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Is a Skilled Nursing Facility's Rehospitalization Rate a Valid Quality Measure?

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Objective. To determine whether the observed differences in the risk-adjusted rehospitalization rates across skilled nursing facilities (SNFs) reflect true differences or merely differences in patient severity.

Settings. Elderly Medicare beneficiaries newly admitted to an SNF following hospitalization.

Study Design. We used 2009–2012 Medicare data to calculate SNFs' risk-adjusted rehospitalization rate. We then estimated the effect of these rehospitalization rates on the rehospitalization of incident patients in 2013, using an instrumental variable (IV) method and controlling for patient's demographic and clinical characteristics and residential zip code fixed effects. We used the number of empty beds in a patient's proximate SNFs during hospital discharge to create the IV.

Principal Findings. The risk-adjusted rehospitalization rate varies widely; about one-quarter of the SNFs have a rehospitalization rate lower than 17 percent, and for one-quarter, it is higher than 23 percent. All the IV models result in a robust finding that an increase in a SNF's rehospitalization rate of 1 percentage point over the period 2009–2012 leads to an increase in a patient's likelihood of rehospitalization by 0.8 percentage points in 2013.

Conclusions. Treatment in SNFs with historically low rehospitalization causally reduces a patient's likelihood of rehospitalization. Observed differences in rehospitalization rates reflect true differences and are not an artifact of selection.

Key Words. Skilled nursing facility, quality of care, rehospitalization, readmission, ACA

The Centers for Medicare and Medicaid Services' (CMS) Hospital Readmission Reduction Program now holds hospitals responsible for their Medicare patients' readmission rates in the 30 days post discharge. One major determinant of the readmission rate is how well the skilled nursing facility (SNF) that the patient is discharged to prevents readmissions. Twenty percent of all patients from hospital are discharged to SNFs for postacute care (MedPAC 2015), and these patients have higher readmission rates compared with patients discharged to other settings. Rahman et al. (2016) demonstrated that the treating SNF has relatively larger influence on rehospitalization than the originating hospital. If a hospital sends patients to low-quality SNFs, then more patients will be readmitted and that hospital will be financially penalized. Since most Nursing Home Compare measures reported by CMS are uncorrelated with hospital readmission rates (Neuman, Wirtalla, and Werner 2014), hospitals need reliable information on which SNFs have the lowest readmission rates. In an effort to provide such information, CMS added a SNF-specific readmission rate to Nursing Home Compare online reporting system in April 2016.

It remains unclear, however, if the readmission rates posted on the Nursing Home Compare website reflect true quality or are merely the result of favorable selection. Although the published readmission rates are risk adjusted, there is concern that the risk-adjustment methodology is imperfect (Kansagara et al. 2011). If the published rates reflect true differences across SNFs, then hospitals should use this new information and consider directing patients to SNFs with low risk-adjusted readmission rates. However, if the published rates are the result of selection (low hospital readmission rates are due entirely to the admission of healthier patients to the SNF), then sending patients to SNFs with low rates will not improve the readmission rate to that hospital; the information will be misguided.

It is essential, therefore, for hospitals to know if the Nursing Home Compare readmission rates reflect the SNF's ability to impact rehospitalization. We used Medicare claims data to reproduce CMS's SNF-level risk-adjusted readmission rates. We then looked at whether the Nursing Home Compare risk-adjusted readmission rate (based on past years) predicts future readmissions. We used instrumental variable (IV) methodology to control for selection and to estimate the causal effect of the true readmission rate.

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Conceptual Framework

We want to estimate the causal relationship between the SNF's historical risk-adjusted rehospitalization rate (during 2009–2012) and future (2013) incident patients' rehospitalization. We hypothesize that the SNF's rehospitalization rate is a valid measure of quality of SNF care, that is, that a low-rehospitalization SNF can better prevent a readmission than a high-rehospitalization SNF. To test this hypothesis, we examined whether treatment of a patient in a low-rehospitalization SNF causally reduces the likelihood of patient's rehospitalization, after controlling for selection. More specifically, our aim is to estimate the following equation:

$$R_{ihzn} = \beta PriorRate_n + X_i\delta + \theta_h + \gamma_z + u_{ihzn} \tag{1}$$

R_{ihzn} is a binary variable indicating hospital readmission of individual i who was residing in zip code z and was discharged from hospital h to SNF n in 2013. $PriorRate_n$ is the historical risk-adjusted rehospitalization rate of SNF n that treats individual i. X_i is a vector of individual characteristics. γ_z are patient's residential zip code fixed effects. θ_h are hospital fixed effects. Our hypothesis is $\beta \geq 0$.

By our hypothesis, the SNF rehospitalization rate, $PriorRate_n$, is a permanent marker of nursing home care and should be positively associated with R_{ihzn}. However, this statistical association between these two variables is combination of two effects—the quality of SNF care effect and the patient selection effect. Thus, our main statistical challenge is to isolate the patient selection effect.

The patient selection effect implies that patients are not randomly admitted to SNFs. Instead, some SNFs will admit patients who are disproportionately less likely to be rehospitalized, *and this selection is not entirely observable.* Although risk adjustment may reduce the amount of selection bias, it is quite possible that CMS's methodology is imperfect, and that even after risk adjustment, the rates are partly due to selection. If variation in SNF rehospitalization rates is entirely driven by the patient selection effect, then random assignment of patients to SNFs with different rehospitalization rates will not affect the chance of rehospitalization, and in our empirical model, we will find that $\beta = 0$. In such a case, the SNF-level rehospitalization rate has no predictive power for a future patient, meaning that any difference across SNFs in the past rehospitalization rate is due to selection and not quality differences.

Although the patient selection effect with respect to prior rehospitalization rate could in theory be either positive or negative, the prior literature strongly suggests that selection exaggerates the true rehospitalization rates. The prior literature has revealed that minority race (Mor et al. 2004; Rahman and Foster 2015) and low-income (Rahman et al. 2014a,b) Medicare beneficiaries are more likely to be admitted to low-quality SNFs. Similarly, residential neighborhoods play a key role in quality of care (Baicker et al. 2004; Baicker, Chandra, and Skinner 2005). Patient characteristics and zip code fixed effects in equation (1) are likely to capture these effects, mitigating this empirical problem. To the extent that our empirical model does not capture these effects, however, β is overestimated.

However, hospitals may try to strategically match patients and SNFs to reduce the likelihood of readmission. If this happens, then the patients who are more likely to be rehospitalized are sent to high-quality SNFs, where the marginal effect of quality on lowering the rehospitalization rate is higher. If hospitals behaved this way, then high-quality SNFs could attract sicker patients. Several studies have found such selection results. For example, the effect of treatment in nonprofit SNFs, estimated using an IV method, is larger than that estimated using an ordinary least-square (OLS) method (Grabowski et al. 2013; Hirth et al. 2014). These studies argued that nonprofit status can be considered a marker of quality and interpret their finding as nonprofit SNFs receiving unobservably sicker patients. Similarly, other studies (Rahman et al. 2013; Schoenfeld et al. 2016) concluded that hospitals sends unobservably risky patients to their preferred SNFs at a disproportionately higher rate. To the extent that our empirical model does not capture these effects, β is underestimated.

This article uses two methods to control for the patient selection effect. First, we included fixed effects both for the patient's residential zip code and for the treating hospital. Residential zip code fixed effects control for any underlying difference between patients residing in different neighborhoods. Hospital fixed effects take care differences between patients treated in different hospitals and the effect of hospital's quality of care.

Second, we used an IV method, which is commonly used in empirical analyses to control for selection on unobservables. Within a hospital and a residential zip code, patients who go to high-rehospitalization SNFs are unobservably different from patients who go to low-rehospitalization SNFs. We argue that the average rehospitalization rate of the SNFs available to a patient who lives in a given zip code discharged from a specific hospital on a given day is a valid instrument. It is correlated with the patient's choice, because it uses the rehospitalization rates only of SNFs that patients discharged from that hospital are likely to go to. It also exploits daily variation in the occupancy rate at those SNFs. Yet the instrument is unrelated to the health conditions of that patient.

Data

Data Sources

The empirical strategy requires that we construct the SNF-specific risk-adjusted rehospitalization rate and then use it to predict future rehospitalization at the patient level. In addition, we need to control not only for observable patient characteristics and health status but also find a natural experiment to predict admission to the SNF that is independent of the patient's health status. In short, we need several years of Medicare patient-level claims data and eligibility data, including zip code residence, which will be used to create IVs.

We used Medicare Part A claims and Medicare enrollment files from 2009 to 2013 to identify patients who were discharged from hospital to the SNF and to calculate the SNF-specific rehospitalization rate. The Medicare Enrollment data include beneficiary enrollment information, such as the beneficiary unique identifier, state and county codes, zip code, sex, race, age, Medicaid eligibility, and monthly managed care indicators (yes/no). Medicare claims data include Medicare claims for inpatient, SNF, home health (HHA), hospice, and outpatient services. All Medicare claims include dates of services, up to 25 diagnoses, procedure codes, charges, and reimbursements.

We used Minimum Data Set (MDS) to track number residents in the SNF on a given day. We used this information to create our IV. The MDS assessment forms are completed for all residents (including Medicare fee-for-service, Medicare Advantage [MA], Medicaid and private pay patients) in certified SNFs upon admission and then at least quarterly thereafter. We also used the Online Survey Certification and Reporting (OSCAR) System for nursing home characteristics and The American Hospital Association (AHA) for hospital characteristics.

Study Cohort

We included all Medicare fee-for-service (FFS) beneficiaries who were discharged directly from general acute-care hospitals to the SNF for postacute care. Individuals with a nursing home stay in the 1-year period prior to the qualifying hospitalization event were excluded because we were concerned that the choice of SNF could be influenced strongly by past experience. We also excluded observations with a hospitalization claim within 3 months of prior to the index hospitalizations. For such patients, our IVs approach would not be valid. We used data for the years 2009–2013: the first 4 years of data were used to create SNFs' risk-adjusted rehospitalization rates and 2013 data were used to estimate the effect of the treating SNF's historical risk-adjusted rehospitalization rate on patient's hospital readmission. About 1.5 million FFS Medicare beneficiaries are newly admitted to SNF following an acute hospitalization each year.

Rehospitalization rates for SNFs with low numbers of admissions are highly volatile from year to year. Therefore, to ensure stable facility-level rehospitalization rates, we restricted our study to the 14,182 SNFs with at least 40 admissions in 2009–2012. We used this restriction based on the rule of thumb that if $n \geq 40$, then the t-test can be used even for a clearly skewed distribution. From these facilities, a total of 5,456,058 patients were used to calculate SNFs' rehospitalization rates for 2009–2012. We tested the effect of historical rehospitalization rate using 1,280,927 FFS community-based Medicare beneficiaries newly discharged from hospital to SNF between January and November 2013. We did not include SNF admissions in December 2013 because we needed 1-month follow-up time data to identify any 30-day rehospitalization.

Variables

The main explanatory variable is the SNF's historical risk-adjusted rehospitalization rate from 2009 to 2012. To calculate SNFs' historical risk-adjusted rehospitalization rates, we followed an earlier study (Rahman et al. 2016). The measure was constructed in three steps. First, we regressed the 30-day hospital readmission onto patient's age, sex, race, dual eligibility, Deyo comorbidity (Deyo, Cherkin, and Ciol 1992), hospital length of stay, and diagnosis-related group (DRG) fixed effects from the index hospitalization claim and hospital's state fixed effects using the OLS method, and we predicted the likelihood of 30-day rehospitalization for each individual. Second, we collapsed the data to SNF level to calculate the actual number of readmissions and the predicted number of readmissions which is the sum of predicted probabilities. Third, the SNF's rehospitalization rate is then calculated as ratio of the observed to the predicted number of readmission, multiplied by the mean readmission rate (20.34 percent in 2009–2012). Of note, there are several differences between this risk-adjustment method and the method developed by RTI for CMS. First, we do not have Hierarchical Chronic Condition score data that has been used in CMS method. Instead, we used DRG fixed effects and a Deyo comorbidity index. Second, unlike CMS method, we risk adjust for race, dual eligibility, and geographic region (hospital state). Third, our measure is not annual and rather based on prior 3 years. Finally, our outcome measure does not exclude planned hospital readmission. However, in our opinion, these differences should not generate any meaningful difference in ranking of SNFs in terms of rehospitalization rate.

Our main outcome variable is patient-level 30-day rehospitalization, defined as whether the patient was readmitted to a hospital within 30 days of hospital discharge to the SNF.

We included demographic characteristics of the patients from enrollment data: age, gender (male = yes/no), and race (white = yes/no, black = yes/no). We included three clinical characteristics of patient from index inpatient claims: Deyo comorbidity index calculated from the diagnoses listed on the Medicare claims (Deyo, Cherkin, and Ciol 1992), hospital length of stay, and DRGs. We also included SNF admission month dummies to capture seasonality in rehospitalization rates.

We also created two distance variables to be used in forming the IV: the distance from patient's residential neighborhood to the SNF and the distance from patient's discharging hospital to the SNF. We geocoded all the SNFs using the address on the OSCAR file. We used geocodes of hospitals from AHA file. We used zip code centroids as a proxy for individuals' residential location. We calculated patient-to-SNF distances using the Haversine formula (Sinnott 1984). All distances were measured in miles.

Besides the rehospitalization rate, we used two SNF characteristics. The first measure is the capacity of the SNF measured by the maximum number of patients residing in the SNF on a given day of 2013. This is roughly same as the number of beds in the SNF. Second, we included the number of empty beds, which is measured as the deviation of the number of patients on any given day from the capacity of the SNF. These two variables were calculated using the Residential History File (RHF) algorithm to the MDS (Intrator et al. 2011). The RHF is a per-person chronological history of nursing home utilization and location of service. To create the RHF, assessments from MDS data are used to create episodes of nursing home use with the calendar days for every nursing home patients.

Instrumental Variable

We need an IV that is highly correlated with the historical risk-adjusted rehospitalization rate of the treating nursing home but is not directly related to the individual patient's outcome of whether she is rehospitalized. Conceptually, our IV for a patient is the weighted average of historical rehospitalization rate of the SNFs where patient's index hospital discharged patients during the study period. Formally,

$$IV_{iht} = \sum\nolimits_{n \in CS_h} w_{ihtn} \times HRSRR_n \tag{2}$$

Thus, IV for patient i discharged from hospital h on date t is the weighted mean of $HRSRR_n$ of all SNFs n in patient's choice set CS_h. CS_h is defined as the set of SNFs used by the hospital h during the study period. The weights (w_{ihtn}) are the probabilities that patient i would select SNF n from among all SNFs that hospital h discharges to. The probabilities are estimated based on the following choice model:

$$w_{ihtn} = \exp(V_{ihtn}) / \sum\nolimits_{j \in C^i} \exp(V_{ihtn}) \tag{3}$$

where $v_{ihn} = \delta_1 bed_n + \delta_2 PriorRate_n + \delta_3 D\_IN_{in} + \delta_4 D\_HN_{hn} + \delta_5 emptybed_{tn}$

Here, w_{ihtn} is function of distance from hospital to each SNF in the choice set (D_HN_{hn}), distance from residential zip code to each SNF in the choice set (D_IN_{in}), total number of beds in SNF n (bed_n), number of empty beds in SNF n before the discharge date t ($emptybed_{tn}$), and SNF's previous rehospitalization rate ($PriorRate_n$). This choice model is based on a McFadden's choice model (McFadden 1974, 1978), as has been previously applied to examine nursing home choice (Rahman et al. 2013, 2014b; Rahman and Foster 2015; Schoenfeld et al. 2016).

Based on the estimated choice model, we predicted two sets of weights (probabilities going to alternative SNFs): (i) weights depending on distances and number of empty beds (assuming δ_1 and $\delta_2 = 0$) and (ii) weights depending on SNF's total capacity and the historical rehospitalization rate (assuming δ_3, δ_4, and $\delta_5 = 0$). Following the argument of Rahman et al. (2013), we used the mean rehospitalization rate based on the first set of weights (i.e., based on exogenous variable) as the IV and the mean rehospitalization rate based on the second set of weights (i.e., based on endogenous variables) as a control variable.

This IV has several advantages. Because it is an average of the rehospitalization rates of the nearby SNFs, it is highly correlated with the rehospitalization rate of the chosen SNF. In other words, the instrument strongly predicts the endogenous variable in the first-stage regression. Because it varies by discharge date for a given patient and hospital, it allows us to still control for zip code and hospital fixed effects. Because it is not based on the patient's actual health status or choice, it can be excluded validly from the main equation.

ANALYSIS

A key step of IV analysis is to examine whether the instrument is balanced with respect to the covariates. Because our statistical model includes residential zip code fixed effects, we split the sample by whether the IV was above or below of its zip code level median to check for balance in the observable characteristics.

Equations (4) and (5) specify the first and second stages of IV regression, respectively.

$$PriorRate_{in} = \theta IVRate_i + \mu ControlRate_i + X_i\delta + \theta_h + \gamma_z + u_{ihzn} \quad (4)$$

$$R_{ihzn} = \beta \widehat{PriorRate}_{in} + \mu ControlRate2_i + X_i\delta + \theta_h + \gamma_z + u_{ihzn} \quad (5)$$

These specifications are same as the model (1) except the two new variables. First is the IV: $IVRate_i$, which is the mean rehospitalization rate of the choice set of patient i based on the first set of probabilities which are based on distances and empty beds and is included only in the first stage. Second is a control variable: $ControlRate_i$, which is the mean rehospitalization rate of the choice set of patient i based on the second set of probabilities based on capacity and rehospitalization rates and is included in both the stages. $\widehat{PriorRate}_{in}$ is the predicted rehospitalization rate of the treating SNF of individual i calculating based on the first-stage regression specified by equation (4).

We estimated these equations as linear probability model. We used the typical fixed-effect 2SLS estimation (using the *xtivreg2* command in Stata) to estimate equations (4) and (5) with only one-way (zip codes) fixed effects. In a two-way fixed-effects model that involves both hospital and residential zip code fixed effects, we used the two-stage residual inclusion method. We used *felsdvreg* command in Stata developed by Cornelissen (2008) that fits a linear model with two high-dimensional fixed effects. We also performed a Hausman test to determine whether the historical rehospitalization rate is endogenous while estimating its effect on 30-day rehospitalization in a zip code fixed-effect model.

RESULTS

We first calculated the historical rehospitalization rate of SNFs using 2009–2012 data, using a risk-adjustment methodology which is fairly similar to the one that CMS uses for Nursing Home Compare. Among the 14,182 SNFs in our sample, the mean rehospitalization rate was 20.26 percent with standard deviation of 4.76. About one-quarter of the SNFs had a rehospitalization rate lower than 17 percent, and one-quarter of the SNFs have a rehospitalization rate higher than 23 percent (Figure S1). One percent of the SNFs had a rehospitalization rate lower than 8.6 (1 percentile), and another 1 percent of SNFs had a rehospitalization rate over 31.1 (99th percentile).

The first two columns of Table 1 present patient characteristics and the characteristics of the SNFs to which patients were admitted. The 30-day hospital readmission rate among newly admitted SNF patients in 2013 was 18.5 percent. The average age of our cohort was 79.4 years. Sixty-four percent of these patients were female and 10 percent of patients were African American. The mean Deyo comorbidity index was 1.8. The median distance between the hospital and admitting SNF is 3.8 miles. The median distance between the residential zip code and the admitting SNF is 4.9 miles.

Table 2 presents the estimated choice model using a 10 percent random sample. We also report the marginal effects of a one standard deviation change in each of the explanatory variables. These marginal effects are based on the chosen SNF of a patient; that is, change in likelihood of going to the SNF chosen by a patient if an explanatory variable changes by 1 standard deviation (Rahman et al. 2014b). A 1 standard deviation increase in distance from hospital or residential zip code reduces the likelihood of admission to the chosen SNF by 11 percentage points. Similarly, if the number of empty beds in the SNF chosen by a patient increases by 1 SD, the likelihood of going to that SNF increases by 0.7 percentage points. Furthermore, patients are also less likely to go to SNFs with higher historical rehospitalization rates.

Our instrument appears to be strong and valid.

The instrument also appears to be a strong predictor of the endogenous variable, rehospitalization rate of the chosen SNF, in the first stage (Table 3). In the absence of any fixed effects, the expected adjusted readmission rate due to proximity and empty beds has almost a one-to-one correlation with the rehospitalization rate of the chosen SNF. In the most stringent model, with both hospital and residential zip code fixed effects, an increase in the IV by 1 percentage point results in 0.32 percentage point increase in the

Table 1: Patient Characteristics among All New SNF Admissions and above and below the Median of the IV

	Entire 2013 New SNF Cohort, N = 1,280,927		*IV< within Zip Code Median of IV, N = 608,606*		*IV≥ within Zip Code Median of IV, N = 627,211*	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Outcomes						
Any 30-day rehospitalization	18.5%	0.388	18.1%	0.385	18.9%	0.391
Characteristics of the admitted SNF						
Historical risk-adjusted rehospitalization rate	20.53	4.17	20.14	4.15	20.90	4.16
Capacity	119.78	71.51	119.10	71.48	120.44	71.53
Empty beds	10.59	7.44	10.51	7.39	10.66	7.49
Distance from hospital to SNF	9.95	33.77	9.43	32.55	10.45	34.91
Distance from zip code to SNF	32.83	171.33	33.25	172.99	32.42	169.71
Patient characteristics						
Age	79.38	10.79	79.54	10.72	79.33	10.82
Female	0.64	0.48	0.64	0.48	0.64	0.48
Black	0.10	0.30	0.10	0.30	0.10	0.30
White	0.86	0.35	0.86	0.34	0.86	0.35
Medicare Medicaid dual eligible	0.29	0.45	0.28	0.45	0.30	0.46
Deyo comorbidity index	1.78	1.80	1.78	1.81	1.79	1.81
Hospital length of stay	7.17	6.57	7.08	6.43	7.24	6.66
Predicted risk-adjusted rehospitalization rate based on choice set and conditional logit coefficient						
Based on risk-adjusted rehospitalization rate and capacity coefficients (control variable)	20.16	1.42	20.03	1.41	20.28	1.41
Based on distances and empty bed coefficients (IV)	20.78	2.40	20.27	2.38	21.27	2.31

IV, instrumental variable; SNF, skilled nursing facility.

rehospitalization rate of the chosen SNF. The associated t-statistic is 47.97 implying an F-statistic of 2301. The chi-square statistic of the Hausman test is 41.012 with p-value .0000. Thus, it rejects the null hypothesis of exogeneity of historical rehospitalization rate.

The last four columns of Table 1 compare patient characteristics above or below the zip code level median of the IV. Although some of the paired comparisons were statistically significantly different at the 5 percent level due to our very large sample size, the patient characteristics were virtually identical across the two samples. The fact that none of these measured explanatory variables are correlated with the instrument is consistent with our contention

Table 2: Estimation of the Choice Function Used to Calculate the Instrumental Variable

Variable	*Coefficient*	*z-statistic*	*Marginal Effects*
Distance from hospital to SNF	−0.123***	−296.00	−0.111
Distance from zip code to SNF	−0.127***	−303.55	−0.117
No. of empty beds before admission date	0.011***	36.26	0.007
SNF's historical risk-adjusted rehospitalization rate	−0.020***	−25.93	−0.007
Capacity of SNF	0.001***	23.04	0.007

Notes. The choice function is estimated using 123,572 patients (random 10 percent sample) newly admitted to SNF in 2013. Capacity of SNF is defined as the highest number of patients the SNF had on a given day between 2009 and 2013. The median number of SNFs in patient's choice set was 90 (mean 111.8). Pseudo R-squared of this regression was 0.3446. The marginal effects show change in likelihood of admission to the chosen SNF if the relevant characteristics of the chosen SNF changes by one standard deviation (see Table 1 for standard deviation).
***$p < .01$.

that there are no obvious sources of confounders that would invalidate the instrument.

Table 4 presents the estimated relationship between rehospitalization and treating SNFs' historical adjusted rehospitalization rate. The simplest OLS specification that controls for only patient characteristics shows that an increase of SNF's historical rehospitalization by 1 percent increases patient's likelihood of 30-day rehospitalization by 0.56 percentage point. When we control for patient's residential zip code and hospital, adding the fixed effects to the model, this association reduces to 0.46 percentage points. When we control for unobserved patient characteristics using IV estimation, the effect size moves toward 1. The most comprehensive IV model that uses both hospital and zip code fixed effects reveals that a 1-percent increase of the SNF's historical rehospitalization rate increases patient's likelihood of 30-day rehospitalization by 0.8 percentage point. Because the number of empty beds in alternative SNFs in the patient's choice set is the main source of variation in our IV, and a higher number of empty beds to relative capacity may imply lower quality of SNF care, we estimated models including the number of empty beds and capacity of the treating SNF of the patient. Inclusion of these SNF-level variables had no effect on our estimated effect.

Conclusion

We address a timely and important policy question: If hospitals want to reduce their readmission rate due to CMS's Readmission Reduction Program, should

Table 3: Relationship between Risk-Adjusted Rehospitalization of the Chosen SNF and the Instrumental Variable (First Stage)

Variables	*No Fixed Effects*	*With Zip Code Fixed Effects*	*With Zip Code Fixed Effects and Hospital Fixed Effects*
Predicted risk-adjusted rehospitalization rate based on distances and empty beds coefficients (IV)	0.961754*** [506.84]	0.6209179*** [165.74]	0.3206565*** [47.97]
Predicted risk-adjusted rehospitalization rate based on risk-adjusted rehospitalization rate and capacity coefficients (control variable)	0.0074368** [2.32]	0.1494898*** [23.82]	0.5055727*** [2.95]
Partial R-squared	0.1883	0.0310	
F-statistics	2.6e+05	27,469.12	2,301.12

Notes. All regressions include patient's age, sex, race, dual eligibility, Deyo comorbidity index, hospital length of stay, distance of chosen SNF from hospital, and distance of chosen SNF from patient's residential neighborhood. t-statistics are square brackets.
***$p < .01$.

they try to direct their patients to SNFs that historically have had a lower rehospitalization rate? Or, do nursing home rehospitalization rates, even when risk-adjusted, merely reflect differences in case mix? We find that the historical risk-adjusted SNF rehospitalization rates from 2009 to 2012 predict rehospitalization for patients in 2013 after controlling for observed and unobserved case mix.

Based on our finding, hospitals should encourage their patients to select SNFs that have lower risk-adjusted rehospitalization rates through such strategies as quality ratings and patient education. However, hospitals must ultimately allow Medicare FFS patients to choose their SNF. Hospitals are not allowed to narrow the choice set or mandate that a patient go to a particular SNF. Nevertheless, because of the high rate of rehospitalizations from the SNF relative to other settings, shifting patients to a low-rehospitalization SNF

Table 4: Effect of SNF-Level Historical Risk-Adjusted Rehospitalization Rate on Individual Patient's Likelihood of Being Rehospitalized from the SNF within 30 days of SNF Admission

Model specification	*OLS Estimations*	*IV Estimations*
Without any fixed effects	0.561*** [67.64]	0.617*** [30.02]
With Zip code fixed effects	0.488*** [46.22]	0.86953*** [14.59]
With Zip code fixed effects and hospital fixed effects	0.455*** [41.25]	0.801*** [3.11]
With Zip code fixed effects, hospital fixed effects, and capacity and empty beds of the treating SNF	0.454*** [41.00]	0.803*** [3.12]

Notes. All regressions include patient's age, sex, race, dual eligibility, Deyo comorbidity index, hospital length of stay, distance of chosen SNF from hospital, and distance of chosen SNF from patient's residential neighborhood. *t*-statistics are square brackets.
***$p < .01$.

can have a significantly reduce the likelihood of being penalized under CMS's Readmission Reduction Program.

As a back-of-the-envelope calculation, imagine an average hospital with 300 discharges of the applicable conditions (acute myocardial infarction, heart failure, and pneumonia) with 54 (18 percent) rehospitalized cases (based on 2014–2015 data in Zuckerman et al. 2016). Assuming that 20 percent of hospitalized patients were discharged to the SNF, this hospital has 60 SNF discharges. In our data, 25 percent of patients were discharged to the highest rehospitalization quartile SNFs, which had an average rehospitalization rate of 26 percent. Thus, 15 patients with applicable conditions were discharged to the highest rehospitalization quartile SNF and 4 of them were rehospitalized. If this typical hospital could shift all of its applicable discharges under the readmission program from the highest to the lowest rehospitalization rate SNFs (reducing historical risk-adjusted rehospitalization rate from 26 to 15 percent for these patients), they could avoid roughly 1.32 readmissions annually and decrease the hospital's overall risk-adjusted readmission rate by 0.5 percentage points. This type of shift could dramatically reduce the likelihood of being penalized under the program.

The shifting of discharges from high to low readmission SNFs makes the assumption that low readmission SNFs, with excess beds, are in operation in all hospital markets. The average SNF rehospitalization rate is quite high in some markets, and there might not be excess capacity at a low readmission SNF in these markets. Thus, these results suggest there could be value in hospitals partnering with certain SNFs to introduce programs to lower their readmission rates. The extreme version of this model would be a hospital-owned SNF, but this model could also apply to the relationships hospitals establish with freestanding SNFs. For example, ACOs and hospital networks are currently developing strategies to develop preferred networks of SNF partners (Mor and Besdine 2011; Maly et al. 2012; Lage et al. 2015). Moreover, previous data suggest that when hospitals concentrate their discharges in a particular SNF, they will have lower readmission rates from this SNF (Rahman et al. 2013).

Shifting patients across high- and low-readmission SNFs also has potential implications for disparities in care by race and socioeconomic status. If higher resource patients are disproportionately steered to low readmission SNFs, then this steering could exacerbate disparities in care. Of course, if the patients being steered to low readmissions SNFs are fairly representative of the overall distribution of patients, then the steering will have less impact on disparities.

From a consumer perspective, CMS has recently introduced SNF readmissions on the Nursing Home Compare website. This study has confirmed that this measure is a valid indicator of the likelihood of readmission for future SNF patients. Recent work suggests patients are selecting higher quality SNFs based on the Nursing Home Compare website rankings (Neuman, Wirtalla, and Werner 2014; Werner, Skira, and Konetzka 2016). Now that the website is reporting SNF readmissions, having patients choose low readmission SNFs will further encourage SNFs to compete on this measure, which would lower the overall rate of SNF readmissions in the market. Because this measure will also be incorporated into the more widely used and reported 5 Star Rating system, tracking its relative influence on patients' and families' choices versus hospitals' selection of SNFs into their emerging postacute care networks will be challenging but important for future policy considerations regarding public reporting and selective referral patterns.

This study has several limitations. First, we did not exclude planned hospital readmission while calculating the 30-day rehospitalization rate measure and assumed that it will be similar to the risk-adjustment approach that has been used in the past. Second, the treatment effect is averaged over lots of different markets, even though we know rehospitalization rates vary substantially by market just as Medicare spending does. It may be that the effects of the average hospital may only be large in markets with higher variation in rehospitalization rates. We estimated our model separately for high- and low-rehospitalization hospitals (Table S1) and found that steering patients to low-rehospitalization SNFs has higher returns for hospitals with high rehospitalization rate. This result is consistent with Rahman et al. (2016). Third, rehospitalization rates are dropping substantially across the country (Zuckerman et al. 2016). Whether the same effect of selecting lower rehospitalization SNFs will be as strong once the overall rehospitalization rate drops is unclear. Fourth, although it appears that the instrument that we proposed is valid, the data are still observational and we cannot be sure that some other process might be determining both our instrument and the outcomes. Finally, we should emphasize the limitation that our results are based only on claims data for Medicare fee-for-service beneficiaries. However, assuming that the within-SNF readmission rates are similar across fee-for-service and MA beneficiaries, our results might be particularly relevant for MA plans because they can actively direct patients to low-readmission SNFs by restricting SNF choice, which is not allowed for fee-for-service beneficiaries.

This study validates a quality measure that was recently released on the Nursing Home Compare website. Unlike existing measures on the website, this new measure is particularly salient to hospitals interested in minimizing readmissions under CMS's Readmission Reduction Program. Moving forward, it will be important to monitor how consumers, SNFs, and hospitals respond to this new measure.

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Supporting Information

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

Appendix SA1: Author Matrix.

Figure S1. Distribution of SNF's Historical Risk Standardized Rehospitalization Rate.

Table S1. 2SLS Regression of 30-day Rehospitalization onto Historical Risk-Adjusted Rehospitalization Rate of Admitting SNF.