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Enhancing Administrative Data to Predict Emergency Department Utilization: The Role of Neighborhood Sociodemographics

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Abstract

Much of emergency department use is avoidable, and high-quality primary care can reduce it, but performance measures related to ED use may be inadequately risk-adjusted. To explore associations between emergency department (ED) use and neighborhood poverty, we conducted a secondary analysis of Massachusetts managed care network data, 2009–2011. For enrollees with commercial insurance ($n=64,623$), we predicted any, total, and total primary-care-sensitive (PCS) ED visits using claims/enrollment (age, sex, race, morbidity, prior ED use), network (payor, primary care provider [PCP] type and quality), and census-tract-level characteristics. Overall, 14.6% had any visit; mean visits per 100 persons were 18.8 (± 0.2) total and 7.6 (± 0.1) PCS. Neighborhood poverty predicted all three outcomes (all $P < .001$). Holding providers accountable for their patients' ED use should avoid penalizing PCPs who care for poor and otherwise vulnerable populations. Expected use targets should account for neighborhood-level variables such as income, as well as other risk factors.

Keywords

Emergency Service; Hospital; utilization; claims analysis; electronic health records; small-area analysis; risk assessment; poverty

Use of the emergency department (ED) in the United States is growing¹ and expensive.² Numerous studies have estimated that about half of all outpatient (non-admitted) ED visits are potentially avoidable.^{3–7} Potentially avoidable ED visits include those for low-acuity and non-emergent conditions, such as a hangnail; conditions that could be treated in a primary-care setting, such as a urinary-tract infection; and conditions that might be prevented or avoided, such as an asthma exacerbation. These types of ED visits are sometimes referred to as primary-care sensitive (PCS),^{6,8,9} a term that highlights the association with primary care without saying that all such use is inappropriate.

Whether because of reduced access to primary care or other complex social, behavioral, or physical reasons, lower-income individuals use the ED more. The association between neighborhood poverty and increased ED use has been recognized since at least the 1980s,¹⁰ and it persists after adjusting for numerous other risk factors.^{10–13} However, whether to risk-

adjust quality measures for socioeconomic status is controversial, as demonstrated by the recent debate over a draft report by the National Quality Forum discussing socioeconomic status (SES)-based risk adjustment.¹⁴

Using Andersen's behavioral model of health care utilization as our conceptual model, factors influencing ED utilization can be classified as need factors, predisposing factors, enabling factors, and health behaviors.^{15,16} Seen through this lens, administrative data, such as diagnosis codes from encounters and beneficiary characteristics such as age and sex, may have limited power to predict ED use because they capture partial data in only two categories: need and predisposition. In this study, we developed enhanced models predicting both overall and PCS ED utilization by incorporating data from multiple sources, including expanded clinical data from the electronic medical record (EMR), data about the health care system, and information about the neighborhoods in which enrollees lived.

Methods

Data sources

Our data on individuals and their providers comes from a managed care network (MCN) in Massachusetts that sought to develop a performance measure based on practice-level ED use. The MCN includes an academic medical center, several hospitals, and over a thousand providers; our study included primary care providers (PCPs) affiliated with the academic medical center who saw at least 100 persons in our sample during our study period. We also incorporated data from the 2011 American Community Survey, conducted annually by the U.S. Census Bureau.¹⁷ Our study was approved by the University of Massachusetts Medical School institutional review board.

Study sample

Study subjects were residents of Massachusetts who were enrolled for at least one month in each of two consecutive years in one of four large commercial insurance plans (Plans 1–4) and whose PCP was affiliated with the MCN and had used the All scripts EMR system since at least 2009. Each enrollee's affiliation with a PCP was determined based on the PCP listed in that enrollee's EMR. Among enrollees who had more than one PCP in their records, we selected the match with greatest number of encounters first, then the last visited provider in the appropriate base year. We excluded five enrollees who could not be matched to a provider. We split the data into a development sample, consisting of individuals observed in 2010 (base year) and 2011 (prediction year), and a validation sample, consisting of individuals observed in 2009 and 2010.

Measures

Using data from the base year, we measured and predicted three subsequent-year outcomes: (1) any outpatient ED visit (yes/no), (2) total number of outpatient ED visits, and (3) total number of PCS ED visits. Primary care sensitive visits were categorized using the New York University (NYU) ED algorithm of Billings et al.¹⁸ It assigns each ED visit a probability of belonging to each of nine categories: (1) nonemergent; (2) emergent, primary-care treatable; (3) emergent, preventable/avoidable; (4) emergent, not preventable/avoidable; (5) mental

health; (6) substance use; (7) alcohol; (8) injury; and (9) unclassifiable. Each visit's nine probabilities sum to 1. Categories 1–4 take on values from 0 to 1; categories 5–9 are either 0 or 1. *Nonemergent* refers to conditions for which treatment was not required within 12 hours;¹⁹ *primary-care-treatable* refers to visits identified, originally through chart review, as requiring only resources typically available in primary care settings; and *preventable/avoidable* refers to visits with the same principal diagnoses as ambulatory care sensitive hospitalizations, another indicator of potential gaps in primary care.²⁰

The probabilities for categories 1–4 were based on detailed chart review of approximately 6,000 ED visits at New York hospitals in the 1990s;¹⁸ if 10 out of 40 ED visit charts for a certain diagnosis (such as a sore throat) were judged primary-care-treatable, then the probability of any such ED visit being primary-care-treatable is .25.

Prior users of the algorithm have typically measured PCS ED use by categorizing each visit as PCS or not, depending on whether the sum of the probabilities in a designated subset of the categories (e.g., categories 1–3 or categories 1 and 2) exceeded a threshold, such as .50.²¹ This method discards information, unnecessarily inflates the number of people with zero outcomes, and depends upon an arbitrary choice of threshold that strongly influences the outcome distribution. For example, with a .50 threshold, 10 ED visits, each with a probability summing to .60, counts for 10, whereas with a .75 threshold, they count for nothing. To avoid these problems, we developed an alternative approach. To calculate our third outcome, we summed the values of the first three categories to create a number between 0 and 1 for each visit, referred to as prob_PCS; for each person, we sum all of the prob_PCS values from all ED visits during the year to derive the total number of PCS visits during the 12-month prediction period. Thus, the equation is a weighted sum of ED visits,

$$\text{Total PCS ED visits} = \sum (w_j * \text{ED}_j)$$

where w is derived from the NYU ED algorithm's probabilities associated with each diagnosis code, and j is an individual.

For example, suppose a person had three ED visits: two for palpitations (International Classification of Diseases, Ninth Revision, Clinical Modification [ICD-9-CM] code 785.10) and one for other chest pain (786.59). Palpitations is assigned a prob_PCS of .44, and chest pain is .61. Summing prob_PCS across all three visits yields a total of 1.49 PCS visits.

Although diagnosis codes change over time, at the time of this study, the NYU ED algorithm had not been updated by its original developers since 2003. To include additional diagnosis codes, we used a version updated in 2009 by the Massachusetts Center for Health Information and Analysis (CHIA) (personal communication, April 30, 2013). This update incorporated new codes with input from the original developer and an emergency medicine physician, but it involved no new data abstraction.³ When applied to our 2010 sample, the update reduced the percentage of unclassifiable claims from 14.8% to 10.1%, meaning that less than 2% of individuals in the sample had any unclassifiable visit during the year. With a very low incidence rate, these visits are those that could not be classified by the algorithm

because they did not have enough of those visits in the original sample to determine their probabilities of being in the different categories. Details on unclassifiable visits in this analysis have been previously published.²² The updated NYU ED algorithm is available from the authors.

Following standard practice, we excluded ED encounters that resulted in an inpatient admission (approximately 15%), as such visits are considered unlikely to be PCS.^{12,13} We also did not count unclassifiable visits or visits categorized as related to an injury, alcohol or drugs, or mental health as PCS.

Practice and provider characteristics—Practice and provider characteristics were obtained from MCN administrative records. Practice characteristics included location, practice specialty, and a provider quality score. The specialties, as defined by the MCN, were family practice, internal medicine, maternal/pediatrics, and multispecialty/other. The provider quality scores, developed by the MCN as part of its internal rewards program, were based on 21 quality and efficiency measures (primarily Healthcare Effectiveness Data and Information Set [HEDIS] measures, such as well-child visits).²³

Problem list variables—We used the Allscripts EMR problem lists to identify 10 conditions (arthritis, asthma, cancer, congestive heart failure [CHF], chronic obstructive pulmonary disease [COPD], depression, diabetes, hypertension, overweight, and tobacco use) from the “priority conditions” developed by the Agency for Healthcare Research and Quality.²⁴ These problem lists included both diagnosis codes from the *International Classification of Diseases, Ninth Revision, Clinical Modification* (ICD-9-CM) and free-form descriptions. We used a two-stage algorithm to identify conditions in either format.

We used the manual at <http://www.icd9data.com/> to map ICD-9-CM codes to conditions and also developed descriptive search terms using a software programming technique known as regular expression matching²⁵ to search the free-text fields. Regular expressions are strings of letters and special characters (operators) that can be used to match substrings and portions of text in a text-based variable (here, the description field in a problem list). For example, for arthritis, we first flagged every record containing any ICD-9-CM code from 714.00 to 716.99. We then searched the description fields for the word “arthritis” in either upper- or lowercase. We then flagged and removed records that contained the terms allergic, bacterial, bowel, infect* (using a wildcard character, *, to match any word that started with “infect,” such as “infectious”), reactive, and septic, to exclude acute forms of arthritis. We then scanned all remaining records with the relevant diagnosis codes to ensure that the preliminary set of arthritis cases was accurate and that no other description field terms should be included or excluded.

In addition, we generated a list of enrollees who had at least one claim for any of the 10 conditions but who had not been flagged by the problem list algorithm for that condition and randomly selected 25 cases per condition for detailed review. Two researchers independently reviewed all problem list entries for each enrollee to determine whether any diagnosis codes or description field terms should be added to the algorithm. See our supplementary material for further details.

Morbidity measurement—DxCG Intelligence version 4.1 (Verisk Analytics, Jersey City, NJ) was used to classify diagnoses from the base-year utilization files into hierarchical condition categories and to generate both concurrent and prospective morbidity scores. The concurrent score uses one year's data to characterize the expected impact of illness burden in the same year, whereas the prospective score predicts that impact in the next year. Morbidity scores were normalized to the study sample and top-coded at the 99.5th percentile (normalized prospective risk score: mean=1, standard deviation [SD]=1.34; normalized concurrent risk score: mean=1, SD=1.93).

Small-area analysis—Area-based measures, such as median income and percentage of residents living in poverty, are publicly available and have often been used to provide insight into socioeconomic status.^{26–29} Not only are these measures reasonable proxies of individual characteristics, but also they measure contextual predisposing and enabling factors in the residential environment that are relevant in Andersen's model.

To explore the effects of geography on ED utilization, we matched enrollee addresses to 2011 American Community Survey data from the U.S. Census Bureau. We assigned each enrollee to a census tract (CT)—a small area, more homogeneous than ZIP codes with respect to population characteristics, economic status, and living conditions.^{27,29} In 2011, there were 1,478 CTs in Massachusetts and an average of 4,406 persons per CT, but approximately 700 ZIP codes. We used five-year estimates from 2011, the most reliable and precise estimates of neighborhood-level characteristics available.³⁰

On the basis of our theoretical framework and review of the literature, we examined neighborhood variables that could be associated with ED utilization. These were median age, percentage Black, percentage Hispanic, percentage unemployed, mean travel time to work, percentage foreign-born, percentage who speak English less than very well, percentage high school graduates, median house value, percentage owner-occupied housing, percentage vacant housing units, median household income, and percentage in poverty. Some of these are well documented as risk factors for ED use, such as those related to education and poverty.^{10,26,31–41} We studied other factors, such as mean travel time to work, to explore potential associations with ED use, despite a lack of prior research demonstrating an association.

We also investigated the role of relative distance from enrollees' homes to the nearest ED as opposed to their PCP. We operationalized "distance" based on each enrollee's home address; the address of his or her PCP practice, obtained from the MCN; and the addresses of all hospitals with EDs in Massachusetts, obtained from the Massachusetts College of Emergency Physicians (personal communication, November 1, 2013). We geocoded all addresses using ArcGIS version 10.2 (Esri, Inc., Redlands, CA) to compute the difference in driving distance from home to PCP versus home to nearest ED for each enrollee.

Poverty analysis—In our descriptive analyses, we used CT-level median household income data and the 2009–2010 federal poverty threshold (FPT) for a family of four (FPT: \$22,050) to create three categories of neighborhood income: less than 200% FPT, 200–399% FPT, and 400% FPT or more.³⁸ For our regression models, we used a continuous measure:

the percentage of individuals in the CT living in poverty (defined, following the U.S. Census Bureau, as less than 200% of the FPT) divided by 10, so that the poverty coefficient indicates the effect of a 10% increase in the fraction of the population living in poverty.

Statistical analyses

We described the population's sociodemographic and clinical characteristics, calculated the prevalence of ED visits, and examined bivariate associations between potential predictors and any ED use.

We then used multivariable logistic regression to predict the likelihood of any ED visit, used zero-inflated negative binomial regression to predict the number of ED visits, and explored several strategies to predict the number of PCS ED visits: two-part (hurdle) models, using a logistic regression to predict any ED visit in the first part and either an ordinary least-squares model or a generalized linear model (GLM) in the second part to predict the number of PCS ED visits among those with any ED use; and GLMs with a log link and either a Gaussian or gamma family (distribution). For each model, we calculated the squared correlations between actual and predicted outcomes (R^2) and chose as final the model specification with the highest R^2 .

The base model was built using factors exclusively from administrative data, with age, sex, race, morbidity scores, and prior ED use (coded as any or none) as covariates. For age category, the 40–64 group was used as the reference group, because it was both the largest (46% of the development sample) and had the lowest unadjusted ED use rate (12.8% in 2011). Three enhanced models included additional covariates drawn from payor and practice characteristics (from the MCN's administrative records), neighborhood characteristics (from the census), and EMR data (from All scripts). We evaluated improvements in model fit and performance in base models compared with enhanced models by comparing R^2 s and inspecting graphs of predicted and actual results within quantiles of predicted risk in both development and validation samples.

We explored several model development strategies, including forced entry of all potential risk factors, as well as forward and backward stepwise selection with Bonferroni corrections to account for the number of simultaneous significance tests.⁴² All risk factors that were statistically significant in one or more of these approaches were retained in the final models.

For each of the three outcome variables, or Y s, the validation proceeded as follows. Fit the model to predict Y from the predictors X in the development sample only; use that model to calculate the predicted risk ($\hat{Y}$) as a function of X for observations in the validation sample; then compare mean $\hat{Y}$ s with mean Y s within quantiles of predicted risk to see how well the models fit the validation sample.

We examined practice-level variations only among practices with panels of at least $n=100$ enrollees in the development sample, which reduced the number of practices from 56 to 47. We examined differences in average observed outcomes (O s), average expected outcomes ($\hat{Y}$ s or E s), and observed-to-expected (O/E) ratios of these practice-level means. For each outcome, we calculated the usual pooled estimate of its SD across all practices and divided it

by the square root of n to estimate the standard error (SE) for a practice of size n . Analyses were conducted in Stata/IC version 11.2 (Stata Corp., College Station, TX) and SAS version 9.2 (SAS Institute, Research Triangle Park, NC).

Results

Baseline characteristics

Enrollees—The development sample, with data from 2010–11, had 53,112 observations; the validation sample (2009–10) had 54,337 observations; combined, the dataset included 107,449 observations on 64,623 unique individuals. Table 1 provides sociodemographic and clinical characteristics by sample. During the prediction periods, the samples had similar rates of any ED use (development: 0.147 ± 0.001 ; validation: 0.142 ± 0.001), mean number of ED visits (0.189 ± 0.002 ; 0.181 ± 0.002), and mean number of PCS ED visits (0.076 ± 0.001 ; 0.073 ± 0.001).

Small-area analysis—About 92% of enrollees lived in Worcester County, another 5% in Middlesex County, and 1% in Norfolk County. The associated PCPs were clustered in central Massachusetts, whereas both enrollees and hospital EDs were spread across the state. Thus, the median (interquartile range [IQR]) driving distance to an enrollee's PCP was 5.8 (7.3) miles, and the median (IQR) driving distance to the nearest ED was 5.1 (5.2) miles. The median difference was 1.0 mile—meaning that half the individuals had to drive at least one mile farther to reach their PCP than to reach the nearest ED, which we refer to as the “extra distance to their PCP.” Only 10% of enrollees lived more than 10 miles from a hospital with an ED, but 25% lived more than 10 miles from their PCP.

Unadjusted effects of poverty on ED utilization

Figure 1 shows the unadjusted relationship between neighborhood income category and ED utilization. Individuals living in neighborhoods with median family incomes of less than 200% of the FPT were most likely to have any ED visit (19% compared with 15% for middle income [$P=.041$] and 13% for high income [$P=.017$]) and had the highest means for both total ED and total PCS ED visits (all $P<.05$). Additionally, those in middle-income neighborhoods (200–399% of FPT) had higher ED utilization than those in the highest-income neighborhoods (400% or more of the FPT).

Prediction models and predictors

Our base models, predicting ED utilization using age, sex, race, morbidity score, and prior use, had lower R^2 than models that also included payor, PCP type and quality, problem list conditions, and neighborhood poverty (enhanced models). The biggest improvements in R^2 were seen when adding variables derived from the enrollees' CT of residence; these added about 1 percentage point to the R^2 for each measure. For outcome 1, any ED use, the highest R^2 was 4.3%.

For outcome 2, total ED visits, the highest R^2 was 5.1%. For outcome 3, total PCS ED visits, the highest R^2 was obtained with a GLM model with a log link and Gaussian distribution (4.17%); the alternative specifications of the most predictive models produced R^2 s of 3.58%

4.10% (detail not shown). All of the results we report for the PCS ED outcome are from the enhanced GLM.

Outcomes in the validation data were consistent with predictions based on the models built with the development data. This is illustrated in Figure 2, which plots the actual ED utilization in the validation sample and the predicted utilization by quantile of predicted risk for each outcome measure.

Table 2 shows coefficients from the most-predictive, enhanced models for each outcome measure. In our final enhanced model, the top 10 predictors of PCS ED use, as ranked by the standardized coefficients (z-scores), were any prior ED use in the base year, having asthma, being age 18–24, the prospective morbidity score, having depression, living in a higher-poverty neighborhood, being age 1–10, being younger than one year of age, using tobacco, and being female (all $P < .001$).

After adjusting for other factors, having any ED visit in the base year was the strongest predictor of all three outcomes. The prospective morbidity score was also significantly associated with increased risk of all three types of ED use, as was having asthma, CHF, or depression, and using tobacco. Black race was also significantly associated with increased risk on all three outcomes.

Having any inpatient stay in the base year was associated with a significant decrease in the total number of ED visits the following year, but was not significantly associated with the other two outcomes. Compared with other age groups, infants were at the highest risk of having any ED visit; each age group was at significantly elevated risk of ED utilization relative to the reference group (age 40–64). Being female was associated with decreases in both the probability of any ED ($P = .019$) and total ED use ($P = .074$), but an increase in PCS ED visits ($P < .001$). There were also significant differences in total and PCS ED use by payor.

Extra distance to the PCP was not independently associated with the likelihood of having any ED visit; however, the total number of ED visits was 0.003 higher for every one mile of extra distance ($P = .014$); and the number of PCS ED visits was 0.01 higher for every one mile of extra distance ($P = .033$).

Of the 10 selected conditions noted in EMR problem lists, nine were significantly associated with increased risk on at least one outcome (Table 2). Asthma, CHF, depression, and tobacco use were associated with increased risk on all three outcomes. Arthritis and hypertension were associated with higher risk for both any and total ED visits, but not with total PCS ED visits. Cancer was significantly associated with fewer ED and PCS ED visits. Individuals with overweight in their problem list had significantly more ED visits, whereas those with diabetes were more likely to have any ED visit. Chronic obstructive pulmonary disease was not significantly associated with any of our three ED use outcomes.

The relationship between ED utilization and neighborhood income persisted in models that included age, sex, race, prior ED use, morbidity score, EMR-based problem list conditions, payor, provider specialty, and provider quality. In our most predictive enhanced models, for

every 10-percentage-point increase in the percentage living in poverty in an enrollee's CT of residence, the coefficient for any ED visit increased by 0.111 (odds ratio [95% confidence interval]: 1.12 [1.08–1.16]), total ED visits increased by 0.01, and total PCS ED visits increased by 0.02 (Table 2).

Figure 3 illustrates differences in O/E ratios for practices when regression models predicting ED utilization include or exclude the neighborhood poverty variable. For this analysis, we specified two regression models of PCS ED use: one included the percentage in poverty in the CT as a predictor, and the other omitted that variable. We then calculated and plotted the two sets of O/E ratios and 95% confidence ratios. Figure 3A (top) shows O/E ratios and 95% confidence intervals by practice, sorted from smallest to largest, when the percentage in poverty in the CT is included in the model as a predictor. Figure 3B (bottom) shows the O/E ratios for the same practices when the percentage in poverty in the CT is omitted from the model as a predictor. We sorted by practice size to draw attention to the fact that predicted and actual values tend to converge as practice size increases.

Two practices are highlighted with black ovals in the figure: Practice X, with 295 enrollees; and Practice Y, with 887 enrollees. Both are family medicine practices. For those two practices, models predicting total PCS ED visits were sensitive to whether neighborhood poverty was included. The circled practices have O/E ratios that were significantly different from 1.0 with poverty included, but not without.

Discussion

In this study, models enhanced with data about enrollees' providers, payors, clinical conditions, and neighborhoods predict several aspects of ED utilization better than models using claims data alone. People in lower-income neighborhoods, even after adjusting for commonly used risk factors, remain more likely to go to the ED, have more ED visits, and have more PCS ED visits than people living in higher-income neighborhoods. When profiling practices on PCS ED visit use, we find that some practices had meaningfully different O/E utilization ratios depending on whether neighborhood poverty was included as a predictor. Thus, practices with disproportionately many enrollees from low-income neighborhoods will be put at a disadvantage if their expected-use targets do not account for the socioeconomic status of their patients (and, conversely, practices with wealthier patients will look better than they should). Therefore, models to set risk-adjusted performance targets for ED use should incorporate such readily available neighborhood-level variables. Otherwise, targets for ED use—even if adjusted for traditional case-mix variables—may be unfair.

As a simple example of the practical implications of risk-adjusting an ED use target, suppose that the two practices circled in Figure 3 were eligible for a \$25 bonus per enrollee if the provider's O/E ratio were less than 1. Practice A, with a panel of 295 patients, would receive a bonus of \$7,375 if its patients' ED use was risk-adjusted for SES, and a \$0 bonus if it were not. Practice B, with 887 patients, would not receive any bonus under an SES risk-adjusted model, but would get a bonus of \$22,175 if the target was not risk-adjusted for SES.

Having used the ED previously was the strongest predictor of future ED utilization, perhaps reflecting some combination of individual preferences for the ED as a place of care and persistent problems in accessing care elsewhere. Out of the 10 priority conditions we studied, the strongest clinical predictors of all three ED outcomes were asthma, CHF, depression, and tobacco use. Age was also a strong predictor of ED use, with those in the 18–24, 1–10, and younger than one year age groups being at highest risk of increased PCS ED utilization.

Higher PCP quality scores were associated with a slightly reduced risk of any ED visit ($P<.001$) and fewer ED visits ($P<.001$), but the effect was borderline significant for PCS ED visits ($P=.050$). Therefore, the evidence that PCP quality (as measured using HEDIS quality measures) is a significant factor predicting total PCS ED use is somewhat equivocal, but the trend toward significance, combined with the results for the other outcomes, suggests a likely association. Thus, applying this modeling approach requires decision-makers to consider the possible effects of “baking in” prior practice-level quality on targets for quality improvement.

Our findings are similar to those reported in prior studies in terms of the associations found between ED utilization and age, race, neighborhood income, and prior ED use.^{10,13,33,43–45} As with the effects of neighborhood poverty, the association between PCP quality and ED use has been known since at least the 1980s.⁴⁶ Of the four conditions identified as strongly and consistently associated with increased risk of ED use in our study, asthma and depression have been reported as risk factors in prior work,^{47–49} whereas CHF and tobacco use have not, to our knowledge.

Limitations

This study was limited by a geographically constrained population that included only those people insured by one of four commercial insurers in Massachusetts. Our sample population was mostly White and relatively healthy, with lower ED use than the state average. Massachusetts is also a relatively wealthy state, with 98% of the population covered by health insurance.⁵⁰ Additionally, we had only 47 practices in our sample. Thus, our findings may not generalize to other populations.

A limitation of the EMR data we used is that the information represents “present-moment” characteristics and may not accurately reflect enrollees’ characteristics at the time of an ED visit (or at the end of the base year, in the case of a prospective model). For example, an enrollee’s smoking status in our data may not have matched what it was at the time of his or her ED visits. We were also unable to verify the accuracy of the EMR problem lists.

Another important limitation is that the version of the NYU ED algorithm we used was last updated in 2009, and did not account for changes in ICD-9-CM diagnosis codes between 2009 and 2010. Moreover, using diagnoses to classify individual visits has inherent limitations, including the fact that coding practices may vary among providers. The algorithm itself has been criticized for insensitivity to changes in access to care.^{51,52} Future research using our PCS measure is needed to determine whether the methods we propose are better able to capture such changes.

In addition, all individuals in this study were assigned to a participating PCP in the managed care network using established methods. We do not know whether patients were aware of their PCP assignment. Future research is needed to better understand the implications of various PCP attribution methods when developing primary care quality measures.

Finally, we treated people with partial-year observations the same as those with full-year observations. We know, from the MCN's records, that most enrollees were present for all 12 months of both the base and prediction periods, and the vast majority had at least six months of observation in each period. However, because of data limitations, we were not able to incorporate into our analyses the number of months each enrollee was present.

Partial-year observations have several implications for practical implementation of these methods. For retrospective analyses (to set benchmarks for providers based on 2 years of recent data for the purposes of performance measurement and quality improvement efforts), treating people with partial-year observations the same as those with full-year observations could bias the model's benchmarks for providers with more individuals with partial-month data. Future research on implementation of a PCS ED use performance measure would require a partial-eligibility data analysis. One option for handling the potentially unobserved utilization in the target year would be to calculate annualized rates using the number of months of eligibility divided by the number of months in the prediction year as a weight (i.e., eligibility fractions).⁵³

That said, predictive models used for case management purposes would be built in a manner similar to the models used in this analysis, because analysts in concurrent predictive scenarios do not know, in advance, for how many months in the future an enrollee will remain enrolled. However, when using predictive modeling to support case management efforts, having missing months of eligibility in the base year presents a problem when calculating risk scores. If we are missing months of observation, we may be biasing the risk scores downward (underestimating morbidity, and thus risk of future expenditures, utilization, or both). We are not aware of any published research that provides a solution for appropriately dealing with partial-year eligibility in the base year, aside from Medicare's approach for new enrollees: to calculate risk scores based only on age and sex.

We were limited in our ability to evaluate the effects of additional factors that have been shown in previous research to be associated with ED use, such as marital and employment status, educational attainment, personal/family income, perceived health status, and satisfaction with care. Elsewhere, we have reported the effects of some of these additional factors in an analysis of Medical Expenditure Panel Survey data.⁵⁴

Conclusions

Emergency department risk models allow managed care organizations to set targets for expected PCS ED use for panels of patients against which actual PCS ED use can be judged. Although such approaches hold appeal for payors wanting both to reduce unnecessary ED use and to reward PCPs for their role in doing so, failure to account for neighborhood-level socioeconomic factors in these models may inappropriately penalize PCPs for social factors unrelated to the quality of care provided. Future research is needed to understand more fully

how best to account for neighborhood poverty in these models and, in turn, how best to apply these tools to safely reduce PCS ED utilization without penalizing providers for social factors outside of their control.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.

Emergency department use varies significantly by neighborhood income category.

Notes:

ED: emergency department; PCS: primary-care sensitive.

Low: median household income in census tract was <200% of federal poverty threshold (FPT); **Mid:** 200–399% of FPT; **High:** >400% of FPT. Differences significant at $P<.001$ using chi-square or one-way ANOVA tests, as appropriate.

Source: Managed care network development data (n=53,112).

Figure 2.

Model predictions compared with actual utilization in the validation sample, by predicted quantile of risk.

Notes: The solid lines correspond to actual emergency department (ED) utilization within each quantile of predicted risk in the validation sample; the dashed lines represent predicted ED utilization in the validation sample, based on the characteristics of the development sample. Models adjusted for all covariates listed in Table 2 (age; sex; race; morbidity; primary care provider [PCP], ED, and inpatient use in base year; payor; PCP type; PCP quality score; extra distance to PCP; neighborhood percentage in poverty; and 10 conditions from problem lists).

PCS: primary-care sensitive.

Source: Managed care network development and validation samples ($n_{\text{obs}}=107,449$ in 64,623 unique individuals), 2009–2010.

Figure 3A

Figure 3B

Figure 3.

Figure 3A. Practice-level observed-to-expected ratios for total primary-care sensitive emergency department visits when poverty is included as a predictor.

Notes: The two circled practices are family practices with 295 and 887 patients, respectively. The smaller practice's observed-to-expected (O/E) ratio is not significantly different with poverty included in the model, whereas the larger practice would be judged as having significantly higher primary-care-sensitive (PCS) emergency department (ED) use than expected with poverty included. Models adjusted for all covariates listed in Table 2 (age; sex; race; morbidity; primary care provider [PCP], ED, and inpatient use in base year; payor; PCP type; PCP quality score; extra distance to PCP; neighborhood percentage in poverty/10; and 10 conditions from problem lists).

Source: Managed care network development data (n=53,112), 2010.

Figure 3B. Practice-level observed-to-expected ratios for total primary-care sensitive emergency department visits when poverty is *not* included as a predictor.

Notes: The two circled practices are family practices with 295 and 887 patients, respectively. The smaller practice would be judged as having significantly lower primary-care-sensitive (PCS) emergency department (ED) use than expected with poverty omitted, whereas the larger practice would no longer be judged an outlier. Models adjusted for all covariates listed in Table 2 except neighborhood percentage in poverty/10.

Source: Managed care network development data (n=53,112), 2010.

Table 1
DEMOGRAPHIC AND CLINICAL CHARACTERISTICS IN THE BASE YEAR, BY SAMPLE

	Development (2010)		Validation (2009)		P-value
	N enrollees	%	N enrollees	%	
N	53,112		54,337		
Age (as of Jan. 1 of base year)					<.001
< 1	920	1.7%	749	1.4%	
1–10	5,889	11.1%	5,178	9.5%	
11–17	4,555	8.6%	4,187	7.7%	
18–24	5,075	9.6%	4,978	9.2%	
25–39	11,516	21.7%	10,641	19.6%	
40–64	25,237	47.5%	24,770	45.6%	
65+	1,145	2.2%	2,609	4.8%	
Female	27,983	52.7%	27,199	50.1%	.344
Race/ethnicity					.006
White	38,075	71.7%	36,947	68.0%	
Black	1,362	2.6%	1,323	2.4%	
Other	2,771	5.2%	2,563	4.7%	
Unknown	12,129	22.8%	12,279	22.6%	
Neighborhood income category					.089
Low (<200% FPT)	3,528	6.7%	3,585	6.6%	
Middle (200–399% FPT)	31,947	60.2%	32,365	59.6%	
High (400+ FPT)	17,637	33.2%	18,387	33.8%	
Primary care provider type					<.001
Internal medicine	25,700	48.4%	25,657	47.2%	
Family medicine	14,278	26.9%	15,229	28.0%	
Maternal/pediatrics	13,056	24.6%	13,340	24.6%	
Other	78	0.2%	111	0.2	
Insured ^a					<.001
Plan 1	29,935	55.1%	26,791	50.4%	
Plan 2	8,578	15.8%	9,585	18.0%	

	Development (2010)		Validation (2009)		P-value
	N enrollees	%	N enrollees	%	
Plan 3	10,265	18.9%	10,819	20.4%	
Plan 4	5,559	10.2%	5,917	11.1%	
Selected conditions from problem lists					
Arthritis	3,824	7.2%	3,628	6.7%	.001
Asthma	6,481	12.2%	6,566	12.1%	.552
Cancer	11,225	21.1%	10,943	20.1%	<.001
Chronic obstructive pulmonary disease	215	0.4%	180	0.3%	.046
Congestive heart failure	253	0.5%	142	0.3%	<.001
Depression	7,431	13.4%	7,628	13.4%	.905
Diabetes	8,541	16.1%	8,322	15.3%	.001
Hypertension	12,655	23.8%	11,960	22.0%	<.001
Overweight	5,812	10.9%	5,862	10.8%	.415
Tobacco use	8,827	16.6%	9,021	16.6%	.938
	Mean	SD	Mean	SD	P-value
Concurrent morbidity score (top-coded) ^b	1.52	2.97	1.36	2.61	<.001
Prospective morbidity score (top-coded) ^b	1.40	1.87	1.28	1.72	<.001
Provider quality score	1.08	0.85	1.10	0.87	.006

^aInsurer: the private company through which the enrollee received health insurance.

^bTop-coded at the 99.5th percentile.

FPT: federal poverty threshold. Source: Managed care network data, 2009–10.

Table 2
COEFFICIENTS, Z-SCORES, AND P-VALUES FROM MODELS OF THREE OUTCOME MEASURES

	Outcome 1—Any ED Visit (Logit)			Outcome 2—Total ED Visits (ZINB)			Outcome 3—Total PCS ED Visits (GLM)		
	Coef.	Z	P	Coef.	z	P	Coef.	Z	P
Basic demographics									
Age <1	1.00	10.57	<.001	0.87	10.36	<.001	0.93	5.89	<.001
Age 1–10	0.59	11.60	<.001	0.49	10.33	<.001	0.56	6.02	<.001
Age 11–17	0.66	12.68	<.001	0.58	12.38	<.001	0.39	3.74	<.001
Age 18–24	0.53	11.57	<.001	0.52	12.81	<.001	0.67	8.16	<.001
Age 25–39	0.19	5.15	<.001	0.18	5.40	<.001	0.33	4.69	<.001
Age 40–64 (Reference)									
Age 65+	0.14	2.31	.021	0.17	3.06	.002	0.13	1.18	.239
Female	−0.06	−2.34	.020	−0.04	−1.78	.074	0.23	4.93	<.001
Black	0.19	2.53	.012	0.18	2.73	.006	0.26	2.2	.028
Prior utilization									
Any ED visit in base year	0.80	26.12	<.001	0.74	27.66	<.001	1.02	22.17	<.001
Any inpatient stay in base year	−0.11	−1.78	.076	−0.12	−2.11	.035	−0.15	−1.33	.183
Morbidity from claims & clinical conditions from electronic medical record									
Prospective morbidity score	0.09	12.41	<.001	0.07	11.91	<.001	0.07	6.66	<.001
Arthritis	0.12	2.53	.011	0.1	2.32	.020	0.06	0.67	.500
Asthma	0.35	9.93	<.001	0.29	9.5	<.001	0.51	8.95	<.001
Cancer	−0.06	−1.63	.103	−0.06	−2.1	.036	−0.17	−2.53	.011
Congestive heart failure	0.44	2.91	.003	0.47	3.88	<.001	0.98	4.73	<.001
Chronic obstructive pulmonary disease	0.17	0.96	.337	0.23	1.58	.114	0.26	0.82	.412
Depression	0.39	11.06	<.001	0.36	11.53	<.001	0.38	6.34	<.001
Diabetes	0.08	2.08	.037	0.04	1.08	.278	0.05	0.78	.437
Hypertension	0.07	2.11	.035	0.07	2.1	.035	0.11	1.67	.095
Overweight	0.07	1.72	.085	0.09	2.54	.011	0.02	0.31	.757
Smoker	0.29	8.68	<.001	0.28	9.37	<.001	0.32	5.44	<.001

	Outcome 1—Any ED Visit (Logit)			Outcome 2—Total ED Visits (ZINB)			Outcome 3—Total PCS ED Visits (GLM)		
	Coef.	Z	P	Coef.	z	P	Coef.	Z	P
Insurer^a and provider measures									
Plan 1	−0.01	−0.35	.728	−0.05	−1.2	.231	−0.1	−1.23	.219
Plan 2	−0.05	−0.96	.337	−0.01	−0.13	.894	−0.03	−0.32	.747
Plan 3	0.02	0.34	.733	−0.18	−4.22	<.001	−0.33	−3.92	<.001
Plan 4 (Reference)									
PCP type: Maternal/pediatric	0.07	1.89	.058	0.06	1.88	.060	0.14	1.88	.059
PCP type: Family med (Reference)									
PCP type: Internal med	0.04	1.1	.271	0.03	0.88	.379	0.05	0.87	.387
PCP type: Other	−0.28	−0.7	.482	−0.16	−0.46	.648	0.11	0.14	.891
Mean PCP quality score	−0.06	−4.03	<.001	−0.06	−4.34	<.001	−0.05	−1.96	.050
Residence-based measures									
Extra distance to PCP	0.00	1.17	.243	0.003	2.46	.014	0.01	2.13	.033
Percent living in poverty in CT/10 ^b	0.11	6.22	<.001	0.01	5.84	<.001	0.02	6.2	<.001

^aInsurer: the private company through which the enrollee received health insurance.

^bThis coefficient refers to the effect of a 10% increase in the percentage of the population in the CT who have household incomes below 200% of the federal poverty threshold.

Coef: coefficient; CT: census tract; ED: emergency department; GLM: generalized linear model; PCP: primary care provider; PCS: primary-care sensitive; SE: standard error; z: z-score (standardized coefficient); ZINB: zero-inflated negative binomial. **Bold** indicates statistically significant *P*-values. Source: Managed care network data, 2010–11.