ORIGINAL RESEARCH

Hospital Variation in 30-Day Mortality for Patients With Stroke; The Impact of Individual and Municipal Socio-Demographic Status

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Background**—**Thirty-day mortality after hospitalization for stroke is commonly reported as a quality indicator. However, the impact of adjustment for individual and/or neighborhood sociodemographic status (SDS) has not been well documented. This study aims to evaluate the role of individual and contextual sociodemographic determinants in explaining the variation across hospitals in Norway and determine the impact when testing for hospitals with low or high mortality.

Methods and Results**—**Patient Administrative System data on all 45 448 patients admitted to hospitals in Norway with an incident stroke diagnosis from 2005 to 2009 were included. The data were merged with data from several databases to obtain information on vital status (dead/alive) and individual SDS variables. Logistic regression models were compared to estimate the predictive effect of individual and neighborhood SDS on 30-day mortality and to determine outlier hospitals. All individual SDS factors, except travel time, were statistically significant predictors of 30-day mortality. Of the municipal variables, only the municipal variable proportion of low income was statistically significant as a predictor of 30-day mortality. Including sociodemographic characteristics of the individual and other characteristics of the municipality improved the model fit. However, performance classification was only changed for 1 (out of 56) hospital, from "significantly high mortality" to "nonoutlier."

Conclusions**—**Our study showed that those stroke patients with a lower SDS have higher odds of dying after 30 days compared with those with a higher SDS, although this did not have a substantial impact when classifying providers as performing as expected, better than expected, or worse than expected. **(*J Am Heart Assoc*. 2019;8:e010148. DOI: 10.1161/JAHA.118.010148.)**

Key Words: health disparities • hospital performance • quality indicators • socioeconomic position • statistical model

Public reporting of 30-day mortality after admission to the hospital is a widely used measure of hospital performance.[1–3] In Norway, 30-day mortality statistics following stroke, acute myocardial infarction, and hip fracture have been reported annually as quality indicators for all hospitals since 2012.[4,5] These indicators are published as part of a national quality indicator system initiated by the Ministry of Health. A central purpose of the indicator system is to classify providers as performing as expected (normal or nonoutlier), better than expected (outlier), or worse than expected (outlier).

It is widely agreed that outcome measures, such as mortality, should be adjusted for case mix in order to account for variations in the risk composition of hospital populations.[1,3] This risk adjustment accounts for patient-associated factors before comparing outcomes across different hospitals. There is, however, an ongoing debate about whether the case-mix adjustment should include socioeconomic and other sociodemographic factors.[6–9] Some argue that risk adjustment is necessary to achieve fair comparison, whereas others argue that it may exaggerate the performance score of hospitals that treat the most vulnerable patients and thus mask differences in quality. There is no consensus on methodology or on a standard set of sociodemographic variables for case-mix adjustment.

A central methodological issue is whether sociodemographic status (SDS) variables should be applied at an individual level, neighborhood (contextual) level, or both. Both low individual SDS and living in a socioeconomically disadvantaged community have been shown to be associated with higher stroke mortality.[10–17] Some studies have shown that neighborhood SDS, easily estimated, with high completeness and at less cost, may be more important than individual SDS.[18,19]

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An accompanying Table S1 is available at https://www.ahajournals.org/doi/suppl/10.1161/JAHA.118.010148

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Clinical Perspective

What Is New?

- We found that adding sociodemographic factors for the individual and municipality of residence led to minor improvements in model performance compared with only using administrative data, but hardly influenced hospitals' outlier status.

What Are the Clinical Implications?

- This study demonstrates that although sociodemographic factors can be used to predict 30-day stroke mortality, statistical adjustment for these factors is of little importance when identifying hospitals that perform worse than expected with regard to overall stroke mortality.

Few studies have investigated the extent to which sociodemographic factors explain hospital variation in stroke mortality. However, some studies in Norway have shown that sociodemographic factors at a municipal level account for the majority of geographical variance in both overall mortality and mortality among patients hospitalized with acute myocardial infarction.[18,20] Other international studies have shown that sociodemographic factors explain some of the variation across hospitals. Most research has been focused on readmission, readmission after coronary artery bypass grafting,[7] congestive heart failure readmission,[21] and stroke readmission.[22] These studies found a predictive effect of SDS on individual outcomes, but no substantial impact of adjustment for SDS on hospital performance ratings.

In this study, we investigated the relative effect of individual and contextual sociodemographic factors on mortality after hospitalization for stroke in all Norwegian hospitals from 2005 to 2009 and the impact of adjustment for these factors on the identification of outlier hospitals.

Material and Methods

Data Availability

Data were obtained from Norwegian hospitals and Statistics Norway. The data sets comprise data for individual patients and hospitalizations. Confidential information regarding health status for a single patient may thus be revealed if the data were shared or made public. The data are handled strictly confidentialy by the Norwegian Institute of Public Health.

The study was approved by an institutional review committee, Regional Committees for Medical and Health Research Ethics (REC), and no informed consent was required.

Material/Data Source

We used Patient Administrative System (PAS) data from all Norwegian somatic hospitals from 2005 to 2009, which were extracted directly from the hospitals using an in-house developed system,[23] and included information on diagnosis codes, codes for medical procedures, age, sex, date, and time of ward admission/discharge. All permanent residents in Norway have a Personal Identification Number (PIN). Information on time of death, patients' vital status (eg, inhabitant, emigrated, or dead), marital status in the year of hospitalization, and identifier of spouse, if any, was added from the National Registry operated by Statistics Norway, through this unique PIN. Educational level and income at the year of hospitalization were obtained from linkage with data from the Educational Database and tax records, both operated by Statistics Norway. The corresponding characteristics of spouses were added, using the spouse identifier. Travel time in minutes by car from the residential address to the first hospital to which the patient was admitted was calculated by Statistics Norway.

Study Population

All patients hospitalized in all acute care somatic hospitals in Norway from 2005 to 2009 were included. The analytical unit comprised episodes of care constructed from single ward stays or by linking subsequent ward stays where transfers occurred within 8 hours, including transfer between hospitals.[4] Among all episodes of care, patients with a primary diagnosis of stroke (I61, I63, and I64) according to the *International Classification of Diseases*, *Tenth Revision* (*ICD-10*) were included. For transferred patients, the diagnosis must occur at the first hospital in the episode of care. Episodes of care were excluded if the admission date was missing, the PIN not valid, status unknown (living or dead), or the patient was lost to follow-up because of emigration. An episode of care constituted a readmission if within 28 days after the day of discharge of a previous episode and was excluded from the final sample. Moreover, patients with missing or invalid data on level of education (<2%), income (<0.2%), or municipal variables (<2%) were excluded.

Measurement

The key dependent variable of interest was defined as all-cause death within 30 days of admission to hospital. The key independent variable was hospital; 7 small hospitals were excluded from the study because they had <80 admissions from 2005 to 2009, resulting in inclusion of 56 hospitals. The small hospitals were excluded because the probability of zero events is high, potentially causing convergence problems in the logistic regression models.

Individual-Level Measures

The Charlson comorbidity index (CCI) was calculated based on all diagnosis codes recorded in admissions during the last 3 years before, but not including, the current episode; the revised *ICD-10* implementation of Quan et al[24] was used. Previous admissions were calculated as the number of episodes of care during the previous 2 years. Type of stroke was categorized as intracerebral hemorrhage (I61), cerebral infraction (I62), or unspecified (I64). Marital status was categorized in 3 groups: married, unmarried, or previously married (divorced, separated, or widowed). For the married patients, their income was set to own plus spouse's income divided by 1.7, which is a factor commonly used to reflect the economic advantages of a sharing household. Educational level was assessed as the highest educational level attained by the patient or a spouse, following the Norwegian Standard Classification of Education (NUS).[25] Income and education were calculated as sex- and birth-cohort–specific tertiles, named relative income and relative education.

Municipal-Level Sociodemographic Measures

To obtain a measure of the socioeconomic status of the municipal, we explored different municipal characteristics that are known to be related to health outcomes. Our selection of variables was based on a report from the Norwegian Ministry of Health, which allocates funding based on several characteristics of the Regional Health Authorities.[26] In Table S1, we have listed the proposed characteristics and our choice of variables. Accordingly, the following municipal-level variables were explored: proportion of low income (Organization for Economic Cooperation and Development [OECD] scale 60%[27]), proportion with only lower secondary school, average social benefit per capita, proportion of unemployed, proportion of retired old-age pensioners, proportion of disability retirement benefit recipients, proportion of non-Western immigrants, proportion of widowers, and proportion of divorced/separated. Municipal characteristics were collected from 2005 to 2009 from official statistics from Statistics Norway.[28] Municipal variables were measured as the ratio of proportion in the municipal divided by the proportion in the population.

Statistical Analyses

Model development

Five models were developed: null model (model 0): age, sex, calendar year, type of stroke, CCI, and number of preadmissions, base model (model 1): model 0 plus hospital; model 2: model 1 plus individual SDS; model 3: model 2 plus SDS on a municipal level; and model 4: model 1 plus SDS on a municipal level. Logistic regression analysis was used to assess the relation between risk factors and mortality. To account for an observed secular trend in mortality over time, the calendar year was added to the analyses as a numerical value (eg, 1 for 2005, 2 for 2006, . . ., and 5 for the year 2009).

In the development of the model, the following variables were modeled as categorical: sex, type of stroke, relative level of education, relative income, and marital status. Age and municipal variables were modelled using natural splines using 3 knots located by quantiles,[29] whereas preadmissions, CCI, and travel time in minutes from residential address to first hospital were modeled as fractional polynomials.[30]

Inclusion of variables and 2-way interactions between variables were tested by a step-wise elimination method based on the Bayesian information criterion criteria. This led to inclusion of interaction terms between age and CCI, age and type of stroke, and type of stroke and CCI. In addition, we excluded travel time from the models and only kept the municipal variable proportion of low income.

Model comparisons

Model performance of model 3 (full model) was assessed using various summary statistics, including the c-statistic and the Hosmer–Lemeshow statistic. The Hosmer–Lemeshow test is sensitive to the number of groups, and our choice for the number of groups was adapted from Paul et al.[31] The different models (models 1, 2, 3, and 4) were compared by a likelihood ratio test. To account for the large sample size, which is likely to claim even small differences as significant, we applied 1% level of significance for testing.

Identifying outlier hospitals was conducted through multiple significance testing. The regression coefficient of each hospital was compared with a reference value. The reference value was the 10% trimmed mean of the regression coefficients. Multiple testing was performed using Guo–Romano with an indifference interval of 0.02.[32]

All data management and statistical analyses were performed using R software (versions 3.2.3 and 3.5.1; R Foundation for Statistical Computing, Vienna, Austria).[33]

Sensitivity Analysis

Percentage of deaths within 30 days is calculated from hospitalizations rather than unique patients, introducing a correlation between hospitalizations for the same patient. In this article, this was handled by including a washout period of 28 days, excluding recurrent stroke episodes per patient. In addition, we included number of previous admissions in the logistic regression model. Patients with many previous admissions may have a higher risk of stroke compared with patients with few or no previous admissions. In the same manner, previous history of stroke may result in higher risk of stroke compared with patients with no previous history of stroke. A sensitivity analysis was done, including adjustment for previous stroke episodes in the models, to evaluate different variants of time since last stroke, for example, previous stroke ever, within 3 years, within 2 years, and within the last year. First, the different variants were included in model 1 to test whether they were statistically significant predictors of 30-day mortality. Second, for those variants which were statistically significant predictors, all the models were fitted. Finally, we identified outlier hospitals for all the models and compared the results with main models.

Results

Patient Characteristics

The study group comprised 49 656 admissions (45 448 patients). 78.6% for ischemic stroke, 13.3% for hemorrhagic, and 8.1% unspecified (Table 1). Mean age was 75 years, 25.0% of the patients had a CCI >1, and around 30% had more than 1 previous hospital admission during the last 2 years. Around 45% of the patients had lower education and 9.2% were unmarried. Crude 30-day mortality was 14.2%.

Predictors

Most of the individual SDS factors, except travel time, were statistically significant predictors of 30-day mortality. Unmarried patients had 39% higher odds of death within 30 days compared with married or those cohabiting, and low-income patients had 13% higher odds of death within 30 days compared with those with high income (Table 2, model 3). The municipal variable *proportion of low income* was a statistically significant predictor of 30-day mortality (both with and without individual SDS factors): Patients living in a municipal with a high proportion of low income had higher odds of death compared with those living in a municipal with a low proportion of low income. Figure 1 shows the log odds ratio for death within 30 days versus proportion of low income in the municipality according to model 3 and model 4 (red line). The odds ratio of death within 30 days for proportion of low income increased slightly when not including individual SDS variables (model 4).

Table 1. Characteristics of the Study Population

	No. (%)
No. of patients	45 448
No. of hospitalizations	49 656
30-d mortality	7072 (14.2)
Age, y, mean	75.3
Females	24 587 (49.5)
Type of stroke	
Ischemic	39 015 (78.6)
Hemorrhagic	6617 (13.3)
Not specified	4024 (8.1)
Charlson comorbidity index (CCI)	
CCI 0 points	37 250 (75.0)
CCI 1 to 2 points	8828 (17.8)
CCI >2 points	3578 (7.2)
No. of previous admissions	
0	25 046 (50.4)
1	11 204 (22.6)
2 to 5	11 190 (22.5)
≥6	2216 (4.5)
Education	
Lower secondary (≤10 y)	22 441 (45.2)
Upper secondary (11–12 y)	17 998 (36.2)
Tertiary (≥13 y)	9217 (18.6)
Income (in NOK 1000)	
0 to 99	634 (1.3)
100 to 199	31 268 (63.0)
200 to 299	12 681 (25.5)
300+	5073 (10.2)
Marital status	
Married/cohabiting	22 883 (46.1)
Unmarried	4590 (9.2)
Previously married	5473 (11.0)
Distance to hospital, min	
<60	40 762 (83.3)
60 to 120	4644 (9.5)
120 to 180	1417 (2.9)
180+	2102 (4.3)

NOK indicates Norwegian Krone.

Comparison of Models

There was significant variation in mortality after hospitalization of stroke at a hospital level, proven by a likelihood ratio test, comparing a model with hospitals as fixed effect (model 1) with the model without the hospitals as fixed effect (model 0; P<0.001). Adding individual SDS factors, model 2, increased the model fit tested by the nested likelihood ratio test, with a P value of <0.001. Adding municipality SDS factors, model 3, further increased the model fit, with P value 0.037 from the likelihood ratio test. Including only municipality SDS factors, model 4, increased the model fit from

Table 2. Adjusted Odds Ratios for the Individual Sociodemographic Variables

Sociodemographic Variables	Adjusted OR (95% CI)	
	Model 2*	Model 3†
Relative education		
Low	1.10 (1.01–1.19)	1.10 (1.01–1.12)
Medium	0.98 (0.91–1.06)	0.98 (0.90–1.05)
High	1	1
Relative income		
Low	1.13 (1.04–1.23)	1.14 (1.04–1.24)
Medium	1.07 (0.99–1.16)	1.08 (0.99–1.16)
High	1	1
Marital status		
Unmarried	1.39 (1.25–1.54)	1.39 (1.25–1.55)
Previously married	1.04 (0.97–1.11)	1.04 (0.97–1.11)
Married	1	1

*Adjusted for age, sex, Charlson comorbidity index, number of preadmissions, education, income, and marital status.
†Adjusted for age, sex, Charlson comorbidity index, number of preadmissions, education, income, marital status, and proportion of low income in the municipality.

model 1 (without SDS factors), but not from model 3 (with individual and municipality SDS factors). The Hosmer–Lemeshow test showed adequate goodness of fit (P=0.90), and the model discrimination, measured by c-statistics, was 0.8 for the full model (model 3). Adding SDS factors (either model 2, 3, or 4) resulted in a change of classification from "significantly high mortality" to "nonoutlier" for 1 hospital. Figure 2 shows only minimal differences between hospital-level estimates when comparing models. Results from the sensitivity analysis show that including previous history of stroke in the models had no effect when identifying outlier hospitals; data not shown.

Discussion

In this study, we found that marital status, income, and education were statistical predictors of 30-day mortality at the individual level. One contextual variable—the proportion of low income in the municipal of residence—was found to independently (and also in addition to individual income) predict 30-day mortality after stroke. Including individual and contextual sociodemographic characteristics improved the model fit. However, outlier status was changed for only 1 hospital.

Comparisons With Other Studies

Our study, in line with similar studies, found a protective effect of marriage on survival after hospitalization following an acute stroke. A recent study found that the odds ratios of being married versus unmarried for all-cause 1-year mortality

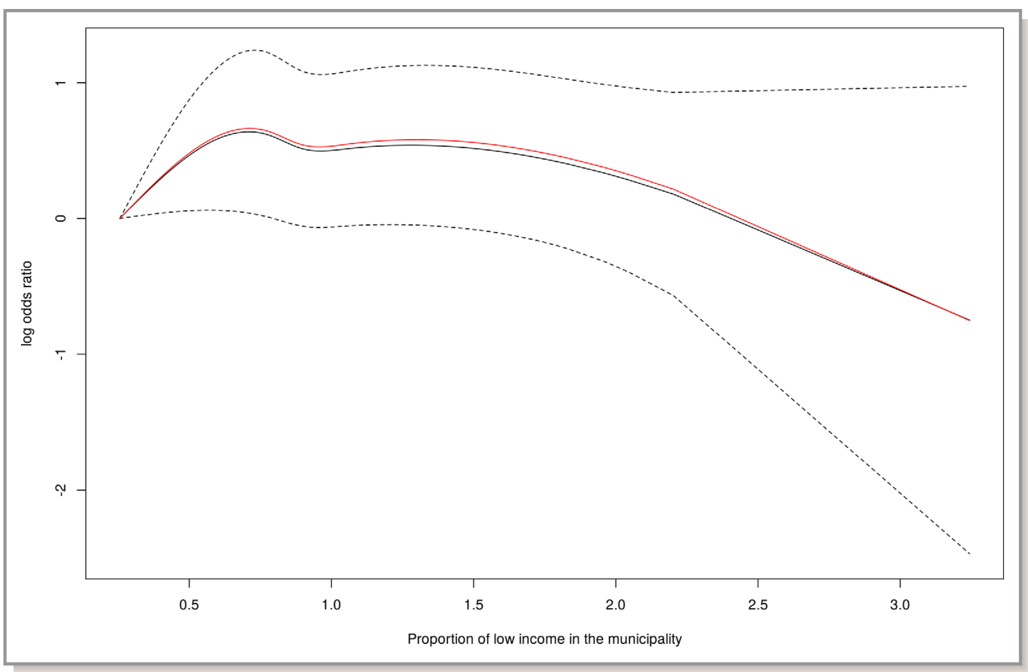

Figure 1. Log odds ratio for death within 30 days vs proportion of low income in the municipality, risk-adjusted, with 95% CI according to model 3. The red line is the log odds ratio of low income according to model 4 (not including individual sociodemographic status variables).

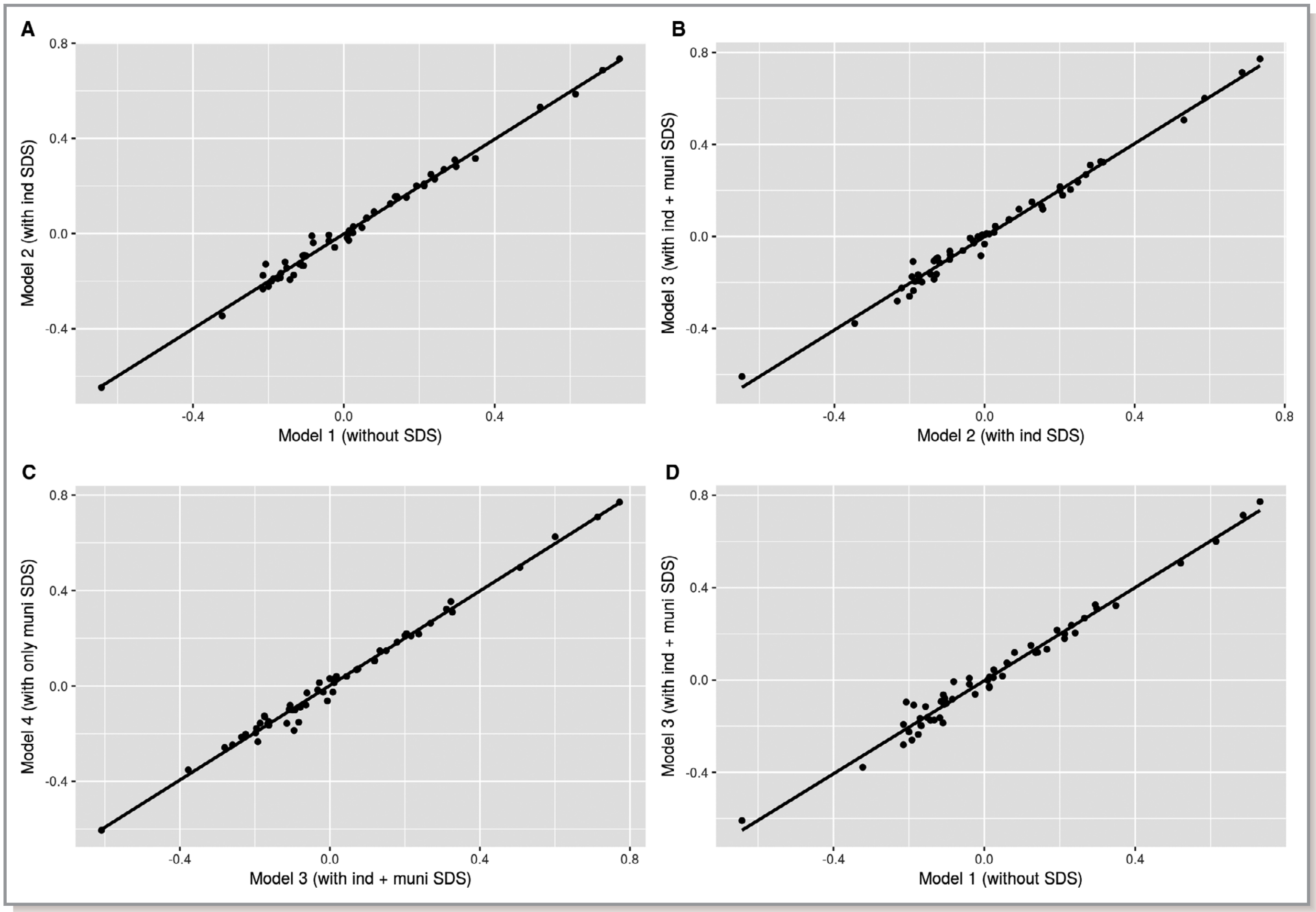

Figure 2. Comparison of the hospital-level estimates on the linear predictive scale using different models. **A**, Model 1 without sociodemographic status (SDS) variables and model 2 with individual (ind) SDS variables. **B**, Model 2 with individual SDS and model 3 with individual and municipal (muni) SDS. **C**, Model 3 with individual (ind) and municipal SDS and model 4 with only municipal variables (none-individual SDS variables). **D**, Model 1 without SDS variables and model 3 with individual and municipal SDS.

for patients with stroke was 0.70.[34] In comparison, our study found that the odds ratio was 0.72 (eg, 1/1.39) for 30-day mortality. The results of a population-based study using data from a Swedish stroke register (Riks-Stroke) showed that low income, leaving education directly after lower secondary school, and living alone were independently associated with increased mortality after the acute phase of stroke.[35] Similar to other studies, our estimates show low income, rather than low education, to have a stronger effect on mortality.[12,15]

The previously mentioned studies have used individual measures of SDS. However, it is also interesting to investigate the independent effect of neighborhood SDS on mortality. Several studies have found that living in socioeconomically disadvantaged communities is associated with higher stroke mortality.[10,16] But what about the association between neighborhood SDS and individual SDS? In our study, we found an effect of both individual SDS and neighborhood SDS, in concordance with Yan et al,[17] who also found an effect of individual SDS after adjusting for neighborhood factors. Our study also found that the effect of the individual factors hardly changed with the inclusion of neighborhood factors, and that the model that included both individual and neighborhood factors (model 3) was slightly better than the model with neighborhood factors only (model 4). It should be noted that only 1 hospital changed its outlier status when including only neighborhood SDS compared with only including individual SDS.

In the “Methodological development and evaluation of 30-day mortality as a quality indicator for Norwegian hospitals” report, individual SDS variables were included.[23] Although they were significant, the effect was minimal compared with strong predictors such as age and frailty. As shown in the current study, the overall magnitude of the changes in hospital effect estimates was minor when SDS variables were included. Most recent research on the impact of socioeconomic status (area-based) measures on hospital profiling have been concentrated around 30-day readmission models. A study of coronary artery bypass grafting in California showed no effect of individual SDS on mortality, although insurance status predicted stroke and readmission.[7] A study among US veterans hospitalized with stroke concluded that models that included social risk factors did not affect hospital comparisons based on 30-day readmission rates.[22] Inclusion of the Agency for Healthcare Research and Quality–validated socioeconomic status index score in a 30-day readmission model did not impact hospital-level profiling in New York City.[21]

Interpretation of Results

We found that when adjusting for socioeconomic characteristics of the individual and municipal of residence, only 1 hospital changed its outlier status. In this article, we also controlled for directional errors as proposed by Guo and Romano, because we are not only interested in determining outlier status, but also whether hospitals have significantly higher or lower mortality. Thus, larger changes in the model performance may be necessary to affect the profiling using this methodology.

Some hospitals with large numbers of patients with low SDS are concerned that they are disadvantaged by the measures. They argue that adjusting for these factors is necessary for fairness in comparison, and that hospitals should not be responsible for community factors that affect patient outcomes. However, our study showed that including SDS only had a minor effect on the estimate for each hospital (see Figure 1), and only 1 hospital changed its status from a high-mortality hospital to nonoutlier hospital, when including individual SDS factors (model 2).

Strengths and Limitations

It would be desirable to include several other prognostic factors when calculating the 30-day mortality, for example, National Institute of Health Stroke Score, occupation, and lifestyle, which we were not able to adjust for in this study. Accuracy of stroke severity is important, given that it is considered an important prognostic factor and could therefore potentially change hospital outlier status.[36] Whereas education and income are 2 important socioeconomic measures, socioeconomic status is a complex concept with many other important components, such as occupational class, social status, or others. Conventional risk factors for stroke (eg, hypertension, hyperlipidemia, smoking, obesity, and sedentary lifestyle), which we were not able to adjust for, may account for some of the differences in stroke mortality between socioeconomic groups according to a systematic review.[37]

Models 3 and 4 included many municipal sociodemographic factors, but only low income was significantly associated with mortality. Thus, most of the factors we included were not useful in terms of improving the prediction of mortality after stroke, and other variables not included may be more important. Level of socioeconomic deprivation in a patient's area of residence was included in the definition of Dr Foster's Hospital Standardized Mortality Ratio,[38] which is often used as an indicator of hospital performance. There are several different deprivation indices, such as Carstairs, Townsend, the European Deprivation Index, etc. Our included variables of municipal SDS are similar to the above-mentioned measures. However, we were not able to procure information on some of the key variables needed in the indices mentioned, for example, percentage of families below the poverty level, percentage of single-parent households with children aged <18 years, and percentage of occupied housing units with >1 person per room (overcrowding). A strength of the included municipal variables is that they are easily obtained with high data completeness and without the need for individual-level data collection.

In conclusion, we found that adding sociodemographic factors for the individual and/or municipal of residence led to minor improvements in model performance compared with only using administrative data, but hardly influenced the hospitals' outlier status. In other words, this study found an empirical effect of adjustment on the hospital outcome measure; therefore, including SDS factors may improve the model, but may not be necessary. However, to meet critics from hospitals with a large number of patients with low SDS concerning unfairness in comparison, it may be desirable to include SDS in the model.

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Disclosures

None.

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SUPPLEMENTAL MATERIAL

Table S1. A list of different municipal characteristics based on the Norwegian Official Report.

Characteristics listed in the report	Our corresponding proposed definition	Variable	Median (min–max)
Proportion of low income	Proportion of low income	Median income in 100,000 NOK	389’ (282–543’)
Proportion with only lower secondary school	Proportion with only lower secondary school	Proportion with only lower secondary school (%)	34.7 (17.4–61.1)
Proportion of social benefit recipients	Average social benefit per capita	Average social benefit per capita in NOK	737 (0–2,332)
Proportion of unemployed	Proportion of unemployed	Proportion of unemployed (%)	1.3 (0.4–4.3)
Share outside the workforce	Share of retired old-age pensioners	Proportion of retired old-age pensioners (%)	15.3 (7.3–25.0)
	Proportion of disability retirement benefit recipients	Proportion of disability retirement benefit recipients (%)	6.6 (2.4–13.8)
Proportion of non-western immigrants	Proportion of non-western immigrants	Proportion of non-western immigrants (%)	1.5 (0.0–12.2)
Proportion of asylum seekers	*Not possible to obtain at a municipal level*	-	-
Proportion of widowers	Proportion of widowers	Proportion of widowers (%)	6.4 (3.0–11.6)
Proportion of separated /divorced	Proportion of separated /divorced	Proportion of separated /divorced (%)	7.9 (3.8–13.6)
Living index	*No longer calculated*	-	-

In addition, the median and range summarized by the 356 municipalities for the suggested variables.

*NOK – Norwegian Krone