Online Appendix

“Vertical Integration and Cream Skimming of Profitable Referrals: The Case of Hospital-Owned Skilled Nursing Facilities”

David Cutler, Leemore Dafny, David C. Grabowski, Steven Lee, Christopher Ody

Code and public data are available in the AEA Data and Code Repository, see Cutler et al. (2025)

Appendix A: Detailed descriptions of variables

A.1 Five-Star Quality Rating System

Since December 2008, CMS has rated SNFs using the Five-Star Quality Rating System. During our study period, this system consisted of three separate components: the health inspections rating, the staffing rating, and the quality measures rating. The health inspections rating is based on the results of comprehensive, annual recertification inspections. The staffing rating is based on nursing home staff hours and staff turnover rates. The quality measures rating is based on predetermined function and health status indicators of SNF patients. These ratings are also aggregated into a single, overall five-star rating for the SNF.

We use quality data from the Nursing Home Compare Five-Star Ratings data for 2009–2012 in our analysis (Centers for Medicare and Medicaid Services, 2009–2012). We take monthly ratings average them across each year to create annual quality measure averages for each SNF. Data is not available for swing-bed SNFs. We report differences in quality measures for integrated and unintegrated SNFs in Table A1 below.

A.2 SNF referrals and price

We define a *SNF referral* as a SNF stay that commences within 10 days of a patient’s inpatient discharge. This is a shorter window than Medicare’s reimbursement rule for SNF care, which allows for reimbursements for SNF visits occurring within 30 days of a qualifying inpatient stay. We limit our definition of a SNF referral to within 10 days of inpatient discharge because our focus is on steering by hospitals, which is arguably more likely in the period immediately after discharge. We use the average daily Medicare reimbursement for a given SNF visit as our measure of *price*. A patient may face different reimbursement rates throughout the course of their stay as they are reassessed for their care needs at predetermined intervals. Thus, our measure accounts for the price of patient care throughout the evolution of their stay in the SNF, not just the initial reimbursement at the point of referral.

A.3 Risk Adjustment and Predicted Spending Estimates

For each patient-level quality and patient spending outcome variable, we construct a patient-level prediction variable. We calculate these measures following a methodology similar to the one for calculating *predΔprice*. We predict the relationship between each outcome measure and characteristics reported on the patient's inpatient stay for all patients in the training sample. We then use the estimated coefficients from these regressions to generate predicted outcomes for patients in the estimation sample.

Each patient admitted to a SNF following a hospital stay in the training sample is first grouped within a DRG. For mortality and readmission, within each DRG, we run a logistic regression to predict each patient's risk for the outcome based on the patient's Charlson Comorbidity Index, age, sex, race, and Medicaid-eligibility at the time of their inpatient stay.[1] The Charlson Comorbidity Index measures a patient's degree of chronic disease; we construct it using the patient's first 10 listed diagnoses on their inpatient stay record and the formula developed in Charlson et al. (1987). For predicted patient SNF cost and predicted patient non-SNF cost, the procedure is similar, except we run an OLS regression and the resulting predictions are winsorized at the 1st and 99th percentiles. Finally, we use the coefficients on patient characteristics from these regressions and apply them to patients in the estimation sample. We note that due to small sample sizes within certain DRGs, the logistic regression may produce incomplete predictions for subgroups within those DRGs. Thus, in specifications with patient-level prediction variables, patients without a predicted value for an included variable will be dropped from the sample. For all specifications with observations dropped in this way, results with and without patient-level prediction variables are similar.

[1] We include a dummy variable for age >=65 and interact this dummy with age and age squared, i.e. allow a quadratic function of age for older beneficiaries.

A.4 Hospital Characteristics

We use Hospital Cost Reports data (Centers for Medicare and Medicaid Services 2007–2012, n.d.) to capture the characteristics of each hospital based on the earliest year of appearance in the dataset, typically 2007. We extract information on a hospital's region, ownership type, size, profit margin, and occupancy rate. For ownership type, hospitals are classified as not-for-profit, for-profit, or government-owned. Hospital size is based on total available beds, grouped into small (<100 beds), medium (100-199 beds), and large (≥200 beds). For profit margin, because data on profit margins is noisy, we use the 3-year average over 2005-2007. A small number of hospitals report negative revenues (due to large adjustments) or profit margins greater than 1. We remove such hospitals from the analysis of heterogeneous responses across hospitals described in Section IV.A., and winsorize profit margins within each year at the 1st and 99th percentiles before computing the 3-year average.

A.5 Actual and Potential Price Increase Captured by Vertically Integrated Hospitals

We calculate both the price increase actually captured by vertically integrated hospitals and the theoretical maximum price increase that could have been captured. We begin by using equation (4) **Error! Reference source not found.** to predict the self-referral probability for each patient (*baseline prediction)*. We then consider two counterfactual self-referral probabilities. First, we calculate self-referrals in the absence of a policy response by re-predicting self-referral probability but setting *Post* = 0 for all observations (i.e., *no response prediction*). Second, we calculate self-referrals under a scenario where the average self-referral rate within a hospital is fixed but only the patients with the highest *predΔprice* are self-referred (i.e., *maximum response prediction*). This prediction reflects a counterfactual scenario where hospitals only self-refer the patients with the highest change in profitability after the policy change, holding constant their total rate of self-referrals (which, as discussed in the text, may be constrained for multiple reasons).

To obtain the price increase captured through self-referrals, for each observation we subtract the *no response prediction* from the *baseline prediction* and multiply by *predΔprice*. To obtain the theoretical maximum price increase that could have been captured, we subtract the *no response prediction* from the *maximum response prediction* and multiply by *predΔprice*. We sum these two increases over all patients admitted to each vertically integrated hospital in the last quarter of the post-period, the fourth quarter of 2012.

Appendix B: Constructing our instrumental variable for price: ***pred∆price***

B.1 Conceptual Explanation

As previously described, the RUG-III to RUG-IV reform changed the number of RUG codes, the mapping of patient characteristics into codes, and the prices associated with each code. Ideally, we would observe exogenous patient characteristics that could be used to assign each patient to a RUG-III code and a RUG-IV code. The difference between the patient's Medicare reimbursement rate ("price") under these two systems could then serve as an instrument for the change in patient reimbursements after RUG-IV's adoption. However, SNF providers have incentives to distort patient characteristics reported on the RUG assessments (under either iteration) to maximize reimbursements, and therefore patients with similar characteristics (as recorded on a SNF claim) may have different true health states before and after the RUG update.

To address the fact that SNFs might alter their responses to these questions because of a reimbursement rate change, we implicitly use the fact that the responses to these questions will be correlated with the information on the patient's inpatient admission, such as the patient's demographics, DRG code, and comorbidities. For example, we expect the types of SNF services needed by a 70-year-old receiving a hip replacement to differ from the types of SNF services needed by an 80-year-old recovering from a major stroke. Indeed, the most common RUG-III code for the hip replacement patient is "RUL", while the most common code for the stroke patient is "RUB." Patients in both codes have roughly similar needs but with one crucial difference: patients with the "RUL" code need additional "extensive services," such as IV medication or ventilator use. Thus, as expected, the "RUL" code carries with it a 12.5 percent higher reimbursement. The definition of "extensive services" changed in the RUG update, causing many patients who would have been coded as "RUL" under RUG-III to be coded as "RUB" patients under RUG-IV.[2] These patients became relatively less profitable to treat due to

[2] This change is confirmed using the claims data. In 2009, under the RUG-III system, 70-year-old hip replacement patients were most commonly assigned the "RUL" code, and 80-year-old stroke patients were mostly commonly

the RUG update. Our instrument is constructed solely from these mechanical variations in reimbursement induced by the RUG transition.

The following subsections provide a more detailed description of the steps to calculate *predΔprice*. In the first step, we exploit the backwards compatibility of the RUG systems to construct an expected price shock for each RUG-III code. In the second step, we associate training sample patient characteristics with the expected price shock. In the third and final step, we extrapolate these calculations to create a patient-level measure of the shock for all patients in the estimation sample, *predΔprice*.

B.2 Constructing an expected payment shock for each RUG-III code

We calculate an expected reimbursement shock for patients in each RUG-III code using the following procedure. First, we determine the distribution of RUG-IV codes that corresponds to each RUG-III code, using post-period patient-level assessment data from the MDS. Then, we assign RUG-III codes probabilistically to RUG-IV codes.

We first require a transition matrix from RUG-III to RUG-IV codes, that is, for a given individual assigned a particular RUG-III code, we would like to understand their theoretical RUG-IV code. However, as noted in Section I, the patient assessment used to construct RUG-III codes is not forward compatible with the patient assessment used to construct RUG-IV codes, meaning it is not possible to assign patients treated under the RUG-III system to a RUG-IV code. However, the patient assessments are backwards compatible, i.e., given the information on a patient's assessment under the RUG-IV system, it is possible to construct the patient's RUG-III code.

To create an estimate for how the RUG update mechanically altered RUG codes, we access the MDS data from 2010Q4 to 2011Q3. During this period, reimbursement was based on each patient's RUG IV code, but patients were also assigned to a RUG-III code in the MDS data. First, we omit data from the first quarter in this sample to account for any noise generated by

assigned the "RUB" code. However, in 2011, the first full calendar year under the RUG-IV system, 70-year-old hip replacement patients "switched" to "RUA" and "RUB" codes (49 percent of patient days), with much fewer "RUL" codes compared to under RUG-III. The coding distribution was relatively unchanged for the stroke patients, Therefore, the profitability of 70-year-old hip replacement patients relative to 80-year-old stroke patients declined due to the RUG reform.

SNF adoption of the new patient assessment system supporting the transition from RUG-III to RUG-IV. Then, we obtain for each RUG-III code the distribution of possible RUG-IV codes.

Formally, let J be the set of 53 RUG-III codes[3], and for each $j \in J$, denote the base RUG-III prices in FY2010: $RUGPrice_j^{2010}$. Let K be the set of 66 RUG-IV codes, and for each $k \in K$, denote the base RUG-IV prices in FY2011: $RUGPrice_j^{2011}$. We define P_{jk} to be the probability that a patient with RUG-III code of j would be categorized as having RUG-IV code k; $\Sigma_{k \in K} P_{jk} = 1$. We obtain P_{jk} from the MDS data. Importantly, given the characteristics of these patients, the assignment to a RUG-III and RUG-IV code is deterministically based on Medicare's assignment methodology; thus, we hold fixed both patient illness and potential upcoding when calculating this transition matrix.

For each RUG-III code j, the anticipated percent price increase from the reform is then:

$$pred\Delta price_j = \frac{\sum_{k \in K} P_{jk} RUGPrice_k^{2011} - RUGPrice_j^{2010}}{RUGPrice_j^{2010}}. \tag{A1}$$

B.3 Constructing a reimbursement shock for patients in the estimation sample

Recall that Medicare claims data lacks patient-level RUG-III codes after the update. However, a patient's need for nursing services and for rehabilitation services largely dictates the intensity of the shock to reimbursement rates. Therefore, we predict each patient's simulated price change using characteristics reported on the patient's inpatient stay that will be correlated with the need for nursing and rehabilitation services. To establish this relationship, we initially restrict the sample to SNF claims that follow a hospital stay in our training sample—between October 2007 and March 2008.

We group patients in the training sample by their inpatient diagnosis code (DRG). For each DRG, we estimate a patient-level regression that predicts each patient's simulated price change based on the patient's comorbidities, age, sex, and Medicaid-eligibility at the time of their inpatient stay. Specifically, within each group, we run a linear regression to predict each patient's RUG-III-based price change (as determined by equation (A1)) utilizing the patient's

[3] The RUG code "AAA" is assigned to the small minority of patients who do not receive a SNF assessment. Patients with RUG code "AAA" are removed from the process of calculating RUG-IV distributions and determining the relationship between patient demographics and predicted price changes.

first 10 listed comorbidities, age, sex, race, and Medicaid-eligibility at the time of their inpatient stay.[4,5] Each patient observation is weighted by the total SNF spending in his or her first SNF stay following discharge. These regressions allow us to flexibly capture variation across patients that is correlated with needs for nursing and rehabilitation services and are therefore predictive of the price shock. Consider the two most common DRGs in our training sample, 470 (Major Joint Replacement or Reattachment of Lower Extremity without Major Complication or Comorbidity) and 871 (Septicemia or Severe Sepsis without Mechanical Ventilation (96+ hours) with Major Complication or Comorbidity). The regression for DRG 470 shows that patients dually eligible for Medicaid have a 1.9 percentage point higher simulated price change, while being Black or female is not predictive of the simulated price change. For DRG 871, female patients have a 0.4 percentage point higher simulated price change and Black patients have a 0.8 percentage point higher simulated price change.

We next use these estimated coefficients to predict predicted price changes for each patient in the estimation sample. Finally, we winsorize the predicted price changes at the 1st and 99th percentiles.[6] We refer to the predicted values as *pred*Δ*price*, even though they differ from the variable defined above. Note that *pred*Δ*price* varies across patients based on the likelihood that the patient would have been in each of the 53 RUG-III groups, as predicted by the patient's characteristics; as a result, there are thousands of unique values of *pred*Δ*price*.

B.4 Constructing *pred*Δ*price'*

We construct *pred*Δ*price'* using a procedure analogous to that used to construct *pred*Δ*price* but relying only on patient DRG. Specifically, after obtaining $pred\Delta price_j$ from equation (A1), we identify patients in the training sample by their DRG. We then compute the average RUG-III-based price change for each DRG. We apply this average price change for each patient in the larger estimation sample based on their DRG at the time of their inpatient stay. Finally, we winsorize the predicted price changes at the 5th and 95th percentiles.

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[4] Patient RUG codes may change throughout the length of their stay. All RUG-III codes for the first SNF stay post-discharge are considered in these regressions.

[5] In the regression, age for individuals below 65 is set to 0. Medicare beneficiaries below 65 are individuals with End Stage Renal Disease and younger adults with disabilities; we include an indicator variable for over 65 to allow for fixed differences in the elderly and non-elderly groups. We also include both a linear age term and a quadratic age term. In the analysis, comorbidities for each patient are included as a single linear term through the Charlson Comorbidity Index, which determines the 10-year survival for patients based on their comorbidities.

[6] We confirm the main results are consistent across specifications with winsorized and unwinsorized $pred\Delta price$.

Appendix C: Bootstrapping Confidence Intervals for the Effect of *predΔprice* on Self-referrals

In estimating the effect of *predΔprice* on self-referrals, we implicitly employ a two-step procedure, one which constructs *predΔprice* based on patient characteristics and another which estimates a regression of self-referral on *predΔprice*. There is potentially a concern that error in estimating the first step is not incorporated into the estimates in the second step. To address this concern, we bootstrap our two-step procedure. Due to the large number of observations and fixed effects, we employ a Bayesian bootstrap in which weights are assigned to observations.

Let i index patients in the estimation sample, j index patients in the training sample, and b index iterations of the bootstrap procedure. We assume that the vector of weights on the training sample, $\overrightarrow{W}$, has a symmetric Dirichlet distribution such that $\overrightarrow{W} \sim Dir(1)$. Since independently distributed Gamma distributions form a Dirichlet distribution (up to a scaling parameter), we draw analytic weights $w_j^b, w_i^b \sim \Gamma(1, 1) = exp(1)$. Then, we estimate the relationship between the expected payment shock and patient characteristics in the training sample (described in Appendix A.2) with these weights. We can use the estimated relationship to predict the expected shock for patients in the training sample, giving $pred\Delta price_i^b$. Finally, we estimate our standard regression of self-referral on the price shock, replacing $pred\Delta price_i$ with $pred\Delta price_i^b$ and using w_i^b as patient weights.

We perform B = 1,000 iterations of this procedure. Using the estimated confidence intervals from each of these iterations, we construct a bootstrapped confidence interval using the 2.5th percentile of the coefficient estimates and the 97.5th percentile of the coefficient estimates.

Appendix D: Matching Integrated Hospitals to Unintegrated Hospitals

To compare most-preferred SNF referral behavior between integrated and unintegrated hospitals, we match the two hospital groups based on hospital characteristics. For the purposes of this section, we refer to integrated hospitals whose most-preferred SNF is also its VI SNF as the "treatment" group and unintegrated hospitals as the "control" group.

We use a nearest-neighbor matching procedure where control group hospitals are matched to treatment group hospitals with replacement, meaning one control group hospital could be matched to multiple treatment group hospitals. Treatment group hospitals are matched to exactly one control group hospital. Matching is based on measured distance between hospitals; hospitals are exact matched on quintile of most-preferred SNF referral rates and quintile of number of SNF discharges, and then distance is computed based on bed size, CBSA population, ZIP code median income, average margin, occupancy rate, and ownership type using the Mahalanobis metric.[7] The absolute standardized difference in means substantially shrinks for almost all covariates before and after matching, with standardized differences below 0.14 for all covariates and below 0.07 for all but one covariate.

Appendix E: 2SLS Estimates of the Effect of Self-Referral on Patient Outcomes

To obtain a 2SLS estimate of the effect of self-referral on patient outcomes, we estimate the first-stage model

$$
\begin{aligned}
self\text{-}referral_{it} = {} & \gamma^0_{h(i)t} + \gamma^1_{h(i)} \cdot pred\Delta price_i \\
& + [\gamma^2 \cdot quarter_t + \gamma^3 \cdot post_t + \gamma^4 \cdot post_t \cdot quarter_t + \gamma^5 \cdot \mathbb{1}(quarter = 0)_t] \\
& \qquad \times pred\Delta price_i \\
& + [\gamma^6 \cdot quarter_t + \gamma^7 \cdot post_t + \gamma^8 \cdot post_t \cdot quarter_t + \gamma^9 \cdot \mathbb{1}(quarter = 0)_t] \\
& \qquad \times pred\Delta price_i \times integrated_{h(i)} \\
& + \delta \cdot X_i + \varepsilon_{it}
\end{aligned} \tag{E1}
$$

and the second stage model

[7] Using hospital zip codes, we assign hospitals to CBSAs using a zip code to CBSA crosswalk (United States Department of Housing and Urban Development 2012). CBSA population is from the United States Census Bureau (2010–2011). Zip code median income is from the American Community Survey (University of Michigan Population Studies Center 2006–2010).

$$
\text{(E2)} \quad \begin{aligned} Y_{it} = \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i \\ + [\beta^2 \cdot quarter_t + \beta^3 \cdot post_t + \beta^4 \cdot post_t \cdot quarter_t + \beta^5 \cdot \mathbb{1}(quarter = 0)_t] \\ \times pred\Delta price_i \\ + [\beta^6 \cdot quarter_t + \beta^7 \cdot \mathbb{1}(quarter = 0)_t] \times [pred\Delta price_i \cdot integrated_{h(i)}] \\ + \beta^8 \cdot self\text{-}\widehat{referral}_{it} + \alpha \cdot X_i + \eta_{it}. \end{aligned}
$$

The variables capturing the differential impact of the predicted price change in the post-period for integrated hospitals relative to unintegrated hospitals (i.e., *post · predΔprice · integrated* and *post · quarter · predΔprice · integrated*) serve as instruments for *self-referral*, with the identifying assumption (supported by the pre-trends analysis) being that these measures affect outcomes only through their impact on the probability of self-referral.[8]

Table E1 below presents the first stage, reduced form, and 2SLS estimates of the effect of self-referral on *mortality* and ln(*spending*). Neither of the 2SLS estimates is statistically distinguishable from zero, and the confidence intervals are wide. Thus, while we do not find evidence that outcomes are impacted by self-referral, we are unable to rule out economically meaningful increases or decreases in these outcomes.[9]

Appendix F: Heterogeneity and Robustness Analyses

This appendix summarizes our heterogeneity and robustness analyses. All tables and figures referenced appear at the end of this file.

[8] We perform weak identification tests by calculating Kleibergen-Paap Wald F statistics of 10.64 and 9.24 for the *mortality* and ln(*spending*) models respectively. Using standard Stock-Yogo weak identification test critical values for 2 instrumental variables and 1 endogenous regressor, given a 5% significance test, the cutoff for 10% maximal IV bias size is 11.59 and the cutoff for 15% maximal IV bias size is 8.75.

[9] The 95%-level confidence interval for the predicted impact of self-referral on mortality is [-0.12,0.71], and baseline mortality in the sample is 0.19. The 95%-level confidence interval for the predicted impact of self-referral on ln(*spending*) is [-0.80,1.41]. Given evidence of weak instruments, the precision of these estimates is less than what is currently reported. Further, Anderson-Rubin confidence sets for both models are empty, indicating either endogeneity or heterogeneous treatment effects. Estimating an OLS version of equation (E2) for *mortality* and ln(*spending*), we find that *self-referral* is negatively associated with both outcomes. For mortality, the coefficient (standard error) on *self-referral* is -0.06 (0.0008) and, for ln(*spending*), the coefficient (standard error) on *self-referral* is -0.35 (0.002). We perform Durbin-Wu-Hausman tests for both specifications to test for endogeneity of *self-referral*. We fail to reject the null hypothesis of exogeneity of *self-referral* at the 5% significance level (specifically, $p = 0.10$ for mortality and $p = 0.23$ for ln(*spending*)), which indicates that OLS estimates may not be biased.

Table A11 reports the results of our analysis of heterogeneity by hospital characteristics. For each characteristic, we report the combined effect of the treatment in the final quarter in Table A11.

Figure A6 graphs the coefficient estimates and standard errors from the hospital behavioral response analysis described in Section IV.B.

Figure A7 graphs the coefficient estimates and standard errors for the main specification, equation (1), after excluding HRRP-targeted DRGs from the estimation sample. The key result showing an increase in the post-shock relationship between *predΔprice* and self-referral rates is apparent. We also re-estimated equation (2) using self-referral as the dependent variable, first with the entire estimation sample and then with the sample excluding HRRP-targeted DRGs. Using the entire estimation sample, the estimated effect of the price shock in the final quarter of our analysis is 0.63 with a standard error of 0.14. Excluding HRRP-targeted DRGs, the analogous estimate 0.52 with a standard error of 0.16. The difference in these estimates is not statistically significant.

The subsections below (Appendix F.1 and F.2) provide additional details on the analysis of sensitivity to included controls, described in Section IV.D in the text.

Figure A10 and Figure A11 depict the time-varying relationship between *predΔprice* and *self-referral* separately for integrated GACs and integrated CAHs, and the difference in this relationship for the two groups, respectively. Comparing the two groups using a parsimonious specification which replaces the quarterly interactions with a pooled post-period indicator and permits different pre- and post-period trends confirms no difference in pre-period trends and a statistically different post-period trend. The results indicate that by the end of 2012Q4, a one percentage point change in predicted price increases a hospital's propensity to self-refer a patient by 0.8 percentage points, which is larger in magnitude than the effect we calculate from estimating equation (4).

F.1 Description of Control Variables

For the sensitivity analysis in Section IV.D, we consider six sets of patient-level controls. *Distance-to-facility measures* are the distance to the closest hospital, distance to the closest SNF, and these distances squared.[10] *Income measures* are the median income in the patient's zip code and median income squared (University of Michigan Population Studies Center 2006–2010). *Predicted health-related risk* includes out-of-sample predicted outcome measures for death, readmission, and spending; these are described in Section II.C of the text. *Medicare plan choice* includes dummies for the patient's Part D plan type (employer direct plan, regional preferred provider organization (PPO), non-PPO managed care organization, stand-alone prescription drug plan (PDP), Limited Income Newly Eligible Transition Plan (LINET), or no plan) and for whether the individual's premium was paid by their state of residence (as is possible for some duals). *Prior year facility visits* includes dummies for inpatient, ER, readmission, and physician's office visits in the prior year, respectively. *Discharge day/month* includes the day of week and the month of year of discharge.

F.2 Analysis and Results

We conduct the sensitivity analysis by estimating equation (4) with the inclusion of the six sets of patient-level controls. First, we select the number of control sets, N, to include in the equation. Second, for a given N, we include that number of control sets to equation (4) and estimate the coefficient. We repeat this for each possible N ranging from 1 to 6 and for each possible combination of N control sets. For all specifications, we compute the coefficient on *predΔprice* at the end of 2012 as our coefficient of interest. Finally, we compute the mean, median, minimum, and maximum of the coefficients of interest obtained from a given N. For example, if $N = 2$, we first estimate 15 regressions representing every possible combination of 2 control sets chosen from 6 overall. Then, we compute our coefficient of interest for each regression. Finally, we compute the mean, median, minimum, and maximum of these 15 coefficients.

In Figure A9, we plot the mean, median, minimum, and maximum of the estimates for each N. We find that although there is slight attenuation compared to our original estimates, the

[10] Distance to closest SNF is determined using the LTCFocus database of SNFs from the Brown University School of Public Health (LTCFocus, 2008–2012). LTCFocus is sponsored by the National Institute on Aging (1P01AG027296) through a cooperative agreement with the Brown University School of Public Health. Distance between zip codes is from the National Bureau of Economic Research (2010).

coefficient of interest is relatively unchanged with the inclusion of controls. Crucially, we reject the null hypothesis of no effect in 2012Q4 for all specifications in the sensitivity analysis.

References

Centers for Medicare and Medicaid Services. 2007–2012. *Hospital Cost Reports, 2007–2012*. Washington, DC: U.S. Department of Health and Human Services. https://www.cms.gov/data-research/statistics-trends-and-reports/cost-reports (accessed February 2019).

———. 2009–2012. *Nursing Home Compare Five-Star Ratings, 2009–2012.* Washington, DC: Department of Health and Human Services. https://www.cms.gov/medicare/health-safety-standards/quality-safety-oversight-general-information/five-star-quality-rating-system/five-star-quality-rating-system-archives (accessed July 2021).

———. n.d. *Hospital 2552-1996 and Hospital 2552-2010 Forms and Provider Reimbursement Manuals*. https://www.cms.gov/Regulations-and-Guidance/Guidance/Manuals/Paper-Based-Manuals-Items/CMS021935.

Charlson, Mary E., Peter Pompei, Kathy L. Ales, and C. Ronald MacKenzie. 1987. "A New Method of Classifying Prognostic Comorbidity in Longitudinal Studies: Development and Validation." *Journal of Chronic Diseases* 40 (5): 373–83.

LTCFocus. 2008–2012. *SNF Facility Data, 2008–2012*. Providence, RI: Brown University School of Public Health. Public Use Data sponsored by the National Institute of Aging (P01 AG027296) through a cooperative agreement with the Brown University School of Public Health. Available at www.ltcfocus.org. https://doi.org/10.26300/h9a2-2c26 (accessed July 2021).

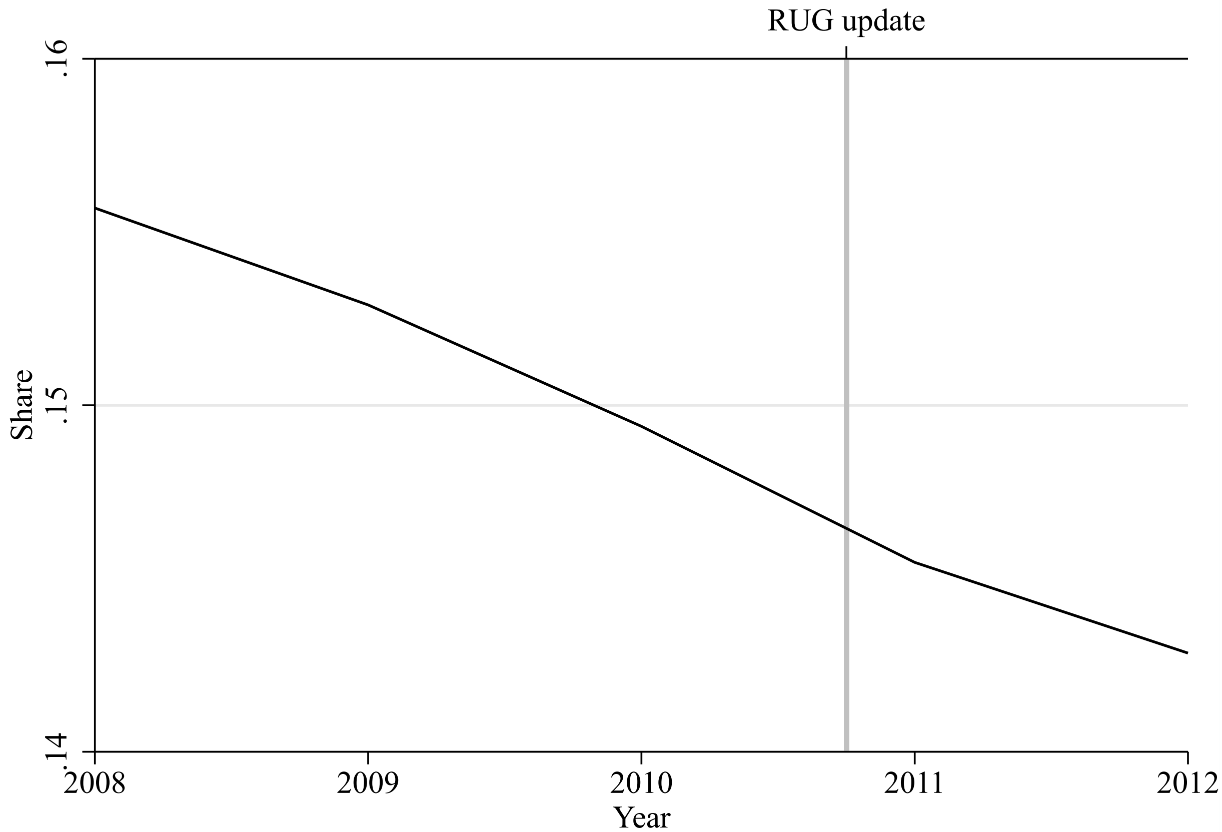
National Bureau of Economic Research. 2010. *Zip Code Distance Database*. https://data.nber.org/distance/2010/sf1/zcta5/.

United States Census Bureau. 2010–2011. *Metropolitan Area and County Totals*. https://www2.census.gov/programs-surveys/popest/datasets/2010-2011/metro/totals/.

United States Department of Housing and Urban Development. 2012. *USPS ZIP Code Crosswalk Files.* https://www.huduser.gov/apps/public/uspscrosswalk/home.

University of Michigan Population Studies Center. 2006–2010. *ZIP Code Characteristics: Mean and Median Household Income*. Archived at Internet Archive. https://web.archive.org/web/20200421144441/https://www.psc.isr.umich.edu/dis/census/Features/tract2zip/.

Figure A1: Share of Vertically Integrated SNFs



Notes: Figure reflects the share of SNFs which are integrated with a hospital. The sample of SNFs in each year includes all SNFs with at least one inpatient referral from integrated or unintegrated GACs. The number of SNFs in the sample is roughly constant during this period, with N ranging between 16,533 and 16,649. The vertical line represents the quarter in which the RUG update took effect. A SNF is considered vertically integrated in a year if it is owned by a hospital at any point in that year. The shares reported are higher than those reported by Rahman, Norton, and Grabowski (2016), as is the total number of SNFs in our sample; these differences may be due to our inclusion of swing-bed SNFs.

Table A1: SNF Quality Ratings by Integration Status

	(1) Integrated SNFs	(2) Unintegrated SNFs	(1) - (2) Difference
Overall star rating	3.725	2.945	0.780
	[1.039]	[1.220]	
Health inspection rating	3.688	2.786	0.901
	[1.204]	[1.190]	
Quality measures rating	2.280	3.082	-0.801
	[1.261]	[1.113]	
Staffing rating	4.354	2.980	1.375
	[0.861]	[1.112]	
Observations	3,236	55,152	

Notes: Table presents averages of SNF-year ratings over 2009-2012. Because ratings are reported monthly, annual data are constructed as a simple average of monthly reports. Standard deviations appear in brackets immediately beneath. Each SNF-year is weighted by the total number of patients referred to that SNF in that year. All ratings are from the SNF Five-Star Quality Rating System (https://www.cms.gov/medicare/quality-safety-oversight-certification-compliance/five-star-quality-rating-system-archives) where SNFs are given monthly ratings from 1 to 5 stars. Data is only available beginning in 2009, and data is not available for swing-bed SNFs (which only account for 3 percent of SNF patients during the study period). The "health inspection", "quality measures", and "staffing" ratings are components of the overall rating given to SNFs. The number of integrated SNFs ranged from 763 to 873 in each year; the number of unintegrated SNFs ranges from 13,674 to 13,927.

Table A2: Sample Selection

Sample	Number of hospitals	Number of claims: All	Number of claims: SNF discharges
Initial sample	5,169	52,980,531	10,291,481
Hospitals with claims in all years	4,726	52,463,754	10,197,855
Critical access hospitals	1,346	1,850,395	510,385
Swing-bed SNF ownership in all years	956	1,341,992	380,104
General acute-care hospitals	3,380	50,613,359	9,687,470
SNF ownership in all years (Integrated hospitals)	1,019	10,859,289	2,306,869
No SNF ownership in any year (Unintegrated hospitals)	2,133	35,687,083	6,575,890

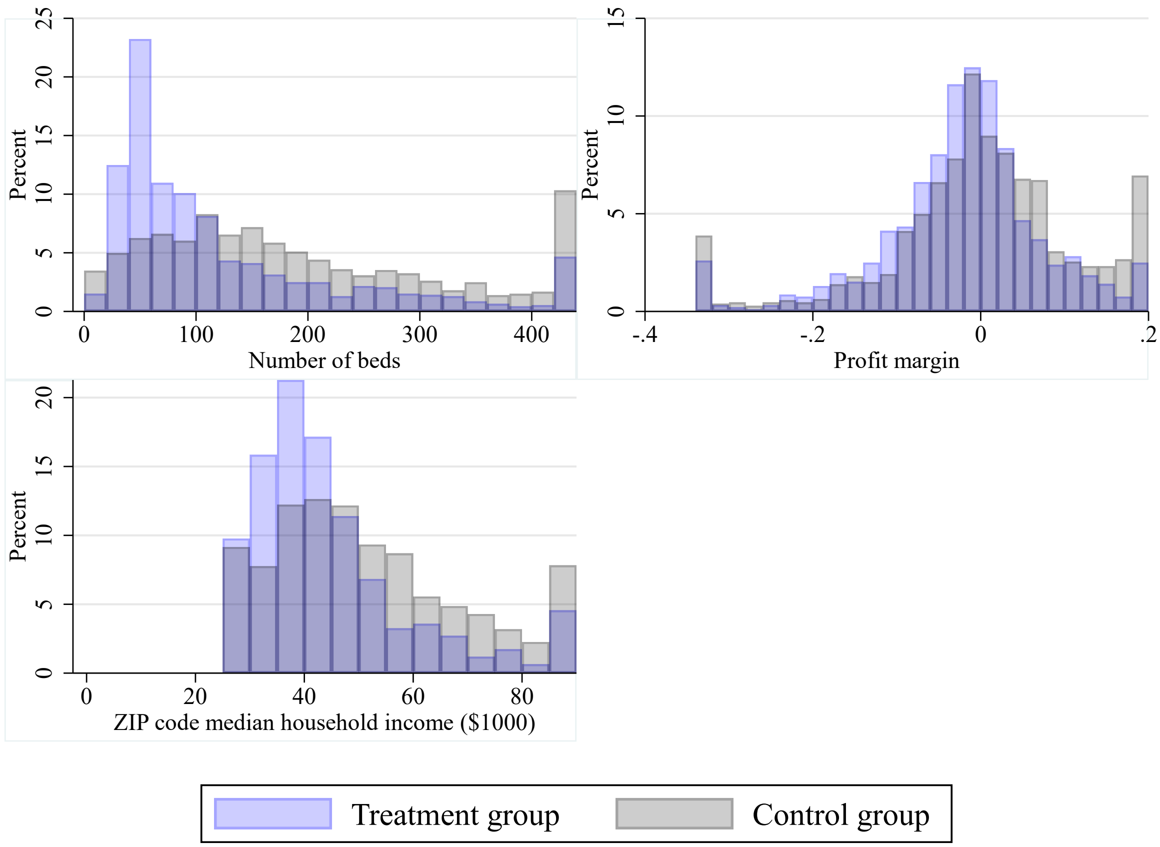
Notes: Initial sample includes inpatient Medicare claims from general acute-care hospitals and critical access hospitals during April 2008 to December 2012. Integrated and unintegrated hospitals–shaded above–are used in the main estimation.

Table A3: Hospital Characteristics by Integration Status

	(1) Integrated hospitals	(2) Unintegrated hospitals	(1) - (2) Difference
Number of beds	132.658	210.783	-78.125
	[142.045]	[184.027]	
Ownership type			
For-profit	0.183	0.271	-0.087
	[0.387]	[0.444]	
Not-for-profit	0.569	0.605	-0.036
	[0.495]	[0.489]	
Region			
Northeast	0.150	0.176	-0.026
	[0.357]	[0.381]	
Midwest	0.210	0.247	-0.037
	[0.407]	[0.431]	
South	0.481	0.391	0.090
	[0.500]	[0.488]	
West	0.160	0.187	-0.027
	[0.366]	[0.390]	
ZIP code median household income ($1000)	45.333	52.711	-7.378
	[17.928]	[21.115]	
Occupancy	0.511	0.606	-0.095
	[0.184]	[0.196]	
Net operating margin	-0.032	-0.014	-0.019
	[0.166]	[0.200]	
Observations	921	1,725	

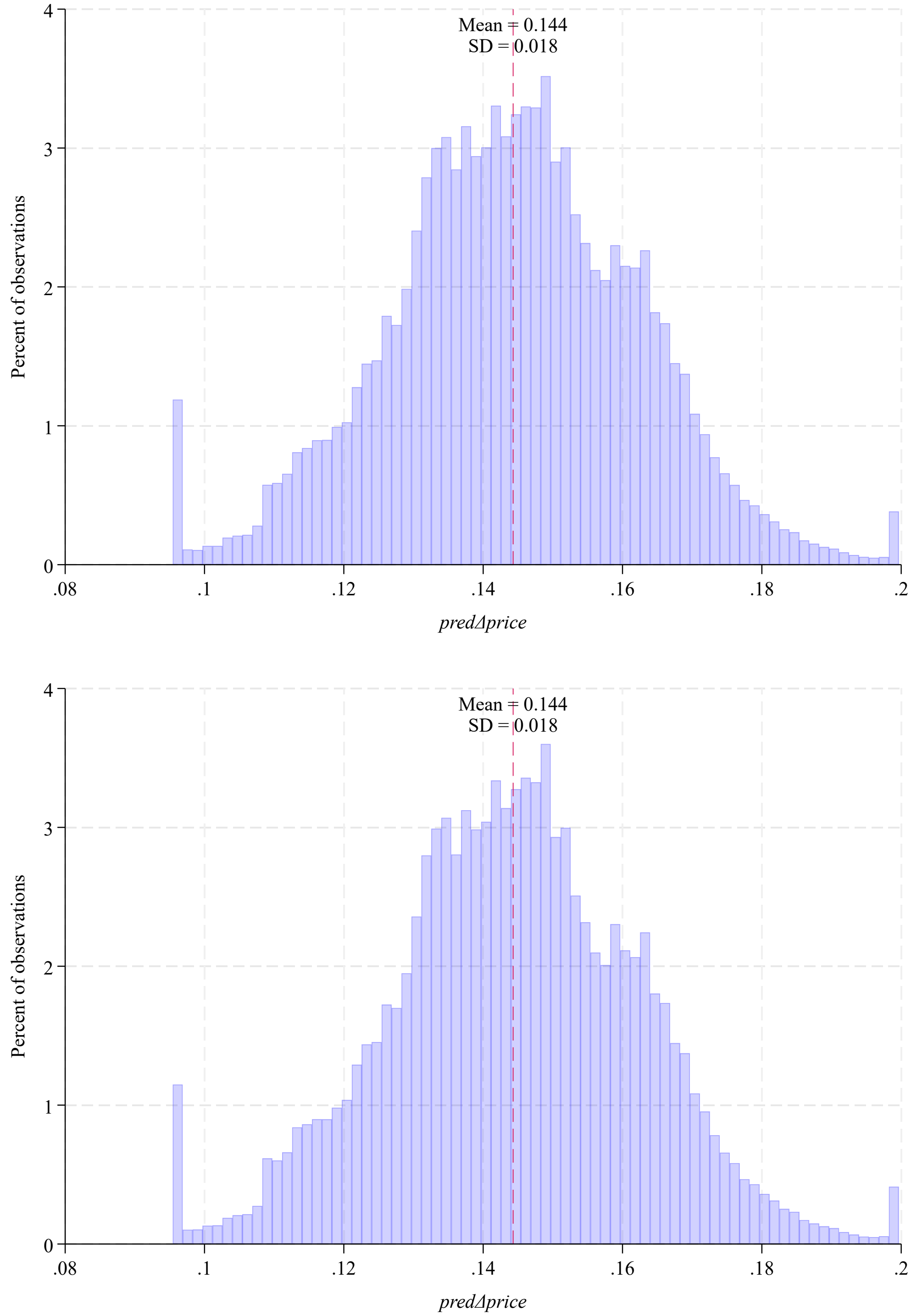
Notes: Table reports sample means for each variable. Standard deviations appear in brackets immediately beneath. Differences in means across samples are presented in the last column. Stars denote the result of a two-sample t-test for difference in means: p<0.10, p<0.05, p<.01. The unit of observation is a hospital in 2010. Hospitals are restricted to those general acute-care hospitals which have consistent SNF integration status from 2008-2012, either consistently owning or consistently not owning a SNF through this period. Hospitals are further restricted to only those reporting data for hospital size, ownership type, net operating margin, and ZIP code. Hospital regions are defined using U.S. Census designated regions (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

Figure A2: Distribution of Selected Hospital Characteristics by Hospital Group



Notes: Figure reflects the distribution of selected hospital characteristics within integrated hospitals ("Treatment group") and unintegrated hospitals ("Control group"). The unit of observation is a hospital. Each characteristic is winsorized at the 5th and 95th percentiles.

Figure A3: Distribution of *Pred∆price* Comparing Pre- and Post-periods



Notes: Figure reflects the distribution of *pred*∆*price* among patients in the estimation sample. The top panel is for patients in the pre-period and the bottom panel is for patients in the post-period. The unit of observation is an inpatient Medicare discharge. Values of *pred*∆*price* are winsorized at the 1st and 99th percentiles.

Table A4: Patient Characteristics by *Pred∆price*

Variable	(1) *Pre-RUG update* Below median *pred∆price* Mean/SD	(2) Above median *pred∆price* Mean/SD	(3) *Post-RUG update* Below median *pred∆price* Mean/SD	(4) Above median *pred∆price* Mean/SD	(1)-(2) Difference	(3)-(4) Difference
Age	77.888	80.799	77.605	80.455	-2.911	-2.850
	[10.437]	[10.859]	[10.638]	[11.162]		
Female	0.602	0.679	0.594	0.669	-0.077	-0.074
	[0.489]	[0.467]	[0.491]	[0.471]		
Black	0.061	0.151	0.063	0.156	-0.090	-0.092
	[0.239]	[0.358]	[0.243]	[0.362]		
Dual-eligibility	0.170	0.498	0.173	0.502	-0.328	-0.329
	[0.376]	[0.500]	[0.378]	[0.500]		
Charlson comorbidity index	1.564	1.087	1.546	1.102	0.477	0.444
	[1.695]	[1.296]	[1.673]	[1.310]		
Hospital stay >=3 days	0.966	0.946	0.968	0.947	0.020	0.020
	[0.181]	[0.225]	[0.177]	[0.223]		
Self-referral	0.103	0.070	0.086	0.058	0.033	0.028
	[0.304]	[0.256]	[0.281]	[0.235]		
N	2,305,071	2,348,652	2,136,309	2,092,727		

Notes: Table reports sample means for each variable. Standard deviations appear in brackets immediately beneath. Differences in means between groups are presented in the last two columns. Stars denote the result of a two-sample t-test for difference in means: p<0.10, p<0.05, p<.01. The unit of observation is an inpatient Medicare discharge.

Table A5: Distribution of *Pred∆price* by Inpatient Diagnosis

Diagnoses	Above-median *pred∆price* Share	Below-median *pred∆price* Share	Observations
Major hip and knee joint replacement/reattachment	0.11	0.89	1,958,999
Septicemia or severe sepsis	0.48	0.52	1,910,322
Heart failure and shock	0.24	0.76	2,210,175
Hip and femur procedures (excl. mjr. jnt.)	0.96	0.04	595,786
Kidney and urinary tract infections	0.93	0.07	1,196,356
Simple pneumonia and pleurisy	0.28	0.72	1,727,158
Renal failure	0.78	0.22	1,158,128
Intracranial hemorrhage or cerebral infarction	1.00	0.00	1,046,724
Chronic obstructive pulmonary disease	0.07	0.93	1,749,516
Respiratory infections and inflammations	0.73	0.27	644,745
Nutritional and misc. metabolic disorders	0.91	0.09	969,260
Gastrointestinal hemorrhage	0.67	0.33	1,023,644
Cardiac arrhythmia and conduction	0.78	0.22	1,257,028
Cellulitis	0.21	0.79	726,474
Acute myocardial infarction	0.44	0.56	657,111

Notes: Table reports the percent of patients within each set of diagnoses below- and above-median *pred∆price*. Selected diagnoses are the 15 most common inpatient diagnoses for SNF referred patients in the estimation sample. Diagnoses are ordered by number of SNF referred patients. The sample includes patients discharged from integrated and unintegrated hospitals.

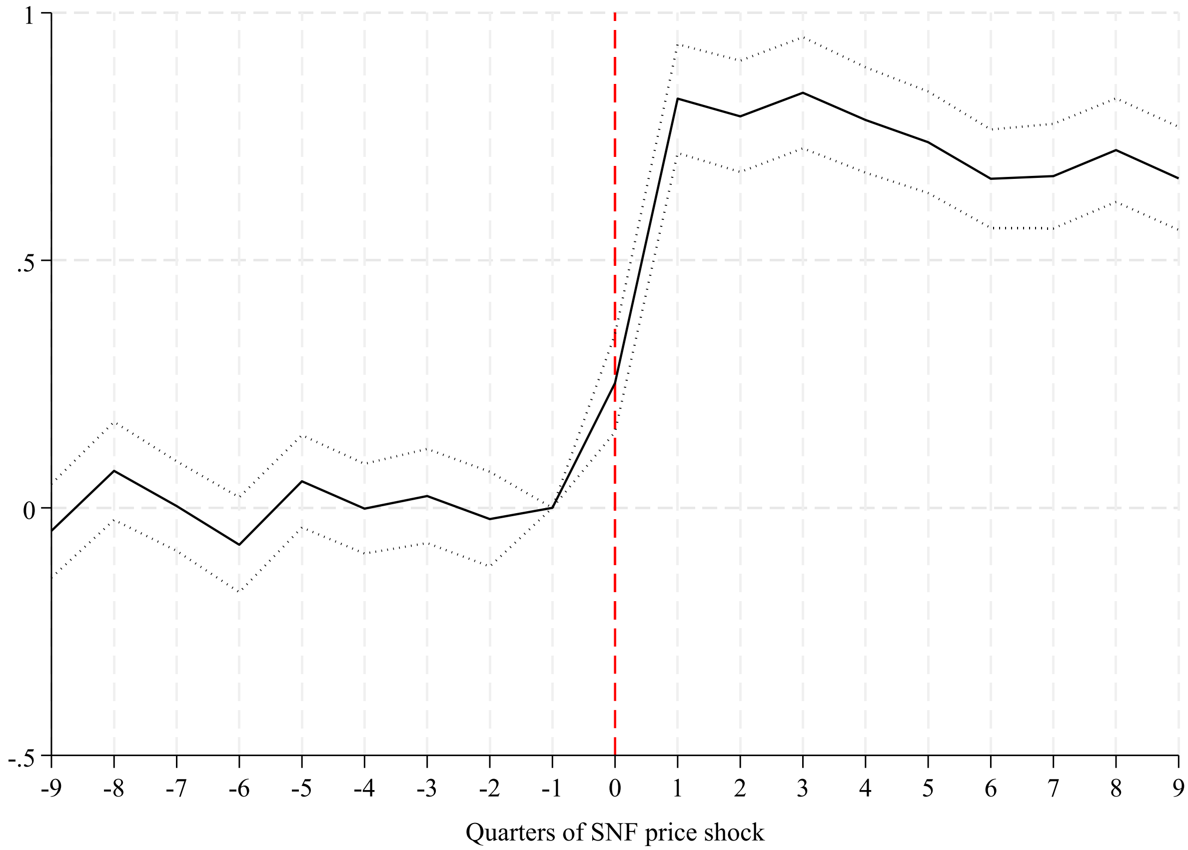
Table A6: Effect of *Pred∆price* on Ln*(price)*

	(1)	(2)
Post · *pred∆price*	1.241	0.830
	[0.042]	[0.040]
Post · *Quarter* · *pred∆price*	-0.057	-0.022
	[0.008]	[0.007]
Quarter · *pred∆price*	0.018	0.000
	[0.005]	[0.004]
Quarter = 0 · *pred∆price*	0.344	0.250
	[0.045]	[0.043]
SNF-Quarter fixed effects	No	Yes
Observations	2,247,952	2,247,952

Notes: p<0.10, p<0.05, p<.01. Unreported controls include: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects. Standard errors clustered by *pred∆price* are in brackets. The sample includes patients discharges from integrated hospitals to SNFs from 2008Q2 to 2012Q4. Observations with missing ln*(price)* are omitted. Column (1) repeats results reported in column (1) of Table 2.

Figure A4: Time-Varying Effect of *Pred∆price* on L*n(price)*

(After Adding SNF-Quarter Fixed Effects)



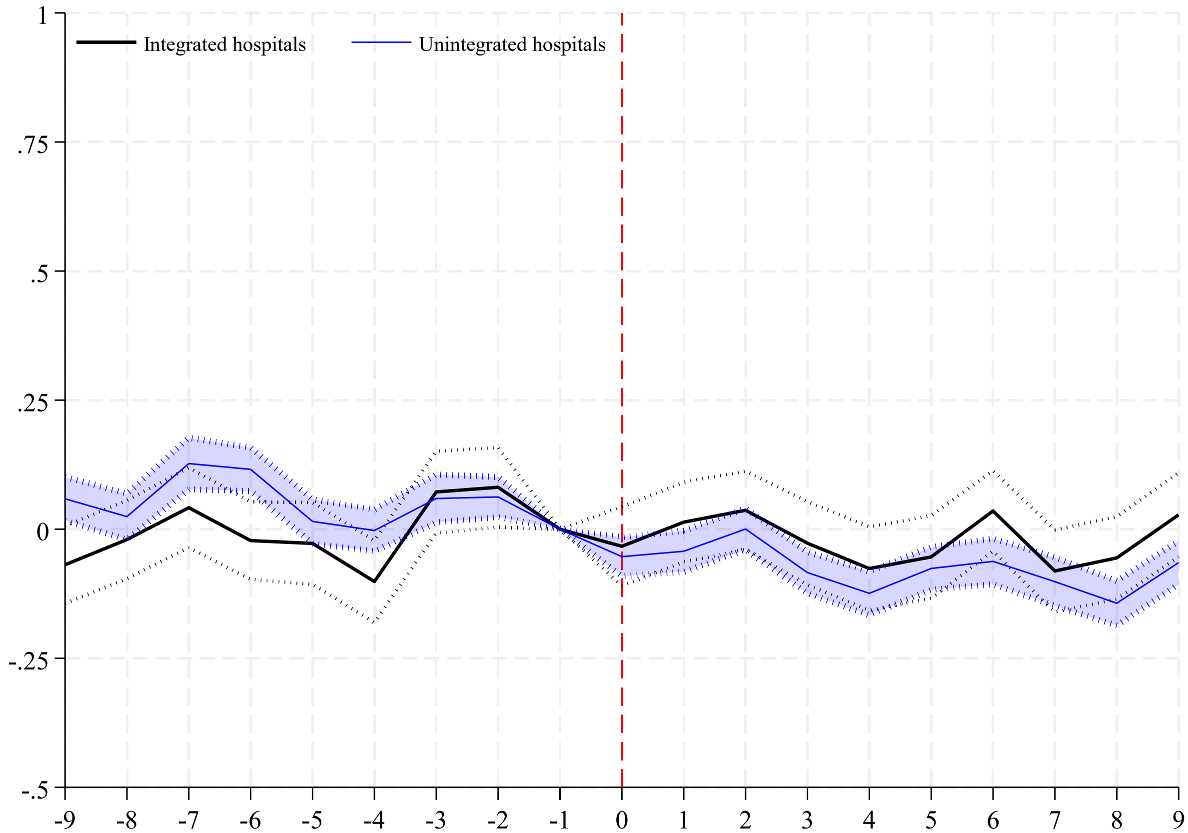
Notes: The solid line plots the coefficient estimates on the lags and leads of *pred∆price* obtained from estimating equation (1) in the text but including SNF-quarter fixed effects. The dependent variable is the log of the average daily price for the patient's SNF stay. The dotted lines represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price*. The dashed vertical line represents data during the transition quarter, $t = 0$. The estimation sample includes patients discharged to SNFs from integrated hospitals. The model includes: (1) interactions between hospital-specific indicator variables and *pred∆price*; (2) hospital-quarter fixed effects; and (3) SNF-quarter fixed effects.

Table A7: Effect of *Pred∆price* on Self-Referrals

Post · pred∆price	0.258
	[0.109, 0.381]
Post · Quarter · pred∆price	0.046
	[0.017, 0.381]
Quarter · pred∆price	0.005
	[-0.011, 0.024]
Quarter = 0 · *pred∆price*	-0.000
	[-0.187, 0.165]
Combined effect of price shock in 2012Q4	0.627
	[0.311, 0.855]
Dependent variable mean	0.326
Observations	2,306,869

Notes: p<0.10, p<0.05, p<.01. Unreported controls include: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects. Bootstrapped 95 percent confidence intervals are reported in brackets. The combined effect gives the impact of the price shock on the outcome in 2012Q4. To construct the confidence intervals, observations in the training sample are drawn 1,000 times using a Bayesian bootstrap. For each sample draw, the entire estimation procedure is performed. Then from the resulting estimates, we construct the bootstrapped confidence interval by taking the 2.5th percentile of the estimated coefficients and taking the 97.5th percentile of the estimated coefficients. The sample includes patients discharges from integrated hospitals to SNFs from 2008Q2 to 2012Q4.

Figure A5: Effect of *Pred∆price* on SNF Referral



Notes: Each solid line plots the coefficient estimates on the lags and leads of *pred∆price*, obtained from estimating a version of equation (5) which adds unintegrated hospitals to the estimation sample and includes an interaction term between integration status and the lags and leads of *pred∆price*. The solid blue line for "Unintegrated hospitals" plots the coefficient estimates for unintegrated hospitals. The solid black line for "Integrated hospitals" plots the computed coefficient estimates, adding the coefficient estimates for unintegrated hospitals and the coefficient estimates for the integration status interaction term. The dotted lines and the light blue shaded area represent 95 percent confidence intervals around the point estimates, based on standard errors clustered by *pred∆price*, for the "Integrated hospitals" estimates and "Unintegrated hospitals" coefficient estimates, respectively. The dashed vertical line represents data during the transition quarter, $t = 0$. The estimation sample includes patients discharged from integrated and unintegrated hospitals. The model includes: (1) interactions between hospital-specific indicator variables and *pred∆price*; (2) hospital-quarter fixed effects; and (3) propensity for SNF referral control variable.

Table A8: Share of SNF Discharges to the Most-Preferred SNF, by Hospital Category

	Integrated		Unintegrated
Statistic	**Most-preferred = Owned SNF**	**Most-preferred ≠ Owned SNF**	
25th percentile	0.29	0.18	0.14
50th percentile	0.38	0.29	0.21
75th percentile	0.50	0.41	0.29
Average	0.41	0.31	0.23
N	636	381	2,103

Notes: Unit of observation is the hospital. Each observation is weighted by its SNF discharges. Utilizes data from 2008Q2-2010Q3.

Table A9: Effect of *Pred∆price* on Ln*(spending)*

(Robustness to Alternative Treatment of Physician Costs)

	(1)	(2)	(3)
Post · pred∆price · Integrated	0.100	0.329	0.231
	[0.179]	[0.411]	[0.367]
Post · Quarter · pred∆price · Integrated	0.009	-0.013	0.011
	[0.031]	[0.071]	[0.065]
Quarter · pred∆price · Integrated	-0.014	-0.052	-0.046
	[0.022]	[0.050]	[0.047]
Quarter = 0 · *pred∆price · Integrated*	-0.088	-0.368	-0.363
	[0.211]	[0.469]	[0.414]
Post · pred∆price	0.571	0.538	0.371
	[0.083]	[0.192]	[0.171]
Post · Quarter · pred∆price	-0.069	-0.072	-0.075
	[0.015]	[0.033]	[0.030]
Quarter · pred∆price	0.030	0.045	0.056
	[0.011]	[0.024]	[0.021]
Quarter = 0 · *pred∆price*	0.244	0.411	0.254
	[0.099]	[0.228]	[0.203]
Predicted ln(*spending*)	0.835	0.838	
	[0.006]	[0.007]	
Predicted ln(*spending*) (all costs)			0.606
			[0.007]
Combined effect of price shock for *Integrated* in 2012Q4	0.170	0.228	0.323
	[0.329]	[0.768]	[0.707]
Excludes physician and DME costs	Yes	Yes	No
Medicare sample	100pct	20pct	20pct
Dependent variable mean in pre-period	9.761	9.764	9.902
Observations	8,418,055	1,687,683	1,687,349

Notes: p<0.10, p<0.05, p<.01. Unreported controls include: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects. Standard errors clustered by *pred∆price* are reported in brackets. The combined effect gives the impact of the price shock on the outcome for integrated hospitals relative to unintegrated hospitals in 2012Q4. The sample includes patients discharges from both integrated and unintegrated hospitals to SNFs. Observations missing the relevant cost risk-adjustment factor are dropped. Observations are weighed by patient-level predicted spending. Each column represents the same specification estimated with differing definitions of spending for different patient samples. Column (1) reports results for spending excluding physician and durable medical equipment costs for the 100pct Medicare sample. Column (2) reports results for non-SNF spending excluding physician and durable medical equipment costs for the 20pct Medicare sample. Column (3) reports results for non-SNF spending including physician and durable medical equipment costs for the 20pct Medicare sample. The sample of hospitals includes general acute-care hospitals that own a SNF from 2008 to 2012 (indicated by *Integrated*) and general acute-care hospitals that never own a SNF from 2008 to 2012.

Table A10: Effect of *Pred∆price* on 90-Day Health Outcomes

	(1) *Mortality*	(2) *Readmission*	(3) Ln*(spending)*
Post · pred∆price · Integrated	0.061	0.019	0.100
	[0.073]	[0.094]	[0.179]
Post · Quarter · pred∆price · Integrated	0.017	0.024	0.009
	[0.013]	[0.016]	[0.031]
Quarter · pred∆price · Integrated	-0.012	-0.019	-0.014
	[0.009]	[0.011]	[0.022]
Quarter = 0 · *pred∆price · Integrated*	0.192	0.002	-0.088
	[0.082]	[0.112]	[0.211]
Post · pred∆price	0.067	0.067	0.571
	[0.035]	[0.048]	[0.083]
Post · Quarter · pred∆price	0.004	-0.008	-0.069
	[0.007]	[0.009]	[0.015]
Quarter · pred∆price	-0.005	-0.004	0.030
	[0.004]	[0.006]	[0.011]
Quarter = 0 · *pred∆price*	-0.035	0.049	0.244
	[0.042]	[0.057]	[0.099]
Risk of mortality	0.899		
	[0.003]		
Risk of readmission		0.890	
		[0.007]	
Predicted ln(*spending*)			0.835
			[0.006]
Combined effect of price shock for *Integrated* in 2012Q4	0.195	0.215	0.170
	[0.132]	[0.172]	[0.329]
Dependent variable mean in pre-period	0.187	0.394	9.761
Observations	8,839,160	8,877,084	8,880,901

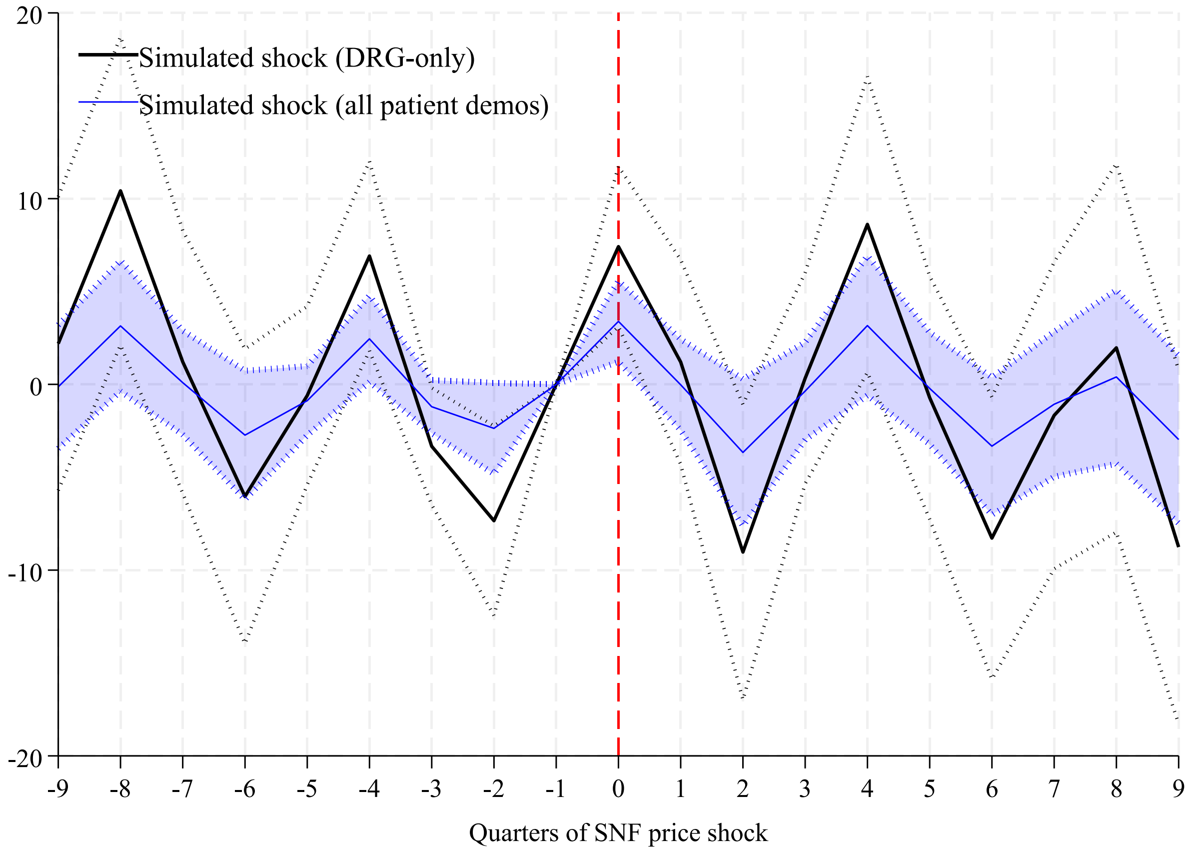
Notes: p<0.10, p<0.05, p<.01. Unreported controls include: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects. Standard errors clustered by *pred∆price* are reported in brackets. The combined effect gives the impact of the price shock on the outcome for SNF-owning hospitals relative to non-SNF-owning hospitals in 2012Q4. The sample includes patients discharges from both integrated and unintegrated hospitals to SNFs. Observations with missing the relevant patient-level, risk-adjustment factor are omitted. Observations in the ln*(spending)* specification are weighed by patient-level predicted spending. The sample of hospitals includes general acute-care hospitals that own a SNF from 2008 to 2012 (indicated by *Integrated*) and general acute-care hospitals that never own a SNF from 2008 to 2012.

Table A11: Effect of *Pred∆price* on S*elf-Referral*
(Heterogeneity by Hospital Characteristics)

	(1)
Combined effect of price shock for omitted category in 2012Q4	1.066
	[0.876]
Combined effect of price shock compared to omitted category	
Region == Northeast	0.440
	[0.419]
Region == South	0.462
	[0.359]
Region == West	-0.388
	[0.421]
Ownership type == Government	0.375
	[0.539]
Ownership type == Not for-profit	0.287
	[0.450]
Hospital size == Medium	0.347
	[0.347]
Hospital size == Small	0.177
	[0.428]
Margin quartile == 2	0.356
	[0.383]
Margin quartile == 3	0.420
	[0.378]
Margin quartile == 4	-0.008
	[0.379]
Occupancy	-1.981
	[1.024]
Observations	2,301,980

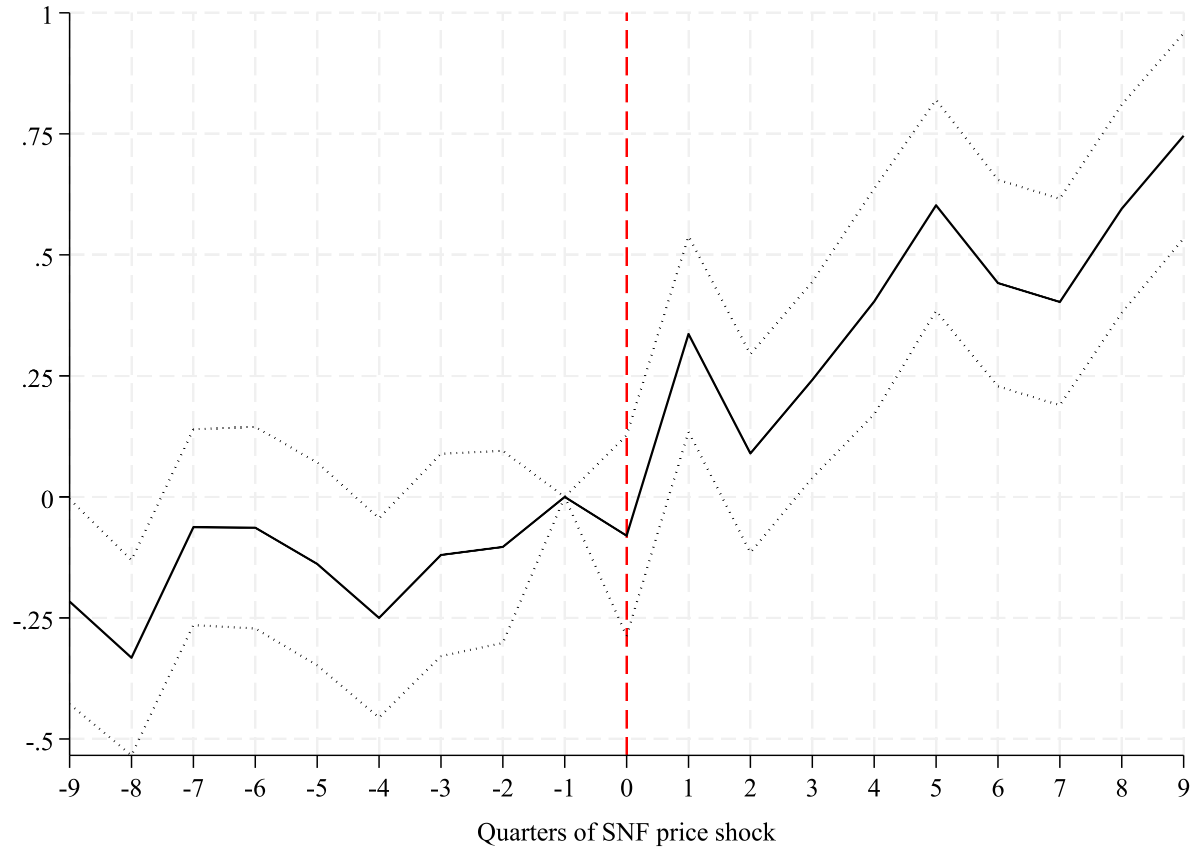
Notes: $p<0.10$, $p<0.05$, $p<.01$. Unreported controls include: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects. The omitted categories are the Midwest region, not for-profits, large, and bottom quartile of average margin. Standard errors clustered by *pred∆price* are reported in brackets. The sample includes patients discharges from integrated hospitals to SNFs. Observations from hospitals with incomplete hospital information are dropped from the sample. Hospital information is based on the Medicare Cost Reports. Large hospitals are hospitals with 200 or more beds, medium hospitals are hospitals with 100 to 199 beds, and small hospitals are hospitals with fewer than 100 beds. Hospital regions are defined using U.S. Census designated regions (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

Figure A6: Effect of *Pred∆price'* on *PatientPop*



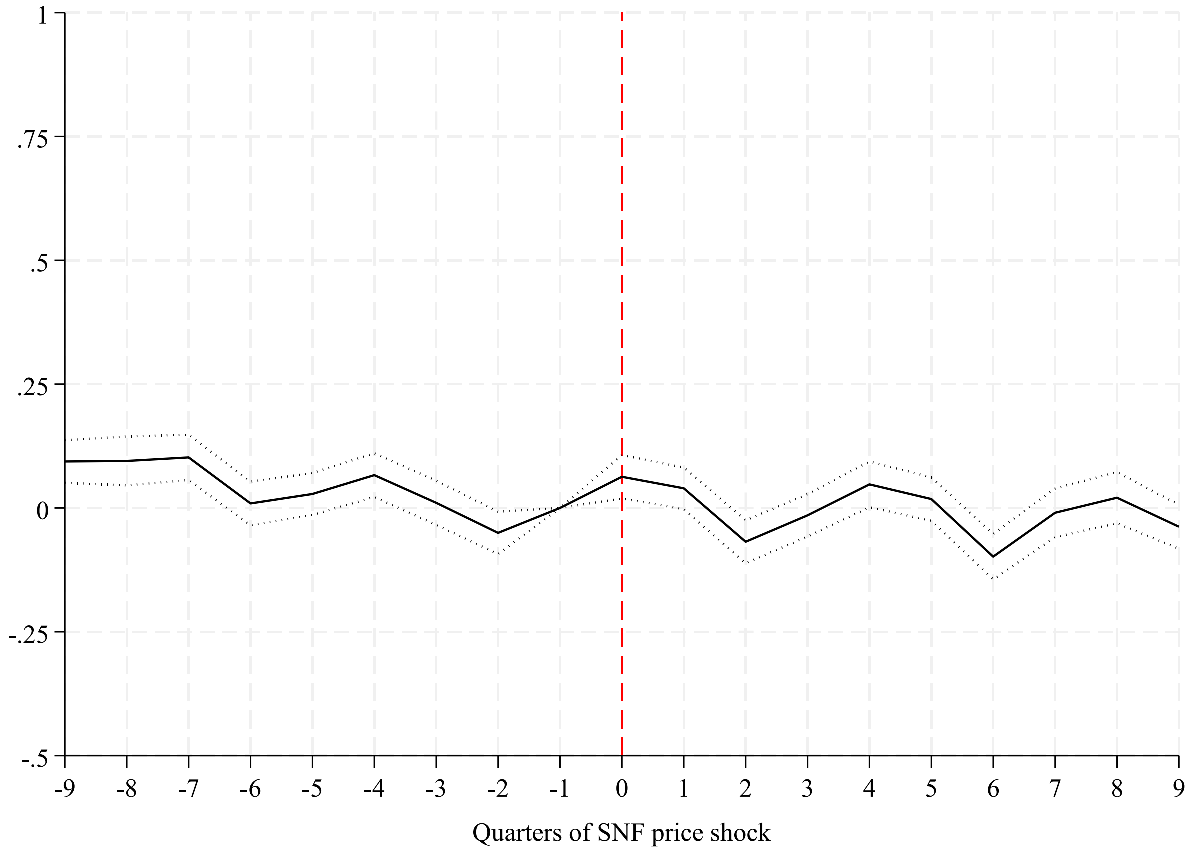
Notes: The solid black line plots the coefficient estimates on the lags and leads of *pred∆price'* (*pred∆price* calculated at the DRG-level), obtained by estimating a version of equation (3) in the text but using *pred∆price'* as the independent variable and hospitalization as the outcome variable. The solid blue line plots the coefficient estimates on the lags and leads of an alternative version of *pred∆price'* which is an average of *pred∆price* for a hospital-DRG-quarter triad. The dotted lines and the light blue shaded area represent 95 percent confidence intervals around the point estimates, based on standard errors clustered by *pred∆price'*, for the solid black line and solid blue line, respectively. The dashed vertical line represents data during the transition quarter, $t = 0$. The unit of observation is a hospital-DRG-quarter triad. The patient sample includes patients discharged to SNFs from integrated hospitals. The models include: (1) hospital-quarter fixed effects; and (2) hospital-DRG fixed effects.

Figure A7: Effect of *Pred∆price* on Self-Referral
(Robustness to Restricting to Non-HRRP DRGs)



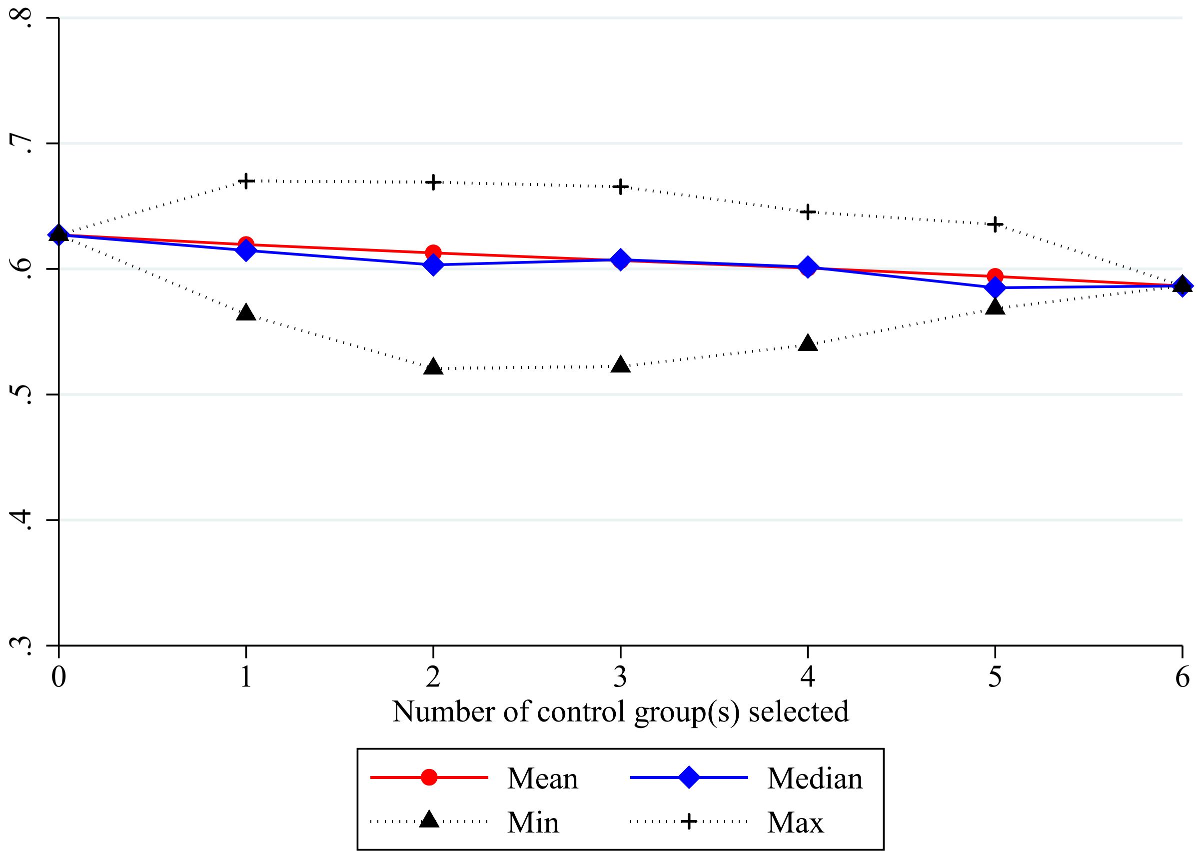
Notes: The solid line plots the coefficient estimates on the lags and leads of *pred∆price*, obtained from estimating equation (3) in the text, restricting the sample to patients with non-HRRP DRGs. The dependent variable is an indicator variable for admission to a SNF owned by the discharging hospital. The dotted lines represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price*. The dashed vertical line represents data during the transition quarter, $t = 0$. The unit of observation is an inpatient Medicare discharge. The estimation sample includes patients with DRGs excluded from the Hospital Readmissions Reduction Program that were discharged to SNFs from integrated hospitals. The model includes: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects.

Figure A8: Effect of *Pred∆price* on *Self-Referral Propensity*



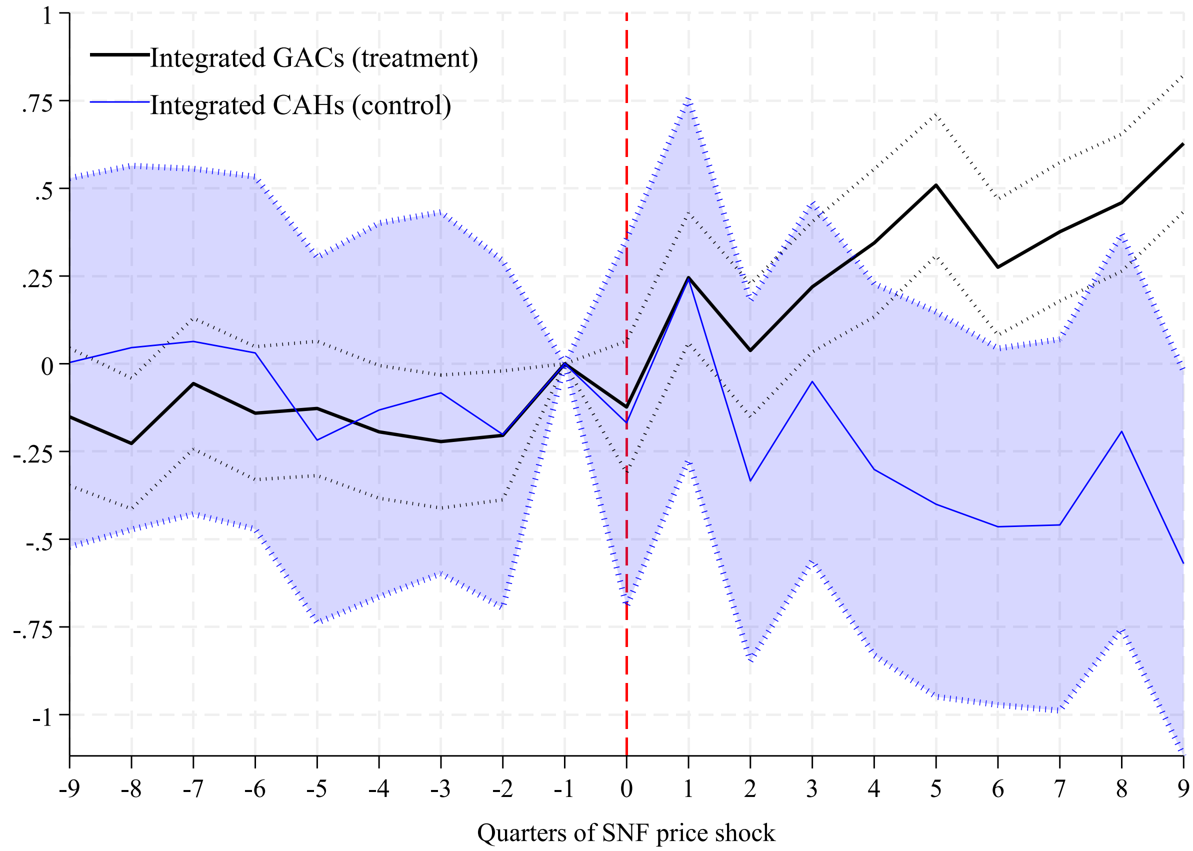
Notes: The solid line plots the coefficient estimates on the lags and leads of *pred∆price*, obtained from estimating equation (3) in the text with self-referral risk as the outcome. The dotted lines represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price*. The dashed vertical line represents data during the transition quarter, $t = 0$. The estimation sample includes patients discharged to SNFs from integrated hospitals. The model includes: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects.

Figure A9: Sensitivity of the 2012Q4 Effect of *Pred∆price* on Self-Referral — Distribution of Possible Estimates



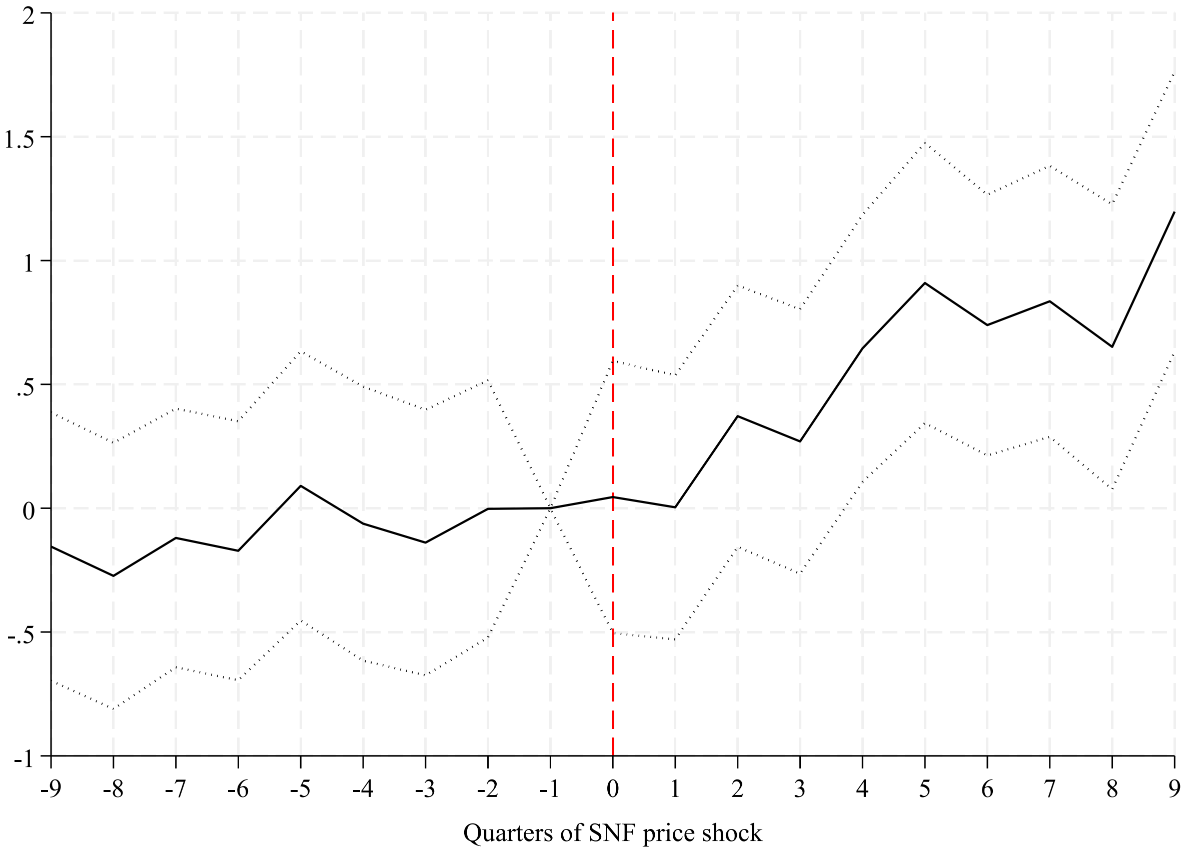
Notes: Each line plots the derived coefficient estimate of the impact of *pred∆price* on self-referral probability in 2012Q4. Estimation is varied by the inclusion of up to 6 groups of controls. For a given number of controls, *N*, *N* groups of controls are sampled with replacement from the 6 groups of controls with regressions run with controls from each sampling. For each *N* from 1 to 5, this procedure is performed 15 times. For each *N*, the mean, median, mininimum, and maximum from the 15 estimates are obtained and plotted. The 6 groups of controls used are: (1) patient's distance to closest hospital, distance to closest SNF, and each of these measures squared; (2) median income in zip code and median income squared; (3) predicted outcome measures for mortality, readmission, and spending; (4) dummies for the patient's Part D plan and for whether the patient's premium was paid by their state of residence; (5) visit in prior year to inpatient facility, emergency room, readmission, and physician's office; and (6) day of week and month of year of discharge.

Figure A10: Effect of *Pred∆price* on Self-Referral



Notes: Each solid line plots the coefficient estimates on the lags and leads of *pred∆price*, obtained from estimating equation (8) in the text. The dependent variable is an indicator variable for admission to a SNF owned by the discharging hospital. The solid blue line for "Integrated CAHs" plots estimates of β^2 and the solid black line for "Integrated GACs" plots estimates of $\beta^2 + \beta^3$. The dotted lines and the light blue shaded area represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price*. The dashed vertical line represents data during the transition quarter, $t = 0$. The estimation sample includes patients discharged to SNFs from both integrated GACs and integrated CAHs. Integrated CAHs include critical access hospitals (CAH) that only own swing-bed SNFs from 2008 to 2012. Each model includes: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects.

Figure A11: Effect of *Pred∆price* on Self-Referral for GACs vs. CAHs



Notes: The solid line plots the coefficient estimates on the lags and leads of *pred∆price* · *GAC*, obtained from estimating equation (8) in the text. The dependent variable is an indicator variable for admission to a SNF owned by the discharging hospital. The dotted lines represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price*. The dashed vertical line represents data during the transition quarter, $t = 0$. The estimation sample includes patients discharged to SNFs from both integrated GACs and integrated CAHs. Integrated CAHs include critical access hospitals (CAH) that only own swing-bed SNFs from 2008 to 2012. Each model includes: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects.

Table A12: Effect of *Pred∆price* on Self-Referrals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post · pred∆price	0.283	0.283	0.283	0.283	0.283	0.283	0.283
	[0.076]	[0.084]	[0.081]	[0.087]	[0.069]	[0.075]	[0.079]
Post · Quarter · pred∆price	0.046	0.046	0.046	0.046	0.046	0.046	0.046
	[0.014]	[0.017]	[0.015]	[0.018]	[0.012]	[0.013]	[0.014]
Quarter · pred∆price	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	[0.009]	[0.013]	[0.011]	[0.013]	[0.009]	[0.009]	[0.010]
Quarter = 0 · *pred∆price*	-0.011	-0.011	-0.011	-0.011	-0.011	-0.011	-0.011
	[0.085]	[0.088]	[0.091]	[0.087]	[0.080]	[0.085]	[0.087]
Clusters:	*pred∆price*	hospital	hospital-quarter	*pred∆price*, hospital twoway	.001-size *pred∆price* bins (k = 106)	.0005-size *pred∆price* bins (209)	.0001-size *pred∆price* bins (1,044)
Observations	2,247,952	2,247,952	2,247,952	2,247,952	2,247,952	2,247,952	2,247,952

Notes: p<0.10, p<0.05, p<.01. Unreported controls include: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects. Standard errors clustered by the reported level of clustering are reported in brackets. Column (3) clusters standard errors by hospital-quarter cells. Column (4) employs two-way clustering by *pred∆price* and hospitals. Column (5) through (7) cluster standard errors by bins of *pred∆price.* The sample includes patients discharges from integrated hospitals to SNFs. from 2008Q2 to 2012Q4. Observations with missing ln*(price)* are omitted.

Table E1: Effect of Self-Referral on 90-Day Health Outcomes

	Mortality			*Ln(spending)*		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	First-stage (Self-referral)	**Reduced form**	**2SLS**	**First-stage (Self-referral)**	**Reduced form**	**2SLS**
Self-referral			0.293			0.309
			[0.213]			[0.565]
*Post · pred∆pric*e *· Integrated*	0.270	0.061		0.258	0.100	
	[0.070]	[0.073]		[0.073]	[0.179]	
Post · Quarter · pred∆price · Integrated	0.046	0.017		0.042	0.009	
	[0.013]	[0.013]		[0.013]	[0.031]	
Quarter · pred∆price · Integrated	0.004	-0.012	-0.014	0.005	-0.014	-0.015
	[0.009]	[0.009]	[0.010]	[0.009]	[0.022]	[0.025]
Quarter = 0 *· pred∆price · Integrated*	0.011	0.192	0.191	0.001	-0.088	-0.090
	[0.086]	[0.082]	[0.085]	[0.084]	[0.211]	[0.215]
Post · pred∆price	-0.004	0.067	0.064	-0.001	0.571	0.576
	[0.001]	[0.035]	[0.034]	[0.000]	[0.083]	[0.080]
Post · Quarter · pred∆price	-0.000	0.004	0.005	0.000	-0.069	-0.070
	[0.001]	[0.007]	[0.007]	[0.000]	[0.015]	[0.014]
Quarter · pred∆price	0.001	-0.005	-0.005	0.000	0.030	0.030
	[0.000]	[0.004]	[0.004]	[0.000]	[0.011]	[0.011]
Quarter = 0 *· pred∆price*	0.003	-0.035	-0.037	-0.001	0.244	0.245
	[0.001]	[0.042]	[0.042]	[0.000]	[0.099]	[0.099]
Risk of mortality	-0.063	0.899	0.918			
	[0.001]	[0.003]	[0.014]			
Predicted ln(*spending*)				-0.006	0.835	0.837
				[0.002]	[0.006]	[0.007]
Kleibergen-Paap rk Wald F Statistic	10.640			9.239		
Dependent variable mean in pre-period	0.086	0.186	0.186	0.086	9.767	9.767
Observations	8,839,160	8,839,160	8,839,160	8,880,901	8,880,901	8,880,901

Notes: p<0.10, p<0.05, p<.01. Unreported controls include: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects. Standard errors clustered by *pred∆price* are in brackets. The precision of standard errors for IV regressions is less than currently reported as they are not adjusted for weak instrument bias. The combined effect gives the impact of the price shock on the outcome in 2012Q4. The sample includes patients discharged from integrated and unintegrated hospitals to SNFs from 2008Q2 to 2012Q4. Observations with missing risk of mortality or missing predicted ln*(spending)* because of missing patient-level risk adjustment factors are omitted. Observations in ln*(spending)* specifications are weighed by patient-level predicted spending. Columns (3) and (6) report coefficient estimates from 2SLS regressions of the effect of self-referral on outcomes, with the predicted price shock for integrated hospitals in the post-period—$Post \cdot pred\Delta price \cdot Integrated$ and $Post \cdot Quarter \cdot pred\Delta price \cdot Integrated$—serving as instruments for self-referral. The sample of hospitals includes general acute-care hospitals that own a SNF from 2008 to 2012 (indicated by *Integrated*) and general acute-care hospitals that never own a SNF from 2008 to 2012.