Risk Adjustment in Capitation Payments to Primary Care Providers

Does It Matter How We Account for Patients' Socioeconomic Status?

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Background: One of the critical challenges with capitation payment to primary care providers is ensuring that the fixed payments are equitable and adjusted for expected care needs. Patients of lower socioeconomic status (SES) generally have higher health care need. Sweden developed a Care Needs Index, which is used in the capitation payments to primary care providers to account for patient SES.

Objectives: We aim to examine the potential value of collecting individual-level rather than geographic-level socioeconomic data to support an equitable payment to primary care providers.

Research Design: We used data from 3 regional administrative care registers, which cover all consultations in publicly funded health care, and Statistics Sweden's registers covering individual background characteristics. We estimated linear regression models and evaluated the model fit using the adjusted R2 with the Care Needs Index at the individual and at the district level. The population consisted of the 3,490,943 individuals residing in the 3 study regions for whom we had complete data.

Measures: The main outcome variable was the number of face-to-face consultations with a GP or a nurse at a primary care practice. We use the R2 to compare the predictive power of the models.

Results: The share of the variation explained did not depend on whether the Care Needs Index was measured at the individual level or the small area level.

Conclusions: SES explains very little variation in primary care visits, and there is no gain from having individual-level information about the individual's SES compared with having district-level information only.

Key Words: risk adjustment, capitation, primary care

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Capitation payment models have gained prominence as an effective mechanism to control costs and incentivize high-quality care.[1] Under a capitation model, primary care providers (PCPs) receive a fixed amount of money per patient for a specified period, regardless of the number of services provided. This model contrasts with traditional fee-for-service arrangements, which often encourage the provision of more services and can lead to increased health care costs without necessarily improving patient outcomes.

Many jurisdictions have implemented a capitation-based mechanism to pay PCPs, whether the payment is made to primary care clinics such as in Sweden,[2,3] the United States[4] or the United Kingdom,[4–6] or directly to general practitioners (GPs), such as in Ontario, Canada.[7] In this paper, we use the terminology GP to refer to physicians practicing family medicine in a primary care setting, which excludes specialists and physicians practicing in hospitals. Some countries are conducting pilot tests to determine the appropriate formulae for the capitation payments, including the variables and weights for risk adjustment.[8,9] Indeed, one of the critical challenges in using capitation payment is ensuring that the fixed payments are equitable and reflect the heterogeneity in health care needs of different patient populations.[10] Hence, capitation payments should be adjusted to the expected utilization of patients. Age and sex are the most common risk adjustment factors used with some jurisdictions also incorporating health status and socioeconomic status[11] (SES).

Risk adjustment methods are increasingly being improved to try to limit patient selection and promote social equity.[12] As concerns are raised over disparities in access to care and health outcomes, equity has specifically been put at the forefront of the National Academies of Sciences, Engineering, and Medicine in the United States.[13] Age and sex are likely the most common because these data are generally easily accessible. Health status adjustments such as with the Ambulatory Care Groups,[14,15] the Johns Hopkins Adjusted Clinical Groups (ACG) Case-Mix system,[16] the Hierarchical Conditions Classification[17,18] or disease counts[6] are commonly used but are not as widely adopted as age and sex.[11] Various approaches have been developed to measure health needs. Although health status algorithms have shown good predictive power, a common critique is the circularity of using diagnoses data to generate health status scores, given these diagnoses require visits.[5] In addition, there is a wide heterogeneity of utilization of services within diagnosis,[19] suggesting underlying needs not accounted for with diagnoses.

There is a growing awareness of the role that the socioeconomic context of individuals may have on their utilization of services and on their health outcomes.[20] A number of studies suggest that social deprivation is associated with higher health care needs. There is no consensus about how SES should be incorporated into capitation payments. One criticism made in studies that include SES variables to model utilization or costs of primary care is that individuals are given a score based on the characteristics of the area where they live, which may not necessarily reflect their actual status.[7,21–23] As risk adjustment methods are being refined and improved, policymakers need more evidence about how to account for deprivation in capitation payment for PCPs.

In the present study, we aim to examine the potential value of collecting individual-level rather than geographic-level socioeconomic data to support an equitable payment to primary care providers with data from 3 regions in Sweden.

INSTITUTIONAL BACKGROUND

Sweden's universal health system is decentralized into 21 independent regions. Within the boundaries set by the national laws, each region stipulates the rules regarding what services ought to be supplied by primary care, as well as the reimbursement rules for health care providers. Despite the large degrees of freedom, there are several similarities between the regions. In our 3 study regions, primary care is provided by group practices—primary care centers—employing around five general physicians as well as nurses and other staff (such as physiotherapists, or occupational therapists), all salaried. The main source of funding for the practices is risk-adjusted capitation for the registered patients. The risk adjustment takes into account the morbidity and SES of each patient. For the morbidity adjustment, the regions use the commercial Johns Hopkins ACG system, which predicts costs based on the patient's age, sex, and diagnoses[14,15] and has been validated in the Swedish population.[24,25] For the SES adjustment, the regions use a measure of social deprivation called the Care Need Index (CNI) developed by Swedish researchers.[26,27] The CNI includes several demographic and socioeconomic characteristics of the patient: age below 5, single parent, elderly person living alone, at most primary education (low education), unemployment, having immigrated from Eastern Europe, Southern Europe outside the European Union, Asia, Africa, or Latin America. The CNI weight is highly correlated with (low) disposable income.[2]

METHODS

Data, Study Population, and Variables

We used data from the regional administrative care registers, which cover all consultations in publicly funded health care, and Statistics Sweden's registers covering individual background characteristics. The datasets were linked by Statistics Sweden using the national personal identifying number. On December 31, 2017, there were 3,491,340 residents in the 3 regions. After excluding 397 individuals with no information on age, our study population includes 3,490,943 individuals (all ages). Of these, 457,258 lived in Östergötland, 1,343,759 lived in Skåne and 1,689,926 in Västra Götaland (VGR).

The main outcome variable was the number of face-to-face consultations with a GP or a nurse at a primary care practice in 2018. All models included age and gender. To construct other risk adjustment variables (SES and morbidity), we proceeded as follows.

To construct a measure of individual SES, we computed the CNI weight of each individual using microdata on the CNI components obtained from Statistics Sweden. Following the approach in previous research,[2] we constructed a dummy variable for each component and multiplied each dummy variable by its weight obtained from Statistics Sweden, and computed the sum. As an alternative measure of SES, we used the dummy variables themselves and household disposable income, respectively.

To compute a measure of individual morbidity, we used a researcher license for the 11th version of the ACG software to compute ACG weights. The weights came from a model calibrated to the primary care expenditures of a Swedish population. The software model was fed with information on the age, gender, and diagnoses registered during 2017 for each individual. To mimic the risk adjustment models used in the different regions, we included diagnoses set in both primary and secondary care when computing the ACG weights for residents in Skåne and Östergötland, but only diagnoses set in primary care for VGR. For the 9999 individuals who had utilized care in more than 1 region, and thus had more than 1 weight, we used the highest ACG weight.

To compute aggregated versions of the risk adjusters, we used Statistics Sweden's categorization of small areas, DeSO, which aims to capture natural geographic boundaries and have a reasonably similar population size. There were 2151 small areas (289 in Östergötland, 822 in Skåne, and 1040 in Västra Götaland). The mean population size was 1662 (SD 532, interquartile range 1362–1960).

Analytical Approach

We estimated linear regression models and evaluated the model fit using the adjusted R2. All models included individual age (in years) and age squared, both interacted by a dummy for female sex. Model 1, the basic model, adjusted only for age and sex. Model 2 added the individual-level CNI weight (SES). Model 3 added the ACG weight. In model 4, the individual-level CNI weight was replaced by the average weight of individuals living in the same small area. In model 5, both the individual-level and district-level CNI weights were included. We ran each regression model on all primary care visits, and separately on visits with GPs and visits with nurses. To examine the statistical significance of individual coefficients, we relied on heteroscedasticity-robust standard errors (models 1–3) or standard errors clustered at the small area level (models 4–5).

We conducted a number of sensitivity tests. We used a Poisson model for count data to see whether it would account better for the variation in the outcome. We also explored a broader way of accounting for area-level differences in care use; specifically, we included district fixed effects which account for all differences between districts, not only differences in SES. We replaced the CNI weight with the dummy variables underlying the calculation of the CNI weight (ie, dummies for being an immigrant, having no more than primary education, etc.) to see whether the weighting itself affected the R2. We used the household disposable income instead of the CNI as a proxy of SES. Finally, we replaced the main outcome variable (the number of visits) with the individual's ACG weight in 2018. The idea was that the ACG may capture dimensions of resource needs not captured by our main outcome, which just counted the number of visits. Ideally, we would have wanted to estimate the model using costs as the outcome, but cost data was not available to us.

We also explored heterogeneity in several dimensions. First, we estimated the separate models for each region. Second, we estimated models stratified by age (0–17 y, 18–64 y, 65+). Third, we explored if the aggregation level of the SES mattered more in more heterogeneous areas. To do this, we divided the population into 4 groups based on the heterogeneity of the CNI within their district, as measured by the district-level coefficient of variation (CV) of the CNI weight. The groups were defined by the quartile limits of the distribution of CVs; ie, group 1 consisted of individuals living in areas with a CV in the lowest quartile of the distribution (most homogeneous), etc.

Ethical Approval

The research reported in this paper was approved by the regional ethics committee in Gothenburg, Sweden (Dnr 068-18, T777-18).

RESULTS

Descriptive Statistics

Figure 1 shows the distribution of the outcome variables. 60% of the study population visited a primary care center at least once during the year; most only made 1 or 2–3 visits. 25% made more than 3 visits. The distribution was similar for physician (Fig. 1B) and nurse visits (Fig. 1C), with 25% of the population visiting a GP (nurse) at least twice (once).

Table 1 shows summary statistics (mean and SD) of the outcomes and the socioeconomic variables.

Table S5, Supplemental Digital Content 1, http://links.lww.com/MLR/C984, shows descriptive statistics by region. The null hypothesis of no difference in means between the regions was rejected for all variables, but the magnitudes of the differences were small for most variables. Figure S2, Supplemental Digital Content 1, http://links.lww.com/MLR/C984 shows that the distributions of the ACG weights are very similar in all regions (Figure S3 Supplemental Digital Content 1, http://links.lww.com/MLR/C984).

Risk Adjustment Models

Table 2 displays the adjusted R2s. For the total number of physician and nurse visits, the base model adjusting for age and sex only explained 10.2% of the variation in the total number of visits (column 1). In addition, adjusting for the individual's CNI increased the adjusted R2 only marginally (from 10.2% to 10.5%; column 2). Adding the adjustment for individual morbidity (ACG) to the CNI increased the R2 to 16.2% (column 3). The share of explained variation did not depend on whether the CNI was measured at the individual level (column 3) or the small area level (column 4). The R2 was also unchanged when including the area-level CNI and the individual-level CNI in the same model (column 5). In other words, SES explains very little variation in primary care visits in this study setting, and there is no gain from having individual-level information about the individual's SES compared with having district-level information only. Although not shown in our results table, the coefficient estimates of the CNI variable were statistically significant ($P < 0.001$; Supplementary Tables S1–S3, Supplemental Digital Content 1, http://links.lww.com/MLR/C984) and of notable magnitude; for instance, an increase in the CNI from 0 (high SES in all dimensions) to 5.13 (the index value for an unemployed person) would increase the mean visits by $5*0.048 = 0.25$ visits in our specification with individual-level CNI. This is more than 10% of the mean of 2 visits/year. Thus, the CNI is a strong predictor of mean care use, even though the uncertainty around the prediction is very large (the R2 is low).

As an alternative way of assessing the model performance, we computed the ratio of observed to predicted visits for each model, aggregated at the district level, and plotted the distributions of this measure of underprediction/overprediction. Supplementary Figure S1, Supplemental Digital Content 1, http://links.lww.com/MLR/C984 shows that the difference between the models including CNI at the individual or district level is small also according to this measure.

The pattern was similar when measuring GP and nurse visits separately, only that the share of explained variation was smaller (in particular for nurse visits).

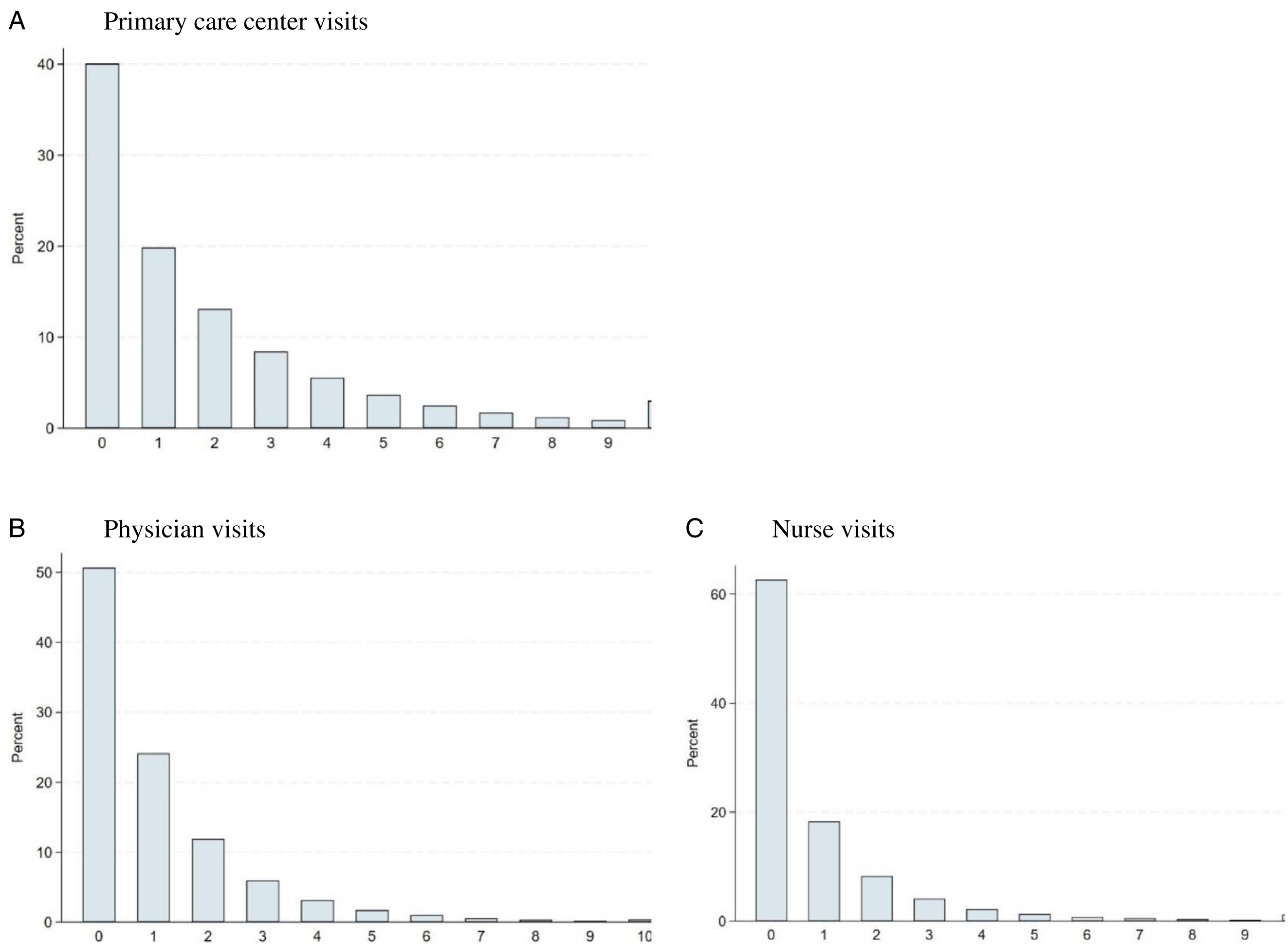

FIGURE 1. Distribution of outcome variables; percent of the study population with 0–9 or at least 10 visits to a primary care center (A), a general practitioner (B), or a district nurse (C).

The sensitivity tests (Supplementary Table S4, Supplemental Digital Content 1, http://links.lww.com/MLR/C984) showed that the explained variation for the total number of visits was similar when including district fixed effects as an alternative approach to the district-level CNI. Moreover, the share of explained variation (pseudo R2) was smaller when using a Poisson model instead of linear regression. Regressions using the ACG weight in 2018 as the outcome variable yielded a higher R2 (23%) (Panel A, Table S4, Supplemental Digital Content 1, http://links.lww.com/MLR/C984). Compared with the specification adjusting only for age, sex, and individual CNI (column 2 in Table 2), the R2 of the model adjusting only for demography and SES was slightly larger when replacing the CNI with the underlying variables included in the index (R2 = 11.1%), and slightly smaller when using disposable income as the measure of SES (R2 = 10.2%)(Panel B, Table S4, Supplemental Digital Content 1, http://links.lww.com/MLR/C984).

The proportion of explained variation was similar in all 3 regions (Panel C, Table S4, Supplemental Digital Content 1, http://links.lww.com/MLR/C984): In model 3, the R2 was 15.5% for Västra Götaland, 19.1% for Skåne, and 21.4% for Östergötland. Notably, a comparison of specifications within each region showed that the R2s were similar regardless of whether CNI was included at the individual or district level. Similarly, the share of explained variation did not depend on the level of aggregation of the CNI adjuster in models estimated separately by age group (Table S6, Supplemental Digital Content 1, http://links.lww.com/MLR/C984) or groups defined by the within-district SES heterogeneity (Table S7, Supplemental Digital Content 1, http://links.lww.com/MLR/C984).

DISCUSSION

We estimated R2 to compare the predictive power of the risk adjustment approaches. We note that our R2s are smaller than those reported in the literature, such as in the United States, where a model could predict 67% of the variance in the primary care activity level,[1] and another 70% of the workload.[28] Our R2 is also lower than those reported (37%) when predicting primary care costs in

TABLE 1. Descriptive Statistics

	Mean (SD)	Q1	Median	Q3
female sex	0.50 (0.50)	0.00	0.00	1.00
age	40.45 (23.90)	21.00	40.00	60.00
age below 5	0.06 (0.24)	0.00	0.00	0.00
old and living alone	0.09 (0.28)	0.00	0.00	0.00
single parent	0.03 (0.16)	0.00	0.00	0.00
moved	0.11 (0.31)	0.00	0.00	0.00
foreign	0.13 (0.33)	0.00	0.00	0.00
low education (primary)	0.06 (0.24)	0.00	0.00	0.00
unemployed	0.04 (0.20)	0.00	0.00	0.00
CNI	2.24 (3.20)	0.00	0.00	4.00
annual disposable income (SEK)	199,516 (408,652)	32,634	173,499	287,677
PCC visits	2.05 (3.67)	0.00	1.00	3.00
Physician visits	1.06 (1.64)	0.00	0.00	2.00
Nurse visits	0.99 (2.86)	0.00	0.00	1.00
ACG	0.99 (1.52)	0.02	0.50	1.19

For binary variables (female sex, age below 5, old and living alone, single parent, moved, foreign, low education, unemployed), the mean is the proportion of the study population with a characteristic.

ACG indicates Adjusted Clinical Groups (measure of morbidity); CNI, Care Need Index (measure of social deprivation); N, 3,490,943; PCC, primary care center; Q1, first quartile; Q3, third quartile; SEK, Swedish Krona.

Sweden, before the inclusion of the CNI.[25] In addition, the R2 for the Västra Götaland region was lower than for the other 2 regions. This may be because of how the ACG is computed, as the Västra Götaland region only includes diagnoses data from primary care visits, while the other 2 regions also include diagnoses from specialist visits.

Socioeconomic health inequalities is a source of concern in most health systems.[29] Risk-adjusted capitation may be a way to counteract adverse incentives to under-provide care for low-SES patients. A challenge in this regard is that third-party payers may not easily access data on SES of their patients, and thus must resort to aggregated measures of deprivation in a larger area.

The results of this study, which was able to observe SES both at the individual and the small area level (with an average population of 1662), may at first suggest that the gain from obtaining individual-level information may be small. However, the results also show that low SES only accounts for a negligible part of the individual-level variation in care use. If individual-level SES had accounted for more of the individual-level variation in care use, it is possible that we would have lost some predictive power by aggregating to the area level. More generally, the consequences of aggregation may depend on the population heterogeneity within the area, although our sensitivity analyses gave similar results in more and less homogeneous districts.

TABLE 2. Risk Adjustment Models

	(1) Base	(2) CNI	(3) CNI & ACG	(4) CNI (district) and ACG	(5) CNI (both levels) and ACG
Y = all visits:					
Adjusted R2	0.102	0.105	0.162	0.162	0.163
Y = GP visits:					
Adjusted R2	0.076	0.083	0.159	0.157	0.160
Y = nurse visits:					
Adjusted R2	0.070	0.071	0.093	0.093	0.093

The table shows adjusted R2s from risk adjustment models. All models adjust for age, age squared, sex, and their interactions.

ACG indicates Adjusted Clinic Group; CNI, Care Need Index.

In the present setting, individual-level and area-level SES measures were equally good at explaining individual-level variation in primary care utilization. This suggests that in the absence of individual-level data on SES, area-level SES can be used for the purpose of calculating a risk adjustment factor of the capitation.

This is aligned with a large body of literature on the effects of social determinants of health[30,31] and on geographic variations[32,33] in health services utilization. The extent to which district-level measures of SES can substitute for individual-level measures of SES could depend on the level of heterogeneity of SES within the district. Although this hypothesis makes theoretical sense, our empirical results show no difference. Similar studies in other contexts or with different measures of SES could be conducted to examine the sensitivity of SES measures to geographic-level heterogeneity.

One may argue that it is useless to adjust for SES when it accounts for so little variation. Yet, we found that the correlation between the CNI and the outcome was of considerable magnitude. This means that providers will have incentives to dump low-SES patients unless the capitation adjusts for SES. This remains true even though the risk adjustment model does not account for much variation. In a nutshell, SES is a good predictor of the mean outcome, but for a given individual, the prediction will be very uncertain on average. Notably, though, it is not certain a priori that risk adjustment based on SES would imply higher capitation for low SES patients. If low SES populations face higher barriers to access, their utilization level may be too low (for a given level of health). In our study context, it is unlikely that barriers to access vary greatly by SES: There is universal health insurance, copayments are low and completely waved for individuals supported by social assistance benefits, there is at least one publicly funded primary care practice in every municipality, and health care providers are required by law to ration care based on need (rather than by willingness to pay). Indeed, the low-SES groups in our study also have higher utilization. Still, this caveat may be relevant for other settings.[34]

Study Limitations

There are multiple factors at various levels (individual, practice, geographic area, and systemic)[10] that can affect the utilization of primary care services and that were not available and thus not included in our analyses. Having additional variables would likely have increased the explanatory power of our models. However, it is unlikely that it would have changed our main conclusion regarding the similarity of the predictive powers of individual-level and aggregate-level SES.

We only had access to data on the number of GP and nurse visits. Our models thus miss important dimensions of the total resource utilization, such as lab tests, procedures, complex versus simple visits, and drug costs. Although we expect that the number of visits is highly correlated with the costs, this is a notable limitation of our analysis.

To our knowledge, this is the first study comparing models using individual and district-level SES to predict primary care utilization. Our findings are relevant to policymakers and researchers concerned about incorporating SES into capitation payments. The results show that using aggregated SES information when no individual-level SES data are available does not necessarily lead to a less accurate risk adjustment model. Notably, though, SES variables may not account for much of the variation in health care utilization. That is, risk adjustment based on SES may add little value over and above other risk adjusters such as age, sex, and diagnoses.

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