Use of Prolonged Travel to Improve Pediatric Risk-Adjustment Models

Scott A. Lorch, Jeffrey H. Silber, Orit Even-Shoshan, and Andrea Millman

Objective. To determine whether travel variables could explain previously reported differences in lengths of stay (LOS), readmission, or death at children's hospitals versus other hospital types.

Data Source. Hospital discharge data from Pennsylvania between 1996 and 1998.

Study Design. A population cohort of children aged 1–17 years with one of 19 common pediatric conditions was created ($N = 51,855$). Regression models were constructed to determine difference for LOS, readmission, or death between children's hospitals and other types of hospitals after including five types of additional illness severity variables to a traditional risk-adjustment model.

Principal Findings. With the traditional risk-adjustment model, children traveling longer to children's or rural hospitals had longer adjusted LOS and higher readmission rates. Inclusion of either a geocoded travel time variable or a nongeocoded travel distance variable provided the largest reduction in adjusted LOS, adjusted readmission rates, and adjusted mortality rates for children's hospitals and rural hospitals compared with other types of hospitals.

Conclusions. Adding a travel variable to traditional severity adjustment models may improve the assessment of an individual hospital's pediatric care by reducing systematic differences between different types of hospitals.

Key Words. Quality assessment, travel time, illness severity

Methods to assess the quality of care delivered by hospitals have grown in importance with monitoring by state agencies (Hannan et al. 1997) and the growth of pay-for-performance plans (Glickman et al. 2007; Profit et al. 2007). Most of these programs rely upon risk-adjusted outcome measures to assess the care provided by hospitals or physician practices. The risk-adjustment method must account for differences in case mix between groups of hospitals that may care for different patients. However, prior work from our group (Lorch et al. 2004, 2008) and others (Srivastava and Homer 2003; Merenstein, Egleston, and Diener-West 2005; Odetola, Gebremariam, and Freed 2007)

has found that patients hospitalized in children's hospitals, located primarily in urban areas, have longer risk-adjusted lengths of stay (LOS) and higher mortality rates. These results are counterintuitive. Children's hospitals have teaching programs and care for the largest volume of pediatric patients in any given geographic region—characteristics typically associated with improved quality. Based on these measurements, then, either children's hospitals counter-intuitively provide substandard care or there are systematic, unmeasured differences in illness severity in these prior analyses.

Measuring severity of illness is more difficult in children. Most children hospitalized for common pediatric conditions are relatively healthy, without comorbid conditions that are frequently used in standard risk-adjustment techniques (Charlson et al. 1987; Elixhauser et al. 1998). These comorbid conditions, along with age, race, gender, insurance status, and admission source, are typically used to construct a risk-adjustment model. We could augment these models by including other validated measures, such as All Patient's Related Diagnostic-Related Groups (Muldoon 1999). However, many of these measures include procedures and diagnoses that occurred during the hospitalization. These adjusted risk-adjustment tools may control for inappropriate care performed by a hospital (Romano and Chan 2000). Other validated methods have augmented the traditional risk-adjustment model for patients requiring intensive care (Pollack, Patel, and Ruttimann 1996; Richardson et al. 2001).

One potential improvement is adding the travel time or distance between a patient's home and the hospital. This improvement is based on prior work in adult patients that found an association between greater travel time and illness severity (Hogan 1988; Adams and Wright 1991; Adams et al. 1991; Welch, Larson, and Welch 1993; Basu 2005; Basu and Mobley 2007).

Address correspondence to Scott A. Lorch, M.D., M.S.C.E., Center for Outcomes Research, The Children's Hospital of Philadelphia, 3535 Market Street, Suite 1029, Philadelphia, PA 19104; e-mail: lorch@email.chop.edu. Scott A. Lorch, M.D., M.S.C.E., is with the Department of Pediatrics, The University of Pennsylvania School of Medicine, Philadelphia, PA; and also with the Division of Neonatology, The Children's Hospital of Philadelphia, Philadelphia, PA. Scott A. Lorch, M.D., M.S.C.E., Jeffrey H. Silber, M.D., Ph.D., and Orit Even-Shoshan, M.S., are with The Leonard Davis Institute of Health Economics, The University of Pennsylvania, Philadelphia, PA. Jeffrey H. Silber, M.D., Ph.D., Orit Even-Shoshan, M.S., and Andrea Millman, B.A., are with the Center for Outcomes Research, The Children's Hospital of Philadelphia, Philadelphia, PA. Jeffrey H. Silber, M.D., Ph.D., is with the Departments of Pediatrics and Anesthesiology and Critical Care, The University of Pennsylvania School of Medicine, Philadelphia, PA. Jeffrey H. Silber, M.D., Ph.D., and Andrea Millman, B.A., are with the Department of Health Care Systems, The Wharton School, The University of Pennsylvania, Philadelphia, PA.

Geocoded measures are relatively easy to obtain with Geographic Information Software using the exact location of the hospital and the child's residence, whereas nongeocoded measures can rapidly measure the distance between zip codes of the hospital and child's residence. If prior work is true, then either variable could augment the traditional risk-adjustment model that uses comorbid conditions, age, source of admission, and other demographic data.

The goal of this project was to determine whether travel variables could explain previously reported differences in LOS, readmission, or death at children's hospitals versus other hospital types. By explaining most of these systematic differences, we could then use these augmented risk-adjustment models to identify high- and low-performing hospitals. First, we will validate the geocoded travel time measure for individual children: Do sicker children travel further for care? Second, we will determine whether any severity adjustment tool beyond the typical comorbidity model could explain differences in LOS, readmission, or death at children's hospitals. Severity adjustment tools used in this analysis to augment the typical risk-adjustment model include geocoded travel time; nongeocoded travel distance; excess travel time; individual hospital market share; and a physiologic-based scoring system developed by MediQual (Iezzoni and Moskowitz 1988).

METHODS

Data Population and Sources

We obtained claims data on all hospital admissions aged 1–17 years to acute care hospitals in Pennsylvania between April 1, 1996, and June 30, 1998, from the Pennsylvania Health Care Cost Containment Council, which checks for data accuracy and validity (The Pennsylvania Health Care Cost Containment Council 2006). Pennsylvania was chosen for this analysis because it has a wide variety of urban and rural areas served by children's and community hospitals. We linked patient records to calculate prior admission and rehospitalization rates. As in previous work (Silber et al. 1999b, 2003; Lorch et al. 2004, 2008), we identified 19 common, unscheduled medical conditions from the principal diagnosis ICD-9CM codes. These 19 conditions were chosen because a variety of hospitals typically treat children with these conditions. We performed analyses on all 19 conditions together and for each condition separately. We limited the analysis to hospitals that cared for more than 20 patients to improve the stability of our model estimates.

Calculation of Augmented Severity Adjustment Measures

We calculated the travel time between each child's residential zip code and the admission hospital using *ArcView* (ESRI Inc., Redlands, CA) because exact street addresses were not made available. Travel time may more accurately capture the costs of traveling to one hospital than miles traveled, particularly for urban patients traveling on high-density roads (Phibbs and Luft 1995). We first assigned a Census Feature Classification Code (CFCC) (U.S. Census Bureau 2007) to each primary, secondary, and tertiary road segment in Pennsylvania and the surrounding states based on characteristics of the road. We then used the typical speed limit for each CFCC to determine the travel time across each road segment. Hospitals were mapped using address and zip code information from the Pennsylvania Department of Health. We determined the shortest estimated travel time (ETT) from the geographic center of the child's zip code to the admission hospital using an algorithm contained in *ArcView* (Dijkstra 1959). This value was used to classify children into one of three groups for our *travel time variable*: those with an ETT < 15 minutes, an ETT between 15 and 30 minutes, or an ETT > 30 minutes. The same procedure was used to calculate the shortest travel time from the geographic center of the zip code to any hospital included in the study. We then calculated the *excess time traveled* (EXTT) by the child, defined as (ETT – shortest travel time to any study hospital). Finally, we rank-ordered the travel times by hospital to determine hospital-specific 75th and 90th percentile travel times for all patients included in this study (Phibbs and Robinson 1993; Gresenz, Rogowski, and Escarce 2004). Children whose travel times were greater than thresholds were coded as “outside” the *hospital-specific 75th or 90th percentile market*, respectively.

Geocoding hospitals is a time-intensive technique that may be difficult for state agencies to implement. To determine the added benefit of using travel time over other less onerous methods, we calculated *nongeocoded straight-line distances* between the zip code centroid of the patient's residence and hospital. Finally, *MedisGroups physiologic scores* were available for this data set. This scoring system uses admission diagnoses and laboratory findings to assign each patient a risk of mortality, ranging from 0 (lowest risk) to 4 (highest risk). In this study, all risk scores over 2 were grouped together because of the few numbers of children in these high-risk groups.

Outcome Definitions

This study analyzed the risk of death, LOS, and 21-day readmission rates as in prior work (Silber et al. 1999b, 2003; Lorch et al. 2004). LOS was calculated as

the number of days between hospital admission and discharge and represented resources used during the hospitalization. *Twenty-one-day readmission rates* were used to account for potentially inadequate care during the hospitalization or inadequate coordination with outpatient providers.

Hospital Groups

We classified hospitals into four groups: children's hospitals; urban nonchildren's teaching hospitals; urban nonteaching hospitals; and rural hospitals. Children's hospitals consisted of those institutions where either (1) at least 90 percent of patients admitted to the hospital were younger than 17 years; or (2) the hospital was in the top fifth percentile in the state for pediatric admissions, and the hospital had either a pediatric residency program or a primary medical school affiliation. This classification combined hospitals whose patient case mix was similar, even if some identified hospitals were not represented by a national organization of children's hospitals. Five of 10 hospitals identified as children's hospitals in this study were members of the National Association of Children's Hospitals and Related Institutions. The results presented in this manuscript did not change significantly when we excluded the nonmember institutions. Teaching status was defined from American Hospital Association data. Rural hospitals were those hospitals whose county was located outside of a Metropolitan Statistical Area (Economic Research Service 2004).

Definition of Confounding Variables

In order to control for expected increases in LOS or risk of death associated with patient-level characteristics, our base model risk-adjustment model included sociodemographic variables such as age, race, gender; the median income of the patient's ZIP code; source of admission; and the presence or absence of specific comorbid conditions associated previously with prolonged LOS or higher hospital charges (Silber, Gleeson, and Zhao 1999a). The comorbid conditions in the final model included diabetes mellitus, sickle cell anemia, cerebral palsy, seizures, asthma, any cyanotic congenital heart disease, trisomy 21, cancer, any immunocompromised state or autoimmune disease, cystic fibrosis, chronic liver or renal disease, mental retardation, or congenital pulmonary or gastrointestinal anomaly. To construct this model, specific variables were added to a predictive model for death, LOS, or readmissions with age, race, and gender. Variables were retained if they remained statistically significant at a 5 percent level. In additional iterations,

variables were dropped if they lost statistical significance and the log-likelihood of the reduced and full models remained statistically similar by the *F*-test. In all models, we included interaction terms that were significant at the 5 percent level after applying the Bonferroni correction for multiple comparisons. Final variables are shown in Tables 1 and 2; other variables that were dropped included transfer status, other area census data besides median income, and rarer congenital anomalies.

For LOS, we constructed a Cox regression model that reported a hazard ratio (HR) for discharge for each patient (Silber, Gleeson, and Zhao 1999a; Austin, Ghali, and Tu 2003; Silber et al. 2003; Lorch et al. 2004, 2008). A discharge $HR < 1$ meant that patients stayed longer if they traveled further. We developed logit models to estimate the effects of travel time on prolonged stay, readmissions, and 30-day mortality. *Stata* version 9.2 (Stata Corporation, College Station, TX) was used for all analyses. We assigned the outcome of a given hospitalized child to the initial admitting hospital regardless of transfers after admission. For the LOS and readmission models, deaths were classified as either the longest stay in the data set or a readmission regardless of the day in which the death occurred. Modeling the few deaths based on the day when the child expired changed the results by < 1 percent. There were no significant differences in the results of the study when we included the year of hospitalization in our analyses.

Statistical Modeling

Our first aim of this study was to determine whether sicker children travel further for pediatric hospital care. We used ANOVA for continuous variables and χ^2 tests for categorical variables to determine univariable associations between predictive factors and longer travel times. We then constructed a multivariable ordinal logistic regression analysis to determine patient-level and hospital-level characteristics associated with traveling greater distances to the hospital. We present stratified analyses based on the type of hospital that cared for the child, as the predictive factors differed between hospital types.

For our second aim, we constructed various Cox and logit models for each of our three illustrative outcomes, adding either a geocoded travel time measure; a nongeocoded travel distance variable; the MedisGroups physiologic score; a hospital-specific market variable; or an excess travel time variable. Each model was compared with the base model using the likelihood-ratio test.

Table 1: Characteristics of Patient Population, Stratified by Estimated Travel Time (ETT)

	Column 1: Total Cohort (N= 51,855)	Column 2: ETT < 15 minutes (N= 37,171)	Column 3: ETT 15–30 minutes (N= 10,027)	Column 4: ETT > 30 minutes (N= 4,657)
<i>Patient-Level Factors</i>				
Age*	6.1 ± 5.0	6.0 ± 5.0	6.1 ± 5.1	6.7 ± 5.3
Male gender	29,093 (56.1%)	20,654 (55.6%)	5,777 (57.6%)	2,662 (57.2%)
Race*				
White	34,821 (67.2%)	22,211 (59.8%)	8,502 (84.8%)	4,108 (88.2%)
Black	10,516 (20.3%)	9,809 (26.4%)	533 (5.3%)	174 (3.7%)
Other	2,466 (4.8%)	2,136 (5.7%)	211 (2.1%)	119 (2.6%)
Missing	4,052 (7.8%)	3,015 (8.1%)	781 (7.8%)	256 (5.5%)
Insurance status*				
Fee for service	21,079 (40.7%)	13,892 (37.4%)	4,762 (47.5%)	2,425 (52.1%)
Medicaid	12,558 (24.2%)	9,219 (24.8%)	2,165 (21.6%)	1,174 (25.2%)
HMO	11,947 (23.1%)	9,471 (25.5%)	1,880 (18.7%)	623 (13.4%)
Other	4,739 (9.1%)	3,521 (9.5%)	922 (9.2%)	296 (6.3%)
Uninsured	1,505 (2.9%)	1,068 (2.9%)	298 (3.0%)	139 (3.0%)
Any comorbidity*	6,805 (13.1%)	4,562 (12.3%)	1,344 (13.4%)	899 (19.3%)
Emergency admission*	29,247 (56.4%)	22,249 (59.9%)	5,016 (50.0%)	1,982 (42.6%)
Condition*				
Asthma	14,237 (27.5%)	11,511 (31.0%)	2,099 (20.9%)	627 (13.5%)
Viral pneumonia	1,190 (2.3%)	829 (2.2%)	247 (2.5%)	114 (2.4%)
Bacterial pneumonia	9,686 (18.7%)	6,907 (18.6%)	2,055 (20.5%)	724 (15.5%)
Croup/bronchitis	4,586 (8.8%)	3,334 (9.0%)	992 (9.9%)	260 (5.6%)
Seizures	1,983 (3.8%)	990 (2.7%)	466 (4.6%)	527 (11.3%)
Gastroenteritis	2,160 (4.2%)	1,589 (4.3%)	441 (4.4%)	130 (2.8%)
Diarrhea	2,908 (5.6%)	2,088 (5.6%)	652 (6.5%)	168 (3.6%)
Diabetes/DKA	2,283 (4.4%)	1,219 (3.3%)	574 (5.7%)	490 (10.5%)
Sickle cell disease	510 (1.0%)	454 (1.2%)	44 (0.4%)	12 (0.3%)
Pyelonephritis	1,766 (3.4%)	1,260 (3.4%)	390 (3.9%)	116 (2.5%)
UTI	786 (1.5%)	575 (1.5%)	144 (1.4%)	67 (1.4%)
Viral meningitis	608 (1.2%)	442 (1.2%)	110 (1.1%)	56 (1.2%)
Bacterial meningitis	182 (0.4%)	93 (0.3%)	39 (0.4%)	50 (1.1%)
Cellulitis	3,373 (6.5%)	2,549 (6.9%)	617 (6.2%)	207 (4.4%)
Concussion	1,357 (2.6%)	854 (2.3%)	347 (3.5%)	156 (3.3%)
Poisoning	1,626 (3.1%)	1,198 (3.1%)	221 (2.2%)	207 (4.4%)

continued

Table 1: *Continued*

	<i>Column 1: Total Cohort (N = 51,855)</i>	<i>Column 2: ETT < 15 minutes (N = 37,171)</i>	<i>Column 3: ETT 15–30 minutes (N = 10,027)</i>	<i>Column 4: ETT > 30 minutes (N = 4,657)</i>
Burns	1,153 (2.2%)	636 (2.2%)	215 (2.1%)	311 (6.7%)
Skull injury	1,021 (2.0%)	443 (2.0%)	267 (2.7%)	311 (6.7%)
Spinal injury	440 (0.8%)	200 (0.8%)	107 (1.1%)	133 (2.9%)
MedisGroups score $\geq 2^*$	1,379 (2.7%)	759 (2.0%)	324 (3.2%)	296 (6.4%)
Type of hospital*				
Urban nonteaching	23,160 (44.7%)	17,735 (47.1%)	4,646 (46.3%)	779 (16.7%)
Children's	17,395 (33.5%)	12,328 (33.2%)	2,556 (25.5%)	2,511 (53.9%)
Urban teaching	3,259 (6.3%)	2,357 (6.3%)	515 (5.2%)	387 (8.3%)
Rural	8,041 (15.5%)	4,751 (12.8%)	2,310 (23.0%)	980 (21.1%)
Outcomes				
LOS*	2.0 [1.3–3.1]	2.0 [1.3–3.0]	2.0 [1.3–3.0]	2.5 [1.5–4.5]
Readmissions*	905 (1.8%)	540 (1.5%)	182 (1.8%)	183 (3.9%)
Death*	116 (0.2%)	47 (0.1%)	21 (0.2%)	48 (1.0%)
Other measures				
Outside 75% radius	11,672 (22.5%)	2,482 (6.7%)	5,345 (53.3%)	3,845 (82.6%)
Outside 90% radius	4,502 (8.7%)	209 (0.6%)	1,825 (18.2%)	2,468 (53.0%)
Excess travel time (minutes)				
0	20,501 (39.5%)	18,081 (48.7%)	2,342 (23.3%)	78 (1.7%)
0–5	16,957 (32.7%)	14,917 (40.1%)	1,912 (19.1%)	128 (2.7%)
5–10	5,229 (10.1%)	3,433 (9.2%)	1,632 (16.3%)	164 (3.5%)
10–15	3,159 (6.1%)	740 (2.0%)	2,218 (22.1%)	201 (4.3%)
15–30	3,220 (6.2%)	0	1,923 (19.2%)	1,297 (27.9%)
> 30	2,789 (5.4%)	0	0	2,789 (59.9%)

* $p < .05$ between columns 2 and 4 (the three travel time strata).

LOS, length of stay.

To determine how the models reduced the systematic bias against children's hospitals for each of these three outcomes, we reported the outcome-specific coefficients for each type of hospitals for all 19 conditions taken together and each condition separately. Between-model differences in these coefficients were measured using the methods of Clogg, Petkova, and Haritou (1995). We included interaction terms between a travel time variable and the four types of hospitals and reported these stratified results if the model likelihood ratios changed at a significance level of 5 percent.

Table 2: Adjusted Risk Factors for Longer Estimated Travel Times for Common Pediatric Hospital Conditions, Stratified by Type of Hospital

	Full Model		Urban Nonteaching Hospitals		Children's Hospitals		Urban Teaching Hospitals		Rural Hospitals	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
<i>Patient-Level Factors</i>										
Male sex	1.08	1.04, 1.13	1.14	1.07, 1.22	1.05	0.97, 1.14	0.86	0.71, 1.04	0.98	0.89, 1.07
Race										
White		Reference		Reference		Reference		Reference		Reference
Black	0.13	0.11, 0.15	0.29	0.22, 0.38	0.11	0.09, 0.13	0.07	0.04, 0.12	0.58	0.39, 0.87
Unknown	0.65	0.60, 0.70	1.02	0.92, 1.12	0.39	0.33, 0.45	0.85	0.56, 1.27	1.07	0.80, 1.44
Other	0.25	0.22, 0.28	0.23	0.17, 0.29	0.27	0.22, 0.31	0.49	0.26, 0.92	1.00	0.68, 1.46
Each additional age in years	1.01	1.00, 1.02	0.99	0.98, 1.00	1.01	1.00, 1.03	1.06	1.04, 1.09	1.01	1.00, 1.02
Rate of prior admissions	5.17	3.62, 7.38	0.99	0.39, 2.52	4.62	2.86, 7.45	10.24	1.86, 56.38	3.88	1.57, 9.61
Emergency admission	0.72	0.69, 0.75	0.87	0.81, 0.93	0.48	0.43, 0.52	0.73	0.58, 0.93	0.90	0.82, 0.99
Insurance status										
Fee-for-service		Reference		Reference		Reference		Reference		Reference
Uninsured	1.00	0.89, 1.13	1.16	0.98, 1.37	0.82	0.62, 1.08	0.68	0.42, 1.08	1.35	1.02, 1.77
Medicaid	1.11	1.02, 1.21	0.77	0.67, 0.87	1.52	1.29, 1.79	1.01	0.68, 1.50	1.27	1.08, 1.50
HMO	0.67	0.63, 0.70	1.07	0.99, 1.16	0.38	0.34, 0.42	0.36	0.29, 0.46	1.18	1.03, 1.36
Other	0.81	0.75, 0.87	1.18	1.04, 1.32	0.67	0.59, 0.76	0.45	0.27, 0.73	1.01	0.85, 1.21
Income <25 k	0.65	0.59, 0.70	1.18	1.02, 1.36	0.31	0.27, 0.36	1.25	0.82, 1.93	3.01	2.52, 3.58
Income >50 k	1.22	1.12, 1.33	0.60	0.53, 0.68	1.91	1.66, 2.20	2.80	1.92, 4.10	8.33	1.65, 42.06
Any comorbidity	1.30	1.22, 1.38	1.06	0.96, 1.18	1.38	1.24, 1.54	1.18	0.87, 1.61	1.28	1.11, 1.48

continued

Interaction terms										
Age × croup	0.94	0.91, 0.97	0.97	0.93, 1.00	0.99	0.93, 1.06	1.04	0.91, 1.20	0.83	0.78, 0.89
Age × diabetes	0.95	0.94, 0.97	0.95	0.92, 0.99	0.98	0.95, 1.01	1.05	0.94, 1.18	0.93	0.89, 0.97
Age × poisoning	0.97	0.95, 0.99	0.97	0.93, 1.01	0.98	0.95, 1.02	0.98	0.85, 1.14	1.00	0.94, 1.06
Age × income > 50 k	0.96	0.95, 0.97	0.96	0.95, 0.98	0.96	0.94, 0.97	0.93	0.89, 0.97	1.33	0.89, 1.98
Age × Medicaid	0.98	0.97, 0.99	1.01	0.99, 1.02	0.96	0.94, 0.98	0.96	0.92, 1.00	0.98	0.96, 1.00
Black × emergency	0.69	0.59, 0.82	0.70	0.49, 1.00	0.89	0.71, 1.12	1.62	0.84, 3.14	1.30	0.76, 2.23
Emergency × burns	0.40	0.31, 0.51	0.96	0.49, 1.90	0.71	0.47, 1.09	0.18	0.11, 0.30	0.50	0.16, 1.57
Emergency × concussion	0.47	0.39, 0.56	0.99	0.65, 1.49	0.73	0.56, 0.96	0.39	0.15, 0.99	0.26	0.16, 0.44
Emergency × poisoning	0.49	0.38, 0.62	1.14	0.67, 1.91	0.67	0.46, 0.97	0.33	0.07, 1.47	0.19	0.10, 0.36
Medicaid × croup	0.75	0.63, 0.88	0.90	0.71, 1.15	0.65	0.42, 0.99	0.30	0.06, 1.43	0.80	0.58, 1.09
Other insurance × skull injury	0.56	0.36, 0.89	0.59	0.25, 1.43	0.95	0.51, 1.76	NA	NA, NA	0.15	0.04, 0.61
Hospital factors										
Urban nonteaching hospitals										
<i>Reference</i>										
Children's hospitals	2.88	2.73, 3.04								
Urban teaching hospitals	1.71	1.56, 1.88								
Rural hospitals	1.99	1.88, 2.11								

Note: All statistically significant associations at a $p < 0.05$ level are shown in boldface type. ORs represent the change in odds of being in a travel time category with a longer travel time with a specified risk factor. Categories were travel time <15 minutes; travel time between 15 and 30 minutes; and a travel time >30 minutes. CI, confidence interval; OR, odds ratio.

RESULTS

During the time period of this study, we identified 51,855 children hospitalized with one of the 19 conditions listed in Table 1. A total of 142 hospitals cared for at least 20 children in this study; the median number of eligible admissions per hospital was 215.5, with a 10th–90th percentile range of 49–707. The median ETT threshold for the hospital-specific 75 and 90 percent radii in the study was 15 minutes (interquartile range [IQR] 10–19.5) and 20.5 minutes (IQR 15.5–27.5), respectively. This median ETT threshold was significantly higher for the 39 rural hospitals (median 75 percent threshold 19 minutes and 90 percent threshold 27.75 minutes) compared with nonrural hospitals, while the thresholds for the 10 children's hospitals had a wide interquartile (6.5–34 minutes for 75 percent threshold) and overall range of values (4.5–54.5 minutes for 75 percent threshold).

Column 1 of Table 1 shows basic demographic information for the study population. The average age of the cohort was 6.1 ± 5.0 years. Over 66 percent of the population was white and 56.1 percent was male. Fee-for-service insurance was the most common insurance, followed by an equal percentage of children with HMO or governmental insurance. Children's hospitals cared for approximately 33 percent of the patients, rural hospitals cared for 15.5 percent of the cohort, and urban nonteaching hospitals cared for 44.7 percent of the children.

Aim 1: Patient and Hospital Characteristics of Long ETT

Specific patient-level and hospital-level characteristics were associated with longer ETT in univariable analysis (Table 1, columns 2–4). Measures of increased illness severity were associated with longer ETT, such as high severity conditions such as seizures or bacterial meningitis, having a concurrent comorbid condition, or being previously admitted within 3 months of the studied hospitalization. A higher percentage of children with longer travel times had a MedisGroups score of 2 or greater. More white children and children with fee-for-service insurance had an ETT > 15 minutes, whereas fewer children with HMO insurance had an ETT > 15 minutes. Over 60 percent of the children who traveled more than 30 minutes to the hospital went to a children's hospital, and the majority of patients with long travel times also had EXTs over 5 minutes. Children with travel times above 30 minutes also had longer LOS (median 2.5 versus 2.0 for children who traveled <30 minutes) and higher mortality rates (1.0 percent versus 0.1–0.2 percent for children who traveled <30 minutes).

Multivariable Analyses. Table 2 presents the full ordinal logistic predictive model for children who travel further for hospital care. The three outcome measures used in this model were a travel time < 15 minutes, 15–30 minutes, and more than 30 minutes. The odds ratios (ORs) show how a specific risk factor would change the odds of being in a longer travel time category. Across all hospital types, patients with previous admissions and white race were more likely to have longer ETT. Emergent admissions were more likely to travel than nonemergent, direct admissions. Many serious principal diagnoses were associated with longer travel times regardless of the hospital type where they were admitted, such as seizures and diabetes ketoacidosis.

For other factors, their association with longer travel time depended on where the child was admitted. Children who traveled to children's hospitals were more likely to have a more serious principal diagnosis, such as seizures or bacterial meningitis; more likely to have a comorbid condition; and more likely to reside in a high-income area. Comorbid conditions, although, were not associated with longer travel times for urban hospitals, and for urban nonteaching hospitals, residing in a high-income area was associated with a lower likelihood of traveling. These results suggest that longer travel times are associated with illness severity, although the degree of this association varies by the admission hospital type.

Aim 2: Improvement with Augmented Risk-Adjustment Models

For each outcome, all five types of travel or physiologic-based variables improved upon the base risk-adjustment model by the log-likelihood test. The model that included the MedisGroups physiologic score showed the largest improvement among the five potential types of variables. For these augmented risk-adjustment models to be used in assessing the care delivered by an individual hospital, the individual model must reduce or eliminate any systematic differences between different types of hospitals. Figure 1 shows the association between types of hospital and each of our outcome measures for different augmented risk-adjustment models. Models that included a distance variable are indicated with a large diamond or triangle (nongeocoded distance) or a small square, small triangle, hollow circle, or hollow diamond (geocoded travel time). As with prior work, using the base risk-adjustment model found longer LOS (discharge HR 0.83, 95 percent confidence interval [CI] 0.81–0.85), higher odds of a readmission (OR 1.60,

Figure 1: Adjusted Coefficients for Different Hospital Types Compared with Urban Nonteaching Hospitals for LOS (A), Readmissions (B), and Mortality (C)

95 percent CI 1.34–1.91), and higher odds of death (OR 3.21, 95 percent CI 1.74–5.92) among children attending children’s hospitals compared with urban nonteaching hospitals in Pennsylvania. However, as shown by the large filled diamond (15 mile distance cutoff) and small filled square (15-minute travel time cutoff) bars, inclusion of a travel variable significantly reduced this interhospital difference for LOS (HR 0.90, 95 percent CI 0.87–0.92 for both variables) and readmissions (OR 1.14, 95 percent CI 0.91–1.44 for travel time, OR 1.21, 95 percent CI 0.97–1.51 for nongeocoded travel distance). For mortality, the adjusted difference between children’s hospital and urban nonteaching hospitals was significantly reduced for models that included the 30-minute travel time variable (hollow circle) and the 15 mile distance variable (large filled diamond). Models that included the other severity adjustment tools also reduced this difference between children’s hospitals and other hospital types, but to a lesser degree than the travel models. Rural hospitals showed a similar pattern; the travel variables provided the greatest reduction in LOS or readmission compared with the base risk-adjustment model as denoted by the starred observations in Figure 1. Coefficients for urban teaching hospitals showed little change with the addition of either the travel or physiologic risk variables. When the MedisGroups score was added to either travel model, there was no change in the coefficient on any hospital variable; however, these coefficients were significantly different than the model with the MedisGroups variable alone (Figure 1).

Note: Each symbol represents the coefficient for each type of hospital, with the bars showing 95 percent confidence intervals, after adjusting for age, sex, gender, admission condition, presence of comorbid conditions, source of admission, insurance status, and significant interaction terms. After the coefficients for the base model (solid circle) are presented, the following models are shown from left to right, as indicated by the numbers above the models: distance models (solid diamond and square), #1; MedisGroups models (solid square, small circle, small diamond), #2; travel time models (small square and hollow circle for travel time, small triangle and hollow diamond for excess travel time), #3; and hospital-specific market models (hollow triangle and square), #4. Coefficients statistically significant from the base risk-adjustment model are indicated with a star, while coefficients statistically significant from the 15-minute travel time model are indicated with a plus.

Aim 3: Travel Time for Specific Conditions

Table 3 shows the association between LOS or readmission rates and a travel time of 15 minutes or greater for each individual condition. The travel time variable was associated with higher odds of a readmission for conditions that are typically of lower illness severity, such as asthma, gastroenteritis, diarrhea, and urinary tract infections. Longer travel time was consistently associated with longer LOS for most conditions except for those with the highest severity, such as diabetes ketoacidosis, bacterial meningitis, and sickle cell crisis. When we limited our analyses to those conditions that were statistically significant, the augmented risk-adjustment models that included a travel variable continued to reduce the difference between children's hospitals and other hospitals to the greatest extent: for LOS, the HR for both travel models was 0.91 and 0.92, respectively (95 percent CI 0.89–0.94 for both models), and for read-

Table 3: Impact of a Travel Time > 15 Minutes on Length of Stay (LOS) and Readmission Rates, by Individual Admitting Condition

Condition	Discharge Ratio for LOS (95% CI)*	OR for Readmission (95% CI)
Asthma	0.98 (0.94–1.02)	1.46 (1.04–2.04)
Viral pneumonia	0.84 (0.74–0.95)	0.73 (0.27–2.02)
Bacterial pneumonia	0.88 (0.84–0.92)	1.07 (0.76–1.52)
Croup/bronchitis	0.90 (0.84–0.96)	1.56 (0.87–2.80)
Seizures	0.80 (0.73–0.87)	0.71 (0.43–1.15)
Gastroenteritis	0.85 (0.77–0.93)	2.64 (1.43–4.90)
Diarrhea	0.89 (0.82–0.96)	1.64 (0.94–2.87)
Diabetes/DKA	1.03 (0.95–1.12)	0.82 (0.43–1.56)
Sickle cell disease	0.96 (0.72–1.26)	0.85 (0.25–2.96)
Pyelonephritis	0.96 (0.87–1.18)	1.82 (0.82–4.03)
UTI	1.00 (0.86–1.18)	4.50 (2.00–10.2)
Viral meningitis	0.99 (0.82–1.18)	1.24 (0.49–3.12)
Bacterial meningitis	1.07 (0.80–1.43)	†
Cellulitis	0.92 (0.85–1.00)	2.23 (1.19–4.17)
Concussion	0.70 (0.63–0.79)	3.72 (1.28–10.8)
Poisoning	0.82 (0.73–0.92)	1.01 (0.33–3.08)
Burns	0.91 (0.80–1.02)	0.69 (0.19–2.48)
Skull injury	0.61 (0.53–0.69)	1.38 (0.60–3.15)
Spinal injury	0.70 (0.58–0.85)	1.56 (0.38–6.35)

Note: Complications for which a travel time >15 minutes was significantly associated at a $p < .05$ level with LOS or readmission rates are shown in boldface type.

*Discharge ratio < 1 = longer LOS.

†Too few readmissions for stable estimates.

CI, confidence interval; OR, odds ratio.

mission, the ORs were 1.23 (95 percent CI 0.87–1.75) for the travel time model and 1.25 (95 percent CI 0.90–1.78) for the travel distance model.

DISCUSSION

Prior work has suggested that children's hospitals have longer LOS, higher readmission rates, and higher mortality rates compared with other types of hospitals. However, the addition of a travel variable to a traditional risk-adjustment model—whether geocoded travel times or nongeocoded travel distances—reduced these systematic differences (Figure 1). Other severity adjustment tools, such as the inclusion of excess travel time or the MedisGroups physiologic score, improved our assessment of a patient's risk without further reducing the differences between types of hospitals. Augmenting traditional risk-adjusted models with a travel variable, then, may identify poorly performing hospitals without systematically favoring or penalizing hospitals based on their location and role in the community. Although the travel time variable may provide a more accurate assessment of the travel costs for families with ill children, the specific travel variable used in the augmented risk-adjustment model should be based on the benefits and costs of using each type of variable.

Why may travel time improve the severity adjustment of these models? We can draw insights from our analyses of which patients typically travel further to receive care. These children appear sicker by all available measurements: they are more likely to have high-severity conditions, such as bacterial meningitis or diabetes ketoacidosis; they are more likely to have one or more comorbid conditions; they are more likely to have had a prior admission; and they have higher MedisGroups scores (Table 1). However, even when we include this available information in our severity adjustment models, the use of any travel time variable improved the severity adjustment models, especially for conditions of lower usual illness severity (Figure 1). Prior work in myocardial infarctions (McClellan, McNeil, and Newhouse 1994; Piette and Moos 1996) and asthma (Jones, Bentham, and Horwell 1999) found an association between higher mortality rates and longer travel distances. Longer travel times, then, appear to further distinguish those children at higher risks of a poor outcome within specific diagnoses or among children with a comorbid condition. What is not clear is whether these patients are traveling because the parents believe that their children are sicker, or whether their local physicians are preferentially referring them to the larger, regionalized centers.

Similar to prior work (Lorch et al. 2004), these data also suggest that the type of hospital where patients receive care is equally as important as whether patients travel at all: children traveling to children's hospitals appear to be the sickest patients with a given condition or set of comorbid conditions, as children's hospitals received the greatest improvement in assessment when a travel variable was included in our risk-adjustment models. The fact that rural hospitals also experience an improvement in assessment suggests that access to care may continue to be an issue for children residing far from medical care. This fact occurs even though rural hospitals compete for patients of higher income or higher severity with larger urban centers (Bronstein and Morrissey 1990; Tai, Porell, and Adams 2004; Liu, Bellamy, and McCormick 2007).

Although prior work suggests that patients who bypass hospitals either do not have insurance or are sicker, especially rural patients (Hogan 1988; Adams et al. 1991), the addition of a "bypass" travel variable to our augmented model did not reduce the systematic difference between hospital types any further than the absolute travel time variable (Figure 1). It is possible that at any given hospital, the actual number of patients traveling long excess distances is small, and most of these children were already traveling long distances. Also, factors that lead a patient to bypass the nearest hospital, such as the lack of health insurance, may be captured in the traditional risk-adjustment model.

The other interesting finding from this study is that hospital-specific measures of travel did not improve our results over either the travel time or travel distance models. This result emphasizes how different the organization of pediatric care is from adult care in the United States, particularly in states with large children's hospitals: many local community hospitals either do not care for children or have very small pediatric wards with little experience managing any sort of medical complexity in a child. Thus, hospitals that care for sick children may have wider markets than the typical adult hospital. For example, several large children's hospitals had 75 percent thresholds over 50 minutes (compared with 13.5 minutes for urban hospitals) and 90 percent thresholds of over 75 minutes. For Medicare patients, prior work on the markets of rural hospitals showed similar results (Adams et al. 1991; Goody 1993; Liu, Bellamy, and McCormick 2007). Using the hospital-specific radii method for severity adjustment may not account for the regionalization of pediatric care that occurs in most parts of the United States.

One concern about augmenting a risk-adjustment model is "adjusting away" differences in quality between hospitals. For example, if hospitals poorly treat their asthmatic patients and as a result the children require in-

tensive care or mechanical ventilation, the risk-adjustment model should not include these variables (Romano and Chan 2000). Augmenting the typical risk-adjustment models with a travel variable would cause this bias only if (1) poor hospitals were the only hospitals accepting patients who travel or (2) hospitals were providing poor care only to those patients who travel. The majority of patients who travel for pediatric hospital care go to hospitals that should provide at least similar care to other hospitals in the community. These hospitals would include children's hospitals and other teaching hospitals. As for differential treatment of patients solely based on where they reside, it is unlikely that a poorly performing hospital would only prolong the LOS, increase the readmission rate, or increase the mortality rate of patients traveling greater distances. The fact that all three outcome measures used in this paper were influenced by prolonged travel suggests that this variable is somehow assessing previously unmeasured illness severity.

These results suggest several policy implications. First, these results could be used by state agencies in their assessment and publication of hospitals' performance or in pay-for-performance assessments. Secondly, these data can also help health planners identify areas of greater need for pediatric hospital care and resources. Similar work has been published for trauma networks (Branas et al. 2005). Finally, the fact that children with HMO insurance were less likely to travel suggests that insurers may influence the place of initial hospitalization for children with common medical conditions.

Travel time did not eliminate the differences between hospitals for the mortality outcome, possibly because detailed clinical data were not available for each child. For each of the models, although, travel time added significant information even when the MedisGroups score was included in the risk-adjustment model. Thus, a travel variable may serve as an adequate proxy for situations where detailed clinical data are not available for risk adjustment. While Pennsylvania has a large variety of rural and urban hospitals, these results may not be generalizable to states with one central children's hospital or many smaller community hospitals that equally care for children. Finally, our results concern common pediatric conditions that make up the majority of pediatric admissions to any hospital. The care of more complex conditions that are typically regionalized, such as cancer and congenital heart disease, may not benefit from such a change to the risk-adjustment model.

Thus, using a travel time variable helps to improve severity adjustment in the assessment of pediatric hospital care, likely by adding otherwise unobserved information about these children. The performance of hospitals with

large geographic markets, such as children's hospitals and rural hospitals, are most likely to be affected by the inclusion of travel time. When detailed clinical data are not available, policy makers should further investigate methods to improve the assessment of hospital performance.

ACKNOWLEDGMENTS

Joint Acknowledgment/Disclosure Statement: This project was funded by Agency for Healthcare Research and Quality Grant #HS-09-983, "Conditional Length of Stay: A Pediatric Outcome Measure." All authors were involved in the initial conceptualization of the grant, data acquisition and analysis, and the drafting of the manuscript.

Disclosures: None.

Disclaimers: None.

REFERENCES

- Adams, E. K., R. Houchens, G. E. Wright, and J. Robbins. 1991. "Predicting Hospital Choice for Rural Medicare Beneficiaries: The Role of Severity of Illness." *Health Services Research* 26 (5): 583–612.
- Adams, E. K., and G. E. Wright. 1991. "Hospital Choice of Medicare Beneficiaries in a Rural Market: Why Not the Closest?" *Journal of Rural Health* 7 (2): 134–52.
- Austin, P. C., W. A. Ghali, and J. V. Tu. 2003. "A Comparison of Several Regression Models for Analysing Cost of CABG Surgery." *Statistics in Medicine* 22 (17): 2799–815.
- Basu, J. 2005. "Severity of Illness, Race, and Choice of Local versus Distant Hospitals among the Elderly." *Journal of Health Care for the Poor and Underserved* 16 (2): 391–405.
- Basu, J., and L. R. Mobley. 2007. "Illness Severity and Propensity to Travel along the Urban–Rural Continuum." *Health Place* 13 (2): 381–99.
- Branas, C. C., E. J. MacKenzie, J. C. Williams, C. W. Schwab, H. M. Teter, M. C. Flanagan, A. J. Blatt, and C. S. ReVelle. 2005. "Access to Trauma Centers in the United States." *Journal of the American Medical Association* 293 (21): 2626–33.
- Bronstein, J. M., and M. A. Morrissey. 1990. "Determinants of Rural Travel Distance for Obstetrics Care." *Medical Care* 28 (9): 853–65.
- Charlson, M. E., P. Pompei, K. L. Ales, and C. R. MacKenzie. 1987. "A New Method of Classifying Prognostic Comorbidity in Longitudinal Studies: Development and Validation." *Journal of Chronic Diseases* 40 (5): 373–83.
- Clogg, C. C., E. Petkova, and A. Haritou. 1995. "Statistical Methods for Comparing Regression Coefficients between Models." *American Journal of Sociology* 100 (5): 1271–93.

- Dijkstra, E. W. 1959. "A Note on Two Problems in Connexion with Graphs." *Numeriske Matematik* 1: 269–71.
- Economic Research Service. 2004. "Rural-Urban Continuum Codes" [accessed on May 16, 2008]. Available at <http://www.ers.usda.gov/Data/RuralUrbanContinuumCodes/>
- Elixhauser, A., C. Steiner, D. R. Harris, and R. M. Coffey. 1998. "Comorbidity Measures for Use with Administrative Data." *Medical Care* 36 (1): 8–27.
- Glickman, S. W., F. S. Ou, E. R. DeLong, M. T. Roe, B. L. Lytle, J. Mulgund, J. S. Rumsfeld, W. B. Gibler, E. M. Ohman, K. A. Schulman, and E. D. Peterson. 2007. "Pay for Performance, Quality of Care, and Outcomes in Acute Myocardial Infarction." *Journal of the American Medical Association* 297 (21): 2373–80.
- Goody, B. 1993. "Defining Rural Hospital Markets." *Health Services Research* 28 (2): 183–200.
- Gresenz, C. R., J. Rogowski, and J. J. Escarce. 2004. "Updated Variable-Radius Measures of Hospital Competition." *Health Services Research* 39 (2): 417–30.
- Hannan, E. L., A. L. Siu, D. Kumar, M. Racz, D. B. Pryor, and M. R. Chassin. 1997. "Assessment of Coronary Artery Bypass Graft Surgery Performance in New York. Is There a Bias Against Taking High-Risk Patients?" *Medical Care* 35 (1): 49–56.
- Hogan, C. 1988. "Patterns of Travel for Rural Individuals Hospitalized in New York State: Relationships between Distance, Destination, and Case Mix." *Journal of Rural Health* 4 (2): 29–41.
- Iezzoni, L. I., and M. A. Moskowitz. 1988. "A Clinical Assessment of MedisGroups." *Journal of the American Medical Association* 260 (21): 3159–63.
- Jones, A. P., G. Bentham, and C. Horwell. 1999. "Health Service Accessibility and Deaths from Asthma." *International Journal of Epidemiology* 28 (1): 101–5.
- Liu, J. J., G. R. Bellamy, and M. McCormick. 2007. "Patient Bypass Behavior and Critical Access Hospitals: Implications for Patient Retention." *Journal of Rural Health* 23 (1): 17–24.
- Lorch, S. A., A. M. Millman, X. Zhang, O. Even-Shoshan, and J. H. Silber. 2008. "The Impact of Admission Day Crowding on the Length of Stay of Pediatric Hospitalizations." *Pediatrics* 121: e718–30.
- Lorch, S. A., X. Zhang, P. R. Rosenbaum, O. Evan-Shoshan, and J. H. Silber. 2004. "Equivalent Length of Stay in Pediatric Patients Hospitalized in Rural and Non-Rural Hospitals." *Pediatrics* 114 (4): e400–8.
- McClellan, M., B. J. McNeil, and J. P. Newhouse. 1994. "Does More Intensive Treatment of Acute Myocardial Infarction in the Elderly Reduce Mortality? Analysis Using Instrumental Variables." *Journal of the American Medical Association* 272 (11): 859–66.
- Merenstein, D., B. Egleston, and M. Diener-West. 2005. "Lengths of Stay and Costs Associated with Children's Hospitals." *Pediatrics* 115 (4): 839–44.
- Muldoon, J. H. 1999. "Structure and Performance of Different DRG Classification Systems for Neonatal Medicine." *Pediatrics* 103 (1, suppl E): 302–18.

- Odetola, F. O., A. Gebremariam, and G. L. Freed. 2007. "Patient and Hospital Correlates of Clinical Outcomes and Resource Utilization in Severe Pediatric Sepsis." *Pediatrics* 119 (3): 487–94.
- Phibbs, C. S., and H. S. Luft. 1995. "Correlation of Travel Time on Roads versus Straight Line Distance." *Medical Care Research and Review* 52 (4): 532–42.
- Phibbs, C. S., and J. C. Robinson. 1993. "A Variable-Radius Measure of Local Hospital Market Structure." *Health Services Research* 28 (3): 313–24.
- Piette, J. D., and R. H. Moos. 1996. "The Influence of Distance on Ambulatory Care Use, Death, and Readmission Following a Myocardial Infarction." *Health Services Research* 31 (5): 573–91.
- Pollack, M. M., K. M. Patel, and U. E. Ruttimann. 1996. "PRISM III: An Updated Pediatric Risk of Mortality Score." *Critical Care Medicine* 24 (5): 743–52.
- Profit, J., J. A. Zupancic, J. B. Gould, and L. A. Petersen. 2007. "Implementing Pay-for-Performance in the Neonatal Intensive Care Unit." *Pediatrics* 119 (5): 975–82.
- Richardson, D. K., J. D. Corcoran, G. J. Escobar, and S. K. Lee. 2001. "SNAP-II and SNAPPE-II: Simplified Newborn Illness Severity and Mortality Risk Scores." *Journal of Pediatrics* 138 (1): 92–100.
- Romano, P. S., and B. K. Chan. 2000. "Risk-Adjusting Acute Myocardial Infarction Mortality: Are APR-DRGs the Right Tool?" *Health Services Research* 34 (7): 1469–89.
- Silber, J. H., S. P. Gleeson, and H. Zhao. 1999a. "The Influence of Chronic Disease on Resource Utilization in Common Acute Pediatric Conditions. Financial Concerns for Children's Hospitals." *Archives of Pediatrics and Adolescent Medicine* 153 (2): 169–79.
- Silber, J. H., P. R. Rosenbaum, O. Even-Shoshan, M. Shabbout, X. Zhang, E. T. Bradlow, and R. R. Marsh. 2003. "Length of Stay, Conditional Length of Stay, and Prolonged Stay in Pediatric Asthma." *Health Services Research* 38 (3): 867–86.
- Silber, J. H., P. R. Rosenbaum, L. F. Koziol, N. Sutaria, R. R. Marsh, and O. Even-Shoshan. 1999b. "Conditional Length of Stay." *Health Services Research* 34 (1, part 2): 349–63.
- Srivastava, R., and C. J. Homer. 2003. "Length of Stay for Common Pediatric Conditions: Teaching versus Nonteaching Hospitals." *Pediatrics* 112 (2): 278–81.
- Tai, W. T., F. W. Porell, and E. K. Adams. 2004. "Hospital Choice of Rural Medicare Beneficiaries: Patient, Hospital Attributes, and the Patient–Physician Relationship." *Health Services Research* 39 (6, part 1): 1903–22.
- The Pennsylvania Health Care Cost Containment Council. 2006. "Hospital Performance Report. 49 Common Medical Procedures and Treatment" [accessed on July 19, 2007]. Available at <http://www.phc4.org/reports/hpr/05/docs/hpr2005technotes.pdf>
- U.S. Census Bureau. 2007. "TIGER/Line[®] Files. What are the TIGER/Line Files and How Are They Used? – Overview and Trademark Information" [accessed on October 25, 2007]. Available at <http://www.census.gov/geo/www/tiger/overview.html>
- Welch, H. G., E. B. Larson, and W. P. Welch. 1993. "Could Distance be a Proxy for Severity-of-Illness? A Comparison of Hospital Costs in Distant and Local Patients." *Health Services Research* 28 (4): 441–58.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.

Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting materials supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.