Applied Economics, 1988, **20**, 969–984

Disaggregation of the demand for hospital care

R. C. J. A. VAN VLIET* and E. K. A. VAN DOORSLAER‡

**Erasmus University, Econometric Institute, Rotterdam, The Netherlands* and ‡*University of Limburg, Department of Health Economics, Maastricht, The Netherlands*

I. INTRODUCTION

In many fields of economics, researchers have been forced to test their theoretical models of individual behaviour on aggregate data because of lack of individual data. However, the aggregation level of data can have a strong influence on the results of empirical econometric research. It is not surprising then that the theoretical problems associated with aggregation have received a great deal of attention among econometricians (see, e.g. Theil, 1954; Green, 1964; or Van Daal and Merkies, 1984).

In this article we want to confront some of the results of the theoretical literature on aggregation with the empirical consequences of aggregation in the context of the analysis of demand for hospital care. There has been an evolution in the estimation of hospital demand functions from macro to micro studies which has resulted in diverging findings. Most studies of aggregate demand at the regional level estimated extremely large effects of hospital bed supply whereas studies based on individual data typically found health status to have a dominant influence on hospital utilization. Very often, comparison of these studies is difficult because different data sources and model specifications have been used. In this article, we will estimate the *same* demand functions on both the macro and micro level using one data base in order to facilitate comparison.

For this purpose, we use data on some 230 000 individuals who are insured with a private health insurance company in the Netherlands. The empirical analysis presented in Section IV is preceded by a discussion of the peculiarities of hospital demand functions (Section II), and by a theoretical examination of the consequences of aggregation (Section III).

II. THE DEMAND FOR HOSPITAL CARE

Demand functions for hospital care cannot be derived from a straightfoward application of standard consumer theory in the same way as the demand for other goods and services. Feldstein (1977) has argued that in-patient treatment decisions can best be explained by viewing the patient–physician relationship as one of incomplete agency; i.e. treatment decisions do not only reflect the patient's preferences and situation but also physician self-interest, peer pressure and some medical ethical concern. Such 'partially benevolent' behaviour on the part of physicians generates a rather peculiar form of hospital care demand functions: apart from relative prices, income and 'taste' variables – i.e. the 'usual' demand variables – a vector of supply measures is added to reflect this direct influence of physician-

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agents on demand. The resulting empirical demand equation in a general implicit form then looks as follows (Pauly, 1980):

$$Q_D = D(P, X, Z)$$

where quantity demanded, Q_D, is measured by admissions and length of stay once admitted to the hospital, P is a vector of relevant user money and time prices, X includes other individual demand determinants such as income, health status, insurance coverage, and family size, and the Z vector represents a number of regional availability indicators of hospital beds and physicians.

Pauly (1980) has pointed out that an empirically estimated availability effect of the number of hospital beds or physicians per capita on the admission rate or length of hospital stay does not necessarily imply that suppliers create demand for their own services. One other explanation is chronic excess demand which allows for non-price rationing of services. Secondly, the effect of availability may also represent the response of use to changes in the time or convenience cost of care. And finally, regional supply of facilities may not be exogenous but may also be related to levels of demand in the past. This identification problem can be resolved by using predicted values of the supply variables in a two-stage procedure (see, e.g. Fuchs and Kramer, 1973) but this method breaks down because it is difficult to find 'truly exogenous' variables to explain supply. Pauly (1980) therefore suggests we avoid the use of aggregate data and use individual observations instead. It is, of course, unlikely that regional quantities of beds or physicians will respond to individual demand.

In this article, we do not want to settle the issue of whether or not demand creation is the theoretical explanation for the observed availability effects. We rather want to illustrate the impact of aggregation by analysing the same data set at both the macro and micro level.

A clear example of diverging findings from micro and macro analyses in the present context, is provided by some American studies. Analysing the 1970 US Health Interview Survey, Pauly (1980) concluded that the number of hospital episodes of individuals in a year and their length of stay when hospitalized are hardly affected by the availability of hospital beds, and not at all by the measures of physician availability. Health status appeared to be the primary determinant of use. The former conclusion is consistent with similar findings in the micro study of May (1975) but sharply contrasts with the results of all macro studies on hospital demand. Fuchs (1978), for instance, analysed the same data as Pauly but aggregated it to regional rates. He estimated an elasticity of 0.3 of surgery rates with respect to surgeon availability. Pauly suggests that, apart from aggregation effects, omitted variable bias (especially lack of health status measures) may also account for this finding.

Practically all studies of demand for hospital care in the Netherlands have used aggregate regional data on utilization rates in the 1960s or early 1970s (see Van Doorslaer and Van Vliet, 1986, for a survey). At that time, the government used a 90% occupancy rate requirement to determine hospital tariffs. This requirement, which has been abolished since the mid-1970s, may have contributed to the extremely high bed elasticities which were estimated, *ceteris paribus*, in most of these studies: on average 0.6 for admission rates and 0.3 for mean length of hospital stay. Similar figures were found for the USA and Britain (see, e.g. Cullis *et al.*, 1979; Van Doorslaer and Van Vliet, 1987). Availability of medical specialists was most times estimated to have rather small, negative but rarely significant effects on admission rates and length of stay.

Because our analysis is based on Dutch data it is useful to point out briefly a few characteristics of the Dutch health care system. Until 1986, about 70% of the population was

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voluntarily or compulsorily insured with the semi-public sickfunds whereas most of the other 30% bought private insurance coverage (in 1986, the voluntary sickfund insurance was abolished). The distinction between the two schemes is mainly based on income: the privately insured roughly constitute the upper three deciles of the income distribution. They can choose between a variety of insurance options including various degrees of cost-sharing with associated premium reductions, whereas the publicly insured have complete coverage for most types of medical services. General practitioners are paid on a capitation basis for public and on a fee-for-service basis for private patients. Specialists are usually affiliated with one or more hospitals and remunerated fee-for-service, private fees being on average about twice as high as public fees. Since 1983, the output-based per diem financing of the hospitals has been supplemented by prospective reimbursement with fixed budgets per hospital.

Before we present the empirical results of our attempt to disaggregate the hospital demand functions, we will first discuss some theoretical consequences of aggregation in the next section.

III. AGGREGATION OF INDIVIDUAL VERSUS CONTEXTUAL VARIABLES

In the previous section, we pointed out that empirical demand functions for hospital care should contain, apart from the usual set of demand-determining variables, also a number of so-called availability indicators like regional bed and specialist density. These variables, which can only be defined on a regional level without direct equivalents on the individual level, are sometimes called 'contextual' (see, e.g. Langbein and Lichtman, 1978). The distinction between contextual and non-contextual (or individual) variables is important because the implications of aggregation are markedly different. We will subsequently discuss the consequences of aggregation for the measures of association, aggregation and specification bias, precision of estimates and consistency of regression results on both the micro and macro levels.

Measures of association

Because contextual variables do not vary between individuals within the same region, the within-region variance is zero and the total variance is equal to the variance between the regions (when weighted with the size of the region). This implies that grouping individual observations to the regional level in question (e.g. by taking arithmetic means), does not change the variances of the contextual variables, and that covariances of these variables with other (non-contextual) variables are not affected. Consequently, correlations between contextual and non-contextual variables increase when going from micro to macro level. This is not necessarily true for correlations between non-contextual variables which may increase, decrease, or remain invariant.

In general, it can be shown that grouping tends to inflate standardized measures of association for contextual variables (see also Cramer, 1964). Therefore, correlation coefficients, R^2's and beta-weights are not well suited for cross-level comparisons. The elasticity figure, on the other hand, which is independent of both the unit of measurement and the level of aggregation, seems to be the most relevant statistic to use in cross-study comparisons when the aggregation levels of the data vary widely.

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Aggregation and specification bias

The above conclusions imply that if we regress a non-contextual variable y on a contextual variable z, then the (OLS) regression coefficient $\hat{\beta}_z$ determined by estimating this equation on the micro level, is equal to the (WLS) coefficient $\hat{\bar{\beta}}_z$ obtained on the macro level. Thus, no aggregation bias can occur for contextual variables in a bivariate regression equation. It can be shown that this conclusion also holds for the multivariate regression equation *if* all explanatory variables are contextual. If, however, the explanatory variable (say x) is defined on the individual level then the relationship between $\hat{\beta}_x$ and $\hat{\bar{\beta}}_x$ will depend on the relative changes of cov (x, y) and var (x) due to grouping.[1]

In this particular case, the distinction between aggregation and specification bias can be described as follows: aggregation error arises if the expected value of $\hat{\bar{\beta}}_x$ differs from the expected value of $\hat{\beta}_x$ while no relevant explanatory variables are omitted. Specification error arises when incorrect specification of the model leads to correlation between the independent variable and the error term (e.g. omitted variable bias).

In general the expected values of these estimators can be written as

$$E(\hat{\beta}_x) = \beta_x + \frac{\text{cov}\,(x, \varepsilon)}{\text{var}\,(x)} \quad \text{and} \tag{1}$$

$$E(\hat{\bar{\beta}}_x) = \beta_x + \frac{\text{cov}\,(\bar{x}, \bar{\varepsilon})}{\text{var}\,(\bar{x})} \tag{2}$$

where ε denotes the regression error term at the micro level while $\bar{x}$ and $\bar{\varepsilon}$ are the equivalents of x and ε at the macro level. It is only when both the aggregate and individual level models are specified correctly, i.e. when cov $(x, \varepsilon) = 0$ and cov $(\bar{x}, \bar{\varepsilon}) = 0$, that the estimators are unbiased. Because, for a contextual variable, cov $(z, \varepsilon) =$ cov $(\bar{z}, \bar{\varepsilon})$ the direction of any specification bias is the same at both levels of aggregation. This result does not necessarily hold for the bivariate regression coefficients of the non-contextual variables. Aggregation bias in this case equals the difference between cov (x, ε)/var (x) and cov $(\bar{x}, \bar{\varepsilon})$/var $(\bar{x})$. Only when the specification biases are equal, is there no aggregation bias. However, it is also obvious that aggregation can either increase or decrease total specification bias depending on the relative changes of cov (x, ε) and var $(\bar{x})$ due to grouping.

This means that in the case of misspecified models involving non-contextual explanatory variables, it is impossible to say *a priori* whether aggregation will result in a gain or loss. The danger of this type of bias is that on the basis of aggregate analysis erroneous inferences are made about individual behavioural relationships. This risk of 'ecological fallacy' can be avoided by refraining from cross-level inference and restricting conclusions to the macro relations only.

Efficiency of estimators

Because grouping involves the loss of the information contained in the within-group variation of the observations, it is clear that we can expect some loss of efficiency in going

[1] In an extreme case, when grouping is done according to the values of the dependent variable y (i.e. for each value of y a separate group is used), it can be shown that $\hat{\bar{\beta}}_x \geqslant \hat{\beta}_x$. This means that the aggregation bias increases with the within-group variance of x. In fact, by grouping according to y, a correlation between x and ε is actually produced at the aggregated level and causes specification error (cf. Langbein and Lichtman, 1978).

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from estimation on all individual observations to estimation based on group means, i.e. var $(\hat{\beta}_x) \leqslant$ var $(\hat{\bar{\beta}}_x)$ in a bivariate regression (see, e.g. Johnston, 1972, p. 231). The equality only holds when there is no within-group variation, i.e. when the explanatory variable is contextual.

If we have one contextual and one non-contextual explanatory variable, it can be shown that the relative efficiency loss for the former is smaller than for the latter variable (see for proof Van Vliet and Van Doorslaer, 1987). This result can be generalized to situations where we have several contextual variables and one individual variable.

Consistent aggregation

Estimating relations describing micro behaviour (like hospital care utilization) by means of aggregate data requires consistent aggregation (Van Daal and Merkies, 1984). This means that the macro relations have to be derived from the corresponding micro relations using the same aggregation formula (e.g. the arithmetic means in the preceding sections) for all variables in the equation. The problem is that, in most of the earlier studies of the demand for hospital care, log-linear equations have been estimated with regional arithmetic averages (e.g. Feldstein, 1977; and the Dutch studies alluded to in Section II). But the logarithm of an arithmetic average cannot be disaggregated to any meaningful micro equivalent. If the individual level equation is assumed to be log-linear, then the aggregates have to be defined as *geometric* rather than arithmetic averages. Because the purpose of this paper is to explore the consequences of disaggregation while maximizing the comparability of our results to previous studies we will pursue both approaches in the empirical analysis which follows.

IV. EMPIRICAL ANALYSIS

In order to investigate empirically the consequences of aggregation in the context of the demand for hospital care, we have estimated a number of equations relating admission probability and length of hospital stay to various sets of explanatory variables.[2] The estimations are performed on both the individual data and on an aggregate level.[3] A two-way stepwise procedure will enable us to discriminate between aggregation and specification effects (i.e. omitted variable bias). In this section, we first describe the estimation techniques and the data. Subsequently the estimation results are presented and discussed.

[2]This implies that we do not consider the quality and multi-product nature of hospital output (Steele and Gray, 1982).

[3]Before starting an analysis of hospital utilization, one should try to answer the following question: What is the appropriate level on which to perform the analysis? There are, in principle, four observation levels which can be considered in this case: the patient, the specialist, the hospital, and some geographical level, the choice depending on the data availability and the study objective. Since it is virtually impossible to define unambiguously the service areas of specialists and hospitals and because thus the capacity effects cannot be estimated on these two levels, only the patient and geographic levels are considered in the present study.

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Model specification

We intend to investigate the following four relations on a micro as well as macro level:

$$DADM = f_1(Z, X_1, X_2), \tag{3}$$

$$DADM = f_2(Z, X_1, X_2, X_3, X_4), \tag{4}$$

$$LOS = f_3(Z, X_1, X_2) \tag{5}$$

$$LOS = f_4(Z, X_1, X_2, X_3, X_5), \tag{6}$$

where $DADM$ (at the micro level) is a dummy variable indicating whether or not an individual was admitted to a short-stay hospital at least once in 1984; LOS denotes the length of stay in a short-term hospital once the individual is hospitalized; the vector Z contains information on regional hospital capacity; X_1 and X_2 comprise variables commonly used in macro studies on hospital demand, whereas X_3–X_5 are in principle only available on individual levels (cf. Table 1). Differences between the micro and macro results for these equations will provide indications as to the consequences of *aggregation bias*. The availability of variables X_3–X_5 in our data sets permits an investigation into the extent of *omitted variable bias*. This can be assessed by comparing the estimation results of Equations 3 and 4, and those of Equations 5 and 6.

In order to maximize comparability with previous studies on demand for hospital care we have used the following specifications for the estimation of Equations 3–6:

1 The functions f_i are assumed to be linear in the coefficients.
2 Logarithmic transformations are used of those variables which are on the micro level more or less continuous (length of stay included).
3 In principle, arithmetic (instead of geometric) means are used on the macro level for the variables which are to be transformed, i.e. $\log(\bar{x})$ is used and not $\overline{\log(x)}$. (We will investigate the empirical consequences of this choice below.)
4 For the estimation of the relations (3)–(6) on micro data the least squares method (LS) is used: OLS for (5) and (6), and WLS for (3) and (4). WLS is used in order to correct for the endogenous stratification procedure (see next Section for details).
5 On the macro level the relations are estimated by means of WLS in order to adjust for the number of observations per region and to avoid heteroskedasticity.

Description of data sets and variables

For the empirical analysis in this article we use data sets obtained from the Dutch private health insurance company Zilveren Kruis which were supplemented with data on regional characteristics such as supply of physicians and hospital beds. The basic data files include, for each of the 230 000 insured individuals, information on insurance coverage, age, sex, family size, place of residence, reimbursed medical expenses and hospital admissions in 1983 and 1984. From these data files an admission data set and a length-of-stay data set were constructed, each of which was subsequently aggregated to a regional level.

The dependent variable in the admission data set is $DADM$. This data set was obtained from the original data files by means of 'endogenous stratification' (Maddala, 1983): half of the data set contains information on all the hospitalized persons (approximately 14 000) while the other half is a random sample (with sampling probability 1/16[4]) of the insured

[4] $1/16 \cong 14\,000/(230\,000 - 14\,000)$.

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Table 1. *Description of the variables*[a]

Variable	Description
Dependent variables:	
DADM	Dummy variable; = 1 if at least one admission in 1984
LOS	Length of hospital stay in days (in 1983 or 1984)
Explanatory variables: Equations 3 and 5	
Hospital capacity (Z)	
BED	Number of hospital beds in COROP region per 10 000 population
SPEC	Number of specialists in COROP region per 10 000 population
Regional variables (X_1)	
DIST	Distance from place of residence to nearest hospital (in km)
SF	% of inhabitants who are publicly insured (Holland divided in 24 regions)
GP	Number of GP's per 1 000 population (Holland divided into 180 regions)
Expected consumption (X_2)	
EXDAM	Expected admission probability based on age and sex
EXLOS	Expected length of stay based on age and sex
Additional explanatory variables: Equations 4 and 6	
Individual background characteristics (X_3)	
IGP	Dummy variable; = 1 if person has insurance coverage for costs of care provided by GP's
IDED	Deductible amount for all medical expenses per family per year
IHCL	Dummy variable; = 1 if coverage for more luxury facilities in case of hospitalization
FSIZE	Family size
Admission-specific variables (X_4)	
MED83	Amount of reimbursed health care expenditures in 1983
NADM83	Number of hospital admissions in 1983
Length-of-stay-specific variables (X_5)	
EXLOSD	Expected length of stay based on the admission diagnosis
DMND	Dummy variable; = 1 if discharged on Monday
DFRST	Dummy variable; = 1 if admitted on Friday or Saturday
DSURG	Dummy variable; = 1 if surgically treated
DTWSP	Dummy variable; = 1 if treated by two specialists

[a]The variables which are on the individual level (more or less) continuous have been logarithmically transformed with the exception of *EXDADM*.

persons who were not hospitalized. The reason for this stratification is twofold. First, a multivariate regression analysis on all 230 000 observations exceeds normal computer capacity. Secondly, when the mean of a dependent dichotomous variable is close to 0.5, the least squares method provides an acceptable alternative for theoretically more appropriate methods, such as Logit and Probit. When the mean is close to 1 or 0, as is the case in our

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original data file, the least squares method may produce estimated probabilities above 1 or below 0 (Amemiya, 1981). Of course, the estimation procedure has to be adjusted for this stratification. This was achieved by employing weighted least squares, weights being equal to 1 for hospitalized persons and 16 for those not hospitalized.

The length-of-stay data set contains information on all hospital admissions of the insured individuals in 1983 and 1984. These years were combined in order to obtain for each region a reasonable number of observations, which is important for getting reliable regional averages of the dependent and independent variables to be used in the analysis on aggregate data.

The information in the two above-described data sets was aggregated to the so-called COROP regions which provide a geographical division of the Netherlands into 40 regions situated around primary and secondary regional centres. For the length-of-stay data set, the aggregation amounted to computing the arithmetic means of all variables per region. For the aggregation of the admission data set weighted means were computed, weights being equal to 1 for hospitalized persons and 16 for those not hospitalized. The number of observations per region varies approximately between 20 and 4 000 for both data sets.

The explanatory variables to be used in the equations are grouped into six categories (see Table 1): number of hospital beds and medical specialists per 10 000 inhabitants in the COROP area of residence; other regional variables; expected utilization on the basis of age and sex; individual background characteristics; admission-specific variables; and length-of-stay-specific variables.

The *regional variables* are the distance to the nearest hospital (*DIST*), which is used as an indicator of time price; the percentage publicly insured in the region (*SF*), which affects the proportion of the supply capacity available to the privately insured; and the supply of general practitioners (*GP*) which can be seen as a substitute for hospital care (cf. Feldstein, 1977).

The *expected utilization* based on age and sex is often used in macro studies in order to control for health status differences between regions, the age–sex distribution per region being practically the only health-related indicator available at regional levels. The expected admission probability (*EXADM*) is, for each person, defined as the proportion of all insured in the same age–sex group who have been admitted to a hospital. The expected length of stay (*EXLOS*) is defined analogously.[5]

The category of *individual background characteristics* comprises three insurance coverage variables (*IGP*, *IDED*, *IHCL*) and family size (*FSIZE*). Insurance coverage is, of course, important because it reduces out-of-pocket prices. In so far as home care can be a substitute for hospital care and family size is a proxy for home care possibilities, family size can be expected to affect demand for hospital care negatively.

The *admission-specific variables* are two indicators of medical consumption in the preceding year and thereby indicators of health status: total amount of reimbursed medical expenses (*MED*83) and number of hospital admissions (*NADM*83).[6]

The *length-of-stay-specific* variables are the expected length of stay on the basis of the

[5] In other studies the coefficients of these variables were sometimes restricted to be equal to their expected value of 1 (cf. e.g. Feldstein, 1977). We preferred to test this hypothesis. Furthermore, it turned out that this method of controlling for age–sex differences was empirically equivalent to including a fifth-degree polynomial in age and interaction terms with a sex dummy.

[6] The X_4-variables *MED83* and *NADM83* are, of course, affected to some extent by the supply variables already included in Equation 3, so the coefficients of the latter variables might be biased in Equation 4. The fact that no major changes occurred in the estimated supply effects when *MED83* and *NADM83* were added seems to suggest, however, that this endogeneity has no serious consequences.

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admission diagnosis (*EXLOSD*) and four other variables related to the hospital stay (*DMND*, *DFRST*, *DSURG*, *DTWSP*). The former variable is defined as the average length of stay in Holland for the diagnosis with which the patient is admitted to the hospital, thereby also distinguishing between the specialties of the attending specialists. This variable is supposed to measure case-severity. The other variables are indicators of both health status and treatment policies of the hospital and the attending specialist. They have been shown to affect length of stay considerably (see, e.g. Cannoodt and Knickman, 1984).

The most important – from a demand point of view – variable which seems to be missing in our data sets is (family) income (see Section II). This variable has, however, no particular relevance in the present analysis because, due to the comprehensiveness of insurance coverage in Holland, the money-prices for hospital care faced by most of the consumers are virtually zero. In Table 2 the mean values and variances are reported of the above mentioned variables.

Table 2. *Means and variances* [a]

Variable	Mean [b]	Total variance [c]	Between-variance as % of total variance
DADM	0.063	0.059	0.25
LOS	2.057	0.793	1.83
BED	3.907	0.019	100.00
SPEC	1.911	0.058	100.00
DIST	1.496	0.630	16.05
SF	4.170	0.002	85.98
GP	− 1.038	0.017	59.27
EXDADM	0.063	0.001	4.82
EXLOS	2.407	0.117	8.14
IGP	0.274	0.200	4.39
IDED	2.229	9.395	6.10
IHCL	0.110	0.098	2.76
FSIZE	0.994	0.335	3.81
MED83	2.166	9.261	1.09
NADM83	0.051	0.040	10.04
EXLOSD	2.295	0.394	1.59
DMND	0.116	0.103	0.15
DFRST	0.151	0.128	0.13
DSURG	0.412	0.242	0.60
DTWSP	0.074	0.069	2.48

[a]The number of observations after deletion of missing data is 27094 for the admission-probability data set and 29796 for the length-of-stay data set. For the variables which are contained in both data sets only mean values and variances for the admission data set are presented. The corresponding statistics for the length-of-stay data set do not differ substantially.
The reported statistics are based on (possibly) transformed variables (see specification).
[b]The mean values of the variables in the macro data sets are equal to those in the original micro data sets because the former are in fact weighted means, weights being equal to the number of observations per region.
[c]The total variance of a variable has been computed on the data set with individual information. The between-variance is computed as a weighted variance on the basis of the aggregate data set.

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A remarkable conclusion which emerges from this table is that, as a result of aggregation, 90–99 % of the total variance of those variables which are defined on the individual level, is averaged out. Apparently, the inter-individual variation exceeds the inter-regional by a factor of almost 100. The variances of regional variables (e.g. *SF* and *GP*) are much less reduced, of course. As explained in Section III the contextual nature of bed supply and medical specialists causes their variances to be unaffected by aggregation.

Estimation results

The estimation results of our analysis are reported in Tables 3 and 4. The results with respect to the non-supply variables are, generally speaking, in line with theory and similar findings in the literature.[7] For example, it is found in many studies, the most authoritative being the Rand Health Insurance Experiment (Newhouse *et al.*, 1981; Manning *et al.*, 1987), that the extent of health insurance coverage is an important determinant of health care utilization. In accordance with those studies, we find in the micro version of Equation 5 that people who are insured for the costs of services provided by the GP and those who enjoy more comprehensive coverage for hospital care, have a significantly higher probability of being admitted to a hospital. This effect may not be a pure price effect because it might capture some residual impact of self-selection of the insured in choosing the extent of coverage (see, e.g. Van de Ven and Van Praag, 1981).

As could be expected, *EXADM* and *EXLOS* have coefficients in Equations 3 and 5 close to 1, which are, moreover, highly significant. In Equations 4 and 6 these coefficients are reduced as a result of adding other health-related variables. The estimation results, furthermore, re-emphasize the conclusion that health status is the primary determinant of hospital care utilization.

From Tables 3 and 4 (partial) bed elasticities are calculated which are presented in Table 5 together with the bivariate elasticities. The latter are quite high, which seems to be in accordance with the findings of the supply studies alluded to in Section II. Controlling for relevant explanatory variables, however, causes the bed elasticities with respect to admission probability to become negative in both the micro and macro versions of Equations 3 and 5 which is in contrast to the results of all previous Dutch studies. In another study (Van Doorslaer and Van Vliet, 1987) we argue that the most plausible explanation for this remarkable finding is that structural changes have taken place in the provision of hospital services in Holland since the mid-1970s (see also Section II).

An additional analysis revealed that the disappearance of a positive bed effect on admission probability and the reduced impact on length of stay was almost solely attributable to the inclusion of the expected utilization variables in Equations 3 and 5. This result stresses the importance of controlling for health status. In the remainder of this section we will look at some of the empirical results in more detail and link them with the theoretical implications of aggregation discussed in Section III.

Measures of association. A commonly used measure for the association between two variables is the correlation coefficient. In our data sets the correlations of bed supply with admission probability and length of stay are 0.022 and 0.095 respectively for the micro data

[7]Since we are mainly interested in the effects of supply on hospital utilization, we do not discuss the estimated effects of the other independent variables at length. For more thorough discussions the interested reader is referred to e.g. Andersen *et al.* (1975), Cannoodt and Knickman (1984) and Feldstein (1977).

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Table 3. *Estimation results: admission probability*[a]

	Equation 3				Equation 4			
	Micro		Macro		Micro		Macro	
BED	−0.001	(0.0040)	−0.005	(0.0076)	−0.008[b]	(0.0040)	−0.009	(0.0096)
SPEC	−0.002	(0.0024)	−0.003	(0.0051)	−0.002	(0.0024)	−0.007	(0.0055)
DIST	−0.000	(0.0007)	−0.002	(0.0041)	0.001[b]	(0.0007)	−0.003	(0.0056)
SF	−0.050[b]	(0.0112)	−0.063[b]	(0.0243)	−0.051[b]	(0.0111)	−0.061[b]	(0.0308)
GP	0.011[b]	(0.0042)	0.009	(0.0105)	0.013[b]	(0.0042)	0.018	(0.0167)
EXADM	0.977[b]	(0.0136)	1.054[b]	(0.1575)	0.768[b]	(0.0153)	0.946[b]	(0.2248)
IGP					0.006[b]	(0.0013)	0.014	(0.0174)
IDED					0.000	(0.0002)	0.004	(0.0062)
IHCL					0.003	(0.0017)	−0.003	(0.0431)
FSIZE					−0.004[b]	(0.0010)	0.002	(0.0175)
MED83					0.006[b]	(0.0002)	0.005	(0.0051)
NADM83					0.100[b]	(0.0030)	0.005	(0.0039)
INTERC	0.255[b]	(0.0553)	0.297[b]	(0.1152)	0.258[b]	(0.0548)	0.269	(0.1658)
$\bar{R}^2$	0.025		0.788		0.044		0.780	
F	889.5		25.1		811.4		12.5	

[a]Estimated standard errors are presented in parentheses.
In the last two lines the adjusted R^2-values and the F-values of the equations are reported.
The number of observations is 27 094 for the micro equations and 40 for the macro equations.
See Section IV for the statistical specification of the equations.
[b]Indicates a coefficient which is significantly different from zero (two-tailed t-test, $p < 0.05$).

and 0.522 and 0.711 respectively for the macro data. This clearly illustrates the assertion in Section III that the correlation coefficient is affected by the level of aggregation. The corresponding bivariate *elasticities* are, in contrast, approximately equal as can be seen from the first row of Table 5.

The bottom lines of Tables 3 and 4 show that the fit of the equations is improved by factors ranging from 2.5 to 50 when macro instead of micro data are used. The R^2-values for the length-of-stay equations even reach levels that are rarely encountered in this kind of study. This is mainly due to the inclusion of two comprehensive health indicators, viz. *EXLOS* and *EXLOSD*. Although the coefficients of determination for the micro equations seem to be very low, the F-statistics indicate that they have in fact higher explanatory power than their macro equivalents.

Aggregation and specification bias. If we assume Equations 4 and 6 to be correctly specified then the expected values of the parameter estimators based on the macro data are equal to the corresponding estimators based on the micro data. This implies that the parameter estimates should not be statistically different. Close inspection of Tables 3 and 4 reveals that for the coefficients of the contextual and semi-contextual variables (i.e. hospital capacity (Z) and regional variables (X_1) respectively) this appears to be true. Thus, we do not detect any *aggregation bias* for these variables. The same conclusion holds for Equations 3 and 5.

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Table 4. *Estimation results: length of stay*[a]

	Equation 5				Equation 6			
	Micro		Macro		Micro		Macro	
BED	0.186[b]	(0.0366)	0.226[b]	(0.0785)	0.222[b]	(0.0324)	0.317[b]	(0.0863)
SPEC	0.026	(0.0219)	0.010	(0.0506)	0.025	(0.0194)	0.017	(0.0424)
DIST	0.001	(0.0061)	−0.041	(0.0305)	0.001	(0.0054)	−0.056	(0.0288)
SF	0.212[b]	(0.1026)	0.335	(0.2413)	0.265[b]	(0.0904)	0.257	(0.2264)
GP	0.021	(0.0392)	0.043	(0.1010)	0.042	(0.0348)	0.176	(0.1111)
EXLOS	1.041[b]	(0.0142)	0.972[b]	(0.1434)	0.541[b]	(0.0171)	0.319	(0.2313)
IGP					−0.011	(0.0098)	0.094	(0.1228)
IDED					0.000	(0.0018)	0.021	(0.0449)
IHCL					−0.038[b]	(0.0113)	0.035	(0.1854)
FSIZE					−0.053[b]	(0.0092)	0.454[b]	(0.1458)
EXLOSD					0.661[b]	(0.0074)	1.255[b]	(0.2326)
DMND					0.147[b]	(0.0130)	1.392[b]	(0.6293)
DFRST					0.086[b]	(0.0117)	−0.287	(0.5824)
DSURG					0.083[b]	(0.0089)	−0.260	(0.3092)
DTWSP					0.184[b]	(0.0159)	0.441	(0.3396)
INTERC	−2.088[b]	(0.5101)	−2.118	(1.284)	−2.759[b]	(0.4512)	−4.152[b]	(1.785)
$\bar{R}^2$	0.163		0.813		0.354		0.908	
F	969.4		31.5		1088.2		28.6	

[a]The number of observations is 29 796 for the micro relations and 40 for the macro relations.
[b]Indicates a coefficient which is significantly different from zero (two-tailed t-test, $p < 0.05$).

Most of the parameter estimates for the variables X_2–X_5, which are in principle defined at the individual level, do not differ significantly between micro and macro data. This is, however, mainly due to the very large confidence intervals of these parameters on the macro level, resulting in very few statistically significant coefficients. Exceptions to this general conclusion are the estimated effects of *NADM83* in Equation 4, *EXLOSD* in Equation 6 and, most important, family size (*FSIZE*) in Equation 6: on micro level *FSIZE* is estimated to have an interpretable negative and significant impact on length of stay whereas on the macro level we find a positive and significant coefficient. This provides an illustration of the possible danger of *ecological fallacy* (see Section III): on the basis of the macro result one might be inclined to conclude that family size affects length of stay positively whereas in fact there exists a negative association.

We now turn to *omitted variable bias* which can be assessed by comparing the estimation results of Equation 3 with those of 4 and Equation 5 with 6. We expected especially the inclusion of extra health-related variables (vectors X_4 and X_5) to have mitigating consequences for the estimated supply effects. We observe, however, for the contextual and semi-contextual variables that neither in the admission nor in the length-of-stay equations are the estimated parameters significantly different. This conclusion holds for the micro as well as the macro versions of the relations. The only substantial changes occur for the coefficients of the expected utilization variables, which is obviously a result of the strong

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correlations of these variables with X_4 and X_5. The effects of most of these variables are in themselves not of particular interest, although they increase the goodness of the fit in especially the micro version of Equation 6 considerably as compared to Equation 5.

Efficiency of estimates. We have already mentioned above that grouping of the observations resulted in considerable losses in efficiency. This is primarily due to increased multicollinearity among the independent variables (Section III), which is indicated in our data sets by the increase of the average magnitude of correlations from approximately 0.1 for the micro data to 0.4 for the macro data. Tables 3 and 4 show that the estimated standard errors of the parameters of the contextual variables increase with approximately a factor 2 when going from micro to macro data. This factor is approximately 2.5 for the semi-contextual variables and even larger than 10 for the non-contextual variables. So, in accordance with the theory discussed in Section III, we conclude that grouping leads to considerable efficiency losses which are, moreover, much larger for the parameters of the non-contextual than for those of the contextual variables. The semi-contextual variables take an intermediate position.

Consistent aggregation and simultaneous models. In order to evaluate the empirical consequences of employing arithmetic rather than geometric means – the former being used in most macro studies and the latter being consistent aggregation (see Section III) – we also estimated the macro versions of Equations 4 and 6 on the basis of *geometric means.* The results with respect to the bed elasticities of this alternative specification are reported in the bottom half of Table 5. They do not indicate major changes.

Finally, we also tried a *simultaneous* model with number of admissions affecting length of stay and vice versa. Such models are often used in macro studies. The bottom line of Table 5 shows that this alternative specification hardly changes the supply elasticities. The same conclusion turned out to hold for the other parameters in both equations. In particular, also, the mutual effects of the endogenous variables appeared to be far from significant. Our conclusion is therefore that estimating separate equations for the two hospital utilization variables yields equivalent results.

Table 5. *Estimated bed supply elasticities*[a]

	Admission probability		Length of stay	
	Micro	Macro	Micro	Macro
Bivariate elasticities	0.57***	0.62**	0.57***	0.57***
Equations 3, 5	−0.014	−0.072	0.19***	0.23***
Equations 4, 6	−0.14**	−0.14	0.22***	0.32***
Consistent aggregation	—	−0.26*	—	0.29***
Simultaneous model	—	−0.04	—	0.30***

[a]The elasticities in the upper half of the table are based on Tables 4 and 5. Those in the lower half refer to equations with alternative specifications (see Section IV).
The elasticities with respect to admission probability are calculated at the mean.
[b]The asterisks denote the estimated significance level (using a two-tailed t-test) of the regression coefficients:
*$0.05 < p \leqslant 0.10$;
**$0.01 < p \leqslant 0.05$;
***$p \leqslant 0.01$.

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V. CONCLUSIONS AND DISCUSSION

In this article we have investigated, both theoretically and empirically, the consequences of disaggregating the often estimated demand function for hospital care, the latter being operationalized by admission probability and length of stay. This investigation was inspired by the observation that micro studies of hospital demand yield results that substantially differ from those obtained in macro studies. Particularly, the strongly positive association between supply and utilization found in macro studies, is not supported by the results of micro studies which showed health status to be the predominant determinant of hospital utilization.

The most important consequences of disaggregation appeared to be: *aggregation and specification bias*, which appear to be inherent to all macro studies in which individual behaviour is estimated, had little consequence for the estimated hospital supply coefficients. However, the estimated coefficients in the macro relations of some non-contextual variables differed significantly from the corresponding coefficients estimated on micro data. This implies that one cannot obtain reliable estimates of the effects of non-contextual variables on the demand for hospital care on the basis of macro data. In such situations disaggregated data are indispensable.

With respect to *omitted variable bias* it was found that the inclusion in the equations of some additional explanatory variables, that are usually not available at regional levels, did not affect estimated supply elasticities, neither in the macro nor in the micro equations. Together with the previous conclusion, this suggests that if it is one's objective to estimate the effects of hospital supply on individual utilization then it suffices to use macro data.

The *efficiency* gain of disaggregation was very large for all explanatory variables in our empirical analysis, especially for the non-contextual.

Two important differences in the *statistical specification* between micro and macro studies – viz.: consistent versus inconsistent aggregation, and separate equations for admissions and length of stay versus a simultaneous model – did not appear to lead to diverging results.

Last but not least, an important finding of this study is that, in contrast to previous studies, the regional supply of hospital beds had no positive effect on admissions. This is probably due to major changes which have taken place in the provision of hospital care in Holland during the last 10 years. The elasticity of bed supply with respect to length of hospital stay amounted to approximately 0.2–0.3, which is consistent with previous findings.

The above conclusions do not, of course, demonstrate that the results of previous macro studies concerned with the relation between hospital supply and utilization were not hampered by aggregation, specification and omitted variable bias or by specification peculiarities. We can only conclude that our results do not support the hypothesis that the contradicting findings of macro and micro studies in the past are attributable to these sources of bias. It seems, therefore, that we should look for other explanations. One possibility seems to be the difference in data collection methods between macro and micro studies: macro data generally comprise the *whole* population whereas micro data are collected mostly by means of representative samples of the *non-institutionalized* population with the additional danger of selectivity bias caused by the lower response rates of people in poor health or those who are hospitalized at the time of interview. Our data base does not contain information on institutionalized people either, but since it is an administrative data base it does not suffer from this type of selectivity problem. The former observation combined with the fact that our data base only refers to a subgroup of the Dutch privately insured, leads us to conclude

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that an analysis of recent data on all publicly as well as privately insured is necessary to obtain a more conclusive test of the hypothesis that bed supply no longer affects admission rates in Holland.

ACKNOWLEDGEMENTS

The research reported here was supported in part by a grant from the Dutch health insurance organization Zilveren Kruis which also provided the data base used in this article, a fact which the authors gratefully acknowledge. The conclusions and opinions are those of the authors and do not necessarily reflect the views of the Zilveren Kruis organization.

The authors would like to thank Jan van Dalen, José Geurts, Gerard van de Kuilen and Brigitte Kerbusch for assistance, and the members of the research project 'Health insurance and medical consumption' and an anonymous referee for their comments on earlier drafts of this article.

A preliminary version of this article was presented at the conference on Disaggregation in Econometric Modelling, held at the University of Cambridge, 13–14 April 1987.

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