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Safety-Net Hospitals, Neighborhood Disadvantage, and Readmissions Under Maryland's All-Payer Program

An Observational Study

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Background: Safety-net hospitals have higher-than-expected readmission rates. The relative roles of the mean disadvantage of neighborhoods the hospitals serve and the disadvantage of individual patients in predicting a patient's readmission are unclear.

Objective: To examine the independent contributions of the patient's neighborhood and the hospital's service area to risk for 30-day readmission.

Design: Retrospective observational study.

Setting: Maryland.

Participants: All Maryland residents discharged from a Maryland hospital in 2015.

Measurements: Predictors included the disadvantage of neighborhoods for each Maryland resident (area disadvantage index) and the mean disadvantage of each hospital's discharged patients (safety-net index). The primary outcome was unplanned 30-day hospital readmission. Generalized estimating equations and marginal modeling were used to estimate readmission rates. Results were adjusted for clinical readmission risk.

Results: 13.4% of discharged patients were readmitted within 30 days. Patients living in neighborhoods at the 90th percentile of disadvantage had a readmission rate of 14.1% (95% CI, 13.6% to 14.5%) compared with 12.5% (CI, 11.8% to 13.2%) for similar patients living in neighborhoods at the 10th percentile. Patients discharged from hospitals at the 90th percentile of safety-net status had a readmission rate of 14.8% (CI, 13.4% to 16.1%) compared with 11.6% (CI, 10.5% to 12.7%) for similar patients discharged from hospitals at the 10th percentile of safety-net status. The association of readmission risk with the hospital's safety-net index was approximately twice the observed association with the patient's neighborhood disadvantage status.

Limitations: Generalizability outside Maryland is unknown. Confounding may be present.

Conclusion: In Maryland, residing in a disadvantaged neighborhood and being discharged from a hospital serving a large proportion of disadvantaged neighborhoods are independently associated with increased risk for readmission.

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Safety-net hospitals—those caring for large numbers of severely disadvantaged patients—are likely to have higher 30-day readmission rates and therefore incur more penalties under Medicare's Hospital Readmissions Reduction Program (1, 2). These penalties have fueled controversy about whether the higher readmission rates result from ineffective care in safety-net hospitals, which would make penalties more consistent with the intent of the program, or from challenges associated with serving severely disadvantaged populations, which would be inconsistent with the program's intent.

The effect of socioeconomic factors on individual health status and health care delivery and costs is a growing policy issue as policymakers try to find approaches for addressing this problem. The Improving Medicare Post-Acute Care Transformation Act of 2014 (3) directed the U.S. Secretary of Health and Human Services to conduct "a study that examines the effect of individuals' socioeconomic status on quality measures and resource use . . . ." The Secretary has delivered the first of 2 reports to Congress (4), and the National Academy of Medicine has released a 5-part report titled "Taking Account of Socioeconomic Factors in Medicare Reimbursement" (5). Per the 21st Century Cures Act (6), the Secretary created readmission penalties stratified by the fraction of a hospital's Medicare beneficiaries who are also eligible for Medicaid. This requirement was implemented for fiscal year 2019 (7).

This study examined whether readmission risk is associated with the area disadvantage index (ADI) of the neighborhood where the patient lives and the safety-net index (mean ADI) of the hospital providing treatment. Our analysis focused on data from Maryland, which has a unique hospital rate-setting system, one of whose aims is to decrease financial risks for hospitals that serve disadvantaged patients. We sought to answer 3 questions. First, is readmission risk higher for a patient from a more disadvantaged neighborhood (one with a higher mean ADI) after the hospital's safety-net index and clinical factors are controlled for? Second, is readmission risk higher for a patient treated in a hospital with a higher mean ADI (safety-net index) after the neighborhood disadvantage of the patient and clinical factors are controlled for? Third, what are the rela-

See also:

Editorial comment 131

tive strengths of hospital safety-net index and neighborhood disadvantage as predictors of readmission?

METHODS

Overview

We used Maryland's fiscal year 2015 (1 July 2014 to 30 June 2015) discharge data for this observational study. This analysis was initiated and largely completed as an internal Maryland Health Services Cost Review Commission (MHSCRC) study of whether to use the ADI in the hospital rate-setting process. Thus, in accordance with the MHSCRC and federal policy (8), the study was exempt from institutional review board approval.

Data Sources and Study Population

We used data from Maryland's unique all-payer hospital rate-setting system (9–11). Each hospital's revenues are regulated and each hospital's charges are essentially the same for patients with Medicare, Medicaid, commercial insurance, and no insurance. Noncollectible charges are pooled, and their burden is shared among all hospitals. During the study, Maryland was also transitioning to regulated global hospital budgets.

An important goal of this system is to minimize the financial risk to hospitals that serve disadvantaged patients. That risk has been blamed for effectiveness of care problems attributed to safety-net hospitals. To measure hospitals' financial health, we obtained operating profit margins for all hospitals from MHSCRC's audited cost report data (12). Operating profit margins exclude physician costs and income, philanthropy, and other elements that may vary substantially among hospitals. Although one reason for this study was to assess the fairness of Medicare penalties, we could not duplicate Medicare's risk adjustment methods in our calculations.

All Maryland hospitals report information on all discharges, regardless of source of payment, to the MHSCRC. The database has a unique identifier for each patient, which links admissions and readmissions across hospitals and with the neighborhood where the patient lives. We analyzed data from all discharges for all Maryland residents except newborns, patients who were transferred to another acute care hospital, and those who died.

Predictor Measures

Neighborhood ADI

The ADI, which was developed by Singh and Siahpush (13) and Singh (14) and was updated by Kind (15), Hu (16), and their respective colleagues, combines 17 measures of income, employment, education, and housing collected in the 2009–2013 American Community Survey (17). Kind and colleagues (15) found that, in a national Medicare fee-for-service sample, patients who were discharged with pneumonia, heart failure, and myocardial infarction and who lived in the most disadvantaged 15% of neighborhoods had increased risk for 30-day readmission, even after extensive clinical risk adjustment.

A team at the University of Wisconsin led by 1 of the authors (A.J.H.K.) has computed the ADI for each neighborhood (technically, each census block group) in the United States (18). Each neighborhood received a percentile ranking (with minimum disadvantage in the first percentile and maximum disadvantage in the 100th percentile) that was weighted so that each percentile had the same number of discharges. We applied these neighborhood ADI estimates to each discharge in our data set.

Hospital Safety-Net Index

We defined a hospital's safety-net index as the mean disadvantage (ADI) of its discharged patients, which is a measure of the weighted mean disadvantage of the neighborhoods from which it draws admissions.

Clinical Readmission Risk Index (Case-Mix Index)

Maryland uses the 3M Health Systems All Patient Refined Diagnosis-Related Groups (APR-DRGs)/Severity of Illness index (19, 20) to perform risk adjustment of discharges. The APR-DRGs assigns each discharge to 1 of 314 DRGs on the basis of the reason for admission and to 1 of 4 levels of severity on the basis of diagnoses and other hospital discharge data, for a total of 1256 cells. The case-mix index is the expected readmission rate per 100 discharges, based on Maryland's 2014 statewide readmission rates for each APR-DRG cell. We excluded discharges assigned to cells with fewer than 2 cases in either 2014 or 2015.

Outcome Measure

The primary outcome was unplanned 30-day hospital readmission, which we defined as any admission within 1 to 30 days after a discharge that was identified as unplanned using the Yale-Centers for Medicare & Medicaid Services algorithm (21). The algorithm primarily identifies admissions as planned if they are in certain categories (such as chemotherapy or obstetric delivery) or for a procedure without an acute diagnosis. We could not identify readmissions to or from hospitals outside Maryland. We defined the hospital readmission rate as the number of readmissions to any Maryland hospital per 100 discharges.

Statistical Analysis

We sought to estimate the independent association of ADI and safety-net index with readmission after controlling for clinical risk factors and to compare the relative size of these effects. Our basic approach used generalized estimating equations (GEEs) with marginal modeling. This approach treats clustering effects as nuisance effects and does not estimate cluster-specific values. A key question in the analysis of clustered data, such as patients or discharges nested within hospitals, is whether to center covariates of interest. Hospital-specific centering is difficult to interpret in this framework. Following the methods of Begg and Parides (22) and Enders and Tofighi (23), we addressed this issue by specifying safety-net index as the mean ADI percentile for patients discharged from a given hospital. We specified individual ADI as the raw (uncentered) value for that patient's neighborhood.

We modeled ADI and safety-net index as continuous values rather than categorical measures because diagnostic plots suggested that the association of ADI and safety-net index with readmission risk is linear. To ease interpretation and comparison of coefficients across covariates, we scaled ADI, safety-net index, and case-mix index so that the regression coefficient reflected an increase of 10 units in each covariate.

Fitting a traditional regression model to clustered data usually produces biased SEs. The investigator may use a hierarchical or random-effects approach, which explicitly models the clustering and, depending on the specification, estimates an intercept for each cluster and may estimate a cluster-specific slope for 1 or more covariates. Although such models have many strengths, when applied to binary outcomes they result in regression coefficients that must be interpreted as the effect of a covariate on observations within the same cluster or hospital. This led us to specify a model using a GEE, which yields regression coefficients that may be interpreted as the effect of an explanatory variable after other covariates are controlled for. The GEE models treat correlation of observations within clusters as a nuisance rather than as parameters of analytic interest to be estimated with the model. The GEE models produce regression coefficients of similar magnitude to those from the same class of traditional regression model but adjust the SEs (generally in a positive direction) to account for clustering (24).

We fit a GEE model specifying a Poisson distribution (25). A log-binomial specification, which is a common choice for estimating relative risks with binary data, such as readmissions, did not converge.

We modeled the probability of readmission using covariates reflecting the patient's ADI, the hospital's mean ADI, the patient's case-mix index, and an error term for each patient discharge using the following equation:

$$\log[P(\text{readmission}_{ij})] = \alpha + \beta_{\text{ADI}} * \text{ADI}_{ij} + \beta_{\text{safety-net index}} * \text{safety-net index}_j + \beta_{\text{case-mix index}} * \text{case-mix index}_{ij} + e_{ij}$$

where i indexes discharges, j indexes hospitals, α is the intercept reflecting mean probability of readmission, and e is a discharge-specific error term.

We evaluated sensitivity of the ADI and safety-net index coefficients to inclusion of a hypothetical unmeasured confounder using the method of VanderWeele and Ding (26).

Cluster-robust SEs can be biased downward with data sets containing fewer than 50 clusters. Because our data set contained 47 clusters, we compared the cluster-robust results with those from a multilevel Poisson model with a random intercept for hospital.

Role of the Funding Source

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Results

In fiscal year 2015, Maryland had 5 832 291 residents living in 3908 neighborhoods with a mean population of 1492. There were 47 acute care hospitals with 633 989 discharges, of which 144 632 were excluded (**Table 1**), leaving 489 357 for analysis; 65 698 (13.4% of all discharges) were readmissions. Of the discharges used for analysis, fewer than half would have appeared in an analysis limited to Medicare data. Severely disadvantaged neighborhoods were concentrated in urban Baltimore, which has about 10% of Maryland's population (27); rural areas, such as the Appalachian region of western Maryland and the agricultural eastern shore of the Chesapeake Bay; and some suburbs (**Figure 1**).

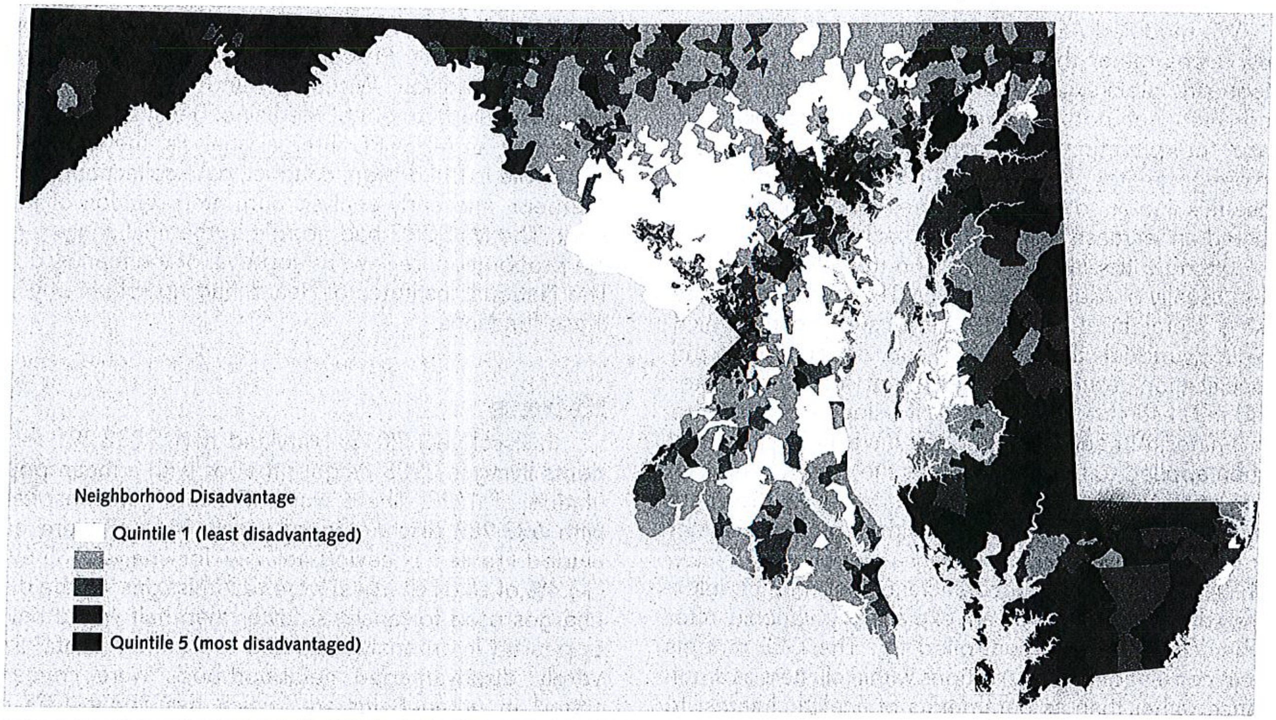
The mean ADI of all Maryland discharges was 57.0. The mean ADI for Maryland residents was 50, indicating that patients from disadvantaged neighborhoods were overrepresented in discharges. The unweighted mean of hospital safety-net index values was 58.5. **Figure 2** shows that the readmission rate for Maryland hos-

Table 1. Geographic Variation in ADI in Maryland, 2010–2013

Variable	Value
Payer, %	
Medicare	33.7
Medicaid	24.1
Medicare and Medicaid	9.8
Any commercial insurance plan and Blue Cross	29.2
Self/uninsured/other	3.6
Final analytic data set, %*	100.0
Total discharges, *n*	633 989
Exclusions, *n*†	
Not Maryland resident	40 972
Neonate	67 410
Transfer	18 288
Died	11 799
No valid identifier	143
No ADI	6002
No case-mix index	297
Total	144 632
Final analytic data set, *n*	489 357

ADI = area deprivation index.
* Percentages may not sum to 100 due to rounding.
† Participants could be excluded for >1 reason.

Figure 1. Variation in ADI in Maryland.

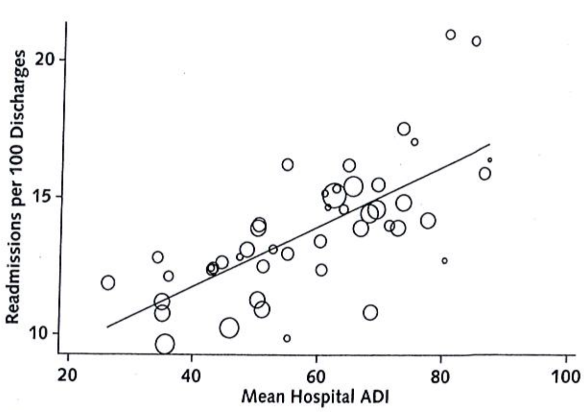


Data are from 2010-2013, the most recent data set available when the analysis was performed (13). ADI = area disadvantage index.

pitals is strongly associated with the safety-net index even after clinical adjustment.

Table 2 shows marginal probabilities of readmission at various levels of safety-net index and ADI. Patients living in neighborhoods at the 90th percentile of disadvantage had a readmission rate of 14.1% (95% CI, 13.6% to 14.5%) compared with 12.5% (CI, 11.8% to 13.2%) for similar patients living in neighborhoods at the 10th percentile. Patients discharged from hospitals at the 90th percentile of safety-net status had a readmission rate of 14.8% (CI, 13.4% to 16.1%) compared with 11.6% (CI, 10.5% to 12.7%) for similar patients discharged from hospitals at the 10th percentile of safety-net index. Thus, the difference in risk associated with moving from the 10th to the 90th percentile of safety-net index (3.2 percentage points [11.6% vs. 14.8%]) was about twice the difference associated with moving from the 10th to the 90th percentile of ADI (1.6 percentage points [12.5% vs. 14.1%]).

Figure 2. Relationship between hospital safety-net index and adjusted readmission rate.



Hospital safety-net index is the mean ADI for a hospital's discharges. Readmission rates were indirectly adjusted for case mix to the statewide average. Points are scaled to reflect discharge volume, which ranged from 263 to 36 060. Correlation = 0.7. ADI = area disadvantage index.

The E-value was 1.14 for ADI and 1.22 for safety-net index, indicating that the observed association between the outcome and the covariate could be explained by an unmeasured confounder with a modest association with both the outcome and the covariate (23). Estimating the amount of confounding necessary to shift an association to the null does not mean that such an unmeasured confounder exists. We estimated results similar to those using a random-effects model, indicating that our results were not biased by the limited number of clusters (hospitals).

DISCUSSION

In Maryland, living in a disadvantaged neighborhood and being discharged from a hospital serving patients from disadvantaged neighborhoods are each independently associated with increased risk for readmission. These findings have practical implications. First, the effect of the neighborhoods in which patients live and in which the hospital serves merits the clinician's awareness because it is associated with readmission, an important clinical outcome. Second, although modest, these effects are similar to the national differences between hospitals that were penalized and those that were not. Third, the association of a hospital's safety-net index with readmission rates is substantial even though operating profit margins are higher in Maryland hospitals with a high safety-net index. Fourth, the association of a patient's neighborhood disadvantage with risk for readmission remains highly significant even after adjustment for hospital safety-net index.

In this analysis, we faced 2 methodological issues that are likely to become more important with growing emphasis on the population's health. First, we emphasize neighborhood disadvantage rather than individual disadvantage because our data characterize neighborhoods, not individuals (28), and the 2 are not interchangeable. Soobader and colleagues (29) reported a correlation of 0.44 between the log of the median neighborhood income and the log of the income of individual residents and 0.41 between mean neighborhood education and individual education. Although statistically significant, these findings mean that neighborhood data predict less than 20% of individual variation in these variables. We should not assume that neighborhood disadvantage is associated with readmission simply because it is a proxy for individual disadvantage.

Public health research is replete with studies of how neighborhood characteristics mediate the link between disadvantage and health outcomes. Mediators include limited primary and urgent care services (30), pollution (31) and poor sanitation, crime (32) and community transience, lead paint and allergens, food deserts (33), and lack of transportation. Overall, the research shows that neighborhoods do affect health (34, 35).

The literature on preventing readmission focuses heavily on the transition from hospital to community (36), but in the weeks after this transition, the characteristics of the neighborhood play a growing role. Arbaje and colleagues (37) found that residents of disadvantaged neighborhoods are less likely to have community supports that would help them to stay out of the hospital. The Moving to Opportunity study (38) showed that diabetes and extreme obesity outcomes improved when participants moved to a more affluent neighborhood, even when the participant's income did not change. If we see neighborhood disadvantage as no more than a proxy for individual disadvantage, we run 2 risks: We may miss powerful information about potentially remediable neighborhood problems, and we may become mired in unprofitable arguments about ecological fallacies.

A second methodological step is that characterizing a provider by the disadvantage of the neighborhoods it serves may be an important tool in population health analysis, especially if Medicaid continues to become less uniform or if we move toward a single-payer system. The idea that a hospital serves a community,

Table 2. Readmission Risk at Different Percentiles of ADI and Safety-Net Index*

Percentile	Marginal Effect† of Safety-Net Index (95% CI)	Marginal Effect† of ADI (95% CI)
10th	0.116 (0.105-0.127)	0.125 (0.118-0.132)
25th	0.121 (0.113-0.129)	0.128 (0.121-0.134)
50th	0.131 (0.126-0.135)	0.132 (0.127-0.138)
75th	0.141 (0.132-0.150)	0.137 (0.133-0.142)
90th	0.148 (0.134-0.161)	0.141 (0.136-0.145)

ADI = area deprivation index.
* Mean ADI among a hospital's discharged patients.
† Estimated with Stata/MP 15 (StataCorp) using the Poisson procedure, the cluster-robust SEs options, and hospital identifier as the clustering variable.

not just individual patients, is still evolving, and the mediators that make the safety-net index a predictor of readmission are still uncertain. The traditional explanations have been that safety-net hospitals are government-owned and not well run; are dependent on Medicare, Medicaid, and uninsured patients and therefore are underfunded; and are filled with safety-net patients who have greater needs than other patients for whom payments are the same. Maryland has no government-owned hospitals. The MHSCRC's cost reports showed a modest positive correlation ($r = 0.23$; $P < 0.001$) between safety-net index and hospital operating profit. This test is just 1 indicator of financial health but suggests that MHSCRC policy is successful in protecting hospitals from 1 type of financial risk that might be associated with elevated safety-net index.

This study had 2 limitations. First, our analyses focused on a single state. **Figure 2** confirms that national findings of excess adjusted readmissions in safety-net hospitals are also present in Maryland and supports application of the findings to other states. However, Maryland has the highest median household income in the United States (39), whereas children in Baltimore have the worst earning prospects among the 50 largest U.S. cities (40). This diversity may make the effects of disadvantage easier to detect. Maryland's hospital rate-setting system is also unique; thus, findings may differ in states where the financial status of safety-net hospitals is more precarious, where the financial incentives to prevent readmissions are different, or where hospital revenue is not largely set by the state. Testing our findings in other states should be a priority, but we acknowledge that some of our findings (such as the effects of protecting hospitals that serve disadvantaged patients) resulted from Maryland's rate-setting experiment and will be hard to test elsewhere.

Second, our findings are subject to potential confounding. We measured neighborhood characteristics but not individual characteristics, such as socioeconomic status and race, which may be associated with ADI, safety-net index, and readmission. Our sensitivity analysis indicated that our study is at least moderately sensitive to such confounding. Although we adjusted for clinical risk, the case-mix index probably does not completely account for patient factors, such as disabilities (41), which may also be related to readmission. However, Kind and colleagues (15), Bernheim and associates (42), and we all found that disadvantage was associated with higher risk for readmission despite using different approaches to case mix (multivariate adjustment, the Centers for Medicare & Medicaid Services method, and APR-DRGs, respectively). Therefore, we doubt that further refinements of codes or algorithms would yield improvements of the magnitude needed to explain away our results.

We were motivated to conduct this study by concern for the fairness of readmission penalties for safety-net hospitals and patients from disadvantaged neighborhoods. Other researchers have addressed whether refined social and clinical measures would or should reduce or eliminate the penalties that safety-net hospitals face (43, 44). That is, in part, an ethical rather than a technical issue: Some are loath to adopt a policy that seems to accept inferior care and outcomes for disadvantaged persons, whereas others see such policies as the most practical way to level the playing field for hospitals that serve those patients.

Our analysis suggests that neighborhood disadvantage is associated with excess risk for readmission in 2 ways. One is the patient's exposure to disadvantage in the neighborhood where they live and often recover after hospitalization. Individual patients bear this risk compared with patients from more advantaged neighborhoods treated in similar hospitals. The other, which is associated with roughly twice the variation in risk for readmission, is indirect, hospital-level exposure that can be measured by the mean disadvantage of a hospital's discharged patients. This indirect exposure is largely independent of a patient's direct exposure to neighborhood disadvantage and deserves further exploration.

This study clarifies the problem more than the solution, which may be paying more for care of patients from disadvantaged neighborhoods (4, 5, 45, 46), decreasing penalties, investing in improving neighborhoods (46, 47), or using a wait-and-see strategy. Although this report does not prove, or even assert, that disadvantaged neighborhoods are the major cause of excess readmissions, it adds to evidence that the association is too strong to ignore.

Demonstrating the association of risk for readmission both with patient exposure to neighborhood disadvantage and the collective disadvantage of a hospital's patients does not tell us what mediates or causes those associations. We urgently need studies that clarify which of the mechanisms linking disadvantage and safety-net patients to readmissions are strongest and most likely to yield returns on investment in preventing readmissions.

From Baltimore, Maryland (S.F.J.); Maryland Health Services Cost Review Commission, Baltimore, Maryland (A.S., G.B.D.); Mathematica Policy Research, Woodlawn, Maryland (S.G.); Telligen Colorado, Greenwood Village, Colorado (J.E.B.); and University of Wisconsin School of Medicine and Public Health and Geriatric Research Education and Clinical Center (GRECC), William S. Middleton Hospital, U.S. Department of Veterans Affairs, Madison, Wisconsin (A.J.K.).

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Reproducible Research Statement: *Study protocol:* See the Methods section of the text. *Statistical code:* Available from Dr. Schuster (e-mail, alyson.schuster@maryland.gov). *Data set:* Hospital-level data are largely available from the Maryland Health Services Cost Review Commission Web site (www.hscrc.state.md.us/pages/default.aspx). Census block group-level ADI estimates are available from reference 18. Person-level data are available only by special application to the MHSCRC.

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EDITORIAL

Area Deprivation and Inequalities in Health and Health Care Outcomes

Although the United States has made remarkable progress in improving the overall health of its population during the past several decades, substantial health disparities persist among various social groups and geographic areas, and in many instances, these disparities have widened over time (1). Despite the decline in mortality, persistent or increasing inequalities in life expectancy, infant mortality, all-cause mortality, and mortality from several major causes (such as cardiovascular disease, cancer, diabetes, respiratory disease, and HIV/AIDS) have been reported (2-8). To analyze health inequalities over time, many of these studies have used area deprivation indices (ADIs). Without reliable patient-level measures of socioeconomic status, such as education, income, or occupation, researchers have linked census-based ADIs to administrative databases, including the National Vital Statistics System, the SEER (Surveillance, Epidemiology, and End Results) database, and hospital discharge or claims databases (1-9). Such linkages are performed using the common residence-based geocodes that are generally available for persons in both the census and administrative databases.

To identify and monitor health inequality patterns at the population level, Singh and colleagues have developed ADIs for the United States at various geographic levels (for example, census tracts; counties; ZIP codes; cities, towns, or places; metropolitan areas; and states) for 1970, 1980, 1990, 2000, and 2008 to 2012 (2-8). The ADI, derived by using factor analytic methods, has proved to be a powerful tool for documenting and monitoring population health inequalities across time and space (2-8). The ADI has generally consisted of 20 to 22 census-based socioeconomic indicators, which are viewed as broadly representing educational opportunities, labor force skills, and economic and housing conditions in a given geographic area, community, or neighborhood (2-5, 7, 8). Selected indicators of education, occupation, wealth, income distribution, unemployment rate, poverty rate, and housing quality are used to construct the ADI (2-8).

Study findings based on ADIs have indicated large disparities. An updated analysis of a study on life expectancy showed a consistently widening gap between persons in the most deprived socioeconomic group and those in the most affluent group (4). From 2010 to 2012, the life expectancy at birth was 6 years longer for the most affluent group than for the most deprived group (82.0 vs. 75.9 years). The life expectancy of the most affluent group in 1980 was similar to that for the most deprived group in 2012. Infant mortality rate, another important health care quality measure, shows marked disparities by area deprivation level (6), with the relative risk for infant death for the most deprived versus the most affluent group increasing from 1.60 in 1984 to 1986 to 1.72 in 2008 to 2012. A recent analysis of SEER cancer survivorship data showed consistently decreasing patient survival rates for various types of cancer according to area deprivation levels (8). From 1988 to 1999, the 10-year survival rate for patients diagnosed with cancer was 41.0% in the most deprived census tracts (based on decile of socioeconomic status) compared with 60.4% in the most affluent census tracts. The corresponding 10-year survival rates were 65.4% and 82.8% for breast cancer and 69.9% and 84.8% for prostate cancer (8). Disease stage at diagnosis only partly accounted for disparities in patient survival by area deprivation level (8).

With regard to inequalities in the extent of disease, patients with cancer in more deprived neighborhoods are substantially more likely to present with an advanced stage at diagnosis. From 1988 to 1999, patients from the most deprived neighborhoods were 1.5 to 3.0 times more likely to be diagnosed with late- or distant-stage breast, cervical, prostate, and colorectal cancer and melanoma of the skin than those from the most affluent neighborhoods (8).

The study by Jencks and colleagues makes an important contribution to the literature on area deprivation based on the ADI and 30-day hospital readmission rates, a crucial quality measure of the health care system in the United States (9). Using 2015 hospital discharge data from Maryland's all-payer program, they found that, compared with patients living in the most affluent neighborhood decile, those living in the most deprived neighborhood decile (that is, census block group) had a higher readmission risk (14.1% vs. 12.5%). This association was independent of the hospital safety-net index, which was measured by the average deprivation scores for hospitals serving the patient populations and showed a larger marginal effect on readmissions. The study is particularly impressive in that it was able to link the individual-level hospital discharge data to the ADI scores at the census block group level, which allowed the researchers to conduct a detailed analysis of readmissions. Although measuring the effect of neighborhood disadvantage on readmissions is clearly novel, analyses of hospital discharge data sets with inadequate patient sociodemographic information are limiting. The total effect of neighborhood disadvantage on readmissions is probably greater because the hospital safety-net index is derived from neighborhood disadvantage scores, and controlling for the safety-net index dilutes the overall effect of neighborhood ADI. In addition, it would be interesting to know from a policy standpoint whether the effect of ADI on hospital readmissions is greater among persons younger than 65 years or racial/ethnic minorities because the effect of area deprivation on morbidity and mortality has been shown to be greatest among younger persons, those of working age, and ethnic minorities (2, 3, 5-8). Overall, the positive association between neighborhood

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disadvantage and readmission potentially sheds light on whether safety-net hospitals are being treated fairly in the rate-setting system and whether the safety-net index should be adjusted for rate setting. However, the nature of the total effect of neighborhood disadvantage is still unclear and deserves further investigation.

Living in socioeconomically deprived neighborhoods and communities is associated with poor health and health care outcomes. Social and public health interventions, such as antiobesity and tobacco control campaigns, increasing access to health care services, and providing greater access to healthy foods and opportunities for physical activity, have worked previously and have the potential to further improve individual and population health (1, 3, 4, 8). However, improvements in the broader social determinants at the community level (which the ADI captures so well), such as education, poverty reduction, social and welfare services, affordable housing, job creation, labor market opportunities, and transportation, can lead to substantial cost savings through large-scale reduction of inequalities in morbidity and mortality (1, 10).

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