TESTING THE SPATIAL SCALE AND THE DYNAMIC STRUCTURE IN REGIONAL MODELS (A CONTRIBUTION TO SPATIAL ECONOMETRIC SPECIFICATION ANALYSIS)*

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ABSTRACT. This article addresses the problem of specification uncertainty in modeling spatial economic theories in stochastic form. It is ascertained that the traditional approach to spatial econometric modeling does not adequately deal with the type and extent of specification uncertainty commonly encountered in spatial economic analyses. Two alternative spatial econometric modeling procedures proposed in the literature are reviewed and shown to be suitable for analyzing systematically two sources of specification uncertainty, viz., the level of aggregation and the spatio-temporal dynamic structure in multiregional econometric models. The usefulness of one of these specification procedures is illustrated by the construction of a simple multiregional model for The Netherlands.

1. INTRODUCTION

Ideally, economic theories should provide model builders with sufficient prior information to enable the construction of fully specified econometric models. Only then can model builders make an unambiguous choice from a wide range of possible model specifications, based on appropriate econometric/statistical methods that fulfill usual criteria like unbiasedness, consistency, efficiency, etc. Unfortunately, such an ideal framework is not a common situation in economics. In particular, theories do not provide sufficient information regarding the following specific issues:

1. the functional form of equations in a model (e.g., linear or nonlinear);
2. the causal structure of the system concerned (e.g., interdependent or recursive);
3. the statistical properties of the error terms of models;
4. the level of aggregation (geographical scale, group size, etc.);
5. the level of measurement of the variables (e.g., a cardinal or ordinal metric scale); and

*The authors are indebted to Manfred Fischer (University of Vienna) and an anonymous referee for constructive critical remarks on a first draft of this paper. They also thank Annemarie Rima (Free University, Amsterdam) and Nick Koper (Twente University of Technology, Enschede) for their computational assistance.

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Received January, 1984; in revised form August, 1984; accepted November, 1984.

6. the exact specification of the dynamic structure (e.g., time lags, difference or differential equations).

Clearly, there is no single criterion for judging the accuracy and specification of econometric models [see also Shapiro (1973)]. Consequently, economists (and, in general, social scientists) are often confronted with substantial specification uncertainty. Several authors have criticized the so-called traditional approach to econometric model-building in solving the problem of specification uncertainty because of the unjustifiable and nonsystematic use of informal and judgmental information [see Blommestein and Palm (1982), and the references quoted in their article; see also Section 2 of this paper]. In regard to this criticism, several specification methodologies—designed for improving the flaws in current econometric modeling—have been proposed [cf. Blommestein (1983b) for a discussion and an overview].

The aim of the present paper is to present systematic modeling procedures for dealing more adequately with the abovementioned problem of specification uncertainty. In particular, this paper focuses on two sources of specification uncertainty, viz., the lack of a satisfactory theoretical foundation for specifying the level of spatial aggregation and the spatio-temporal structure in many dynamic regional economic models.

The organization of the paper is as follows. The nature of specification uncertainty is discussed in Section 2 in a concise manner. Section 3 introduces in greater detail the problem of choosing an appropriate geographical scale for spatial dynamic models. Various types of spatial aggregation and the relevance of perfect aggregation are discussed in Section 3. Next, Section 4 analyzes specification uncertainty with regard to the spatial dynamic structure of a model. In addition, two procedures for mitigating the risk of misspecification in spatial dynamic regression models are briefly reviewed. Empirical results regarding a simple multiregional model for The Netherlands are presented in the final section.

2. HYPOTHESES ON REGIONAL ECONOMIC STRUCTURE AND THE CONSTRUCTION OF SPATIAL ECONOMETRIC MODELS

It has been emphasized in the Introduction that (spatial) economic theories do not generate sufficient information for completely specifying econometric relationships. It is of fundamental importance, therefore, to obtain a proper understanding of the complex relationship(s) between the nature of hypotheses on (spatial) economic phenomena and their consequences for specifying and designing (spatial) econometric models [cf. Blommestein (1983b)].

Basic or main economic theories deal with so-called generic structures, i.e., a general description of social (economic) structures by a set of concepts, relations, and the like, put together in logical form. In general, all theories are (implicitly or explicitly) based on latent variables reflecting theoretical constructs [see Fischer (1984) and Folmer and Nijkamp (1984)]. Next, with the aid of Hempel's (1966) "bridge principle," which specifies correspondence hypotheses on the basis of measurement theory, the concepts, theoretical constructs, relationships, and the like emerging from basic economic theories are translated into operational categories for the construction of specific economic theories. The bridge principle of Hempel also indicates how the fundamental entities and processes (formulated

according to Hempel's internal principle) of a basic theory are connected with its corresponding empirical domain. Hempel also notes that an operationalization of basic theories is necessary to enable one to test those theories.

However, unlike the specific theories in the natural sciences, a specific economic theory is more than just a testable representation of a basic economic theory [Klant (1979)]. Due to a lack of restrictions (caused *inter alia* by the presence of so-called general *ceteris paribus* clauses), it is usually still possible to deduce so many interpretations of empirical results that a falsification of basic economic theories becomes very difficult. Papandreou (1958) calls these theories semantically insufficient. A specific economic theory, according to Papandreou, is essentially an augmented theory [Papandreou (1958)], i.e., an interpretation (operationalization) of a basic theory made up partly of the specification (according to Hempel's bridge principle) of relations, concepts, and the like from a basic theory, and partly of additional assumptions with respect to functional forms, lag structures, stochastic properties, the classification of variables into endogenous and exogenous variables, the direction of causality, the level of aggregation, and so forth. In regard to this, Cramer (1969, p. 2) has stated:

Unfortunately economic theories set great store by generality, and their models are therefore as a rule insufficiently specific to permit an empirical application. As a consequence, virtually all econometric studies add specific hypothesis of their own which are appropriate to the particular situation under review. The convenient approximations are dictated by the requirements of statistical estimation; they are based on common sense rather than on abstract economic theory.

The general semantic insufficiency of (spatial) economic theories necessitates making additional assumptions—thus introducing substantial specification uncertainty—in order to arrive at a fully specified econometric and empirically testable model. The current (or traditional) approach to econometric modeling solves this kind of specification uncertainty rather informally, so that prior information, information obtained from nonindependent (pre-)tests, etc., are employed in an *ad hoc* and unsystematic fashion. According to Zellner (1979), traditional econometric and statistical analyses tend to concentrate the attention mainly on given models, thereby implicitly ignoring a great deal of specification uncertainty, and relatively little on systematic (=formal) methods for checking whether formulated models are consistent with information in sample data and for improving (i.e., repairing deficiencies of) proposed models.

The major aim of the present paper is to address explicitly the issue of specification uncertainty by focusing on the spatial scale and dynamic structure of spatial regression models. A quasi-formal¹ two-step procedure is proposed to deal more adequately with these two sources of specification uncertainty than the traditional approach to spatial econometric modeling:

(i) Determine the level of spatial aggregation on the basis of relevant criteria such as: the fulfillment of the conditions of perfect aggregation and the level of the mean absolute error of the differences between projections and actual values of endogenous variables.

¹Formal statistical procedures which rigorously and simultaneously take into account two or more specification issues still remain to be developed [cf. Zellner (1979)].

(ii) Given the spatial scale chosen in step (i), determine the spatial dynamic structure, using the statistical procedures to be presented in Section 4 of this paper.

3. THE SPATIAL SCALE IN REGIONAL ANALYSIS

In designing an interregional model describing a complex spatial system, one is always confronted with the problem of the relevant spatial scale (the areal unit problem) and with the problem of combining data from different geographical scales (the aggregation problem). Clearly, before any statistical or econometric analysis can be carried out, one has to specify an appropriate level of spatial detail for both the data concerned and the model to be constructed. With respect to this choice, a trade-off has to be made between the costs of collecting new data at a relevant spatial scale (or transforming them toward a relevant scale) and the significance of results that can be obtained from advanced data analyses. Clearly, the costs involved in gathering precise data at the level of small areal units may be extremely high, and in addition, confidentiality rules may sometimes preclude the collection of data at a detailed spatial scale. It should also be added that in many cases delimitation of areal units is entirely arbitrary (i.e., without any meaning based on economic theory). Usually, only data at a given (e.g., administrative) scale are available, so that no sensitivity analysis regarding results from different scales can be carried out.

It has been demonstrated by several authors that the results of many analyses are scale-specific [see, among others, Carter (1974), Clark and Avery (1976), Duncan, Cuzzort, and Duncan (1961), and Johnston (1984)]. Such results have not only been found in factorial ecology (employing small census-data units), but also in statistical correlation analysis and econometric modeling [see, among others, Alker (1969), Hordijk (1979), Lohmoeller et al. (1985), and Nijkamp, Rietveld, and Rima (1984)]. Very often the outcomes of such analyses lead to making ecological inferences (i.e., statements regarding individual behavior from aggregate analyses), so that false conclusions are likely to be drawn.

A convincing illustration of the danger of this so-called ecological fallacy has been given by Openshaw and Taylor (1981), who have demonstrated that with a particular data set (for 99 counties of the state of Iowa) one may—depending on the level of aggregation of the areal units—obtain correlation coefficients for voting behavior and population age that differ not only significantly in size but even in sign! Their numerical example shows that correlations between variables observed at an aggregate level may not, in general, be used as substitutes for individual data, unless the distribution of attributes of individuals would be equal at each relevant geographical scale. Therefore, it may be meaningful to discuss in greater detail aggregation problems in specifying regional economic models.

Aggregation may, in general, pertain to various dimensions in economic research: individuals, firms, areal units, time periods, and so forth. It leads to a condensation of information and, hence, to a loss of detailed insight [see Orcutt, Watts, and Edwards (1968)], but it may enhance the understanding of complex phenomena by structuring the data so as to focus the attention on their important general features. As far as aggregation of areal units is concerned, various regionalization principles are being used in regional economic and geographical

research, such as the homogeneity principle, the administrative principle, the functionality principle, the nodality principle, etc. None of these regionalization principles, however, justifies a complete and relevant composition of areal units in a spatial system [see Fischer (1982)]. It is a well-known fact that for each of these principles an additional clustering (stopping) rule has to be specified, before a satisfactory regionalization based on an aggregation of data from elementary areal units can be obtained, as otherwise an unambiguous solution is not defined. Without a clear epistemological foundation defining this clustering rule, such an aggregation is merely a statistical exercise and, hence, does not guarantee an unambiguous aggregation of basic areal units.

In addition to an aggregation of areal units, one may also distinguish an aggregation of models or equations pertaining to areal units. In this regard, one may analyze the impact of a particular aggregation level of individual units upon the explanatory power of a model or relationship [see also van Daal (1980) and Akdeniz and Milliken (1975)]. In a recent article, Charney and Taylor (1983) demonstrate quite convincingly that the choice of areal unit may have significant impacts on the results of a multiregional regression model. Similar results can also be found in Baumann, Fischer, and Schubert (1984), who have studied functional regionalization problems in the context of multiregional labor market modeling. In general, one may expect that, whatever the spatial scale of a model, the so-called additivity condition is always satisfied, so that the model results at a certain spatial scale are in agreement with those at a higher spatial scale. This general problem of aggregation in econometric models has been studied in greater detail by Theil (1954).

Suppose the following linear microrelationship:

$$(1) \quad y_{it} = \alpha_i + \sum_{k=1}^K \beta_{ki} x_{kit} + u_{it} \quad (t = 1, \dots, T; i = 1, \dots, I)$$

where

y_{it} = value of a response variable referring to unit i and period t ;

x_{kit} = value of the k th predetermined variable referring to unit i and period t ;

α_i = intercept term for unit i ;

β_{ki} = microparameter related to k th predetermined variable referring to unit i ; and

u_{it} = disturbance term, being independent of x_{kit} (for all k, i, t) and having a zero mean.

Then a macrovariable may be defined as an aggregation over the units i ($i = 1, \dots, I$), i.e.

$$(2) \quad \begin{cases} y_t = \sum_{i=1}^I y_{it} \\ x_{kt} = \sum_{i=1}^I x_{kit} \end{cases}$$

Now the following macrorelationship may be specified:

$$(3) \quad y_t = \sum_{i=1}^I \alpha_i + \sum_{i=1}^I \sum_{k=1}^K \beta_{ki} x_{kit} + \sum_{i=1}^I u_{it}$$

The latter relationship is not necessarily identical to the macrorelationship obtained by rewriting (1) directly in terms of macrovariables, i.e.

$$(4) \quad y_t = \alpha + \sum_{k=1}^K \beta_k x_{kt} + u_t$$

with α and β_k macroparameters and u_t a disturbance term with zero mean.

In case of a linear model, there is a complete correspondence between (3) and (4) (i.e., perfect aggregation), if and only if

$$(5) \quad \beta_{ki} = \beta_{kj} \quad (\text{for all } i, j)$$

provided there are no restrictions on the distribution of the predetermined variables. If (5) does not hold and if, due to the lack of data at a disaggregate level, one uses the results from (4) to infer conclusions regarding variables at a more disaggregate level, a specification error leading to false statements will take place. Condition (5) may be modified if additional constraints on the distribution of these predetermined variables (based on so-called auxiliary or measurement equations) are imposed [see Theil (1954)]. A more extensive discussion of this issue and of econometric test procedures can be found in van Daal (1980).

In conclusion, an aggregate analysis will often exhibit results that are not in agreement with behavioral relationships specified at a disaggregate level. Unfortunately, there has been a strong tendency in (regional) economic and geographical research to use fairly aggregate data, as such data are normally easier to obtain. It should be noted, however, that the use of microdata does not always present an aggregation bias. It has been argued by Kelejian (1980) that in the case of nonlinear microrelationships, the condition for perfect aggregation has almost lost its relevance. Furthermore, Grunfeld and Griliches (1960) and Green (1977) have emphasized another limitation of the aggregation analysis described above: all variables are assumed to be measured at the same level, so that microvariables are not influenced by macrovariables. This problem of an integration of different (spatial) levels has been studied fairly extensively in regional economics, where a distinction has been made between top-down models, bottom-up models, inter-regional models, and regional-national models [see for a survey Issaev et al. (1982)].

The above-mentioned aggregation analysis is essentially a bottom-up approach: interunit linkages and macro-micro impacts are left out of consideration. This leads us to the conclusion that the conventional aggregation analysis is, no doubt, relevant for the specification of regional economic models (especially as far as the additivity condition is concerned), but also that some more specific elements related to the structure of the regional system at hand (e.g., spatial interdependences) have to be taken into account.

In addition to additivity conditions and specific regional system's conditions, one may also judge the appropriateness of a spatial scale in a regression model by

investigating which spatial level predicts “best” at an aggregate (e.g., national) level, for instance, by means of a mean error criterion. This is a useful approach, as in many regional economic models the specification of relationships is taking for granted an unjustified spatial scale (or a spatial aggregation). It is clear that a sensitivity analysis regarding the spatial level of a model is contingent upon its correct specification. As explained in Section 2, a prior validation of statistical or econometric aspects of regional models is fraught with difficulties. The next section will further address the issue of specifying spatial econometric models, with a special emphasis on the choice of regressors and/or the dynamic structure in a model. This part of a specification analysis is codetermined by the choice of spatial scale discussed in this section.

4. TESTING THE DYNAMIC STRUCTURE IN REGIONAL REGRESSION MODELS

Spatial economic dynamics deal with a wide range of spatial economic phenomena such as innovation diffusion processes, spatio-temporal backwash and spillover effects, spin-off effects, and spatial interaction processes. Unfortunately, theories on spatial economic dynamics do not, in general, provide a satisfactory and detailed foundation for a complex specification of the dynamic structure of regional models, such as, the mathematical specification and time lags in relationships [see also Blommestein and Palm (1982)]. This lack of a sound basis for the dynamic structure (error and/or systematic dynamics) in regional economic modeling is one of the important sources of specification uncertainty (cf. also Section 2).

The spatial dynamic structure of a model can be specified more adequately by employing recently developed regionally oriented versions of tests for specification analysis for dynamic models. Two methods for specification analysis will briefly be discussed here, viz., common factor analysis (COMFAC) and economic factor analysis (ECONFAC) [see for more details Blommestein (1983b) and Sargan (1980)]. The main aim of both procedures is to mitigate the risk of misspecification due to the exclusion of relevant variables and/or long time lags. Both COMFAC and ECONFAC commence with a fairly general (unrestricted) model, i.e., the maintained hypothesis—such that the “true” model is nested in it.² Consider the following class of (linear) spatial dynamic models in regression equation form³

$$(6) \quad \gamma(L_s) \text{ vec } Z_s = E_s$$

²The idea of starting a specification analysis with a fairly general model is motivated by Zellner and Palm's (1974) consideration that the rejection of a restricted model, when it is true, will be a less serious error than using a restricted model when the restrictions imposed are incorrect. They argue that the use of improperly unrestricted models leads to the inclusion of some extra parameters which may be a less serious problem than the imposition of incorrect restrictions which lead to incorrect values of the parameters.

³For temporal systems this class of dynamic models in regression equation form can be written as $Z_T \gamma(L) = E$; where $\gamma(L)$ denotes a $(K + 1)$ vector with scalar polynomials in the temporal lag operator L of orders $n_0, n_1, \dots, n_K$, respectively, with $\gamma_0(L)$ operating on the dependent variable Y , and $\gamma_j(L)$ on the vectors with regressor variables $X_j, j \in \{1, \dots, K\}$; $Z_T = [Y \ X_1 \ \dots \ X_K]$; and E a vector with white noise error terms.

where $\gamma(L_s)$ is an $(R \times (R(K+1)))$ matrix made up of $K+1$ $(R \times R)$ polynomial matrices $\gamma_j(L_s^{n_j})$ in $L_s^{n_j}$ of orders n_j , $j \in \{0, 1, \dots, K\}$, $L_s^{n_j}$ the n_j th order spatial lag operator [also called the weighting or contiguity matrix; cf. Cliff and Ord (1973)], $Z_s = [Y X_1 \dots X_K]$ an $(R \times (K+1))$ matrix with observations on the relevant spatial variables, $E_s \sim NID(0, \sigma_{E_s}^2)$ an $(R \times 1)$ vector with white-noise error terms,⁴ and vec , a vectorization operator. Then COMFAC analyses specifications of the following form:

$$(7) \quad \rho(L_s^m) \beta(L_s) vec Z_s = V$$

where $\rho(L_s^m)$ is an $(R \times R)$ polynomial matrix of order m , $\beta(L_s)$ an $(R \times (R(K+1)))$ matrix with polynomial matrices $(\beta_j(L_s^{n_j-m}))$ in $L_s^{n_j-m}$, and $V \sim NID(0, \sigma_V^2)$.

The presence of a spatial common factor $\rho(L_s^m)$ in $\gamma(L_s)$ imposes K restrictions on the $\gamma_j(L_s^{n_j})$. By dividing (7) by $\rho(L_s^m)$, a linear spatial dynamic model with errors generated by a spatial autogressive process of order m , viz., $U = V/\rho(L_s^m)$, is obtained [see Blommestein (1983b) for more details]. Acceptance of the common factor hypotheses,⁵ may, however, lead to restricted models which are nonsensical or difficult to interpret in terms of, for example, behavior of economic agents. In order to cope with these problems, it has been suggested in Blommestein and Palm (1982) to design specification search procedures by imposing, if possible, restrictions based on prior economic theory or other prior considerations. In Blommestein (1983b), the generic term "economic factor" analysis was introduced, in order to distinguish this new class of procedures from the statistical-mechanical kind of procedures like COMFAC.

Next, ECONFAC considers the following particular specification:

$$(8) \quad \gamma^*(L_s) vec Z_s = V^*$$

where $\gamma^*(L_s)$ is an $(R \times (R(K+1)))$ matrix with $K+1$ $(R \times R)$ polynomial matrices $\gamma_j^*(L_s^{n_j^*})$ of orders $n_j^* \geq n_j$, $j \in \{0, 1, \dots, K\}$, and V^* an $(R \times 1)$ vector with error terms (not necessarily white noise). The restrictions imposed on $\gamma(L_s)$ to obtain $\gamma^*(L_s)$ and V^* are to be based on a priori considerations, such as nonlinear cross-equation restrictions in rational expectations models, partial adjustments models for endogenous variables, "error" correction mechanisms, policy intervention rules, or physical-geographical constraints [cf. Blommestein (1983b), for more details].

It is worth noting here that the common parameters used in the above-mentioned framework (the "common parameters" assumption) do not contradict

⁴In both the COMFAC and ECONFAC frameworks, the values of n_j , $j \in \{0, 1, \dots, K\}$ —denoting the largest lag for each variable—are assumed to be sufficiently large, so that E_s may be treated as white noise in system (6). This approach has the following advantages [see also Palm's (1981) discussion of temporal systems]: (a) the interpretation of the parameters is facilitated by the inclusion of all dynamics in the systematic part of the regression equations; (b) in system (6) the OLS estimators are BLUE when no lagged endogenous variables are included.

⁵It is possible that the common factor restrictions are not rejected—according to statistical tests to be mentioned below—but that an economic or other conceptual interpretation of the restricted model cannot be given, or that the restrictions encompass theoretical contradictions.

the assumption of a diverse spatial structure, as the specific interaction pattern aligned to the spatial structure is reflected in the specification of the contiguity matrix serving as a substitute for the representation of regional variations.

Both COMFAC and ECONFAC employ a sequential testing framework for reducing the order of dynamics for all $K + 1$ variables separately or simultaneously, until a test statistic exceeds a chosen critical value. The number of restrictions (π_n , say) imposed on $\gamma(L_s)$ can be tested by means of the likelihood ratio (LR) test, the Wald (WT) test or the Lagrange multiplier (LM) test [cf. Sargan (1975)]. When $H_0: \phi_n(\gamma) = 0$ is true where $\phi_n(\gamma)$ is a $(\pi_n \times 1)$ vector with restrictions written in implicit form, all three tests are asymptotically distributed as $\chi^2_{\pi_n}$.

By means of these tests, a more solid basis for a spatio-temporal specification of regional models can be obtained. Thus, two steps have to be undertaken: (1) the identification of the appropriate regional aggregation level (see the discussion in Section 3) and (2) a spatial econometric specification analysis based on the ECONFAC approach. In the next section, this procedure will be illustrated for a specification analysis of a model for the Dutch regional distribution of disability allowances.

5. EMPIRICAL RESULTS: THE REGIONAL DISTRIBUTION OF DISABILITY ALLOWANCES IN THE NETHERLANDS

5.1 Introduction

Having discussed the main aspects and recent developments in specification analysis, we will present an empirical illustration dealing with the effects of spatial scales on model results. More precisely, we will examine two questions: (1) how do changes in the spatial scale affect the determinants of the number of persons receiving disability allowances in The Netherlands (see Section 5.2); and (2) how do different specifications of dynamic structures of the model influence its explanatory power? (see Section 5.3). In the context of the present paper, the latter analyses will be limited to a systematic study of the spatial dynamic structure of a stock-flow model, whose level of aggregation is determined in step 1 (see Section 5.3).

The present empirical application concerns the number of people receiving disability allowances after having withdrawn from the labor market. The data used can be found in official Dutch statistics. It turns out that substantial regional differences do exist in the share of people receiving such disability allowances. Therefore, it may be meaningful to explore the extent to which these differences can be ascribed to economic indicators such as the unemployment rate. If such an explanation were valid, one might draw the conclusion that hidden unemployment may exist among the recipients of disability allowances. This is interesting, as (until recently) in The Netherlands the number of unemployed persons has been smaller than the number of recipients of disability allowances.

The model used here as an illustration stems from Nijkamp, Rietveld, and Rima (1983), in which a stock-flow approach has been used to explain the number of disability allowance recipients (v). The number of recipients at the end of year t ,

(w_t) , is by definition equal to the same number in the previous year (w_{t-1}) *plus* the inflow (z_t) *minus* the outflow (q_t) during that year:

$$(9) \quad w_t = w_{t-1} + z_t - q_t$$

The number of people leaving the labor market and entering the stock of disability allowance recipients (z_t) depends on the volume of employment at the end of the preceding period (e_{t-1}) . It is assumed that each year a certain proportion of the employed persons starts receiving benefits while this proportion depends on the unemployment rate u_t :

$$(10) \quad z_t = \left[\beta_2 + \beta_3 \left(\frac{u_{t-1}}{1 - u_{t-1}} \right) \right] e_{t-1}$$

so that

$$(11) \quad z_t = \beta_2 e_{t-1} + \beta_3 p_{t-1}$$

with p_{t-1} the number of unemployed at the end of year $t - 1$.

Next, it is assumed that each year a constant fraction of the number of people in the stock of disability allowance recipients leaves the stock:

$$(12) \quad q_t = \gamma w_{t-1}$$

Thus, by substituting (11) and (12) into (9), one obtains the final model:

$$(13) \quad w_t = \beta_1 w_{t-1} + \beta_2 e_{t-1} + \beta_3 p_{t-1} + \epsilon_t$$

where $\beta_1 = 1 - \gamma$, and ϵ_t is a disturbance term (normally distributed with zero mean) also indicating omitted variables. Clearly, all parameters are assumed to be positive with β_1 smaller than 1.

5.2 Testing the Level of Spatial Aggregation

The estimation of relationship (13) has been carried out successively at three spatial levels: country, provinces (12), and counties (40) (so-called COROP areas). Regional data on the response variable was only available for the years 1977–1981. Thus, on a time-series basis the three parameters in (13) can only be estimated on the basis of four observations, implying only one degree of freedom. It is thus no wonder that the results lead to very high outcomes for the coefficients of determination, R^2 , and that statistically significant results are rare. The OLS estimation results for the parameters at the national level are included in Table 1a. The parameters appear to have the right sign but are not significant at a 5 percent confidence level. The outcome for β_3 is remarkably low; it suggests that the

TABLE 1a: Estimated Parameter Values at National Level with Standard Errors in Parentheses

	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	R^2
The Netherlands	0.577 (0.213)	0.063 (0.025)	0.049 (0.074)	0.992

unemployment level has only a minor impact on the number of persons receiving disability allowances.

The OLS estimation results of parameters at the provincial and county level—based on a combined cross-section/time-series approach—are given in Tables 1b and 1c, respectively. For precise details on the regional subdivisions, the reader is referred to Nijkamp, Rietveld, and Rima (1983). The estimated parameter values at both the provincial level (Table 1b) and at the county level (Table 1c) are in many cases significantly different from those at the national level (Table 1a). This, in general, holds true for β_1 , β_2 , and β_3 . One of the conditions for perfect aggregation in a linear regression model is that the parameter values are equal for each aggregation level. As this is not the case in our empirical example, the condition of perfect aggregation is not satisfied.

Having now analyzed the sensitivity of the results for different spatial scales, we will now test their goodness-of-fit to national totals. In particular, it is interesting to examine the extent to which a disaggregate approach leads to more satisfactory projections of the response variable than the macro approach. In that case, the values of the response variable have to be calculated by substituting the estimated parameter values $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ into (13):

$$(14) \quad \hat{w}_t = \hat{\beta}_1 w_{t-1} + \hat{\beta}_2 w_{t-1} + \hat{\beta}_3 w_{t-1}$$

for each of the four periods and each spatial level. The computed outcomes at the national, provincial, and county levels will be denoted as $\hat{w}_t^n$, $\hat{w}_t^{pi}$, and $\hat{w}_t^{cj}$, respectively.

Next, the values of $\hat{w}_t^n$, $\sum_{i=1}^{12} \hat{w}_t^{pi}$, and $\sum_{j=1}^{40} \hat{w}_t^{cj}$ have to be compared with the observed outcomes w_t^n in order to investigate whether a disaggregate approach yields better results. The results are summarized in Table 2 for the four periods concerned. The table shows that in three out of four cases the computed values based on data from a county level lead to more satisfactory results, followed by the results on the provincial level and finally the results on the national level. The

TABLE 1b: Estimated Parameter Values at Provincial Level with
Standard Errors in Parentheses

Province	$\hat{\beta}_1$		$\hat{\beta}_2$		$\hat{\beta}_3$		R^2
1	0.106	(0.144)	0.146	(0.021)	0.187	(0.046)	0.997
2	-0.168	(0.410)	0.172	(0.056)	0.203	(0.092)	0.984
3	0.325	(0.114)	0.127	(0.018)	0.150	(0.040)	0.998
4	-2.697	(1.806)	0.522	(0.251)	0.997	(0.503)	0.982
5	0.379	(0.200)	0.096	(0.026)	0.080	(0.060)	0.991
6	0.505	(0.236)	0.069	(0.026)	0.032	(0.110)	0.971
7	0.614	(0.141)	0.057	(0.016)	0.045	(0.071)	0.991
8	0.424	(0.231)	0.060	(0.020)	0.062	(0.076)	0.981
9	0.787	(0.482)	0.030	(0.040)	0.030	(0.249)	0.971
10	0.622	(0.144)	0.057	(0.016)	0.040	(0.040)	0.998
11	1.040	(0.274)	0.017	(0.047)	-0.139	(0.121)	0.993
12	0.455	(0.166)	0.069	(0.012)	0.258	(0.092)	0.998

TABLE 1c: Estimated Parameter Values at County Level with Standard Errors in Parentheses

County	$\hat{\beta}_1$		$\hat{\beta}_2$		$\hat{\beta}_3$		R^2
1	0.389	(0.111)	0.146	(0.023)	0.236	(0.061)	0.994
2	0.365	(0.135)	0.105	(0.019)	0.165	(0.053)	0.999
3	-0.364	(0.071)	0.186	(0.009)	0.194	(0.015)	1.000
4	0.190	(0.509)	0.111	(0.063)	0.124	(0.107)	0.981
5	0.178	(0.237)	0.124	(0.031)	0.206	(0.084)	0.976
6	-0.337	(0.804)	0.234	(0.133)	0.183	(0.147)	0.939
7	0.133	(0.110)	0.172	(0.020)	0.139	(0.026)	0.999
8	0.459	(0.136)	0.107	(0.021)	0.094	(0.053)	0.993
9	0.172	(0.568)	0.138	(0.084)	0.273	(0.239)	0.945
10	-0.338	(0.240)	0.176	(0.030)	0.192	(0.054)	0.987
11	-0.010	(0.577)	0.145	(0.078)	0.103	(0.095)	0.974
12	-1.674	(0.338)	0.407	(0.051)	0.903	(0.117)	0.994
13	0.116	(0.213)	0.132	(0.029)	0.148	(0.056)	0.996
14	0.327	(0.336)	0.102	(0.045)	0.141	(0.109)	0.991
15	0.433	(0.188)	0.088	(0.023)	0.050	(0.060)	0.981
16	0.566	(0.043)	0.084	(0.006)	0.003	(0.013)	1.000
17	0.505	(0.236)	0.069	(0.026)	0.032	(0.110)	0.971
18	0.473	(0.000)	0.083	(0.000)	0.123	(0.000)	1.000
19	0.604	(0.047)	0.063	(0.006)	0.084	(0.016)	1.000
20	1.090	(0.236)	-0.001	(0.022)	-0.032	(0.139)	0.991
21	0.443	(0.153)	0.104	(0.023)	0.038	(0.118)	0.951
22	0.937	(0.144)	0.026	(0.015)	-0.115	(0.104)	0.991
23	0.547	(0.142)	0.061	(0.014)	0.037	(0.074)	0.989
24	0.819	(0.001)	0.032	(0.000)	-0.045	(0.001)	1.000
25	0.095	(0.128)	0.111	(0.014)	0.111	(0.037)	0.994
26	-0.058	(0.341)	0.103	(0.029)	0.107	(0.122)	0.859
27	0.610	(0.182)	0.038	(0.013)	0.023	(0.103)	0.974
28	0.549	(0.182)	0.044	(0.014)	0.102	(0.061)	0.997
29	0.698	(0.175)	0.034	(0.015)	0.010	(0.050)	0.991
30	0.479	(0.171)	0.062	(0.016)	0.061	(0.070)	0.993
31	0.968	(0.409)	0.020	(0.032)	-0.116	(0.263)	0.979
32	0.683	(0.515)	0.036	(0.045)	0.091	(0.213)	0.970
33	0.696	(0.186)	0.044	(0.021)	0.040	(0.043)	0.998
34	0.490	(0.085)	0.075	(0.009)	0.062	(0.031)	0.998
35	0.508	(0.181)	0.075	(0.021)	0.063	(0.057)	0.995
36	1.114	(0.077)	-0.006	(0.009)	-0.078	(0.020)	1.000
37	2.025	(0.023)	-0.127	(0.003)	-0.490	(0.007)	1.000
38	1.130	(2.695)	-0.000	(0.473)	-0.168	(0.503)	0.932
39	0.715	(0.475)	0.070	(0.083)	0.082	(0.308)	0.962
40	0.445	(0.166)	0.069	(0.012)	0.258	(0.092)	0.998

mean absolute error for the differences between projections and observations on the national level is 2211. For the provincial and county levels, this error is 2075 and 1937, respectively. Consequently, the mean absolute error can be reduced by approximately 6.5 percent by disaggregating towards the provincial level and another 6.5 percent when the county level is used. Thus, by using disaggregate data one may obtain better projections of a response variable on an aggregate level. This

TABLE 2: Comparison of Actual Figures and Computed Figures for Three Types of Areal Units

	1978	1979	1980	1981
w_t^n	557,493	586,327	618,201	635,904
$w_t^n - \hat{w}_t^n$	22	-2,861	4,375	-1,588
$w_t^n - \sum_{i=1}^{12} \hat{w}_t^{pi}$	31	-2,777	4,105	-1,393
$w_t^n - \sum_{j=1}^{40} \hat{w}_t^{sj}$	77	-2,618	3,787	-1,261

is also confirmed by confronting projections for the year 1982 with realized figures. The county results appeared to lead to better projections than the provincial results (although the national results scored in this case even better, but given the statistical basis of the national projections this is not a serious problem). Comparable results have also been found by Charney and Taylor (1983).

In the next section, the spatial dynamic structure of model (13) will be investigated, given the suitable spatial level of aggregation identified in the present section (i.e., the county level).

5.3 Testing the Spatial Dynamic Structure

In this subsection the stock model (13) will be further analyzed for one specific year, viz., 1981. Let us assume that the following model is the true model at the spatial scale of a county (referred to as model M_0 hereafter):

$$(15) \quad \begin{matrix} w_t & = & \beta_1 w_{t-1} & + & \beta_2 e_{t-1} & + & \beta_3 p_{t-1} & + & \epsilon_t \\ (R \times 1) & & (R \times 1) & & (R \times 1) & & (R \times 1) & & (R \times 1) \end{matrix}$$

If this hypothesis is correct, then M_0 should be accepted using the specification procedures introduced in Section 4.

The following model is now chosen as the maintained hypothesis (model M , say):

$$(16) \quad \begin{matrix} Y & = & Z & \gamma & + & V \\ (R \times 1) & & (R \times K) & (K \times 1) & & (R \times 1) \end{matrix}$$

in which $Y = w_t$; $Z = [\iota Y_{-1} Y_1 X X_1]$; $Y_1 = [W^2 Y WY W^2 Y_{-1} WY_{-1}]$; $X = [e_{t-1} p_{t-1}]$; $X_1 = [W^2 X WX]$; $\gamma = (\gamma_0 \gamma_1 \gamma_2 \gamma_3 \gamma_4 \gamma_5 \gamma_6 \gamma_7 \gamma_8 \gamma_9 \gamma_{10} \gamma_{11})^T$ (i.e., a vector with $K = 12$ parameters to be estimated); $V \sim NID(0, \sigma_v^2)$; W^s a spatial lag operator of order s ; $\iota = (1, \dots, 1)^T$; and $R (= 40)$ the number of spatial observations.

It is worth noting that, in light of the outcomes from Section 5.2 (especially Table 1c), it is necessary to take into account the heterogeneity in the spatial structure, i.e., the spatial (structural) differences among the 40 counties. In the absence of precise theoretical information, a parsimonious way of representing this heterogeneity is a spatial lag operator specification.

TABLE 3: Estimated Spatial Stock-flow Models for Analyzing Disability Allowance Recipients in The Netherlands

Model	M	M_0	M_1	M_2	M_3
γ_0	+97.998	—	—	—	—
γ_1	+ 1.030	+1.030	+1.08	+1.031	+1.031
γ_2	- 0.390	—	—	—	+0.005
γ_3	+ 0.150	—	+0.070	—	—
γ_4	+ 0.405	—	—	+0.008	—
γ_5	- 0.153	—	-0.066	+0.001	—
γ_6	- 0.002	-0.002	-0.002	-0.003	-0.003
γ_7	+ 0.017	+0.005	+0.019	+0.018	+0.018
γ_8	+ 0.001	—	—	+0.001	+0.002
γ_9	- 0.016	—	—	-0.032	-0.031
γ_{10}	+ 0.001	—	+0.001	+0.001	+0.001
γ_{11}	- 0.022	—	-0.036	-0.012	-0.013

In addition to the considerations which led to the specification of model M_0 , the significance of spatial interaction (or contiguity) effects will be investigated with the help of model M . It is hypothesized—on the basis of the theoretical grounds discussed at the beginning of this section—that $\gamma_0 = 0$ and all other coefficients are positive. Since a theoretical basis for deciding upon a precise specification of the spatial interactions is not available, we start our specification analysis by including both first-order ($s = 1$) and second-order ($s = 2$) Boolean contiguity matrices [see also Cliff and Ord (1973), Hordijk (1979), and Hordijk and Nijkamp (1979)]. Using the ECONFAC framework (see Section 4) the following hypotheses⁶ are investigated:

M_0 : $\gamma_0 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = \gamma_8 = \gamma_9 = \gamma_{10} = \gamma_{11} = 0$ (absence of spatial interaction);

M_1 : $\gamma_0 = \gamma_2 = \gamma_4 = \gamma_8 = \gamma_9 = 0$ (absence of second-order effects);

M_2 : $\gamma_0 = \gamma_2 = \gamma_3 = 0$ (absence of instantaneous spatial interaction); and

M_3 : $\gamma_0 = \gamma_4 = \gamma_5 = 0$ (absence of lagged endogenous spatial interaction).

The point estimates $\hat{\gamma}_i$ for the models M_0 , M_1 , and M_3 are calculated using a generalization of a search procedure proposed by Ord (1975) for obtaining ML-estimates in first-order spatial interaction models [see Blommestein (1983a)]. The results are included in Table 3.

The following additional results and comments on the results from Table 3 are most relevant in the present context:

1. Model M_0 is to be rejected (at least at a conventional level of significance) according to both a specification test (likelihood-ratio) and misspecification tests

⁶It is not claimed here that these hypotheses have a profound theoretical foundation, i.e., that they represent the predictions of (possibly competing) clearly defined, alternative theories. However, spatial interaction effects, or their absence, embody distinctive conceptual (e.g., behavioral) characteristics [see, e.g., Bennett and Chorley (1978); Cliff and Ord (1981)]. In our case, it was decided to represent the heterogeneity of the spatial structure by means of a spatial lag operator. The view that a basic element of spatial analysis is the potential interaction between spatial structure and the behavior of actors, clarifies why the models $M_0, \dots, M_3$ have a certain theoretical significance.

for the detection of spatial autocorrelation [see Blommestein (1983b) for an elaboration on the use of (mis)specification tests in spatial econometric model-building).

2. Model M_1 cannot be rejected (i.e., vis-à-vis model M) according to the likelihood ratio test statistic. The models M_2 and M_3 are both rejected (vis-à-vis M).

3. The precision of the estimated parameters is (surprisingly) high: except for γ_2 , γ_3 , and γ_5 , both the sign and magnitude of the parameters are stable across the various specifications. In most cases (except for γ_4 , γ_5 in model M_2 , and γ_2 , γ_3 in M_3) the parameters are significant. Standard errors (not shown here) were calculated using the asymptotic covariance matrix derived in Blommestein (1983a).

4. The steady-state solutions of all models are explosive ($\gamma_1 > 1$). Moreover, $\gamma_6 < 0$, which is not predicted by theory (see above).

5. The residuals of model M_1 still exhibit significant spatial autocorrelation, according to spatial correlograms of the residuals. Consequently, in this case spatial correlation analysis is a logical follow-up of specification analysis [see Folmer and Nijkamp (1984)].

6. The problem of circular routes in higher-order spatial lag operators, i.e., W^s for $s \geq 2$, has been taken into account by means of the approach presented in Blommestein (forthcoming).

Spatially autocorrelated residuals, and the fact that $\gamma_1 > 1$, lead to the provisional conclusion that model M_1 is, to a certain extent, still misspecified. Therefore, one of the next steps in future research in specification analysis should be a systematic investigation of both temporal and spatial dynamics, based on an integrated spatio-temporal search procedure.

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