} \chi^2(T) \tag{13}$$

where:

$$\begin{aligned} g_{(\rho)_{|H0}} &= \left[\mathbf{\Sigma}^{-1} \circ \left(\hat{U}'\hat{U}_L \right) \right]' \tau \\ g_{(\lambda)_{|H0}} &= \left[\mathbf{\Sigma}^{-1} \circ \left(\hat{U}'Y_L \right) \right]' \tau \end{aligned}$$

$$\begin{aligned} & I_{\lambda\rho\cdot\varphi} = I_{\rho\lambda} \qquad I_{\rho\cdot\varphi} = I_{\rho\rho} \\ & I_{\lambda\rho\cdot\varphi} = I_{\rho\lambda} \quad I_{\lambda\cdot\varphi} = I_{\lambda\lambda} - I_{\lambda\varphi} I_{\varphi\varphi}^{-1} I_{\lambda\varphi} \\ & I_{\varphi\varphi}^{-1} = \begin{bmatrix} I_{\beta\beta} & 0 \\ & I_{\sigma\sigma} \end{bmatrix}^{-1} \end{aligned} \tag{14}$$

The information that we need in order to obtain the value of the test appears in Mur and López (2009). Likewise:

$$\left.\begin{array}{l} H_0 : \rho_t = 0 \\ H_A : \text{No} \quad H_0 \end{array}\right\}$$

$$\mathbf{LM}^{*}{}_{\text{SEM}}^{\text{SUR}} = \left[g_{(\rho)_{|H0}} - I_{\lambda\rho\cdot\varphi} I_{\lambda\cdot\varphi}^{-1} g_{(\lambda)_{|H0}} \right]' \left[I_{\rho\cdot\varphi} - I_{\lambda\rho\cdot\varphi} I_{\lambda\cdot\varphi}^{-1} I_{\lambda\rho\cdot\varphi} \right]^{-1} \left[g_{(\rho)_{|H0}} - I_{\lambda\rho\cdot\varphi} I_{\lambda\cdot\varphi}^{-1} g_{(\lambda)_{|H0}} \right] \underset{as}{\sim} \chi^2(T) \tag{15}$$

where:

$$\begin{aligned} g_{(\rho)_{|H0}} &= \left[\mathbf{\Sigma}^{-1} \circ \left(\hat{U}'\hat{U}_L \right) \right]' \tau \\ g_{(\lambda)_{|H0}} &= \left[\mathbf{\Sigma}^{-1} \circ \left(\hat{U}'Y_L \right) \right]' \tau \end{aligned}$$

$$\begin{aligned} & I_{\lambda\rho\cdot\varphi} = I_{\rho\lambda} \qquad I_{\lambda\cdot\varphi} = I_{\lambda\lambda} - I_{\lambda\varphi} I_{\varphi\varphi}^{-1} I_{\lambda\varphi} \\ & I_{\lambda\varphi} = \begin{bmatrix} I_{\lambda\beta} & 0 \end{bmatrix} \quad I_{\varphi\varphi}^{-1} = \begin{bmatrix} I_{\beta\beta} & 0 \\ & I_{\sigma\sigma} \end{bmatrix}^{-1} \end{aligned}$$

2.5 Testing for the time-constancy of the parameters of spatial dependence.

We have used different SUR specifications in which the coefficients of spatial dependence that intervene in each cross-section may differ. If the cross-sections refer to consecutive and very near time periods, it is reasonable to wonder if these coefficients remain the same over time.

The results obtained under the assumption of constancy of these parameters are formally equivalent to those presented in the previous subsections, although the estimation algorithms are simpler. For example, the SARMA model of (2) now becomes:

$$\left.\begin{array}{l}\mathbf{A}y = X\beta + u \\ \mathbf{B}u = \varepsilon \\ \varepsilon \sim N(0,\Omega) \Rightarrow \Omega = \Sigma \otimes I_R\end{array}\right\}$$
$$\begin{array}{l}\mathbf{A} = I_{TR} - \lambda \otimes \mathbf{W} = I_T \otimes (I_R - \lambda\mathbf{W}) = I_T \otimes \hat{\mathbf{A}} \\ \mathbf{B} = I_{TR} - \rho \otimes \mathbf{W} = I_T \otimes (I_R - \rho\mathbf{W}) = I_T \otimes \hat{\mathbf{B}}\end{array} \tag{16}$$

where $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$ are two matrices of order (RxR). The number of parameters to estimate reduces to (k+2+T(T+1)/2). If we use a SLM model, where the parameter λ is constant between the different cross-sections:

$$\left.\begin{array}{c}\mathbf{A}y = X\beta + \varepsilon \\ \varepsilon \sim N(0,\Omega) \Rightarrow \Omega = \Sigma \otimes I_R\end{array}\right\}$$
$$\mathbf{A} = I_{TR} - \lambda \otimes \mathbf{W} = I_T \otimes (I_R - \lambda\mathbf{W}) = I_T \otimes \hat{\mathbf{A}} \tag{17}$$

Now, the number de parameters to estimate is (k+1+T(T+1)/2), the same as in the SEM case, under the assumption of constancy:

$$\left.\begin{array}{c}y = X\beta + u \\ \mathbf{B}u = \varepsilon \\ \varepsilon \sim N(0,\Omega) \Rightarrow \Omega = \Sigma \otimes I_R\end{array}\right\}$$
$$\mathbf{B} = I_{TR} - \rho \otimes \mathbf{W} = I_T \otimes (I_R - \rho\mathbf{W}) = I_T \otimes \hat{\mathbf{B}} \tag{18}$$

It is evident that the hypothesis that the same parameter of spatial dependence operates in each cross-section has important consequences, so it should be tested adequately. One simple solution is the likelihood ratio which compares the likelihood of the ample model against that obtained with its restricted version. This procedure requires the estimation of the model of the null hypothesis and of the model of the alternative hypothesis. The Lagrange Multiplier is a more attractive procedure because we only need the estimation of the restricted model[1]. Below, we show the main results.

[1] The Wald test is another alternative that we skip due to length restrictions.

As said, In the SARMA case, we compare the unrestricted specification of expression (2) with the restricted version of (20). These two models are joined by a set of 2(T-1) restrictions that lead us to the composite null hypothesis:

$$H_0: \lambda_1 = \lambda_2 = ... = \lambda_T \text{ and } \rho_1 = \rho_2 = ... = \rho_T \quad \text{vs} \quad H_A: \text{No } H_0 \tag{19}$$

The expression of the Lagrange Multiplier is the usual quadratic form of the score vector on the inverse of the information matrix, in both cases evaluated under the null hypothesis of (23). That is:

$$\mathbf{LM}_{SARMA}^{SUR}(\lambda,\rho) = \left[g(\theta)_{|H_0}\right]' \left[I^{T,R}(\theta)_{|H_0}\right]^{-1} \left[g(\theta)_{|H_0}\right] \underset{as}{\sim} \chi^2(2(T-1)) \tag{20}$$

with:

$$g(\theta)_{|H_0} = \begin{bmatrix} \frac{\partial l}{\partial \beta} \\ \frac{\partial l}{\partial \lambda_t} \\ \frac{\partial l}{\partial \rho_t} \\ \frac{\partial l}{\partial \sigma_{ij}} \end{bmatrix}_{|H_0} = \begin{bmatrix} g_{(\beta)_{|H_0}} \\ g_{(\lambda)_{|H_0}} \\ g_{(\rho)_{|H_0}} \\ g_{(\sigma)_{|H_0}} \end{bmatrix} = \begin{bmatrix} 0 \\ \underset{t=1,...T}{-tr\left(\hat{\mathbf{A}}^{-1}\mathbf{W}\right) + \hat{\varepsilon}'\left[\left(\mathbf{\Sigma}^{-1}\mathbf{E}^{tt}\right) \otimes \left(\hat{\mathbf{B}}\mathbf{W}\right)\right] y} \\ \underset{t=1,...T}{-tr\left(\hat{\mathbf{B}}^{-1}\mathbf{W}\right) + \hat{\varepsilon}'\left[\left(\mathbf{\Sigma}^{-1}\mathbf{E}^{tt}\right) \otimes \mathbf{W}\right] \hat{u}} \\ 0 \end{bmatrix} \tag{21}$$

In the case of the SLM of (6), there are (T-1) restrictions in the null hypothesis:

$$H_0: \lambda_1 = \lambda_2 = ... = \lambda_T \quad \text{vs} \quad H_A: \text{No } H_0 \tag{22}$$

The expression of the Multiplier does not vary:

$$\mathbf{LM}_{SLM}^{SUR}(\lambda) = \left[g(\theta)_{|H_0}\right]' \left[I^{T,R}(\theta)_{|H_0}\right]^{-1} \left[g(\theta)_{|H_0}\right] \underset{as}{\sim} \chi^2(T-1) \tag{23}$$

with:

$$g(\theta)_{|H_0} = \begin{bmatrix} \frac{\partial l}{\partial \beta} \\ \frac{\partial l}{\partial \lambda_t} \\ \frac{\partial l}{\partial \sigma_{ij}} \end{bmatrix} = \begin{bmatrix} g_{(\beta)_{|H_0}} \\ g_{(\lambda)_{|H_0}} \\ g_{(\sigma)_{|H_0}} \end{bmatrix} = \begin{bmatrix} 0 \\ \underset{t=1,...T}{-tr\left(\hat{\mathbf{A}}^{-1}\mathbf{W}\right) + \sum_{s=1}^{R} \sigma^{st} \hat{\varepsilon}_s' \mathbf{W} y_t} \\ 0 \end{bmatrix} \tag{24}$$

Lastly, in the SEM of (11) we obtain:

$$H_0: \rho_1 = \rho_2 = \ldots = \rho_T \quad \text{vs} \quad H_A: \text{No } H_0 \tag{25}$$

with:

$$\mathbf{LM}_{SEM}^{SUR}(\rho) = \left[g(\theta)_{|H_0}\right]' \left[I^{T,R}(\theta)_{|H_0}\right]^{-1} \left[g(\theta)_{|H_0}\right] \underset{as}{\sim} \chi^2(T-1) \tag{26}$$

where:

$$g(\theta)_{|H_0} = \begin{bmatrix} \dfrac{\partial l}{\partial \beta} \\ \dfrac{\partial l}{\partial \rho_t} \\ \dfrac{\partial l}{\partial \sigma_{ij}} \end{bmatrix}_{|H_0} = \begin{bmatrix} g_{(\beta)_{|H_0}} \\ g_{(\rho)_{|H_0}} \\ g_{(\sigma)_{|H_0}} \end{bmatrix} = \begin{bmatrix} 0 \\ -\mathrm{tr}\left(\hat{\mathbf{B}}^{-1}\mathbf{W}\right) + \sum_{s=1}^{R} \sigma^{st} \hat{\varepsilon}_s' \mathbf{W} \hat{u}_t \\ t=1,...T \\ 0 \end{bmatrix} \tag{27}$$

Additional details in relation to the information matrices and some other elements used in obtaining these three Multipliers appear in Mur and López (2009).

3. The GP expenditure in the Danish health care system.

In this section we will analyse (i) the temporal dynamics of the factors which determine the GP expenditure in the GP spending in the regions of Denmark, (ii) we will evaluate the presence of spatial effects and (iii) we will contrast their stability throughout the period studied. We will use the methodology presented in the previous section as an analysis tool, implementing SUR models with spatial effects using the LM battery of contrasts introduced in section 2 to select the most appropriate specification.

3.1. The institutional setting and Data.

The Danish health care system has traditionally been politically, financially and operationally decentralized Pedersen KM et al 2005. Up till 2007 the 14 counties and one hospital authority responsible for health care in the metropolitan area, the Copenhagen Hospital Cooperation, own, fund and run publicly owned hospitals. GPs are private entrepreneurs that contract with the regional public authorities. The number of GPs is regulated by the regional public authorities. Hospital, GP and private practicing specialist services are provided free of charge. The GPs act as gatekeeper to none-acute hospital treatments.

Data were collected from The Key Figure Database at the Ministry of the Interior Health and from The Statistical Bank at Statistics Denmark for the period 1998-2004 forming a balanced panel data set. The dependent variable is GP expenditure per capita in year *t* in municipality *i*. Figure 1 shows the distribution of GP expenditure per capita in 2004.

FIGURE 1 AROUND HERE

The explanatory variables will be classified in **three** categories. The first type of explanatory variable is variables describing the supply of health care which is considered to be exogenous and beyond the municipalities' direct control. The principal supply factor influencing GP utilisation may be the GP/population ratio Evans (1974) Fylkesnes (1993) Grytten et al (1995). The literature on Supplier-Induced-Demand (SID) has argued that an observed positive relationship between the number of services consumed per capita and the physician:population ratio supports the SID hypothesis. The SID hypothesis states that physicians can, because of the information asymmetry and their role as advisor, generate demand when market shares or fee decline. We do not consider the inclusion here of the GP density variable as a test of the SID hypothesis because this requires a more detailed analysis separating SID from availability effects Delattre and Dormont (2003) Carlsen and Grytten (1998) Stano (1995). The availability effect states that more physicians increase the number of services consumed per capita due to lower waiting and travelling costs or less rationing of the health care services Grytten (1995) Carlsen and Grytten (1998) Delattre and Dormont (2003). We *a priori* expect a positive relationship between GP density and expenditure but we will not unambiguously know whether this is because of SID or an availability effect. Other factors include the number of inpatient hospital admissions and the out-patient hospital visit. Studies have shown that higher use of GP services is not associated with the number of inpatient admissions but may be associated with outpatient hospital visits (30-34) meaning that outpatient visits to some degree is a substitute for GP services. A higher number of outpatient hospital visits is therefore expected to decrease GP expenditure. For inpatient admissions the opposite is expected because GP services and inpatient admissions are considered to be complements so that more admissions also require more visits to the GP (Linnala et al (2006) Lindstrom et al (2003) Haynes et al (1999)).

The second category of variables will be exogenous confounding variables including urbanisation, socio-demographic variables (Age, employment). Previous studies have shown that socio-demographic characteristics, income and urbanisation are important determinants (Nolan (1993); Vedsted et al (2004) Vedsted and Olesen (2005)).

Finally, we will control spatial effects in 2 different forms. In the first instance, we will introduce a variable dummy as explanatory factors for each of the 12 countries in which the Danish regions are grouped. Secondly, we will introduce a spatial autoregressive structure or rather we would include a spatial delay of the endogenous as an exogonous variable or rather considering an autoregressive structure in the remainder of the model.

In the Table 1 specifies the variables, their definition, mean and standard deviation and hypothesised relation. The expected sign for variables are also stated in Table 1.

3.2. Resulted

We will use in this subsection the methodology which is presented in section 2 as an instrument to evaluate the impact of the different variables in the GP expenditure. We will consider two cases. In first place, we will estimate a SUR model with coefficient variables where only two temporal cuts (T=2) will be taken into consideration, corresponding to the starting and finishing years of the panel of information which is available (t=1998,2004). In the second case we will estimate the SUR model with four temporal cuts (T=4) introducing intermediate/intervening years (t=1998; 2000; 2002; 2004).

3.2.1. Case I. (T=2).

The corresponding results to the estimation of the SUR model are shown in table 2. The LM test (163,94) as much as the LR (263,11) clearly indicate the presence of a strong correlation between the remainders of the different transversal cuts. We will first of all centre our attention on the specification contrasts developed in section 2. The group/battery of LM contrasts (LM-SUR-LAG ; LM-SUR-ERR and LM-SUR-SARMA) indicate the presence of a strong spatial structure in the remainders of the model. The selection in advance/ a priori of the most suitable model (LAG vs ERR) is determined by the strong contrasts. In this case, as LM-SUR-LAG* < LM-SUR-ERR* we can opt for introducing a spatial autoregressive structure in the remainders of the model (SUR-ERR)

Finally, the stability contrast in the spatial dependency LM-SUR-ERR-Break accepts the null/of no force hypothesis of stability in the spatial dependance. That´s why in this case the most suitable model is a SUR-ERR with stable spatial dependency.

The corresponding results of the estimation of this model (SUR-ERR) can be seen in Table 2 on the right hand side. The increase in the credibility/likeliness of the model is significant, taking into account the value of the LR test.

For to the supply variables, GP density is strongly positively and statistically significant related to GP expenditure independent of model specification which confirms our *a priori* expectations. The positive relationship between GP density and GP expenditure support the SID hypothesis, however, it is not an unambiguous test of the SID hypothesis because we do not know whether this positive relationship is an SID effect due to GPs inducing services or an availability effect caused by lower rationing in areas with high density of GPs. The GP density variables may be endogenous because the causal effect not necessarily needs to go from the number of patients per GP to the number of services per patients but may also go the opposite way. The models where the effect of GP density is controlled for reverse causality show that the positive relationship between GP density and GP expenditure become even more significantly. From a policy perspective this may attract some attention since the GP density is regulated by the Regional authorities, and municipalities may having this result in mind question regions' decisions about GP density in their municipality due to the co-financing reform.

The influence of inpatient admissions and outpatient visits was expected to be positive and negative, respectively, which is confirmed and the results are even robust toward omission of adjustment for panel effects and spatial spillover in the SUR and spatial adjustments models. It has been proved in earlier studies that utilisation of outpatient hospital visits may be a substitute for GP services whereas inpatient is not a substitute but rather a complement, see e.g. (30-33).

Considering the coefficients for the socio-demographic variables, it is notable that only a few of these stand up for the SUR and spatial adjustments. Increasing expenditures for sickness benefits, which is a proxy for health care need, have the expected positive association. The proportion of inhabitants in the age group 70+ years have a positive influence increase GP expenditure. Finally, the proportion of widowed has a negative influence. A similar impression is obtained when looking at the effects of the variables capturing occupational population structures. The number of significant variables is considerably reduced when controlling for panel effects and spatial spillover. Presumably, the significant effects of socio-demographic characteristics reported by the simpler OLS specifications and partly the panel adjusted SUR specification may rely on spurious regression caused by ignored spatial clustering of occupational population structures.

3.2.2. Case II. (T=4).

In the second case we will consider four temporal cuts corresponding to the even years (T=4). Table 3 shows the results which correspond to the estimation of the SUR model. The two diagonality tests of error convariance matrix (LM and LR) confirm that it is appropriate to consider correlations between the remainders of the model. Just as occurred in the previous case (T=2), all the contrasts of spatial dependance present high values, indicating spatial correlation in the remainders of the models. As regards the most correct specification the strong contrasts identify the SUR-ERR model as the most suitable (LM-SUR-ERR*> LM-SUR-LAG*). Finally, the contrast LM-SUR-ERR-Break repels/rejects, the opposite of what happens when only two cuts are considered, the hypothesis of uniformity/likeness of all the coefficients of spatial dependence. Therefore, in this case the most suitable model is a SUR-ERR with different coefficients of spatial dependence.

$$y_t = x_t\beta + u_t \; ; \; u_t = \rho_t \mathbf{W} u_t + \varepsilon_t \quad (t = 1,2,3,4)$$

On the right hand side of Table 3, the corresponding results of this model are shown. We can see the estimated values of ρ_t these present an oscillating behaviour, indicating that these unobservable spatial effects keep certain temporal dynamics

With regards to the rest of the coefficients, their temporal dynamics are very unequal. This way, the GP density variable shows a very pronounced growing tendency. On the other hand the TAX variable shows a decreasing tendency.

4. Conclusions

As a major outcome, the SUR adjustment for panel effects in the form of heterogeneity and temporal dependency across years, together with adjustment for spatial spillover, represent substantial improvements of model fit when analyzing the determinants for GP expenditure and lead to substantial changes regarding interpretation. Simple approaches ignoring these aspects lead to serious overestimation of the effects of several important determinants. The analysis reveals that GP expenditure is closely associated with the number of hospital admissions, outpatient visits and GP density. Outpatient visits seem to be a substitute while hospital inpatient admissions are complementary which is consistent with findings in the literature. GP density is positive related to GP expenditure supporting the SID hypothesis but is, however, ambiguous whether this positive relationship also could be caused by an availability effect (41-43). Finally, the degree of urbanization in the municipality strongly influences GP expenditure.

It is not surprising that the model fit improves substantially when adjusting for dependency across years. Indeed, one would expect the policy of one year – as measured by GP expenditure – to be largely an increment of the previous years' policy. Neither is it surprising that, when adjusting for this incremental nature of GP utilisation policy, the effects of several determinants are reduced or disappear completely.

Furthermore, the presence of a strong spatial spillover points to the existence of local clustering tendencies. These **can be related to omitted explanatory variables** or to local similarities in policies and exert strong influences on explanations of the GP expenditure. **It is especially important to notice that this pattern is still seen after accounting for fixed country-level effects**. Thus, though the tendencies to local similarities in policy may to a large extent be ascribed to regulation from the counties, this regulation is not uniformly administered by the GPs in each of the municipalities in the county. It seems rather to be the case that additional local similarities in policies exist, caused by spatial competition and learning effects, which exert strong influences on explanations of GP utilisation. As a result, municipalities located geographically close are more similar in health policy behaviour than municipalities geographically distant.

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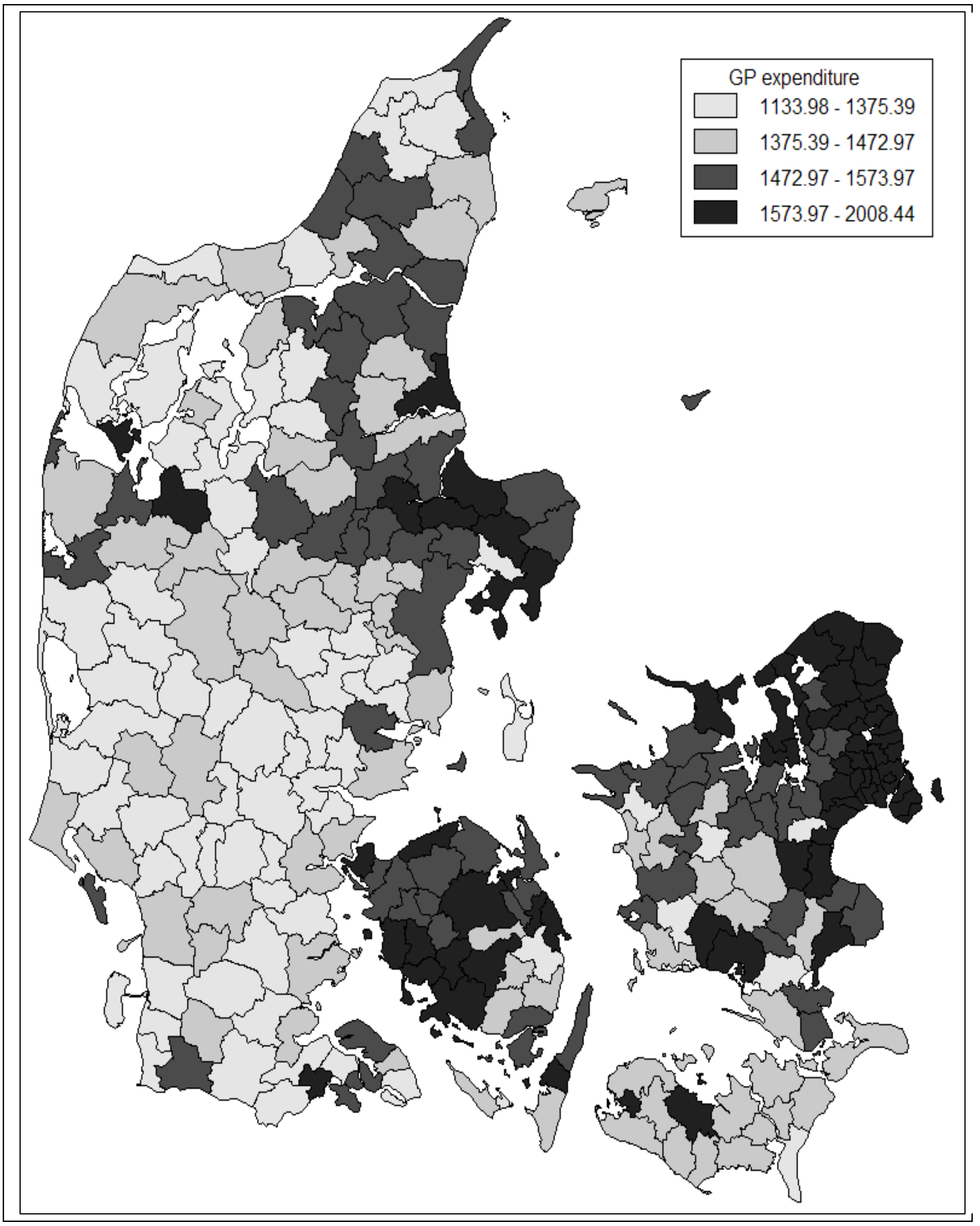

Figure 1. GP expenditure per capita, 2004.

Table 1: Descriptive statistics

	Mean				Hypoth impact
	1998	**2000**	**2002**	**2004**	
Expenditure for GP and private practicing specialists (DKK per inhabitant)	1,121	1,207	1,344	1,490	
Number of GP's per 1000 inhabitants	0,010	0,010	0,011	0,011	+
Number of inpatient hospital admissions per 1000 inhabitants	1,119	1,127	1,122	1,114	+
Number of out-patient hospital visits per 1000 inhabitants	5,925	6,658	8,454	9,070	÷
Percentage of population living in urban areas	0,728	0,727	0,729	0,732	+/÷
Tax deductible income (1000 DKK per capita)	1,016	1,117	1,213	1,288	+/÷
% of the pop. being above 70 years old	0,109	0,110	0,110	0,110	+
% of the pop. being widowed	0,068	0,067	0,066	0,065	+/÷
% of the pop. being employed within public administration	0,037	0,034	0,032	0,030	-
% of the pop. being employed within transportation	0,028	0,027	0,026	0,026	+/÷
% of the pop. being employed within fishing, agriculture, hort. and forestry	0,024	0,024	0,023	0,023	-

Table 2: Estimated SUR and SUR-ERR models. T=2.

	SUR				SUR-ERR			
	1998		2004		1998		2004	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Intercep	1,042	0,000	1,190	0,000	0,979	0,0000	1,149	0,0000
GP Density	1,609	0,070	2,601	0,032	1,740	0,0353	2,460	0,0275
Hospital Admision	0,151	0,000	0,094	0,129	0,183	0,0000	0,125	0,0556
Out-patient visit	-0,012	0,004	0,004	0,538	-0,013	0,0020	0,003	0,6309
Urbanitation	0,068	0,177	0,162	0,018	0,074	0,1186	0,168	0,0090
Tax base	0,165	0,000	0,114	0,000	0,184	0,0000	0,116	0,0005
Age 70+	1,859	0,000	1,541	0,013	1,649	0,0001	1,595	0,0105
Widowed	-2,192	0,004	-0,318	0,774	-1,811	0,0149	-0,287	0,7935
Ocu. Construction	-1,333	0,000	-0,977	0,098	-1,150	0,0013	-0,949	0,1028
Ocu. Fishig/Agric	-1,710	0,000	-1,793	0,012	-1,400	0,0031	-1,583	0,0267
Ocu. Public. Adm.	-0,568	0,093	-0,767	0,159	-0,884	0,0123	-0,991	0,0799
Fixed county effect	See Appendix				See Appendix			
					Coeff.		p-value	
lamnda (spill-over)					0,326		0,0107	
DIAGNOSTIC MEASURES								
	Statistic	p-value						
LM	163,94	0,0000						
LR (S)	263,11	0,0000						
LR (SUR vs SUR-ERR)					25,45	0,0000		
LM-SUR-ERR	21,13	0,0000						
LM-SUR-ERR*	4,00	0,1354						
LM-SUR-LAG	17,93	0,0001						
LM-SUR-LAG*	0,80	0,6703						
LM-SUR-SARMA	21,93	0,0002						
LM-SUR-ERR Break	0,004	0,9509						
Log Lik	779,49				792,21			

Table A2: Extra results from SUR and SUR-ERR models.

	SUR				SUR-ERR			
	1998		2004		1998		2004	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Frederiksborg	-0,063	0,006	-0,020	0,518	-0,057	0,0384	-0,018	0,6463
Roskilde	-0,097	0,000	-0,136	0,000	-0,104	0,0005	-0,144	0,0004
Ribe	-0,232	0,000	-0,172	0,000	-0,226	0,0000	-0,168	0,0000
Vejle	-0,226	0,000	-0,210	0,000	-0,226	0,0000	-0,207	0,0000
Ringkobing	-0,177	0,000	-0,144	0,000	-0,181	0,0000	-0,150	0,0002
Viborg	-0,253	0,000	-0,268	0,000	-0,248	0,0000	-0,265	0,0000
Western_Seeland	-0,266	0,000	-0,312	0,000	-0,259	0,0000	-0,299	0,0000
Storstroem	-0,296	0,000	-0,348	0,000	-0,280	0,0000	-0,329	0,0000
Funen	-0,265	0,000	-0,237	0,000	-0,271	0,0000	-0,230	0,0000
Southern Jutland	-0,180	0,000	-0,183	0,000	-0,186	0,0000	-0,202	0,0000
Aarhus	-0,300	0,000	-0,271	0,000	-0,309	0,0000	-0,289	0,0000
Northern Jutland	-0,218	0,000	-0,214	0,000	-0,219	0,0000	-0,214	0,0000

Table 3: Estimated SUR and SUR-ERR models. T=4.

	SUR (T=4)								SUR-ERR (T=4)							
	1998		2000		2002		2004		1998		2000		2002		2004	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Intercep	1,062	0,0000	1,139	0,0000	1,180	0,0000	1,185	0,0000	1,017	0,0000	1,115	0,0000	1,173	0,0000	1,159	0,0000
GP Density	1,483	0,0640	1,802	0,0374	2,872	0,0026	2,437	0,0276	1,640	0,0277	1,891	0,0230	2,916	0,0017	2,436	0,0157
Hospital Admision	0,135	0,0000	0,117	0,0000	0,114	0,0001	0,133	0,0020	0,152	0,0000	0,125	0,0000	0,119	0,0001	0,161	0,0003
Out-patient visit	-0,010	0,0024	-0,004	0,2706	0,000	0,9632	0,003	0,4997	-0,012	0,0006	-0,005	0,1326	-0,001	0,7279	0,001	0,7823
Urbanitation	0,078	0,0824	0,068	0,1449	0,104	0,0470	0,175	0,0042	0,089	0,0365	0,087	0,0542	0,120	0,0197	0,187	0,0010
Tax base	0,121	0,0001	0,100	0,0001	0,095	0,0001	0,078	0,0033	0,140	0,0000	0,108	0,0000	0,097	0,0000	0,083	0,0017
Age 70+	1,549	0,0000	1,303	0,0008	0,827	0,0441	1,328	0,0079	1,451	0,0001	1,300	0,0007	0,970	0,0176	1,510	0,0022
Widowed	-1,412	0,0278	-0,807	0,2382	0,303	0,6736	0,095	0,9134	-1,154	0,0595	-0,723	0,2792	0,159	0,8213	-0,088	0,9173
Ocu. Construction	-1,262	0,0001	-1,450	0,0001	-1,291	0,0018	-0,841	0,1046	-1,155	0,0003	-1,327	0,0002	-1,287	0,0019	-0,927	0,0686
Ocu. Fishig/Agric	-1,011	0,0154	-1,046	0,0213	-1,070	0,0469	-0,868	0,1595	-0,836	0,0416	-0,930	0,0398	-1,130	0,0347	-0,872	0,1509
Ocu. Public. Adm.	-0,871	0,0058	-1,143	0,0012	-1,359	0,0010	-1,228	0,0149	-1,167	0,0003	-1,455	0,0001	-1,565	0,0002	-1,474	0,0043
Fixed county effect	See Appedix															
lamnda (spill-over)									0,312	0,0000	0,249	0,0000	0,167	0,0000	0,333	0,0000
DIAGNOSTIC MEASURES																
	Statistic	p-value														
LM	1144,08	0,0000														
LR (OLS vs SUR)	1329,55	0,0000														
LR (SUR vs SUR-ERR)									45,4114							
LM-SUR-ERR	36,1146	0,0000														
LM-SUR-ERR*	12,9122	0,0117														
LM-SUR-LAG	29,5629	0,0000														
LM-SUR-LAG*	6,36046	0,1728														
LM-SUR-SARMA	42,475	0,0000														
LM-SUR-ERR Break	13,21	0,0042														
Log LIK	1977,24								2000,0							

Table A3: Extra results from SUR and SUR-ERR models.

	SUR (T=4)								SUR-ERR (T=4)							
	1998		2000		2002		2004		1998	2000	2002	2004	1998	2000	2002	2004
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Frederiksborg	-0,068	0,0024	-0,060	0,0127	-0,081	0,0033	-0,027	0,3868	-0,069	0,0107	-0,064	0,0213	-0,088	0,0036	-0,035	0,3476
Roskilde	-0,104	0,0000	-0,102	0,0002	-0,128	0,0000	-0,144	0,0000	-0,116	0,0001	-0,116	0,0002	-0,138	0,0000	-0,162	0,0000
Ribe	-0,241	0,0000	-0,218	0,0000	-0,184	0,0000	-0,186	0,0000	-0,233	0,0000	-0,212	0,0000	-0,180	0,0000	-0,180	0,0000
Vejle	-0,238	0,0000	-0,225	0,0000	-0,213	0,0000	-0,228	0,0000	-0,240	0,0000	-0,228	0,0000	-0,214	0,0000	-0,230	0,0000
Ringkobing	-0,187	0,0000	-0,181	0,0000	-0,154	0,0000	-0,159	0,0000	-0,191	0,0000	-0,187	0,0000	-0,160	0,0000	-0,167	0,0000
Viborg	-0,264	0,0000	-0,245	0,0000	-0,261	0,0000	-0,278	0,0000	-0,261	0,0000	-0,249	0,0000	-0,265	0,0000	-0,283	0,0000
Western_Seeland	-0,273	0,0000	-0,273	0,0000	-0,318	0,0000	-0,328	0,0000	-0,264	0,0000	-0,268	0,0000	-0,314	0,0000	-0,312	0,0000
Storstroem	-0,299	0,0000	-0,301	0,0000	-0,304	0,0000	-0,352	0,0000	-0,285	0,0000	-0,293	0,0000	-0,297	0,0000	-0,335	0,0000
Funen	-0,274	0,0000	-0,256	0,0000	-0,245	0,0000	-0,252	0,0000	-0,272	0,0000	-0,256	0,0000	-0,241	0,0000	-0,238	0,0000
Southern_Jutland	-0,186	0,0000	-0,215	0,0000	-0,193	0,0000	-0,188	0,0000	-0,200	0,0000	-0,232	0,0000	-0,212	0,0000	-0,221	0,0000
Aarhus	-0,312	0,0000	-0,350	0,0000	-0,312	0,0000	-0,293	0,0000	-0,325	0,0000	-0,366	0,0000	-0,328	0,0000	-0,321	0,0000
Northern_Jutland	-0,232	0,0000	-0,223	0,0000	-0,202	0,0000	-0,233	0,0000	-0,232	0,0000	-0,226	0,0000	-0,204	0,0000	-0,231	0,0000