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"A BUILT BED IS A FILLED BED?" AN EMPIRICAL RE-EXAMINATION

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Abstract—This article provides an empirical re-examination of the relationship between regional hospital bed supply and the utilization of hospital care. It tests the hypothesis that the divergence of findings between studies based on micro-data (at the individual level) and those based on macro-data (at the regional level) is due to aggregation and specification bias. The main conclusion is that neither source of bias can account for the observed differences. Some other possible explanations are put forward. Regardless of the level of aggregation, a positive effect is found of bed supply on length of hospital stay but not on admission rates. This may be the result of major changes which have taken place in the financing of hospital services in the Netherlands during the last decade.

Key words—hospital utilization, aggregation, availability effect

1. INTRODUCTION

The regional distribution of health care facilities in general and of hospital capacity in particular has become a major issue in health care policies in many countries over the last decades. It is therefore not surprising that the relation between the regional availability of hospital beds and hospital utilization has often been studied. In many studies it was found that the correlation between these variables is strongly positive. This resulted in the formulation of the well-known empirical law by Roemer [1]: "A built bed is a filled bed."

Empirical evidence supporting this law was mainly found in macro-studies based on the analysis of regional cross-section data, sometimes combined with time-series data. Micro-studies relating hospital admissions and length of stay of individuals to the hospital capacity of their region, are rather scarce. To our knowledge, the only English-language micro-studies are those of May [2] and Pauly [3]. The latter concludes, on the basis of an analysis of the Health Interview Survey held in 1970 in the U.S.A., that the number of hospital episodes of individuals in a year and their average length of stay when hospitalized, are hardly affected by hospital capacity. This conclusion is in agreement with May's findings. Pauly also suggests a possible explanation for the contrary results of other (macro-) studies: "Past empirical work which has suggested important demand creation effects of these (hospital) services failed to account adequately for the health status of the patient or for differences (in health status) across types of geographic areas."

Several Dutch studies have also investigated Roemer's Law. These studies were mostly based on macro-data and virtually all of them found a strong, positive effect of hospital capacity on admissions; the effect on length of stay appeared to be smaller but significant [4].

A characteristic shared by all studies alluded to so far, is that they are based on data of the sixties and seventies. Since the mid-seventies, however, major changes have occurred in health care organization and financing in many countries. It is therefore not unlikely that also the strength of the relationship between hospital supply and utilization has been affected.

In view of the discrepancies between conclusions based on macro-data and those derived from micro-data and because of the obvious health policy implications of these conclusions, it seems worthwhile to investigate to what extent the estimated effects of hospital capacity: (a) are affected by aggregation bias (i.e. the deletion in macro-studies of variation between individuals within each region) and/or specification bias (i.e. the omission of important explanatory variables), and (b) have changed since the mid-seventies. The analysis is based on a data set which is unique for three reasons. First, the mere size of it (230,000 individuals) enables us to perform the same analysis on an individual level as well as on two aggregate levels; secondly, it contains relatively good indicators of health status (e.g. admission diagnosis); and thirdly, the information is of recent date (1983 and 1984).

The article is organized as follows. In Section 2 a survey of the relevant literature is given. In Section 3 the data and the empirical models are described along with major characteristics of the Dutch health care system. The results of the analyses are reported in Section 4 and discussed in Section 5. Section 6 completes this article with a summary of the main conclusions.

2. SURVEY OF LITERATURE

Two important interpretations of the frequently observed positive relation between hospital

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capacity—in terms of hospital beds—and utilization, are (a) the existence of *permanent excess demand*, and (b) *supplier induced demand* [3, 5, 6]. Unmet or excess demand for hospitalization may cause both more hospital beds to be supplied and more hospital utilization once the beds are available, and therefore the relationship may be spurious. This interpretation is consistent with the standard model of a dynamic market mechanism. A second interpretation of the relationship is that suppliers are able to induce an increase in demand. This may arise because physicians have some discretionary power to determine demand since their medical knowledge is in general superior to that of their patients. Such manipulation of demand may be constrained, among other things, by the relative scarcity of medical facilities, one of which is hospital capacity. Moreover, in Holland it was (until 1984), in general financially attractive for medical specialists and for hospitals to treat patients rather on an in-patient than on an out-patient basis. Professional uncertainty about deducing the correct diagnosis from observed and reported symptoms, about the appropriate treatment of a patient with a given diagnosis and about the outcome of the treatment, might also induce specialists to maximize the utilization of available hospital capacity for safety reasons [7].

Both explanations imply that an increase in bed supply results in a (possibly lagged) rise of hospital utilization. We do not wish to discriminate between the two interpretations but rather test the strength of the supply-utilization relation empirically. Controlling for other factors like health status, which co-determine hospital care utilization, is essential in estimating the magnitude of this availability effect.

Tables 1 and 2 give an overview of American, British and Dutch studies published during the last 25 yr in which, among other things, the effects of bed supply on hospital admissions and length of stay are estimated on the basis of either individual or aggregate data. Comparison of the results of these studies is not straightforward because of differences in data sources (e.g. country and year), methods of analysis, aggregation levels, definition and choice of dependent and independent variables, etc. In the two tables relevant information on these matters is presented along with the estimated effects of bed supply on admissions and length of stay. These effects are reported as elasticities, which can be interpreted as follows: a bed elasticity for admission rate of 0.5 implies that an increase of 10% in the number of beds per capita in a certain region leads to a rise in the admission rate (of that region) of 5% ($=0.5 * 10\%$). Elasticities are the most relevant measures of association for cross-study comparisons because they are independent of both the unit of measurement and the level of aggregation. For the macro-studies, the bed elasticities of admission rate are all significantly different from zero and range from 0.15 to 0.83 with an average of 0.56. The same statistics for length of hospital stay are also significant and range from 0.11 to 0.62 with an average of 0.31. The average bed elasticities are 0.20 for admissions and 0.03 for length of stay (not significant) for the reviewed micro-studies. Similar figures are found in a number of Dutch-language studies [4]. The above-mentioned differences between studies do not allow a detailed comparison of these findings. However, some general observations can be made:

(1) the effects of bed supply on admissions tend to be larger than the effects on length of stay;
(2) the elasticities found in micro-studies are (much) smaller, and sometimes not even significant. This holds for American as well as for Dutch studies;
(3) in several macro-studies differences in health status between regions were not taken into account [e.g. 8, 9, 13, 14];
(4) micro-studies allow for much more independent variables in the regression models;
(5) the estimated effects of the supply of specialists on admissions and length of stay are not significant in most studies and negative but very small in some others;
(6) there are no studies which use data from the eighties;
(7) the number of micro-studies in this field is very limited.

The scarcity of micro-studies is probably due to the vast number of observations necessary to perform an adequate analysis of the admission frequency of individuals. Furthermore, survey data on admissions and length of stay are often unreliable, because people in poor health or staying in a hospital at the time of the interview are generally underrepresented. Moreover, estimated bed availability effects obtained from micro-studies are generally by-products of more general studies into the determinants of health care utilization, including both in-patient and out-patient care. The second conclusion provides ample justification for an investigation into the consequences—for the conclusions about availability effects—of aggregating individual hospitalization data to macro-levels.

Before we outline the research design, it is useful to describe a few characteristics of the Dutch health care system. In the Netherlands it is customary for a patient to enter the health care system through a visit to a physician in general practice. The general practitioner normally provides primary care and decides whether the patient needs (secondary) specialist care. The specialist subsequently decides whether the patient is to be treated on an out-patient or in-patient basis. Roughly speaking, Dutch families with an annual income below a certain level (Dfl. 46,550 in 1983, or about 16,500 U.S.-Dollar) are compulsory insured with the so-called Sickness Fund Organization. In this way, about 70% of the Dutch population was completely insured against (nearly) all medical expenses. They are generally referred to as the *publicly* insured. The other 30% consists of higher income groups and nearly all of them have private health insurance (the *privately* insured). These two insurance schemes do not only differ in coverage, but also in the remuneration for medical care provided to their insured. The short-term general hospitals are non-profit organizations. Most medical specialists are hospital based but they work mainly like private entrepreneurs and are remunerated on a fee-for-service basis.

Table 1. Survey of some American empirical studies into the effect of hospital capacity on utilization

Study	Year and source of data[1]	Geographical areas	Bed elasticities[2] Admission	Length of stay	Remarks
(1)	1957 and 1960, data of one hospital	catchment area of hospital	0.47	0.25	natural experiment: effects of a bed increase increase in utilization for most diagnoses
(8)	1960	48 states	0.69	0.10^{NS}	corrected for effects of physician density, mean income and insurance coverage
(9)	1958–1967, $N = 470$	47 states	0.24–0.41	0.28 0.33	dependent variables: ratios of actual to expected length of stay and of actual to expected admission rate (based on age–sex–colour distributions) corrected for price per hospital day, mean income, trend population density, yes/no Medicaid, GP to total physician ratio
(10)	1957–1966, $N = 480$	48 states	0.76		stepwise analysis corrected for age distribution, mean income, trend and public expenditure on health per capita
(11)	1970 compared with 1960	58 counties in the state of New York	0.56	0.44	path analysis corrected for length of stay and occupancy rate in 1960
(2)	cross-national survey of 1971 ($N = 12{,}000$)	capacity variables on PSU-level	0.22	0.03^{NS}	corrected for age, sex, health status, socioeconomic variables, physician density, time-price of use of medical facilities etc.
(5)	1959–1973, $N = 705$	47 states	0.15	0.18	dependent variables: see [9] independent variables: see [9], plus a quality index and lagged dependent variables
(3)	cross-national survey of 1970 ($N = 41{,}000$)	capacity variables on county or SMSA-level	0.15	NS	corrected for health status, age, sex, family size, working status, insurance coverage, family income, physician density etc.
(12)	data on 278 general practitioners in the state of Washington, 1979	capacity variables on county-level	NS		dependent variable is GP's hospitalization rate corrected for physician-density, GP-characteristics, patient case mix, average income etc.

[1] When a range of years is indicated, the study in question is based on a time-series/cross-section analysis.
[2] The elasticities, if not reported in the original study, are calculated at the mean; NS = not significantly different from zero ($P > 0.05$).

Table 2. Survey of some British and Dutch empirical studies into the effects of hospital capacity on utilization[1]

Study	Year and source of data	Geographical areas		Bed elasticities: Admission	Bed elasticities: Length of stay	Remarks
(13)	1960, one area in Britain with 28 hospitals	catchment areas of hospitals				conclusion 'there is a 1–1 correspondence between bed supply and utilization for medical specialities' no corrections
(14)	1960, British macro-data	11 NHS regions		0.58	0.37	no corrections
(15)	1969 and 1971, Dutch macro-data	120 service areas of hospitals	1969	0.54	0.36	reduced form elasticities
			1971	0.57	0.28	corrected for expected admission rates and length of stay (based on age–sex distribution), GP-density, medical specialists to beds ratio, nurses to beds ratio, nursing home beds, % publicly insured and population-density
(16)	1973, Dutch macro-data on publicly insured	80 sickfund areas		0.66	0.11	reduced form elasticities corrected for referrals from GPs to medical specialists, population-density, GPs population, medical specialists population, nurses/beds, % publicly insured, expected admission rate and length of stay
(17)	1960–1972, Dutch macro-data on publicly insured, $N = 143$	11 provinces		0.29	0.27	reduced form elasticities corrected for GP-density, medical specialist-density, population-density, % of population 65 years and over, % publicly insured, nurses to beds ratio and trend
(18)	1975, British macro-data	13 English health regions and		>1		no correction for health status
		17 health districts in one region		>1		elasticities for general medicine and general surgery
(19)	1974, Dutch macro-data on publicly insured	63 sickfund areas		0.81	0.45	corrected for age–sex distribution (via a health-index, which is mainly based on age and mortality), rest: see [16]
(20)	1973, Dutch macro-data on publicly and privately insured	52 catchment areas	Public	1.00	0.75	bed supply endogenous no correction for expected admission rate
			Private	0.42	0.30	corrected for expected mean stay, rest: see [16]
(21)	1976, Dutch data on ± 3500 privately insured	bed supply per hospital catchment area (123 regions)		bed elasticity of hospital days = 0.86		corrected for health status (via a health-index which is mainly based on age and number of sickness days), insurance coverage, number of specialist out-patient consultations and distance to nearest hospital

[1] See the footnotes of Table 1.

Table 3. Estimated supply elasticities for admission probability[1]

Explanatory variables	Micro-level[3] Beds	Micro-level[3] Specialists	Macro-level: COROP[4] Beds	Macro-level: COROP[4] Specialists	Macro-level: NZI[4] Beds	Macro-level: NZI[4] Specialists
Bivariate elasticities	0.57***	−0.11	0.62***	−0.11	0.68***	−0.11
Model 1:						
Regional variables[2]	0.34***	−0.21***	0.22*	−0.31***	0.33**	−0.22
$\bar{R}^2$	0.001		0.514		0.485	
Model 2:						
Idem, plus expected admission probability based on age and sex	−0.014	−0.033	−0.072	−0.046	−0.034	−0.11
$\bar{R}^2$	0.025		0.793		0.788	
Model 3:						
Idem, plus individual characteristics and other health-related variables	−0.14**	−0.041	−0.14	−0.042	−0.33	−0.14
$\bar{R}^2$	0.044		0.780		0.751	
N	27,094		40		24	

[1]The elasticities are estimated at the mean. $\bar{R}^2$ is the coefficient of determination, adjusted for *df*. The asterisks denote significance levels: *$0.05 < P < 0.10$; **$0.01 < P < 0.05$; ***$P < 0.01$.

[2]The explanatory variables contained in the various categories are: *regional variables*: average distance to hospital, percentage publicly insured and the number of general practioners per 1000 inhabitants; *expected admission probability*: see Section 4.1; *individual characteristics*: family size and three variables indicating insurance coverage; *other health-related variables*: medical expenditures and number of hospitalizations in previous year.

[3]The micro-level models were estimated on a stratified sample of the original data (with 230,000 observations) in order mainly to reduce required computer time. Half of this sample comprised all hospitalized persons and the other half was randomly selected from the group of non-hospitalized persons. The estimation procedure was accommodated to correct for this stratification [24].

[4]The macro-level models were estimated by means of WLS in order to adjust for the number of observations per region and thereby to avoid heteroskedasticity.

3. RESEARCH DESIGN

3.1. *Methodology*

Theoretically, there are at least two possible sources of bias in macro-studies: aggregation bias (i.e. information on the variation between individuals within each region is disregarded) and specification bias (i.e. at regional levels sometimes only limited information is available on hospitalization determining factors which may cause important explanatory variables to be omitted from the regression equations).

The possible danger of ecological fallacy which arises when conclusions about individual behaviour are drawn from analyses of aggregate data ('cross-level inference'), have been studied by many researchers from various disciplines [22, 23]. The contextual nature of bed supply (i.e. bed density can only be defined at a regional level and has no equivalent on the individual level) implies that the estimated bivariate relationship between this variable and length of hospital stay is the same on both individual and regional level [24]. Thus, aggregation bias is not possible in this situation. However, there is no guarantee that this conclusion also holds when more contextual variables and variables defined at the individual level are added to the relation, especially since grouping of observations may substantially increase multicollinearity among the explanatory variables.

In order to investigate the consequences of aggregation, we have estimated a number of regression equations relating admission probability and length of stay to various sets of explanatory variables. The estimations were performed at the individual level as well as at two aggregate levels. This two-way stepwise procedure enabled us to discriminate between specification and aggregation effects. The starting point for the analysis is a basic model (model 1) comprising only five regional variables: hospital capacity, which is measured by the numbers of beds and specialists in the region per 10,000 inhabitants, and three other variables which measure availability of medical facilities in the region (see note 2, Table 3). We will not discuss the expected effects of these and other explanatory variables at length. For this purpose the interested reader is referred to the references given in Table 2. This basic model is a compromise between the models which are used in previous macro-studies and the specific set of variables at our disposal, where health-related variables are left out in this first step. Next, the basic model is expanded with expected admission probability and expected length of stay, giving model 2. The former variable is, for each person, defined as the proportion of all individuals in the same age–sex-group who have been admitted to a hospital. The latter is defined analogously. These variables have frequently been used in other macro-studies to control for differences in health status between regions. Comparing the results of models 1 and 2 will give some indication as to the importance, for the estimated supply effects, of controlling for health indicators. The final model 3 arises from model 2 by adding variables defined at the individual level: family size and insurance coverage. Although these variables have not often been included in macro-studies by lack of data, it is reasonable to assume that they affect at least the admission probability at the individual level. Furthermore, a number of additional health-related variables have been included. The admission equation is supplemented with two indicators of previous medical consumption: the total amount of health care expenditures in 1983 and the number of hospital admissions in that same year. The length of stay equation is expanded with expected length of stay on the basis of the admission diagnosis and four other variables related to the hospital stay. These explanatory variables were not available in most macro-studies. A comparison of the results of models 2 and 3 will provide insight as to what extent specification bias might be a problem in model 2, which contains essentially the same explanatory variables as used in most of the reviewed macro-studies.

3.2. Data

To estimate the above described models, we used data files obtained from the Dutch private health insurance organization 'Zilveren Kruis'. For each of the 230,000 insured individuals (per 1–1–1984) we had information on: (1) the insurance coverage, age, sex and family size; (2) the medical expenditures reimbursed by the insurance company in 1983; and (3) admissions in short-stay hospitals in 1983 and 1984 (in total approx. 30,000 admissions). The data files were supplemented with regional information on the availability of medical facilities and some other relevant variables. Subsequently, we constructed data sets for analysing admission probability (in 1984) and length of stay (in 1983 and 1984). The former variable is based on a dummy indicating whether or not the person in question was admitted to a hospital at least once in 1984.

The explanatory variables for admission probability can be grouped into five categories: (1) supply of hospital beds and medical specialists in the area of residence; (2) other regional variables; (3) expected admission probability based on age and sex; (4) family size and insurance coverage; and (5) other health-related variables. The number of beds in acute, short-stay hospitals and the number of medical specialists working in hospitals are defined per 10,000 inhabitants in the region, where we use two subdivisions of the Netherlands (see below). The number of beds and specialists per region was corrected for cross boundary flows (see [24]). The reason for this commonly employed correction [see e.g. 7 and 20] is, that service areas of hospitals are not restricted to the rather arbitrarily defined geographic regions in which the various hospitals are located. And thus, when calculating the actual supply *available* to a region one has to take into account existing patient flows. Since we use patient flow data on all hospitalizations in Dutch hospitals for this correction, while our analysis covers only a fraction ($\approx 2\%$) of the Dutch population, we avoid the risk of explaining a tautology.

The explanatory variables to be used in the analysis of hospital stay are subdivided into five similar categories. Two important, health-related, variables are the expected length of stay based on the age and sex of the person (category 3) and the expected length of stay based on the admission diagnosis (category 5). The latter is defined as the average length of stay in Holland for the diagnosis with which the person is admitted to the hospital, thereby also distinguishing between the various medical specialties.

The information in the two above described data sets was aggregated to the so-called NZI- and COROP-regions which provide mutually exclusive geographical divisions of the Netherlands into 24 and 40 regions respectively. The NZI sub-division is used in Holland for the planning of health care facilities. The COROP-regions are created around primary and secondary centres.

4. ESTIMATION RESULTS

This section summarizes the estimation results of the models described in Section 3.2. Since in this article we focus on the supply-utilization relations, only the estimated supply-elasticities and their significance levels will be reported. The complete results can be found in another publication [24].

4.1. Admission probability

First, we consider the bivariate relations of bed supply and hospital based medical specialists with the admission probability (see first row of Table 3). It appears that the bivariate bed elasticity is positive and highly significant at both the micro- and macro-levels. This is in accordance with *a priori* expectations and the results of the studies reviewed in Section 2. The specialist elasticity is negative but not significantly different from zero. Because of the contextual nature of both bed and specialist supply, it is not surprising that the estimated elasticities are roughly the same on each of the three levels (see Section 3.1).

Next we turn to the estimation results of the multivariate admission probability equations which are reported in the other rows of Table 3. The supply elasticities of the basic model 1 are considerably lower than the simple elasticities reported in the first row. This results in higher significance levels for specialist supply and lower levels for bed supply. The elasticities are again very similar on the three levels but bed supply is only significant at the 10% level. The bed elasticities are now, and even without taking into account a number of other important explanatory variables, smaller than the elasticities found in most other studies (see Tables 1 and 2).

Addition of the expected admission probability to the equation changes the results drastically. As could be expected, the effect of this variable is positive and very strong. But supply no longer has a significant impact on the admission probability. These conclusions hold for the micro- as well as the macro-equations. Note also the enormous gain in explanatory power in model 2 (measured by $\bar{R}^2$) compared to model 1. All of these observations emphasize the importance of controlling for health status. They, moreover, cast doubt on the conclusions of those previous studies that do not somehow control for health status [8, 13, 14].

In model 3, the set of explanatory variables is extended with family size, three variables describing the insurance coverage of each individual and two indicators of previous year's medical consumption. The only important change in estimated supply elasticities and significance levels occurs for the negative bed supply effect at the individual level, which has become significant at the 5% level. This finding

Table 4. Estimated supply elasticities for length of stay[1]

	Micro-level		Macro-level: COROP		Macro-level: NZI	
Explanatory variables	Beds	Specialists	Beds	Specialists	Beds	Specialists
Bivariate elasticities	0.57***	−0.13***	0.57***	−0.13***	0.55***	−0.12***
Model 1:						
Regional variables[2]	0.47***	−0.15***	0.45***	−0.17***	0.43***	−0.11
$\bar{R}^2$	0.012		0.586		0.611	
Model 2:						
Idem, plus expected length of stay based on age and sex	0.19***	0.026	0.23***	0.010	0.14	0.036
$\bar{R}^2$	0.163		0.813		0.900	
Model 3:						
Idem, plus individual characteristics diagnosis, and other hospital-stay related variables	0.22***	0.025	0.32***	0.017	0.095	0.017
$\bar{R}^2$	0.354		0.908		0.905	
N	29,796		40		24	

[1] See also the footnotes of Table 3.
[2] The explanatory variables contained in those categories not used in the admission probability models are: *expected length of stay*: see Section 4.2; *hospital-stay related variables*: expected length of stay based on the admission diagnosis and four dummy variables indicating whether or not one was hospitalized on Friday or Saturday, discharged on Monday, surgically treated and treated by two specialists.

stands in sharp contrast to all previous studies on this subject. The fact that the goodness of fit of the macro-models decreases when individual variables are included in the relations, suggests that these additional variables are not essential at the aggregate level. In contrast, the explanatory power of the micro-model has improved substantially.

With respect to the differences in estimation results between the COROP and NZI-equations, we may conclude that in general the bivariate as well as the multivariate supply elasticities are somewhat larger in magnitude for the latter. This may be due to the higher aggregation level.

4.2. *Length of stay*

The bivariate relations between bed supply and length of stay are positive and highly significant at both the individual and aggregate level (see first row of Table 4). The supply of medical specialists is negatively correlated with length of stay. Attempts to interpret these relations are rather premature because the influence of other explanatory variables is not yet taken into account. Therefore, we turn to the results of the multivariate analyses which are reported in the other rows of Table 4. The multivariate supply elasticities in the basic model 1 are, on average, about 20% lower than the bivariate elasticities. In line with the results of the literature reviewed in Section 2, we find at the micro- as well as the macro-levels that the effect of bed supply on length of stay is positive and significant. The estimated specialist elasticity is negative and significant on the individual and COROP level but not on the NZI level.

Adding the expected length of stay to model 1 drastically affects the supply elasticities. The bed elasticity has been more than halved in the micro- as well as the macro-equations. Moreover, the bed supply effect has vanished at the NZI level. The bed elasticities on the individual and COROP level are similar to those found in the macro-studies reviewed in Tables 1 and 2. It is remarkable, however, that these results are in contrast to the non-significant effects of bed supply on length of stay found in two micro-studies [2, 3]. The estimated elasticities of specialist supply in model 2 are no longer significant. Note furthermore that the inclusion of expected length of stay has led to substantial increases in the $\bar{R}^2$-values for all levels of aggregation. The large differences between the results of model 1 and 2 emphasize again the importance of controlling for health status.

Comparison of the results of the model 3 equation with those of model 2 shows that addition of the individual characteristics and the hospital-stay related variables (among which expected length of stay based on diagnoses) does not have serious consequences for the estimated supply elasticities. Only the bed elasticity in the COROP-equation is larger in model 3.

The contribution of the added variables to the explanation of length of stay is emphasized by the doubling of the $\bar{R}^2$-value in the micro-equation. The explained variance in the macro-equation reaches a level which is very high in comparison to previous macro-studies on this subject. The finding that the bed elasticities of the model 2 and 3 equations estimated on NZI data are not significant and smaller in magnitude than the corresponding elasticities estimated on the other two levels, is probably caused by a lack of variability between the 24 NZI regions. Apparently, grouping to COROP regions preserves sufficient variation to estimate a supply effect whereas grouping to NZI-regions does not.

We also estimated the length of stay models with supply densities that were not corrected for cross-border admissions (see Section 3.2). These variables are theoretically less appealing but employing them avoids every suspicion of tautology. The most important result of this respecification was that the bed elasticities reduced with approx. 60% in the micro-level models and remained significant. Furthermore, some of the specialist elasticities became significant but were still quite small in magnitude.

5. DISCUSSION

Unlike most previous empirical studies concerned with hospital utilization, we found in our micro- as well as macro-analyses *no* relation between bed supply and *hospital admissions* after controlling for health status (by means of the expected admission probability). We may conclude that the latter is of crucial importance: neglecting to account for differences in health status may lead to erroneous conclusions about the effects of region-related variables such as bed- and specialist-supply on admission probability. This holds for both the micro- and macro-relations.

Furthermore, since the effects of these variables in the comprehensive model 3 equations are similar to those in the restricted model 2 equations (with the exception of the bed supply effect which is non-significant in model 2 and even negatively significant in model 3), we conclude that our analysis rejects the hypothesis that specification bias (i.e. omitted variable bias) is a serious problem in macro-studies relating regional hospital capacity to regional admission rates.

This finding also has some relevance for the scholarly debate that was recently published in *Medical Care*. Blumberg [28] argued that age is not a sufficient proxy for health status in making comparisons of health care use by geographic area because of morbidity variations within age groups. Wennberg [27] replied that, ironically, both age and morbidity measures only explain a very small proportion of variation in U.S. hospitalization rates. On the other hand, small area studies have consistently found a strong statistical association between beds per capita and admission rates. We believe to be the first to show (a) that this effect disappears after age adjustment and (b) that this disappearance is independent of the level of aggregation. The fact that the age-adjusted variation in admission rates for (financially attractive) private patients is unrelated to the availability of beds and specialists per region seems to be in favour of the hospitalization decisions of Dutch clinicians in recent years.

Finally, we already indicated in Section 3.1 that the bivariate regression coefficients between a certain dependent variable and explanatory variables defined on a regional level do not change when the relevant micro-data is aggregated to this regional level. In general, this conclusion also appears to hold for our multivariate empirical results, the major exception again being the significant negative effect of bed supply in the model 3 micro-equations. Thus, aggregation bias does not seem to be able to account for the discrepancies in the results with respect to the effects of bed supply on admissions.

Our results concerning the effects of supply of hospital based medical specialists on admissions are in accordance with the findings of the literature reviewed in Section 2—negative but not significant.

We now turn to the hypothesis that the results, obtained from macro-studies, concerning the effects of bed supply on *length of stay* are affected by aggregation and/or specification bias. The conclusions of our study with respect to this hypothesis are more or less similar to those formulated above for the admission probability, viz.: (a) Controlling for differences in health status between individuals and regions is of crucial importance. (b) The specification bias hypothesis is not supported by our results; in fact, we find a larger impact of bed supply on length of stay in the comprehensive macro-equation containing nine additional health and individual variables which are generally not available in studies on aggregated data (model 3), than in the more restricted model 2. (c) Aggregation bias is detected only for the effects of bed supply in the NZI equations, which seems to suggest that there is a limit to the level of aggregation, i.e. aggregating to larger regions may lead to biased results. This is probably due to decreasing variation in both independent and dependent variables and to increasing multicollinearity. (d) The supply of medical specialists has no significant effect on length of stay in our micro- and macro-equations after controlling for expected length of stay.

Two important questions now remain to be answered:

(1) If aggregation and specification bias do not account entirely for the differences between micro- and macro-studies with respect to the effects of hospital capacity on utilization, what then are the causes of these differences? In answering this question we can, in view of the above discussion, disregard those macro-studies that have failed to account for differences in health status.

(2) Why is it that in our study we do find a positive effect of bed supply on length of stay and no positive effect on admissions, whereas in all reviewed studies the latter effect appears to be stronger than the former?

Since the Dutch health care system differs largely from those in Britain and the U.S.A.—the two countries where most of the reviewed studies relate to—we restrict these questions to:

(1) possible explanations for differences between micro- and macro-studies based on U.S.A. data sources (Section 5.1);
(2) differences between our study and other Dutch macro-studies (Section 5.2).

5.1. Contradicting results in American studies

The average bed elasticities with respect to admissions are about 0.2 for the two micro-studies and 0.6 for U.S.A. macro-studies. These figures are non-significant, and about 0.3 for the average bed elasticities with respect to length of stay. Explanations for these differences might be:

5.1.1. Multicollinearity. In data on aggregate levels the correlations among the independent variables are, in general, much larger than in individual data, which is likely to result in non-stable regression equations, i.e. inclusion or exclusion of one independent variable might lead to drastic changes in the estimated effects of other variables. In our macro-analyses we found that the positive effect of bed supply on length of stay changed from significant to non-significant when we estimated models 2 and 3 on NZI (24 regions) instead of COROP level (40 regions). However, it seems that none of the studies from Tables 1 and 2 used such a high aggregation level with so little variance. Therefore, this explanation is not very convincing.

5.1.2. Statistical models. The relevant equations may be estimated in linear (the two micro-studies) versus log-linear (many macro-studies) forms, on cross-section (micro) versus time-series data and with (some macro-studies) or without simultaneous relations between admission rates and length of stay. Almost all these specifications have been used in one or more macro-studies. Since there do not appear to be systematic differences in the estimated supply effects between these studies, it seems unlikely that different statistical models may explain observed differences in supply effects between micro- and macro-studies.

5.1.3. Additional specification bias. In the present study we have only looked at the consequences of including a relatively small number of individual variables in the admission and length of stay equations. One might wonder what happens when more independent variables are added, e.g. variables indicating socio-economic status and other predisposing variables. Although one micro-study [2] uses a much larger set of independent variables than the other [3], both reach similar conclusions with respect to supply effects. Therefore, additional specification bias does not seem to be a plausible explanation.

5.1.4. Data sources. Two micro-studies use data from two subsequent years of the same survey, which is held among a representative sample of the *non-institutionalized* U.S.A. population. The data used in macro-studies appear to stem from different sources for which it is not always clear which admissions are taken into account and which are not, but they most probably also include admissions of institutionalized people, who have a high medical consumption. The importance of the definition of the study population is clearly shown by the opposite conclusions arrived at by Fuchs [25] and Pauly [3] who both estimated the effect of supply of surgeons on the number of surgical operations, the former using aggregated data of the micro-information used by the latter. Pauly, however, excluded the group of persons in families with incomes below a poverty line because many of them may have had Medicaid coverage not measured in this data set. Pauly concludes that "more surgeons do not mean more surgery", whereas Fuchs finds a significant elasticity of 0.30. The latter result is supported by more recent studies [6, 26] which were, unfortunately, also based on macro-data.

5.2. Comparison of present study with other Dutch studies

The average bed elasticities with respect to length of stay are about 0.3 for the reviewed Dutch macro-studies, which is comparable to the elasticity found in the present study. However, the bed elasticities with respect to admission rates were on average 0.6, whereas they are non-significant in our analysis. Possible explanations for the latter difference might be, apart from the above-mentioned explanations:

5.2.1. Dependent variable. In the present study the annual admission *probability* is analysed whereas in the macro-studies the number of admissions is used. However, an additional analysis, not reported here, in which the probability is replaced by the admission frequency, showed that the estimation results hardly differ [24].

5.2.2. Study population. The macro-studies primarily refer to the group of *publicly* insured in the Netherlands, whereas the present study is based on a selective part of the *privately* insured population, i.e. those insured with one insurance company operating mainly in the western part of the country. The differences between both groups in insurance coverage, health status and remuneration of physicians might explain part of the observed difference in bed elasticities between this and other studies (see Section 2). However, in one macro-study [20] in which the two groups were distinguished, a bed elasticity with respect to admission rate of 0.4 for the privately insured was estimated. Moreover, in a micro-study [21] based on data from the same insurance company that provided the data for the present study, a bed elasticity with respect to the number of hospital days of 0.85 is found. Therefore, the different study populations are unlikely to be able to account for the differences in bed elasticities.

5.2.3. Structural change. In the period between 1973 (the last year used in the reviewed Dutch macro-studies) and 1983–1984 (the years from which our data stem) three major changes have taken place in the provision of hospital services in the Netherlands, viz.: the abolishment of the 90%-*occupancy rate* requirement as the basis for the financing of hospitals, the aiming at *bed reduction* by the Dutch government and the introduction of *hospital budgeting*. Probably also as a result of these measures hospital utilization has dropped considerably in the period 1973–1983. It is likely that the sharpest drops have occurred in regions where hospital utilization was highest, i.e. according to the findings of macro-studies, those regions with high hospital bed densities. As a result of this process the relationship between bed supply and hospital utilization might have been weakened for length of stay and disappeared for admission rate.

6. CONCLUSION

The purpose of this study was to test empirically the hypothesis that differences between the results of micro- and macro-studies with respect to the effects of hospital capacity, are caused by aggregation and specification bias. The former relates to the consequences of the disappearance of within-group variances and covariances as a result of grouping individual data to regional averages; the latter to the fact that in many macro-studies important explanatory variables are omitted from the analyses by lack of data. In accordance with previous studies we have operationalized hospital capacity by bed supply (and to a lesser extent by supply of hospital based medical specialists) and hospital utilization by admission probability and length of stay. We have estimated a number of equations relating the admission probability and length of stay of a sample of Dutch privately insured to various sets of explanatory variables. The same equations were estimated at the individual level as well as at two aggregate levels. This two-way stepwise procedure enabled us to discriminate between aggregation and specification bias.

The findings of our analysis do not support the hypothesis that aggregation and specification bias have led to the divergence of estimated supply effects in studies based on macro- as compared to micro-data. This conclusion is conditional upon controlling for age and sex. Standardization for additional indicators measuring morbidity variations *within* age–sex groups did *not* change the estimated supply effects. Moreover, this refinement hardly affected the goodness of fit at regional levels. Thus, our results are partly in line with Wennberg [27] "... morbidity measures are uncorrelated with hospital utilization" [see also 28]. We found evidence that aggregating to increasing region sizes, leading to decreasing variations and increasing multicollinearity, may result in the disappearance of supply effects. An unexpected result of our multivariate analysis relates to the effect of bed supply on admission probability which is negative and statistically significant at the micro-level. This finding is in contrast with all previous studies. The most plausible explanation for this disagreement seems to be that major changes have taken place in recent years in the provision of especially hospital services in the Netherlands which may have weakened the relation between bed supply and admission rate. The analysis of recent hospitalization data comprising the entire Dutch population may shed more light on this issue.

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