Practice-style spillovers in hospital care: evidence from lower extremity joint replacement surgery

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log notes

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- results of CJR effects on related non-CJR patients added;
- results of robustness checking of heterogeneous CJR effects added - including three penetrations calculated by charge and cost
- results of base year changed to 2013 year added

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- section of Functional form estimating transmission from Medicare policy to private sector added;
- section of functional form heterogeneity added;
- some materials about describing the estimation results and strategy added in intro and strategy sections

Abstract

I analyze Medicare policy effects on how hospitals treat non-targeted patients covered by private insurance. Leveraging on a mandatory alternative payment model, I found that hospitals will follow the way of treating the non-targeted patients as the way treating Medicare patients. I show the model resulted in increased use of Home-with-Healthcare (HHC) discharge and total cost per patient and a decreased use of both Skilled Nursing Facility (SNF) and Home discharge. Larger effects are identified for Private insurance recipients. In addition, this study shows substantial heterogeneity of policy effects. To reveal the type of transmission from Medicare to private sector and evaluate if hospital makes insurance-based decisions, I construct the instrument using predicted outcomes of Medicare patients, then apply the 2SLS on private-insured patients. The results further confirm the following type of transmission, which is almost one-dollar-to-one-dollar increase in total cost. Finally, this study provides evidence of the CJR effects extended to non-CJR patients. (JEL No. I13, I18)

1 Introduction

In 2020, health care expenditure increased to 4.1 trillion, which accounts for 19.7% of total US GDP (CMS, 2020). This expenditure is mostly paid by two public insurance programs - 20% ($829.5 billion) by Medicare and 16% ($671.2 billion) by Medicaid. The gigantic amount of expenditure will also trouble the government in the coming decade, given its projection to reach $6.2 trillion by 2028. To curb spending without harming patients, different payment innovations and models were introduced. The Center for Medicare and Medicaid Innovation has launched 54 models in 10 years, where nearly 1 million healthcare providers have participated in (Smith, 2021). However, the outcomes of these models are mixed. Studies found some models saved money or improved healthcare quality for Medicare beneficiaries while others generated null effects.

However, a large research gap on how Medicare policies affect the healthcare market covered by private insurance still exists. Studies in this field mainly hold two countering viewpoints, ie. cost-shifting versus price-following. The cost-shifting hypothesis claims that, when Medicare reduces the payments, to maximize profits, providers will offset the payment decreases by extracharging private insurance. While the price-following hypothesis says that Medicare has the most bargaining power and the price set by Medicare will serve as the anchor of bargaining. The motivation framework placed by Medicare will be extended to the whole healthcare market. The cost-shifting hypothesis is intuitive, but frontier studies documented the facts favoring the alternative, where most of them focused on price setting.

A Medicare innovation named Comprehensive Care for Joint Replacement Model, the Model hereafter, provides a unique opportunity to shed light on the debate. The Model targets patients undergoing hip and knee replacements (also called lower extremity joint replacements or LEJR). The Model was designed to curb the expenditure by alternative payment type different from the widely applied Fee-For-Service (FFS) payment type. Under FFS, hospitals are reimbursed for each particular service provided. Instead, the Model sets a target price and changes the reimbursement to per episode payment. The Model is the first mandatory model which is randomized national-wide. More details about the Model will be introduced in the following sections.

In this paper, I investigate how healthcare providers respond to the Medicare policy when treating patients with private insurance, who should not be targeted by the Model. I pay close attention to the Model effect heterogeneity. I focus on four different outcomes - discharge locations, length of stay (LOS), total charge, and total cost using the Difference-in-Differences(DiD) and the Difference-in-Differences-in-Differences(DDD) strategies; with inpatient record data from Healthcare Cost and Utilization Project (HCUP) State Inpatient Databases (SID). The database records comprehensive patient, physician, and hospital information, which provides the opportunity to investigate the model.

I first show the Model effects on the Medicare population consistent with the findings of previous research, which serves as a baseline for comparison. Extending the analysis to private-insured patients, I find similar Model effects but on a larger scale. Patients with private insurance are 8-12 percent more likely to be discharged to Home-with-HealthCare(HHC), 2-3 percent less likely to Skilled Nursing Facilities(SNF), and 7-8 percent less likely to Home directly. The cost is 700-800 USD higher on average. These effects are almost twice the size of those on the Medicare population. Nevertheless, there is no significant effect on either LOS or total charge. The CJR model effects, direct and spillover, are consistently observed while checking the robustness.

Then I investigate the policy heterogeneity. Incited by Acemoglu and Restrepo (2020), this study introduces the penetration term to capture the policy heterogeneity, which provides me with a Bartik-like instrument. I focus on four dimensions, HHC-SNF penetration, LEJR penetration, Medicare penetration, and LEJR-Medicare penetration, using a DDD model. These dimensions are related to the channel conveying the CJR model effects. The results show sizeable heterogeneity through these dimensions. For example, hospitals in the high HHC-SNF, LEJR, and Medicare penetration regions will be more likely to discharge patients to HHC. Hospitals in a region with 1.2 HHC-SNF penetration, or with 10% of total cases being LEJR patients, or with half of the total patients paid by Medicare, or 60% of LEJR patients covered by Medicare, will increase the use of HHC by 9 percent and decrease SNF and Home discharge by around 3 percent.

The previous section shows the direct Model effects on the private sector, which can be seen as reduced form estimates. To consider the Model effects causally, I ask if and on what scale the Medicare policy will be transmitted from Medicare patients to the private sector. By looking at the transmission rate, I can also show if the hospital will make decisions based on the patient's insurance type. In particular, I construct an instrument using the predicted outcomes of Medicare patients. The instrument then is used to apply the 2SLS strategy to link and measure the transmission rate. The results of focused outcomes confirm the following type of transmission. I find a one-dollar increase in the cost of treatment for the Medicare patients will increase those for private-insured patients by 0.938 dollars. Similar but smaller transmission rates are found among discharge locations.

Previous findings clearly show the spillover effects following the direct Model effects, which also raises the possibility that the healthcare providers will change their behavior when treating other related patients. To investigate this possibility, I create two samples, one covering those treated by the Model physicians but not under the Model, the other covering patients undergoing related replacement procedures. The results show the policy effects similar to those targeted by the Model.

My study contributes to several strands of research. First, this study sheds light on the debate on Medicare policy effects outside the Medicare population. Medicare as the largest payer has considerable influence outside the Medicare patients; but no consensus has been reached about how the non-Medicare agents respond. Some people worry that reducing the Medicare payments will incentivize hospitals to charge non-public payers more to cover the cost (Morrisey, 1993; Glazer and McGuire, 1994). This concern has been frequently raised at the government level and legislative body (Frakt, 2011). Frakt (2011) provided a detailed review of the research on cost-shifting in the healthcare sector. However, increasing studies showed that the worry of cost-shifting is nothing but a mirage (White, 2013; White and Wu, 2014). They documented the changes in the price charged to non-Medicare agents pegging the one regulated by Medicare. For example, Berenson et al. (2015) showed the Medicare Advantage (MA) rate [1] is usually 105 percent to 120 percent of the traditional Medicare rate, which is the same case of private insurance rate (White, 2013; Clemens and Gottlieb, 2017; Clemens et al., 2017). Research mostly concentrate on price (Duggan and Scott Morton, 2006, 2010; Alpert et al., 2013; Clemens and Gottlieb, 2017), and recent ones started to look at other fields like recruitment (Dranove and Ody, 2019) or physician practices (Song et al., 2015). In the case of the Model, Medicare did not adjust the price directly. Studies found the Model has spillover effects following direct effects on Medicare Advantage patients (Meyers et al., 2019; Wilcock et al., 2020; Einav et al., 2020). A very recent study extended the analysis to the patient with private insurance in Florida(Chen et al., 2022).

This study also contributes to the research investigating policy heterogeneity. Medicare policies do not affect the healthcare market universally and equally. Research showed that Medicare innovations such as Hospital-Acquired Condition Reduction Program are more likely to pose a penalty on teaching institutions and hospitals caring for more patients with socioeconomic disadvantages (Rajaram et al., 2015; Lawton et al., 2020). Increasing studies have split a section to look at heterogeneity (Clemens and Gottlieb, 2017; Einav et al., 2018b; Cooper et al., 2019; Baker et al., 2019; Hausman and Lavetti, 2021). Evidence also showed that the Model incentivizes gain-sharing within hospitals, which introduces the region- or hospital-specific heterogeneity (Sood et al., 2019). Einav et al. (2020) divided the sample by hospital characteristics and investigate the heterogeneity.

Finally, this study contributes to the discussion about alternative payment models in the healthcare sector. Approximately 30 percent of traditional Medicare payments flow through alternative payment models (Obama, 2016). Before the Model, another alternative payment

[1] Medicare Advantage, MA, is a plan providing Medicare services through private sector insurances.

model, the BPCI model, attracted much attention. Most of the studies analyzed the BPCI model from the patient side while only a small but emerging amount of papers concentrate on the provider side (Edwards et al., 2017). As more and more innovations are implemented, researchers turned to focus on the provider side (Dummit et al., 2016; Iorio et al., 2016), which is the direct target of the payment policies. The findings of these studies are varied, which might be due to the small sample size or the voluntary participation design of the model Smith (2021). Later in 2015 comes the CJR model, which drew a lot of research attention (Finkelstein et al., 2018; Meyers et al., 2019; Wilcock et al., 2020; Einav et al., 2020). Chen et al. (2022) is the first to investigate the spillover effect on the private-insured population, and Meyers et al. (2019) is the only research that paid attention to the hospital heterogeneity, which stratified the dataset by hospital characteristics.

The rest of the paper will proceed as follows. Section 2 provides the background information. Section 3 presents the direct and spillover effects of the CJR model based on DID. Section 4 describes our DDD strategy on heterogeneity and presents the estimation results. Section 5 presents the results of the spillover effects on non-targeted non-LEJR patients, and section 6 is the conclusion.

2 Background

This section will provide background information on the CJR model and LEJR procedures. The LEJR is one of the most common and costliest inpatient Medicare procedures, which contains a group of procedures such as hip and/or knee replacements. It had more than 400,000 cases and cost more than 7 billion USD (CMS-Innovation-Center, 2021), which accounted for about 5 percent of Medicare admissions and inpatient spending in that year (Finkelstein et al., 2018). This group of procedures is frequently conducted towards the elderly population; as the population ages, the importance of this procedure will increase, accompanied by a rocketing cost.

The Medicare authority launched alternative payment and expected that these models could give healthcare providers incentives to take action in reducing costs (Siddiqi et al., 2017). However, the voluntary model like Bundled Payments for Care Improvement Initiative is found to be on pace to lose more than $ 2 billion (Smith, 2021). Aiming to further reduce the cost while maintaining the quality, the Model is developed. It is the first mandatory national-wide randomized model, which was designed in 2015 and implemented in April 2016. In July 2015, CMS published the randomization strategy, with 196 metropolitan statistical areas (MSAs) being eligible. As a mandatory model, the Model requires hospitals in the selected MSAs to participate unless they fell in excluding rules (Finkelstein et al., 2018).

The payment was not simply altered to bundled type. To minimize the distorting effect, Medicare will pay healthcare providers by services or procedures provided (FFS type) during the LEJR episode. One LEJR episode contains two periods, treatment and recovery. It covers the time of inpatient and 90 days post-hospitalization, including the use of HHC and SNF. The Model will set a threshold price for each hospital at the end of the year. The target price is calculated according to the hospital's historical LEJR spending, average regional spending, and re-admission. Hospitals that met two conditions - (1) pre-episode spending lower than the target price and (2) outcomes higher than the quality threshold - can receive a one-time bonus payment; while hospitals having pre-episode spending higher than the target price will have to cover the difference by their own. Medicare hoped that this bundled type of payment strategy could create an incentive for hospitals to manage the cost and improve the quality of the whole episode.

The Model was implemented at a certain date and MSAs, which creates sharp cut-offs geographically and chronologically and therefore is ideal for empirical research. Finkelstein et al. (2018) was the first to investigate the Model. They reproduced the MSAs randomization design and reported the interim outcomes from the first year of implementation using Medicare FFS claims data. They identified and documented 75 treated and 121 controlled MSAs, which helps the following research, including mine. They focused on outcomes including discharged locations and the number of days in institutional post-acute care. Their empirical approach found a lower share of patients discharged to institutional post-acute care facilities and lower spending in facilities. However, their study did not find a significant change in overall Medicare expenditures. Three subsequent studies using data from Medicare Provider Analysis and Review showed the spillover effects on the patients covered by Medicare Advantage, an insurance program managed by Medicare but reimbursed through private insurance companies(Meyers et al., 2019; Wilcock et al., 2020; Einav et al., 2020). These studies all found a significant decrease in SNF use, yet the findings of other outcomes are varied. Zhu et al. (2018) conducted telephone interviews with chief medical officers, directors of post-acute care, physician administrators, and other operations executives at the selected hospitals. They found that the treated hospitals responded to the CJR model in many ways, such as reducing SNF referrals, patient expectation management, and strengthening linkages with HHC agencies. The most recent study by Chen et al. (2022) extended the frontier by using LEJR patient claims data from Florida Agency for Health Care Administration and estimated the spillovers on the non-elderly private insured population. The size of spillovers on the private-insured population is similar to that of the Medicare Advantage population. They investigated the procedures performed by LEJR-affected providers, though the identified effects are marginal.

3 Data

The primary data used in this study is the inpatient records from HCUP SID. The SID is the most extensive publicly available all-payer inpatient data in which hospital and location identifiers are available after 2013 in the U.S. In total, the SID encompasses almost 97 percent of all U.S. hospital discharges (CMMS, 2020). Most importantly, the dataset contains vital clinical and non-clinical information about all inpatients, including visit year, month, hospital identifier, Major Diagnostic Category, and payment type (first three types). This information can identify the spillovers at the inpatient visit level.

I collect the data from Arizona, Florida, North Carolina, New Jersey, New York, and Washington. Among these states, 39 MSAs are covered, while 23 are in the control group and 16 are in the treatment group. The CJR model was implemented on April 1st, 2016, and scheduled to end on December 31st, 2020[2]. However, starting from February 1st, 2018, CMS changed the rules: participation is no longer mandatory for the hospitals in the selected MSAs. As a result, the number of participating hospitals decreased from approximately 800 to 465, and the model was no longer ideal for treatment effect estimation. Therefore, this study only covers the years 2013 through the year 2017. In addition, SID data provide the information on admission months, and those visits before April would be seen as before the experiment.

[2]In 2020 the model was extended to March 2021

4 Empirical Strategy

This section will introduce the empirical strategies and regression models. The first part of the empirical strategy consists of a difference-in-differences (DiD) design and a difference-in-differences-in-differences (DDD) design.

The former identifies the Model effects with differences coming from time and locations, and the latter examines the heterogeneity adding one more difference coming from penetrations. The DiD model will compare the changes in outcome variables between patients in treated regions and those in the control ones, identifying the average effect of discharge probability/cost/charge/day to a specific destination as the changes in the treated hospitals to those in the control hospital. To correctly identify the causal effects, DiD requires a parallel trend assumption. This assumption can be guaranteed by the mandatory participation design of the CJR model, which rules out the possibility of self-selection. Table 1 presents the summary statistics by treatment status and year. It clearly shows that the outcomes such as discharge location and LOS are similar between the treated MSAs and control MSAs before the treatment. The empirical model is as follows:

$$y_{ijt} = \pi_1 + \sum_{t \neq 2014} \pi_{2,t}(Treated_{ij} \times \lambda_t) + \Pi' X + \gamma_j + \lambda_t + \varepsilon_{ijt} \tag{1}$$

for each patient i at MSA j in the year t. The patient outcomes y includes discharge locations, length of stay, total charges and costs. X is the vector including a set of patients demographics and hospital characteristics. γ_j is the MSA fixed effect and λ_t is the year fixed effect. $(Treated_{ij} \times \lambda_t)$ is the DiD term and $\pi_{2,t}$ estimates the CJR model effects, which is the parameter of interest. I do not follow the "pre-post dummy" DID term used by Finkelstein et al. (2018) or "pre-only dummy" applied by Meyers et al. (2019); Wilcock et al. (2020); Einav et al. (2020). Instead I drop the 2014 year dummy and use λ_t, which will allow me to present the path of CJR effects during pre- and post-treatment period. The error term ε_{ijt} is allowed to be correlated and clustered at the MSA level.

The DiD coefficients in the baseline model generate an effect estimate averaging across all treated MSAs and implemented years, which does not show the complete picture of the CJR model. I will investigate the heterogeneity by looking at four penetrations, HHC-SNF penetration, LEJR penetration, Medicare penetration, and LEJR-Medicare penetration. These dimensions affect the channel conveying the CJR model effects. HHC-SNF penetration is the relative employment between HHC and SNF at MSA j before 2015. MSA j with an HHC-SNF penetration of 2 means the average number of employees in HHCs is twice as large as those in SNFs before 2015. Such value of HHC-SNF penetration indicates that this region has a more mature network of Home Healthcare providers, and therefore, should have a larger effect by allowing hospitals to allocate the patients from SNF to HHC. LEJR penetration is calculated as the total number of LEJR cases divided by the number of all cases conducted in hospital j before 2015. Medicare penetration is calculated as the share of cases covered by Medicare to total cases in hospital j before 2015 and LEJR-Medicare penetration is the share of Medicare-covered LEJR cases to total LEJR cases in hospital j before 2015. For example, having an LEJR/Medicare/LEJR-Medicare penetration of 50 percent will be meaning that half of the patients were LEJR patients or covered by Medicare or half of the LEJR patients covered by Medicare. We should expect hospitals have higher penetration will have higher exposure to the Model and hence larger effects. Only data before 2015 is used to create the exogeneity. By including these penetration variables, I consider several possible exposures of the treated hospitals towards the CJR model: how mature the HHC service comparing to the SNF service in the MSA; how many LEJR cases the hospital has admitted; and how many LEJR cases were covered by Medicare.

I combine the inpatient records data with the employment data from County Business Pattern (CBP) and extend the baseline model by incorporating the new differences from penetrations. The new difference-in-difference-in-differences (DDD) can be presented as follows:

$$\begin{aligned} y_{ijt} = \pi_1 &+ \sum_{t \neq 2014} \pi_{2,t}(Treated_{ij} \times \lambda_t \times \omega_j) \\ &+ \sum_{t \neq 2014} \pi_{5,t}(Treated_i \times \lambda_t) + \Pi' X + \gamma_j + \lambda_t + \varepsilon_{ijt} \end{aligned} \tag{2}$$

where the control vector X, MSA fixed effects γ_j and year fixed effects $lambda_t$ are the same as before. The triple interaction term, $(Treated_{ij} \times \lambda_t \times \omega_j)$, is the DDD term, while variable ω_j is penetration variable. The penetration variables make the DDD term a Bartik shift-share instrument with the shift from the year and treated regions and share from the penetrations.

The outcome of LOS will be estimated by Poisson regression; total charge and cost will be estimated by General Linear Model (GLM) with log link and gamma distribution. I will take a bit more of the paragraph to explain the strategy of regressing discharge locations, which is different from the method used by all of the other CJR research. The mostly applied method uses logit model to treate several discharge locations separately. Nevertheless, the discharge location is regarded as a categorical variable in this study. To estimate the cardinal discharge, I apply the multinomial logistic regression model (Mlogit) instead. This strategy has two main advantages. First, it allows to ask a different question. I consider the physicians making the discharge decisions out of a choice basket rather than answering "yes" or "no" to several questions. Alternative payment models like CJR are designed to give healthcare providers incentives to choose the possible option with the lowest cost while maintaining the quality. Given the predictable higher cost in the SNF (Glickman et al., 2018; Einav et al., 2020), better managing of disposition can allow hospitals to reduce the cost. Therefore, the question is not 'if the CJR model will affect certain disposition' but 'how will the CJR model affect the disposition choice in general.' With the Mlogit model, the choices are considered simultaneously, and the marginal effects of treatment variables on different dispositions can be summed to 1. The marginal effects under the Mlogit model are hence more interpretable. Second, estimating the model under the Mlogit model is more efficient. Agresti (2018) showed that collapsing the multi-category variable to binary and applying ordinary logistic regression will generate larger standard errors. This problem will be severe when the number of categories is large.

To systematically measure the transmission from treated Medicare population to the private insured population, I consider an instrumental variable strategy. This strategy exploits the effect variation in the proximity of other hospitals in the same MSA. Specifically, I first calculate the hospital average outcomes $\bar{y}_{hjt}$ by hospital h and post-treatment status $\mathbf{1}\{t \in Post\}$ only using Medicare records. Using the collected hospital level average outcomes $\bar{y}_{hjt}$, I estimate the treatment effects using the following equation:

$$\bar{y}_{hjt} = \theta_{iv01} + \theta_{iv02}(Treated_j \times Post_t) + \theta_{iv03}Post_t + \gamma_j + \varepsilon_{hjt} \tag{3}$$

for hospital h in MSA j at time t. The variable of interest is $(Treated_j \times Post_t)$, which is an interaction between the treatment dummy and the after 2015 dummy. This is equivalent to the classical DiD design in hospital level. Then the estimated coefficient $\hat{\theta_{iv02}}$ is then collected and used to predict the outcome change:

$$\bar{y}_{hj,post} = \bar{y}_{hj,pre} + \hat{\theta}_{iv02} \tag{4}$$

The predicted value $\bar{y}_{hj,post}$ will be assigned to each patient who belongs to hospital h. Then the following two-stage least squares regression will be estimated:

$$\begin{aligned} y_{ihjt}^{medicare} = \theta_{iv11} &+ \sum_{t \neq 2014} \theta_{iv12,t}(Treated_{ij} \times \lambda_t \times \bar{y}_{hj,post}) \\ &+ \sum_{t \neq 2014} \theta_{iv13,t}(Treated_i \times \lambda_t) + \Pi'_{iv1}X + \gamma_{1j} + \lambda_{1t} + \varepsilon_{1ijt} \end{aligned} \tag{5}$$

$$\begin{aligned} y_{ihjt}^{private} = \theta_{iv21} &+ \theta_{iv22}\ \hat{y}_{ihjt}^{medicare} \\ &+ \sum_{t \neq 2014} \theta_{23,t}(Treated_i \times \lambda_t) + \Pi'_{iv2}X + \gamma_{2j} + \lambda_{2t} + \varepsilon_{2ijt} \end{aligned} \tag{6}$$

for patient i in hospital h, MSA j and year t. Equations used in two stages are similar to the one used in the heterogeneity analysis. The instrument is included in the first stage and fully interacted with the treatment and year dummy. Then the estimated value from first stage $\hat{y}_{ihjt}^{medicare}$ is included in the second stage to estimate the value of treatment effects being transmitted to the non-targeted private insured patients.

In the last section, I measure the heterogeneity in the model transmission by incorporating the penetrations and IV estimate. Specifically, I estimate the following equation:

$$\begin{aligned} y_{ihjt}^{private} = \theta_{iv31} &+ \theta_{iv32}\ \hat{y}_{ihjt}^{medicare} \times \omega_j + \theta_{ymedi}\ \hat{y}_{ihjt}^{medicare} + \theta_\omega \omega_j \\ &+ \sum_{t \neq 2014} \theta_{33,t}(Treated_i \times \lambda_t) + \Pi'_{iv3}X + \gamma_{3j} + \lambda_{3t} + \varepsilon_{3ijt} \end{aligned} \tag{7}$$

where ω_j is the penetration value similar as before. The coefficient of $theta_{iv32}$ will measure the transmission heterogeneity.

Finally, it is important to highlight a limitation to this empirical strategy. I assume no other trend will be correlated with the treatment. One possibility is that the outcomes might be affected by other hidden factors, such as hospitals implementing new technology or structural change. The region and year-fixed effects will capture these factors to a large extent.

5 Empirical Results

5.1 Summary Statistics

Table 1 presents the summary statistics of control variables and outcomes of the whole population by payment and treatment status from 2013 to 2017. As shown, the average age of Medicare 65+ in the control group before the Model (column 1) is 74.51, while that of the treatment group, column (2), is 74.93; this number is 59.69 versus 59.19 for private insured patients, which shows that the targeted replacement surgeries are very common among the elder population. The replacements are also very commonly conducted as elective surgeries, among the female, or white population. The characteristics of patients mostly parallel the control and treatment groups, in both Medicare and private insured group. One exception is the white population share - around 10 percent higher in the control group compared to the treated group both found in Medicare and private-insured groups.

The lower panel of table 1 presents the summary statistics of the outcomes. We find a lower share of patients in the treated group were discharged home without healthcare and a higher share discharged to SNF compared to their peers in the control group. In average, patients in control group experienced shorter LOS (2.9 days in control group relative to 3.3 days in treated group for Medicare patients, 2.3 days v.s 2.6 days for private insured patients), were charged lower (63,986 USD v.s 70,347 USD for Medicare and 57,770 USD v.s 66,739 USD for private insured) and were treated with lower cost (14,012 USD v.s 15,967 USD and 14,301 USD v.s 16,767 USD). We can also see a larger sample size in the treated group, which is consistent with the Model design. The model is designed to be implemented in the regions with more LEJR procedures practiced and higher cost (Finkelstein et al., 2018; Smith, 2021). The summary statistics of patient demographics in this study are very close to those of the samples used by previous studies focusing on the Model.

Though table 1 provides us a general picture of model outcomes, it will be rash to assert and reach a conclusion about the outcomes of the Model. The next section will show the results from the empirical setting.

5.2 Results: CJR direct effects and "price following"

In the rest of the paper, I will intensively use the term (direct) effects and spillovers, where the former is pointing at the Model effects on the Medicare population and the latter is those on the private-insured population. Figure 1 to figure 4 present the marginal effect estimates of $\pi_{2,t}$ of equation 1, which provides a summary of the baseline findings visually. Four figures correspond to four outcomes - discharge locations, total cost, LOS, and total charge. The 2014 treatment-year dummy is dropped and that year serves as the base for benchmarking. The CJR model was announced in July 2015 and formally implemented in April 2016. Hence, the 2015 estimates are considered to contain much noise given that some of the informed hospitals would react before the formal implementation, though the results indicate this noise to be marginal. The estimates of 2013 show there is no or minimal pre-treatment divergence between the treated patients and control patients.

Several findings are shown. First, both direct effects and spillovers are found, but only in some outcomes. I find that in the treatment years, patients are more likely to be discharged to HHC and less likely to be discharged to SNF and Home directly, which are sizable and statistically significant. In detail, as shown in the summary statistics, the probability of HHC discharge increased by 9.3 percent. The Model increases the likelihood of using HHC by 5.5 percent (59.13 percent of 9.3 percent) in 2016 and 8.5 percent (91.39 percent) in 2017 (table 2). The decreases in other discharges are slightly smaller but also statistically significant. These results are aligned with the empirical findings of previous studies on the Medicare population (Finkelstein et al., 2018; Einav et al., 2020) and spillovers in Florida (Chen et al., 2022).

The results also show significant effects on the total cost. The average cost per patient of the treated group exhibits an increase for Medicare and private-insured populations. The increase in cost might be because that hospitals are risk-averse about the possibility of higher costs in the downstream facilities and therefore treat patients more intensively. In addition, Sood et al. (2019) and Zhu et al. (2018) documented that most of the surveyed hospitals had implemented programs to improve post-hospitalization. These programs include developing a network with home health services or setting up telehealth services for physical therapy. Though part of the reason for implementing these programs was reducing cost, developing programs and networks itself might have higher costs for hospitals. As for two other outcomes - LOS and total charge, I find slight and insignificant increases for both Medicare and private-insured population.

Third, compared to the size of direct effects, the size of spillovers is larger. For example, the effect on discharge location in 2017 is 12.3 percent of the private-insured population while 8.5 percent of the Medicare population. Similarly, the cost effect was 828.6 USD in 2017 for the private-insured population and 709.1 USD for the Medicare population. The findings of the larger size of spillovers are aligned with previous research. For example, Einav et al. (2020) found that patients covered by Medicare Advantage, a non-targeted program under Medicare, are a 3 percent higher the likelihood of being discharged to HHC; Chen et al. (2022) identified a 7.64 percent increase in using HHC of private-insured population and only 2.21 percent increase of the Medicare population.

Summing up, I found that the Model had an impact on the targeted population and sizeable spillovers on the non-targeted population. The Model altered the healthcare providers' choices on discharge location where the use of the most expensive location, SNF, and routine discharge witnessed a decrease, and the use of HHC has been increasing. In addition, the healthcare cost is found to be increasing. Across all outcomes, I found more significant spillover effects than direct effects. These results provide evidence to support the hypothesis of "price following" in the way that hospitals treated the patients with private insurance the same way as they treated the Medicare patients. Yet hospitals do not follow the price but the incentive of decrease the use of expensive discharge when treating the patients paying through private insurance.

5.3 Robustness checking

To rule out the possibility of the non-treatment effect, I consider several conditions that might affect the results. I first investigate changing the base year. The baseline results drop out 2014 year treatment dummy, which serves as the benchmark. To check the robustness, I change the base year to 2013. The results are presented in table 3 and table 4. The results using 2013 as the benchmark year parallel those using 2014 as the benchmark year, which rules out the possibility that this is due to the selection of the benchmark year.

Other results of robustness checking are presented in table 5 and 6, where table 5 contains the estimates of discharge and table 6 contains those of LOS, cost and charge.

In detail, column (1) presents the baseline spillover estimates for comparison. Other than Medicare and private insurance payments, several payments are reported by SID, including Medicaid, self-pay, or no charge. Patients may pay the charges or split the payment in multiple ways. For example, those covered by private insurance might still need to pay a fixed amount of money co-payment themselves. The primary payment type was recorded in the variable Pay1, while residual payments were recorded in variables of Pay2 and Pay3. Column (2) is for the relaxed sample, which contains the patients paying by private insurance and all payments but not Medicare. Column (3) presents the estimates using the sample restricted to those not mentioning Medicare in any payment variable. The results are stable across these two specifications.

The choice of discharge might be affected by the type of healthcare institution. One concern is that the long-term acute care (LTC) hospitals can provide similar care as HHC but induce a higher cost and hence bias our estimates. Einav et al. (2018a) and Eliason et al. (2018) provide an analysis showing LTC hospitals react to the financial incentives by strategic discharge. Column (4) considers this possibility by constricting the sample to the patients admitted to only non-rehabilitation and non-LTC hospitals. In addition, the details of the CJR model were officially announced in 2015 and implemented in 2016. This setting might contaminate the DID model, where some hospitals noticed the CJR model could react before the implementation time. Therefore, column (5) excludes the samples in 2015. Column (6) excludes the patients from Arizona, which is not a treated state. The Model targeted LEJR patients with DRG 469 and 470. Though no study has reported different outcomes between two DRGs, the concern of differences between two DRGs is not yet solved. In this study, 96.3 percent of the observations are in DRG 470, while the rest are in DRG 469. Column (7) presents the estimates with only observations in DRG 470. Across these specifications, the estimates are all similar to the baseline estimates and statistically significant.

6 Heterogeneous model effects

The second part of the paper focuses on the heterogeneity study using the DDD framework. Some previous studies have pointed to the possibility of heterogeneous effects. Meyers et al. (2019) and Einav et al. (2020) investigate the heterogeneity across hospitals by separating the hospital samples by LEJR-related factors, hospital type, and geography. They found some differences across these sub-samples.

In this study, I examine the heterogeneity of CJR model effects through four dimensions, which include both hospital-specific internal factors and the external structure of the local health-care market. These dimensions include (1) relative employment between HHC and SNF in each MSA before 2015, with HHC and SNF employment data from CBP (HHC-SNF penetration), (2) the proportion of LEJR cases to total cases in one hospital before 2015 (LEJR penetration), (3) the proportion of Medicare cases to the total number of cases in the hospitals before 2015 (Medicare penetration), and (4) the proportion of LEJR cases covered by Medicare to the total number of LEJR cases before 2015 (LEJR-Medicare penetration). Penetration calculation was constricted using data before 2015, the year the CJR model is recognized, to guarantee the exogeneity. In this way, the penetrations provide me with Bartik-like variables which further guarantee the exogeneity. Regarding the outcomes, I will only focus on discharge locations and cost, which are found to be significantly affected under the CJR model.

The estimated heterogeneous effects on discharge locations are plotted in figure 5 and 6 and those on cost in figure 7 and 8. The estimated marginal effects of the penetrations are presented in table 7.

The results show significant heterogeneous effects through four dimensions. First, looking at the Home discharge, increases in all penetrations tend to decrease the probability of using Home discharge, which is presented on the left side in the figures and the first row of table 7. The associations are statistically significant across most parts of the levels of the penetrations. It shows that the decrease in the likelihood of direct home discharge is universal among all hospitals, and as hospital exposure to the Model increases, this tendency will be strengthened.

Second, the results on HHC discharge show sizeable and statistically significant effects in decreasing the use across all hospitals, which are presented on the right side of the figures and the third row of table 7. Yet, these effects have varied tendencies through four dimensions - the increases in both HHC-SNF penetration and LEJR penetrations end to increase the HHC discharge probability (on average, 1 fold higher in HHC-INF relative employment MSA will increase that to HHC by 6.7 percent, 1 percent increase in LEJR penetration will increase the use of HHC by 0.3 percent, table 7). These results fall aligned with the assumption that in a region with a more developed HHC sector, hospitals will incline to use HHC. However, high exposure to Medicare or LEJR-Medicare penetration does not change the high use of HHC discharge a lot, though the confidence interval becomes very large.

The change in the use of SNF discharge does not vary a lot through these dimensions. I identified significant decrease use of SNF in a hospital with high HHC-SNF penetration and LEJR penetration. However, when the penetrations related to Medicare patients increase, the effect of decreasing the use of SNF discharge disappears. The null effect in high Medicare penetration hospitals is probably due to the characteristic of SNF use. A hospital with a high Medicare or LEJR-Medicare penetration also means more elder populations were accepted into it. The physicians in this hospital should encounter more complex health situations and the decision of discharge will be more conservative. Therefore high Medicare-related penetration will be affected from both sides, with higher Model exposure and also higher use of SNF in general.

The results on cost are shown in figure 7, 8 and table 7. The results show that patients in hospitals exposed to a higher level of LEJR penetration and a lower level of Medicare and LEJR-Medicare penetrations will tend to induce a higher cost. In detail, a Medicare patient treated in a hospital with 10% of cases being LEJR patients or 35% of total cases covered by Medicare or approximately 55% of LEJR patients covered by Medicare will induce a 1000 USD higher cost. Similar cost increases can also be found among the patients with private insurance, shown in figure 8. The only difference between Medicare and private-insured patients is in HHC-SNF penetration. For Medicare patients, the cost does not change significantly by HHC-SNF penetration, while for private insured patients, treated in the region with a higher HHC-SNF penetration will induce higher cost, as shown in the sub-figure 7(a).

The calculations of the penetrations, LEJR, Medicare, and LEJR-Medicare, use the number of episodes as the numerators and denominators. To check the robustness, I also calculate these 3 penetrations using the cost and charge of episodes, which yield 6 penetrations. I repeat the heterogeneity analysis using these 6 penetrations and present the estimated marginal effects in appendix table A1 and treatment effects in appendix figures. The marginal effects of these 6 penetrations are on a similar scale and the predicted treatment effects shown in the figures parallel those estimated by episode numbers.

The above results show that the Model, though mandatorily changed all payment methods for Medicare patients, did not have a unanimous impact on both targeted and non-targeted patients in hospitals with different characteristics. Instead, the Model effects and spillovers were conveyed differently by the hospital's exposure, including local healthcare provider structure, the penetration of Medicare, and the intensity of LEJR cases.

7 Functional Form Results

Previous sections demonstrate spillover effects of the Model on non-targeted private insured patients following the effects on targeted Medicare patients. The study (as well as many previous studies) estimates the effects separately for Medicare and private-insured patients and shows the results are in parallel, which serves as the reduced-form measures. I push the study further by applying an instrumental variable strategy to directly capture the relative scale of Model effects between Medicare and private-insured patients. This strategy allows me to both directly measure the transmission of Medicare policy to the private sector and show if hospital treats patients with different insurance differently. Incited by Clemens and Gottlieb (2017), who treated the predicted price as the instrument, this study extends the instrument to both total cost and discharge locations, which show significant effects in the previous section.

The results of IV estimates of the Model transmission scale can be found in the table 12. The first panel presents the estimates of cost and the rest is for discharge locations. The first column shows the estimated marginal effects of θ_{iv22}, which is from the first stage. All the estimated marginal effects from the first stage are statistically significant, and those of cost, SNF discharge HHC discharge are very close to 1. The second column presents the reduced form results and column 3 reports the IV estimate of equation 6.

The findings are as follows. First, looking at the estimate of $\hat{\theta}_{iv22}$ in column (3), it clearly shows the following type of transmission. This is to say that hospitals will change the type of treated patients in private-sector as those covered by Medicare, and treat comparable patients with different insurances indifferently at a certain level. The estimated cost coefficient of 0.938 means that for every dollar-cost change for Medicare patients, the policy will change the cost of private-sector patients by 0.938 dollars. The Model has a similar scale of treatment transmission to the private sector on discharge decisions. The coefficient of 0.867 of HHC discharge, for example, means for every one percent change in discharging Medicare patients to HHC will change that of the private sector by 0.867 percent in the same direction. All these estimates are strongly statistically distinguishable from zero, allowing me to reject the null that the treatment changes on Medicare patients have no impact on the private sector. The coefficient estimate of the total cost, 0.938, is very close to the estimate of payment change transmission by Clemens and Gottlieb (2017). However, these estimates are statistically distinguishable from 1, except for that of cost. The estimate of SNF discharge is on a smaller scale than those of other discharges. This is because hospitals tend to discharge patients with more complications to SNF Paredes et al. (2019), and less room for hospitals to manipulate the discharge when treating them. This finding shows that hospitals will take the patient's insurance type into consideration when deciding on discharge. Second, the Mlogit method shows not only the probability changes of the discharge itself but also where these probability changes from, given the patients can only be discharged to one destination among three locations. Recalling the estimated results from the previous section, the Model increases the use of HHC discharge while decreasing those of SNF and Home discharge without Healthcare. As shown, the transmission of discharge probability is not uniformly from the rest two locations. The increases in HHC discharge come mostly from the decreases in Home discharge and some from that SNF discharge. The reduced use of Home discharge, shown in the first panel, mostly goes to the increases in the HHC discharge. That of SNF discharge, however, solely increases the use of Home discharge. To check the robustness and make the patients with different insurances more comparable, I restrict the data to contain those patients with ages more than 55 and less than 75 (65 ± 10, where 65 is the cut-off age for patients who can be covered by Medicare) and estimate again using the restricted data. The results are presented in appendix table A6, which shows identical estimates to the main table.

The results show that hospitals treat private-insured patients which mimics the type of treating Medicare patients at a certain level; this confirms the following type of Medicare policy effects on the private sector from a causality point of view. In the following section, I will investigate the heterogeneity of the transmission in the four dimensions mentioned above.

7.1 Functional Form - heterogeneity

The previous section shows the heterogeneous model effects on the private sector directly, indicating the heterogeneity in reduced form Model effects. In this section, I explore this possibility by looking at the four dimensions measuring in what scale the hospital is exposed to the model: HHC-SNF penetration, LEJR penetration, Medicare penetration, and LEJR-Medicare penetration, using equation 7. By interacting with the penetrations and instrument, this strategy can allow me to show the heterogeneous transmission effect, and hence answer if a hospital makes insurance-based decisions heterogeneously when exposed to a different level of the Model. Different from the heterogeneity analysis shown above, this section presents the Model effect estimates on the private sector scaled by the Model's direct effect.

The estimated marginal effects of θ_{32} in different value of penetrations are plotted from figure 9 to figure 12, which consist of the heterogeneity of home discharge, SNF discharge, HHC discharge and cost respectively. For each of the figures, four dimensions of heterogeneity are investigated separately.

The graphs clearly show the heterogeneity in the policy transmission, which confirms that hospitals are making insurance-based decisions with a consideration of model exposure. The findings are summarised as follows. First, for most of the outcomes, exposure to higher levels of penetrations will increase the scale of transmission from Medicare patients. Taking the home discharge as an example, as shown in figure 9, exposure to a higher level of HHC-SNF penetration and Medicare penetration increases the transmission rate of home discharge from around 0.8 to very close to 1. This is also true for SNF discharge. However, through some dimensions, there is no meaningful change in the transmission rate. The changes in LEJR-Medicare penetration do not affect the transmission rate of four outcomes, while those in Medicare penetration have no impact on SNF and HHC discharge. Interestingly, the transmission rate of HHC discharge decreases when exposed to high levels of penetrations.

8 Other non-CJR patients

Several strands of research show that the Model has long-lasting effects on the practices of physicians (Chen et al., 2022) and connection networks among healthcare providers (Zhu et al., 2018; Sood et al., 2019). Chen et al. (2022) showed that Model-affected providers will significantly change their behaviors in making the discharge decision on patients classified into a closely related MDC. Their study provided evidence showing that the effects might be to a greater extent. There are some patients in the groups related to the replacement procedures but not considered Model targets. Given the sizable spillovers identified on private-insured patients undergoing replacement procedures, there might be other forms of spillovers towards them.

In this section, I investigate the Model effects on three other groups of patients. The first group includes those patients treated by the physicians who conducted LEJR procedures (CJR physicians hereafter), and with a certain diagnosis. My data provide identifiers for up to 5 physicians per episode and in this research, the first two will be used. After collecting, the information CJR physicians will be used to identify them among all episodes classified other than the Model DRGs (DRG 469 and 470). Following Chen et al. (2022), I restrict the patients being classified in MDC-8 [3], which is considered mostly related to the targeted replacement surgeries. The rest of the patients treated by CJR physicians will also be used for comparison. The second group includes patients classified into related DRGs or undergoing related procedures. Specifically, three related DRGs include DRG 483[4], 493[5] and 494[6]; the related procedure group includes most of the replacement procedures. The related procedures are those that have ICD9 diagnosis codes starting at 81, such as 8154 Total Knee Replacement, 8152 Partial Hip Replacement, and 8151 Total hip replacement. Results are estimated using equation 1, and standard errors are clustered at the MSA level. The summary statistics of these two groups can be found in the appendix. We can see the patient demographics closely parallel between the control and treated groups and among Medicare and private patients. Compared to the sample used by Chen et al. (2022), the sample we used in this study is older, has less white population share, higher use of SNF, and shorter stays. The differences might come from different states this study covers.

[3] Diseases & Disorders of the Musculoskeletal System & Connective Tissue
[4] DRG 483 Major Joint and Limb Reattachment Procedures of Upper Extremity
[5] DRG 493, Lower Extremity and Humerus Procedures Except Hip, Foot, Femur with CC
[6] DRG 494, Lower Extremity and Humerus Procedures Except Hip, Foot, Femur without CC/MCC

The estimation results are presented in table 8, 9, 10 and 11; while the results of discharge locations are plotted in figures 13, 14 and 15. No pre-trend before CJR implementation for these patients can be found. Several findings can be shown and most of them are parallel to those of the targeted population. First, increase use of HHC is found among all three related groups, with larger effects identified among private-insured patients than among Medicare patients across three groups. For example, I found a 7.2(9.1) percent increase in Medicare patients and a 4.5(8.2) percent increase in private-insured patients in 2016(2017) for non-treated patients undergoing similar procedures. The effects for other DRG patients and related MDC-8 patients treated by the CJR physicians are smaller. Second, for the related procedure group, shown in table 9, significant drops in the use of Home discharge and SNF use can be found; while for the related DRG group and patients treated by CJR physicians group, most of the HHC increases were coming from the decreases in Home discharge directly, and yet the effects of SNF use are tiny and insignificant. This is different from the findings among the treated patients, which consist significant drop in use in both SNF and Home without Healthcare. The results can be seen in figure 13 and 14. I do not find a significant change in SNF use for private-insured patients across these groups. This might be because private-insured patients are originally younger and in very rare medical situations they will be discharged to SNF. Finally, the findings of all other outcomes are varied. I find significant decreases in the total charge for only Medicare patients for the MDC-8 patients treated by CJR physicians and also related DRG patients. Other effect estimates are very small and insignificant.

To sum up, the above results show alternative payment model effects can extend to many related patients outside of the model target. These spillover effects follow the same direction as the direct effects which provide complementary evidence supporting the price following scheme.

9 Conclusion

Until now, the authority in charge of innovations of payment and healthcare delivery models has launched more than 50 different models (Smith, 2021). Doubtlessly, more models will be tested in the future. Given the size of the healthcare market, quality of services, and pressure of the aging population, it will be crucial to fully understand the effects of these innovations and, more importantly, the changes behind these effects, concerning the debate between "cost-shifting" and "price following".

This paper studies a bundled payment reform model targeting hip and knee replacement using the inpatient record from Healthcare Cost and Utilization Project State Inpatient Databases. Previous studies found that the Model have impacts on both Medicare patients (Finkelstein et al., 2018; Meyers et al., 2019; Wilcock et al., 2020; Einav et al., 2020) and private-insurance covered patients in Florida (Chen et al., 2022). Using the different-in-difference method, I first show the direct effects and spillovers echoing these studies; the Model increases the use of Home-with-Healthcare substantially while decreasing the use of Skilled Nursing Facility home discharge directly. The spillovers on the private-insured population have a larger size than those on the Medicare population. Then, I extend the field of research by looking at the heterogeneity of model effects. I investigate four dimensions covering internal and external factors of the hospitals which might be associated with how the Model effects were conveyed. Four penetrations, HHC-SNF employment penetration, LEJR penetration, Medicare penetration, and LEJR-Medicare penetration in the hospitals, are included using a DDD model. I find significant associations between these penetration factors and the Model effects. Then I look at the scale of transmission from Medicare patients to the private sector by applying a 2SLS strategy. The results confirm the following type of effect with a total cost showing almost one-dollar-to-one-dollar transmission from Medicare patients to private-insured patients. Last but not least, I explore the effects on other patients not covered by the Model. The results show substantial spillover effects.

In conclusion, there is substantial and robust evidence of spillovers of Medicare policy effects on non-Medicare patients via hospital-level changes in practice style, which is in support of the hypothesis of "price following". These effects are greater when the hospital has greater incentives to change their practice styles, such as treating a large share of Medicare patients. The following effects are also larger when the supply of post-acute care is relatively greater. Thus, the impacts of the CJR model are likely much more significant than those reported in the published work that focuses only on Medicare beneficiaries.

Previous studies point out that patients discharged to SNF do not show better outcomes than those discharged to HHC. In this sense, the identified CJR-related changes in hospitals' decisions on discharge location should be due to a re-optimization process rather than clinical evidence.

In addition, cost increases have also been identified. These CJR effects are not homogeneous among all hospitals but heterogeneous across different dimensions. Some of the incentive-based programs go beyond the original design and put penalties on specific hospitals which are vulnerable (Roberson and Reid, 2015) or themselves minority-serving hospitals (Shih et al., 2015; Zogg et al., 2020). There is a potential risk that the cost increases in these hospitals will become a financial burden for some of these hospitals. In addition, physicians make decisions on the discharge locations and the procedures conducted on the patients, which are directly related to cost. Though the CJR studies hinted more broadly that the CJR model was not associated with any worsened patient outcome, we could not reject the possibility that these might happen at the procedure level. Regarding these two points, it will be worthwhile paying attention to, especially on the procedure level research, in the future.

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Figure 1: CJR effects and spillovers on discharge locations

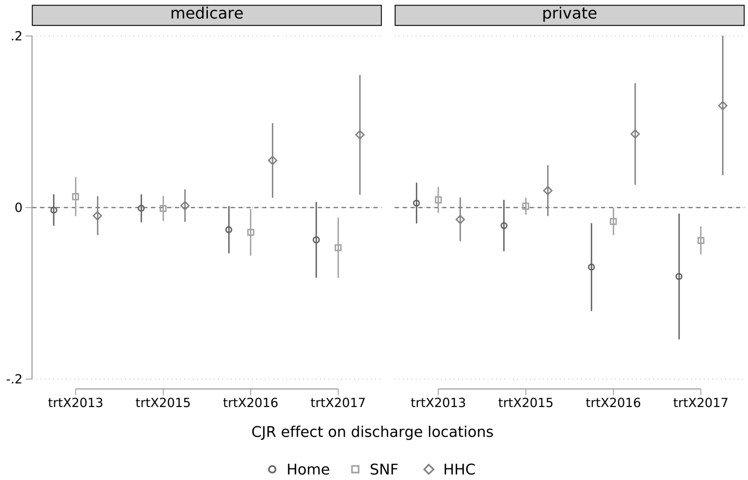


Figure presents the estimated marginal effects with 95 percent confidence interval of discharge locations on Medicare and Private-insured patients. The estimated results is based on equation (1), with error term clustered in MSA level. The results are estimated by Mlogit model.

Figure 2: CJR effects and spillovers on total cost

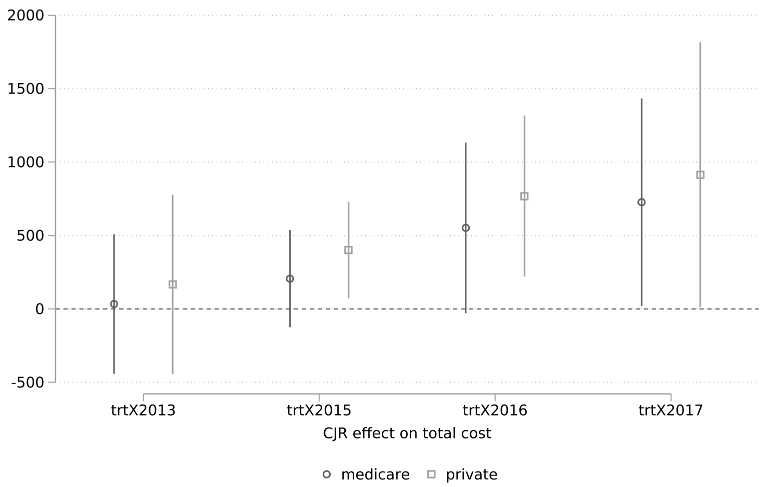


Figure presents the estimated marginal effects with 95 percent confidence interval of total cost on Medicare and Private-insured patients. The estimated results is based on equation (1), with error term clustered in MSA level. The results are estimated by General Linear Model (GLM) with log link and gamma distribution.

Figure 3: CJR effects and spillovers on total charge

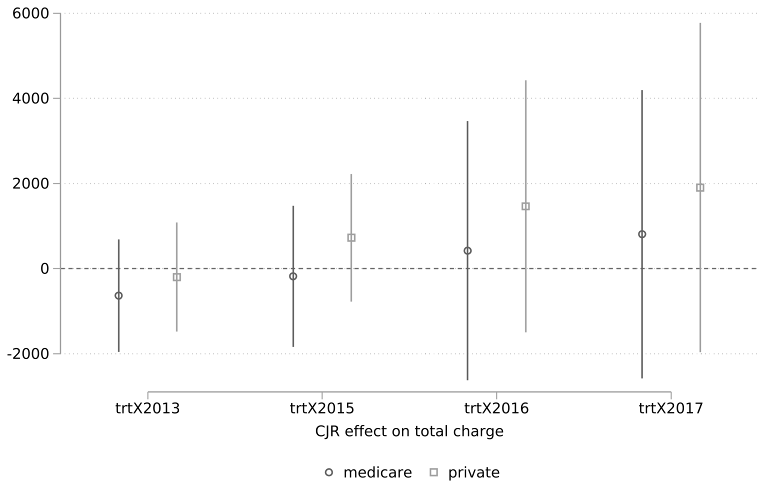


Figure presents the estimated marginal effects with 95 percent confidence interval of total charge on Medicare and Private-insured patients. The estimated results is based on equation (1), with error term clustered in MSA level. The results are estimated by General Linear Model (GLM) with log link and gamma distribution.

Figure 4: CJR effects and spillovers on LOS

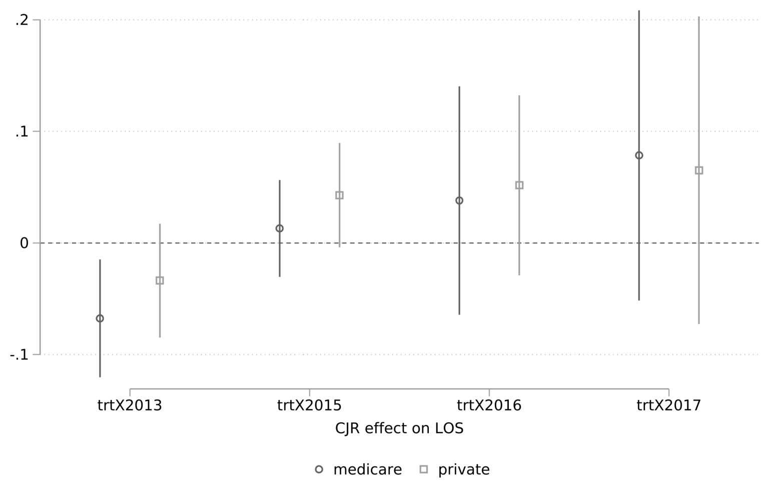
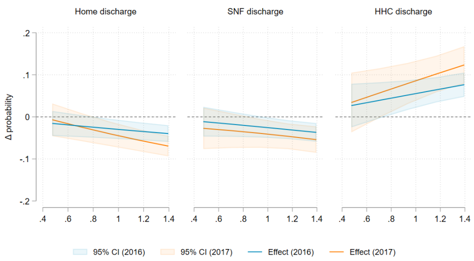
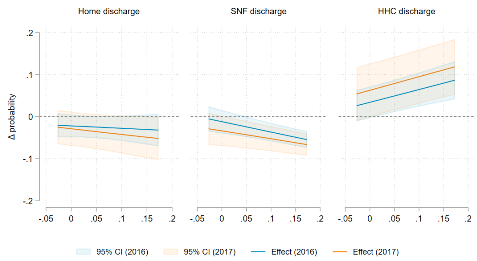


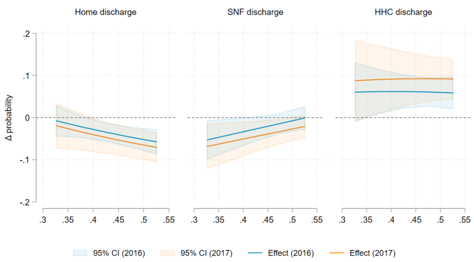
Figure presents the estimated marginal effects with 95 percent confidence interval of length-of-stay (LOS) on Medicare and Private-insured patients. The estimated results is based on equation (1), with error term clustered in MSA level. The results are estimated by Poisson regression.



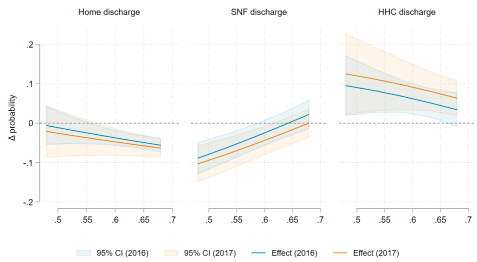
(a) HHC-SNF penetration



(b) LEJR penetration



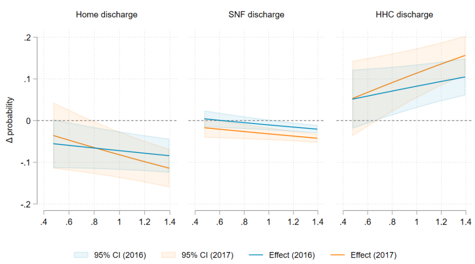
(c) Medicare penetration



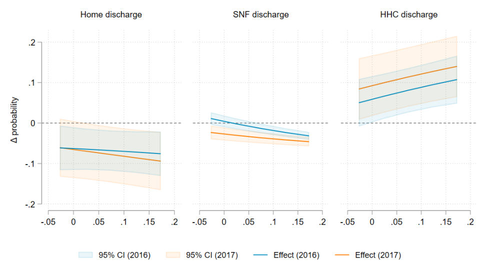
(d) LEJR-Medicare penetration

Figure 5: Heterogeneous effects of discharge on Medicare patients

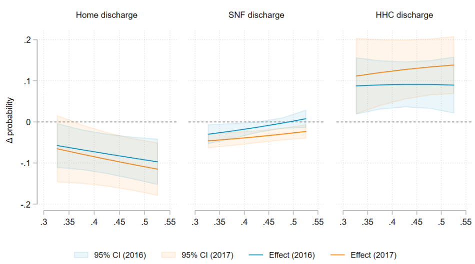
Figure presents the estimated marginal effects of heterogeneous CJR effects on discharge locations with 95 percent confidence interval by four dimensions. Four dimensions of penetration include HHC-SNF penetration, which is the relative employment rate in given MSA between HHC and SNF before 2015 (panel a), LEJR penetration, which is the share of LEJR patients by hospitals before 2015 (panel b), Medicare penetration, which is the share of patients covered by Medicare by hospitals before 2015 (panel c), and LEJR-Medicare penetration, which is the share of LEJR patients covered by Medicare by hospitals before 2015 (panel d). The results are estimated by Mlogit model.



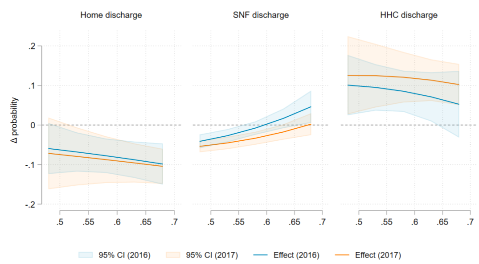
(a) HHC-SNF penetration



(b) LEJR penetration



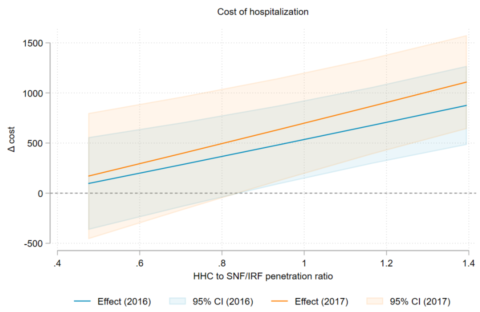
(c) Medicare penetration



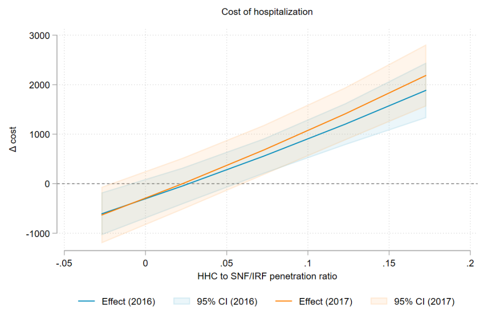
(d) LEJR-Medicare penetration

Figure 6: Heterogeneous effects of discharge on private insurance patients

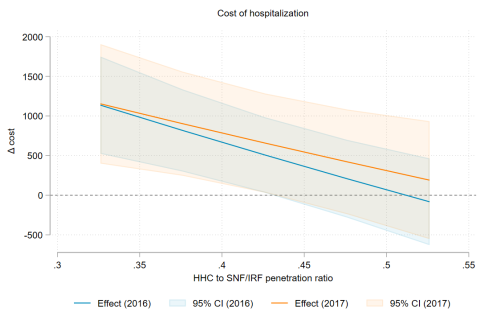
Figure presents the estimated marginal effects of heterogeneous CJR effects on discharge locations with 95 percent confidence interval by four dimensions. Four dimensions of penetration include HHC-SNF penetration, which is the relative employment rate in given MSA between HHC and SNF before 2015 (panel a), LEJR penetration, which is the share of LEJR patients by hospitals before 2015 (panel b), Medicare penetration, which is the share of patients covered by Medicare by hospitals before 2015 (panel c), and LEJR-Medicare penetration, which is the share of LEJR patients covered by Medicare by hospitals before 2015 (panel d). The results are estimated by Mlogit model. After calculating three penetration variables and assigning them to each record, I regularize them by subtracting the mean.



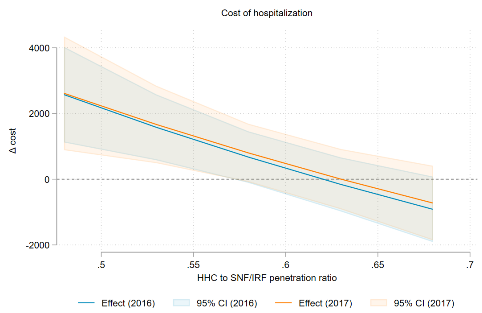
(a) HHC-SNF penetration



(b) LEJR penetration



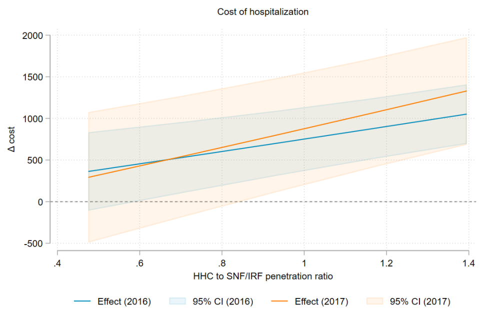
(c) Medicare penetration



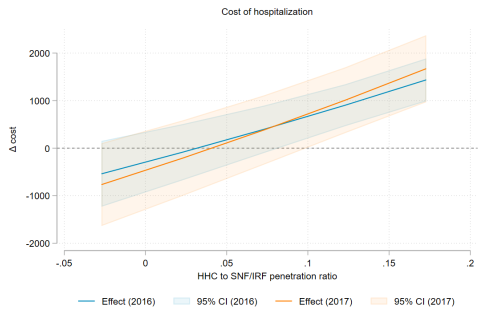
(d) LEJR-Medicare penetration

Figure 7: Heterogeneous effects of cost on Medicare patients

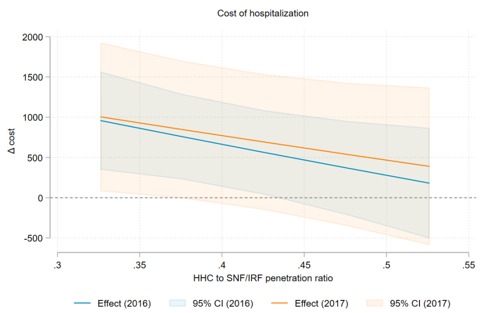
Figure presents the estimated marginal effects of heterogeneous CJR effects on total cost with 95 percent confidence interval by four dimensions. Four dimensions of penetration include HHC-SNF penetration, which is the relative employment rate in given MSA between HHC and SNF before 2015 (panel a), LEJR penetration, which is the share of LEJR patients by hospitals before 2015 (panel b), Medicare penetration, which is the share of patients covered by Medicare by hospitals before 2015 (panel c), and LEJR-Medicare penetration, which is the share of LEJR patients covered by Medicare by hospitals before 2015 (panel d). The results are estimated by Mlogit model.



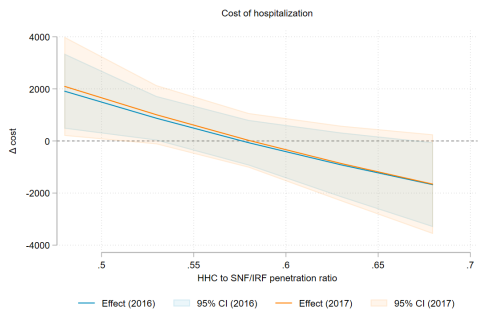
(a) HHC-SNF penetration



(b) LEJR penetration



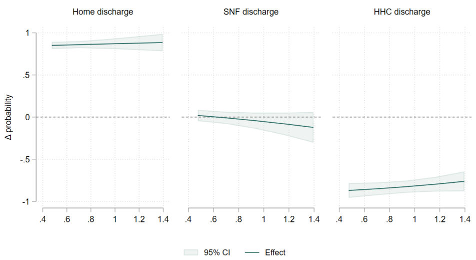
(c) Medicare penetration



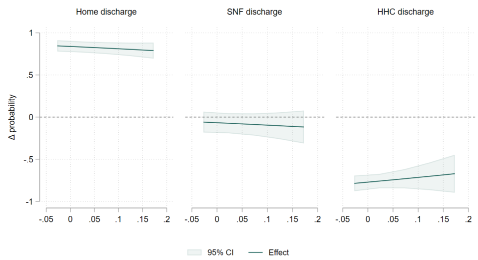
(d) LEJR-Medicare penetration

Figure 8: Heterogeneous effects of cost on private insurance patients

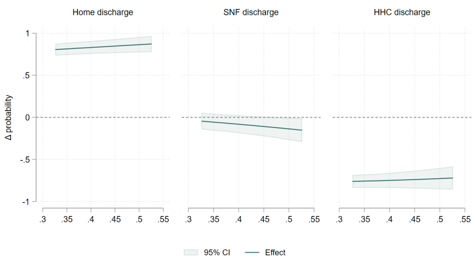
Figure presents the estimated marginal effects of heterogeneous CJR effects on total cost with 95 percent confidence interval by four dimensions. Four dimensions of penetration include HHC-SNF penetration, which is the relative employment rate in given MSA between HHC and SNF before 2015 (panel a), LEJR penetration, which is the share of LEJR patients by hospitals before 2015 (panel b), Medicare penetration, which is the share of patients covered by Medicare by hospitals before 2015 (panel c), and LEJR-Medicare penetration, which is the share of LEJR patients covered by Medicare by hospitals before 2015 (panel d). The results are estimated by Mlogit model.



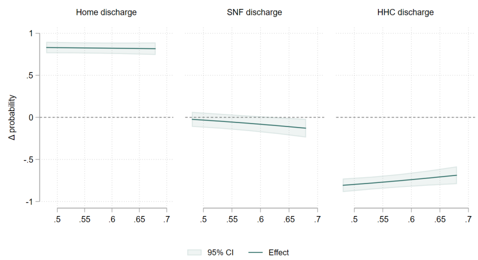
(a) HHC-SNF penetration



(b) LEJR penetration



(c) Medicare penetration

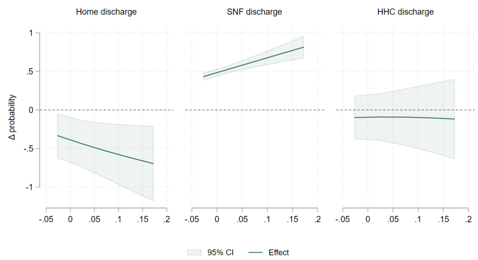


(d) LEJR-Medicare penetration

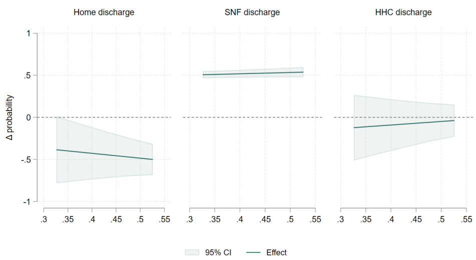
Figure 9: Heterogeneous Transmission effects in Home discharge

Figure presents the estimated marginal effects of θ_{iv22} in Home discharge with 95 percent confidence interval by four dimensions. Four dimensions of penetration include HHC-SNF penetration, LEJR penetration, Medicare penetration, and LEJR-Medicare penetration. The results are estimated by Mlogit model.

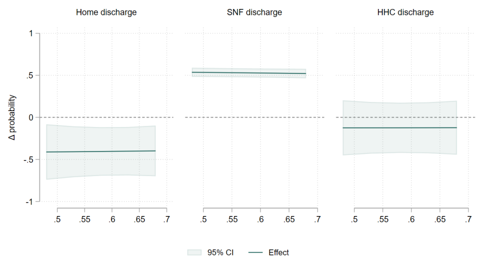
(a) HHC-SNF penetration



(b) LEJR penetration



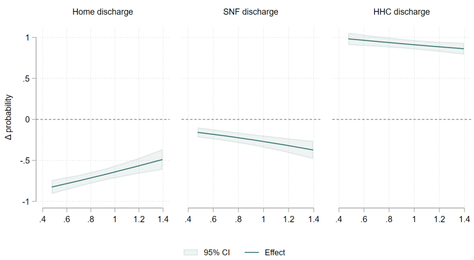
(c) Medicare penetration



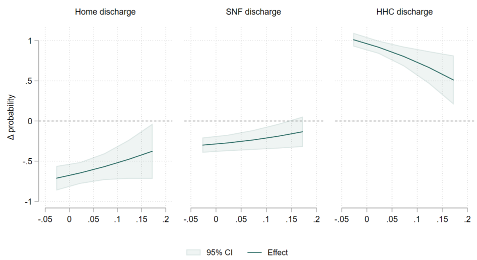
(d) LEJR-Medicare penetration

Figure 10: Heterogeneous Transmission effects in SNF discharge

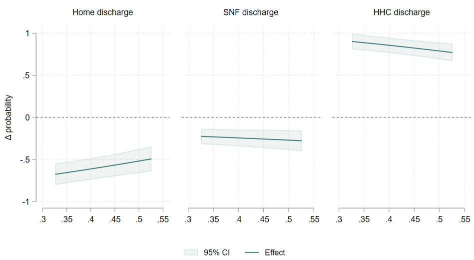
Figure presents the estimated marginal effects of θ_{iv22} in SNF discharge with 95 percent confidence interval by four dimensions. Four dimensions of penetration include HHC-SNF penetration, LEJR penetration, Medicare penetration, and LEJR-Medicare penetration. The results are estimated by Mlogit model.



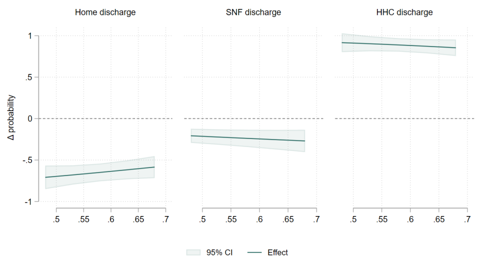
(a) HHC-SNF penetration



(b) LEJR penetration



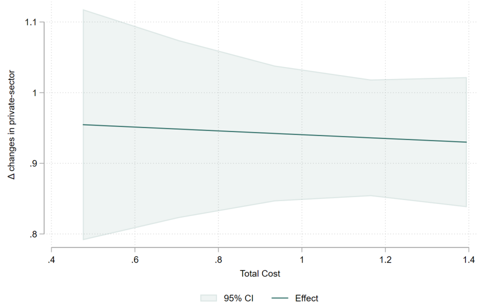
(c) Medicare penetration



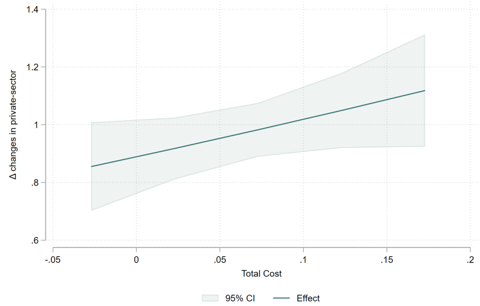
(d) LEJR-Medicare penetration

Figure 11: Heterogeneous Transmission effects in HHC discharge

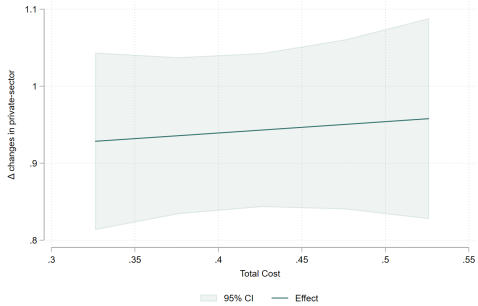
Figure presents the estimated marginal effects of θ_{iv22} in HHC discharge with 95 percent confidence interval by four dimensions. Four dimensions of penetration include HHC-SNF penetration, LEJR penetration, Medicare penetration, and LEJR-Medicare penetration. The results are estimated by Mlogit model.



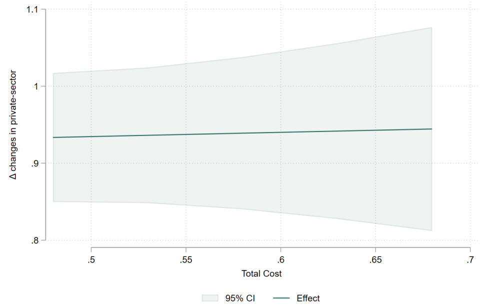
(a) HHC-SNF penetration



(b) LEJR penetration



(c) Medicare penetration



(d) LEJR-Medicare penetration

Figure 12: Heterogeneous Transmission effects in total cost

Figure presents the estimated marginal effects of θ_{iv22} in total cost with 95 percent confidence interval by four dimensions. Four dimensions of penetration include HHC-SNF penetration, LEJR penetration, Medicare penetration, and LEJR-Medicare penetration. The results are estimated by General Linear Model (GLM) with log link and gamma distribution.

Figure 13: Spillovers of non-CJR patients treated by Model physicians MDC-8, discharge location

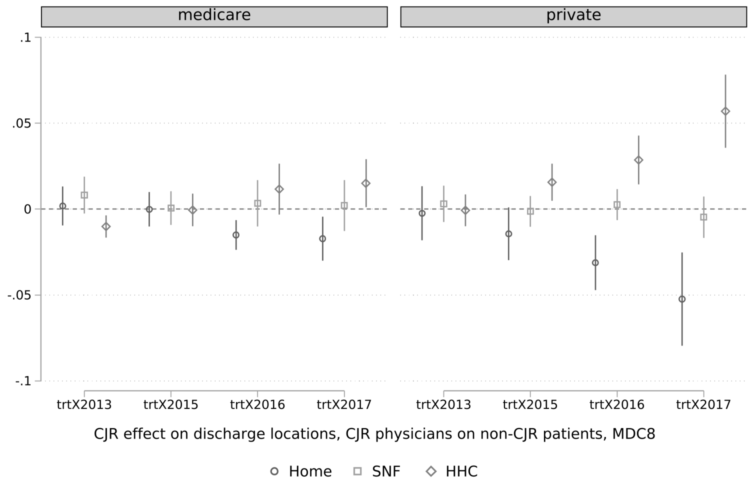


Figure presents the estimated marginal effects with 95 percent confidence interval of discharge locations on three non-CJR patients treated by CJR physicians, classified MDC-8. The estimated results is based on equation (1), with error term clustered in MSA level. The results of discharge locations are estimated by Mlogit model.

Figure 14: CJR spillovers of non-CJR patients undergone 81* procedures, discharge location

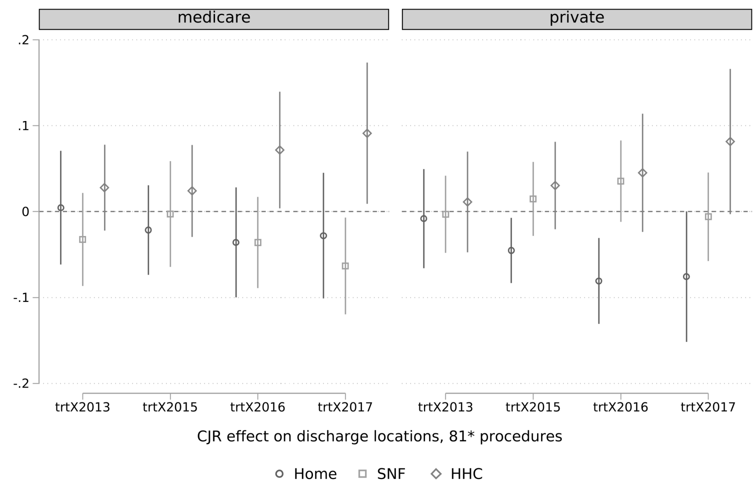


Figure presents the estimated marginal effects with 95 percent confidence interval of discharge locations on three non-CJR patients undergone 81* procedures. The estimated results is based on equation (1), with error term clustered in MSA level. The results of discharge locations are estimated by Mlogit model.

Figure 15: CJR spillovers of non-CJR patients with other DRGs, discharge location

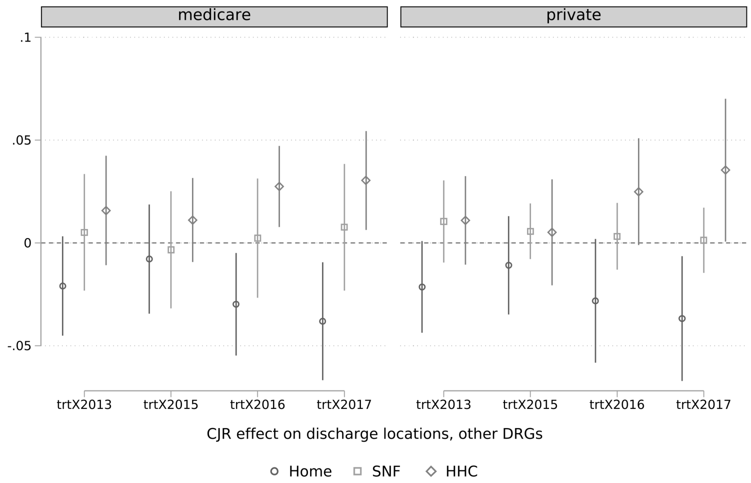


Figure presents the estimated marginal effects with 95 percent confidence interval of discharge locations on three non-CJR patients classified in related DRG, classified MDC-8. The estimated results is based on equation (1), with error term clustered in MSA level. The results of discharge locations are estimated by Mlogit model.

Figure 16: CJR spillovers of non-CJR patients treated by CJR physicians MDC-8, total cost

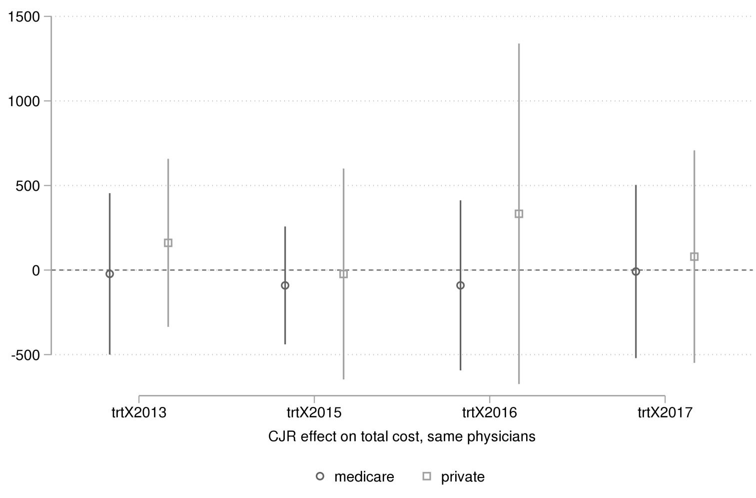


Figure presents the estimated marginal effects with 95 percent confidence interval of total cost on non-CJR patients treated by CJR physicians, classified MDC-8. The estimated results is based on equation (1), with error term clustered in MSA level. The results are estimated by GLM with gamma distribution and log-link.

Figure 17: CJR spillovers of non-CJR patients undergone 81* procedures, total cost

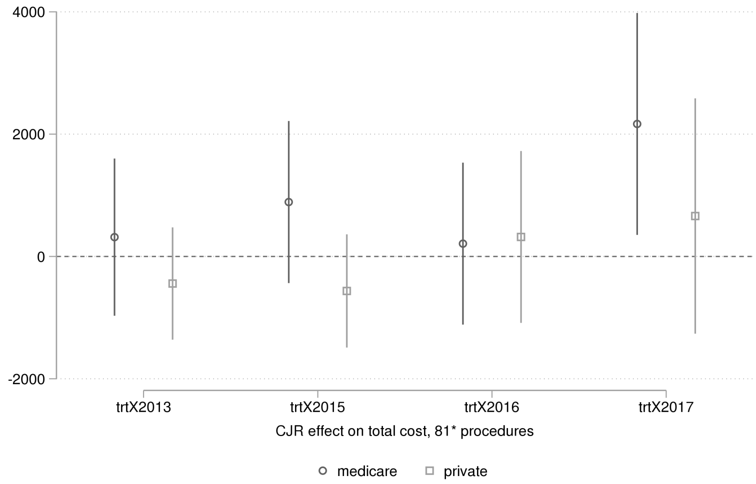


Figure presents the estimated marginal effects with 95 percent confidence interval of total cost on non-CJR patients undergone 81* procedures. The estimated results is based on equation (1), with error term clustered in MSA level. The results are estimated by GLM with gamma distribution and log-link.

Figure 18: CJR spillovers of non-CJR patients with other DRGs, total cost

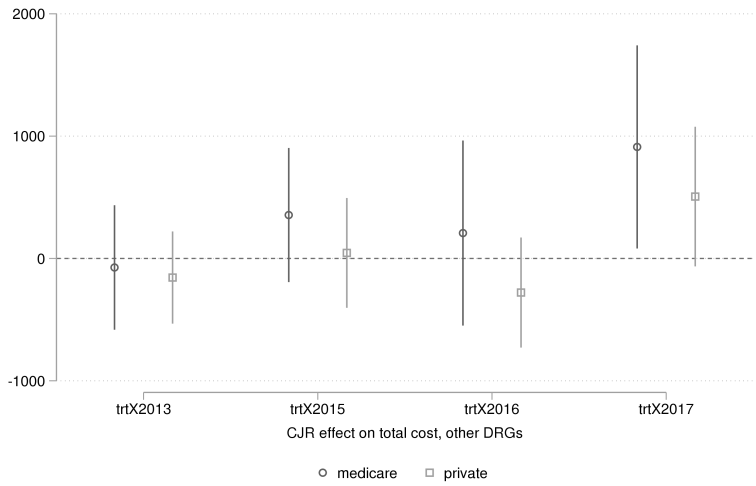


Figure presents the estimated marginal effects with 95 percent confidence interval of discharge locations on three non-CJR patients treated by CJR physicians, classified MDC-8. The estimated results is based on equation (1), with error term clustered in MSA level. The results are estimated by GLM with gamma distribution and log-link.

Table 1: Summary Statistics of controls by payment type and treatment status

	(1)	(2)	(3)	(4)
	Medicare		Private	
	Control	Treated	Control	Treated
Age	74.51	74.93	59.69	59.19
	(6.932)	(7.133)	(8.388)	(8.575)
Female	0.623	0.652	0.566	0.556
	(0.485)	(0.476)	(0.496)	(0.497)
White	0.908	0.805	0.852	0.761
	(0.288)	(0.396)	(0.355)	(0.427)
Black	0.0323	0.0594	0.0721	0.109
	(0.177)	(0.236)	(0.259)	(0.311)
Asian	0.0326	0.0754	0.0447	0.0637
	(0.178)	(0.264)	(0.207)	(0.244)
Other Race	0.0266	0.0598	0.0311	0.0673
	(0.161)	(0.237)	(0.174)	(0.251)
Emergency	0.108	0.135	0.0278	0.0291
	(0.310)	(0.342)	(0.164)	(0.168)
Urgent	0.0397	0.0364	0.0374	0.0326
	(0.195)	(0.187)	(0.190)	(0.178)
Elective	0.853	0.828	0.935	0.938
	(0.355)	(0.377)	(0.247)	(0.241)
Outcomes				
Home discharge	0.238	0.144	0.345	0.264
	(0.426)	(0.352)	(0.475)	(0.441)
SNF discharge	0.368	0.483	0.140	0.207
	(0.482)	(0.500)	(0.347)	(0.405)
HHC discharge	0.394	0.372	0.515	0.529
	(0.489)	(0.483)	(0.500)	(0.499)
LOS	2.888	3.287	2.367	2.633
	(2.021)	(2.349)	(1.522)	(1.759)
Total charge	63986.4	70347.7	57770.1	66739.5
	(33173.3)	(35520.8)	(29714.2)	(31123.1)
Total cost	14012.0	15967.4	14301.1	16767.2
	(5245.1)	(7351.1)	(5089.8)	(7296.8)
N	203506	331136	135792	254026

NOTE: Table presents the summary statistics on the control variables and outcome variables. All statistics are based on the HCUP SID 2013-2017 sample, from 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington).

Table 2: CJR effects and spillovers

	(1) Mdcr 65+	(2) Prvt 65-	(3) Mdcr 65+	(4) Prvt 65-	(5) Mdcr 65+	(6) Prvt 65-
Panel A: CJR effects and spillovers on discharges						
	Home		SNF		HHC	
TreatmentX2013	-0.003	0.005	0.013	0.009	-0.010	-0.014
	(0.009)	(0.012)	(0.012)	(0.008)	(0.012)	(0.013)
TreatmentX2015	-0.001	-0.021	-0.001	0.001	0.002	0.020
	(0.008)	(0.015)	(0.007)	(0.005)	(0.010)	(0.015)
TreatmentX2016	-0.026*	-0.069***	-0.029**	-0.016**	0.055**	0.086***
	(0.014)	(0.026)	(0.014)	(0.008)	(0.022)	(0.030)
TreatmentX2017	-0.038*	-0.080**	-0.047***	-0.038***	0.085**	0.119***
	(0.023)	(0.037)	(0.019)	(0.008)	(0.036)	(0.042)
Observations	608693	305882	608693	305882	608693	305882
Panel B: CJR effects and spillovers on other outcomes						
	LOS		Cost		Charge	
TreatmentX2013	-0.068**	-0.034	33.5	171.3	-636.9	-200.5
	(0.027)	(0.026)	(242.3)	(311.4)	(674.6)	(652.6)
TreatmentX2015	0.013	0.043*	205.9	401.8*	-181.2	724.6
	(0.022)	(0.024)	(168.8)	(168.0)	(846.1)	(765.5)
TreatmentX2016	0.038	0.052	552.2*	767.5***	419.0	1462.3
	(0.052)	(0.041)	(296.1)	(279.8)	(1553.0)	(1510.8)
TreatmentX2017	0.078	0.065	726.6**	913.8**	808.2	1903.1
	(0.066)	(0.071)	(360.6)	(459.9)	(1727.6)	(1974.2)
Observations	608983	306178	608693	305882	608693	305882

NOTE: Table presents the estimated marginal effects from equation (1), by 4 outcomes and targeted status, with error term clustered in MSA level. Outcomes include LOS, cost, and charge. The results of LOS are estimated by Poisson regression while those of total charge and total cost are estimated by General Linear Model (GLM) with log link and gamma distribution.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table 3: CJR effects with base year as 2013, discharge location

	Medicare		Private	
	Baseline	B-2013	Baseline	B-2013
TreatmentX2013(2014)				
Home discharge	-0.003	0.003	0.005	-0.005
	(0.009)	(0.010)	(0.012)	(0.012)
SNF or ICF discharge	0.013	-0.012	0.009	-0.009
	(0.012)	(0.011)	(0.008)	(0.007)
HHC discharge	-0.010	0.009	-0.014	0.014
	(0.012)	(0.012)	(0.013)	(0.013)
TreatmentX2015				
Home discharge	-0.001	0.002	-0.021	-0.026
	(0.008)	(0.014)	(0.015)	(0.018)
SNF or ICF discharge	-0.001	-0.014	0.001	-0.007
	(0.007)	(0.016)	(0.005)	(0.010)
HHC discharge	0.002	0.012	0.020	0.033*
	(0.010)	(0.018)	(0.015)	(0.018)
TreatmentX2016				
Home discharge	-0.026*	-0.023	-0.069***	-0.075***
	(0.014)	(0.016)	(0.026)	(0.025)
SNF or ICF discharge	-0.029**	-0.041*	-0.016**	-0.024*
	(0.014)	(0.022)	(0.008)	(0.012)
HHC discharge	0.055**	0.065**	0.086***	0.099***
	(0.022)	(0.029)	(0.030)	(0.031)
TreatmentX2017				
Home discharge	-0.038*	-0.035	-0.080**	-0.086**
	(0.022)	(0.023)	(0.037)	(0.036)
SNF or ICF discharge	-0.047***	-0.059**	-0.038***	-0.045***
	(0.018)	(0.026)	(0.008)	(0.012)
HHC discharge	0.085**	0.095**	0.119***	0.131***
	(0.036)	(0.043)	(0.041)	(0.043)
N	608693	608693	305882	305882

NOTE: Table presents the marginal effects of CJR treatments on discharge locations estimated from equation (1), with base year changed from 2014 to 2013 and error term clustered in MSA level. Three discharge locations include Home discharge (without healthcare), Skilled Nursing Facility (SNF) discharge and Home-with-Homehealthcare (HHC) discharge. The baseline results are estimated with 2014 as base year; while the B-2013 results are estimated with 2013 as base year. The results are estimated by Mlogit model.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table 4: CJR effects with base year as 2013, other outcomes

	(1) LOS Medicare	(2) Private	(3) Charge Medicare	(4) Private	(5) Cost Medicare	(6) Private
Baseline						
TreatmentX2013	-0.068**	-0.034	-636.010	-200.561	33.532	166.361
	(0.027)	(0.026)	(674.835)	(653.293)	(242.366)	(311.512)
TreatmentX2015	0.013	0.043*	-181.266	724.405	205.903	401.070**
	(0.022)	(0.024)	(846.087)	(765.265)	(168.670)	(167.940)
TreatmentX2016	0.038	0.052	419.038	1462.808	552.209*	767.505***
	(0.052)	(0.041)	(1553.918)	(1510.935)	(296.061)	(279.486)
TreatmentX2017	0.078	0.065	808.245	1903.585	726.654**	913.826**
	(0.066)	(0.070)	(1727.876)	(1974.975)	(360.634)	(459.968)
Base-2013						
TreatmentX2013	0.069**	0.034	640.885	201.066	-33.473	-165.004
	(0.028)	(0.027)	(685.224)	(656.588)	(241.516)	(306.455)
TreatmentX2015	0.082**	0.077*	458.212	927.210	172.079	232.880
	(0.041)	(0.043)	(1174.061)	(1058.258)	(286.971)	(293.139)
TreatmentX2016	0.107	0.086	1062.775	1667.320	517.811	596.454
	(0.067)	(0.053)	(1804.735)	(1726.506)	(457.980)	(508.956)
TreatmentX2017	0.149*	0.100	1454.562	2109.119	691.983	741.603
	(0.081)	(0.077)	(2057.417)	(2241.763)	(555.955)	(711.541)

NOTE: Table presents the marginal effects of CJR treatments on three other outcomes estimated from equation (1), with base year changed from 2014 to 2013 and error term clustered in MSA level. Outcomes include length-of-stay (LOS), episode charge and episode cost. The baseline results are estimated with 2014 as base year; while the B-2013 results are estimated with 2013 as base year. The results of LOS are estimated by Poisson regression while those of total charge and total cost are estimated by General Linear Model (GLM) with log link and gamma distribution.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table 5: Robustness of main results, discharge location

	(1) Baseline	(2) nmdcr	(3) pay2	(4) nrehab	(5) d2015	(6) dAZ	(7) drg470
				TreatmentX2013			
Home	0.005	0.003	0.006	0.009	0.005	0.007	0.006
	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.015)	(0.012)
SNF	0.009	0.005	0.007	0.005	0.008	0.011	0.008
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
HHC	-0.014	-0.009	-0.012	-0.013	-0.014	-0.018	-0.014
	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)	(0.016)	(0.013)
				TreatmentX2015			
Home	-0.021	-0.018	-0.021	-0.011		-0.026	-0.021
	(0.015)	(0.015)	(0.015)	(0.012)		(0.019)	(0.015)
SNF	0.001	-0.005	0.001	0.003		0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)		(0.005)	(0.005)
HHC	0.020	0.023	0.020	0.008		0.024	0.019
	(0.015)	(0.014)	(0.015)	(0.012)		(0.018)	(0.015)
				TreatmentX2016			
Home	-0.069***	-0.067***	-0.069***	-0.048**	-0.069***	-0.074***	-0.070***
	(0.026)	(0.024)	(0.026)	(0.023)	(0.027)	(0.028)	(0.026)
SNF	-0.016**	-0.026***	-0.017**	-0.007	-0.016**	-0.015*	-0.017**
	(0.008)	(0.009)	(0.008)	(0.007)	(0.008)	(0.009)	(0.007)
HHC	0.086***	0.093***	0.085***	0.055**	0.085***	0.090***	0.085***
	(0.030)	(0.028)	(0.030)	(0.026)	(0.030)	(0.033)	(0.030)
				TreatmentX2017			
Home	-0.080**	-0.082**	-0.080**	-0.058	-0.079**	-0.089**	-0.081**
	(0.037)	(0.036)	(0.038)	(0.035)	(0.038)	(0.035)	(0.038)
SNF	-0.038***	-0.046***	-0.038***	-0.026***	-0.038***	-0.035***	-0.037***
	(0.008)	(0.010)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
HHC	0.119***	0.128***	0.118***	0.088**	0.117***	0.125***	0.118***
	(0.042)	(0.041)	(0.041)	(0.038)	(0.042)	(0.040)	(0.041)
N	305,882	379,445	302,274	271,202	243,375	277,694	303,065

NOTE: Table presents the results of robustness checking, which is the estimated marginal effects from equation (1), on discharge locations and by targeted status, with error term clustered in MSA level. Column (1) presents the original spillover estimates, which is the one in table 2 column (2). Column (2) extend the spillover estimates from private-insured patients to all Non-Medicare patients. Column (3) excludes patients with second payment as Medicare. Column (4) excludes patients being admitted to non-rehabilitation and non-LTC hospital. Column (5) excludes the samples in 2015. Column (6) excludes the patients from Arizona. Column (7) exclude patients identified as DRG 469.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table 6: Robustness of main results, length of stay, total cost and total charge

	(1) Baseline	(2) non-medicare	(3) pay2	(4) non-rehabhos	(5) d2015	(6) dAZ	(7) drg470
				LOS			
TreatmentX2013	-0.034	-0.047	-0.037	-0.025	-0.034	-0.024	-0.030
	(0.026)	(0.026)	(0.026)	(0.030)	(0.026)	(0.030)	(0.026)
TreatmentX2015	0.043	0.035	0.041*	0.037		0.048*	0.036
	(0.024)	(0.021)	(0.023)	(0.023)		(0.027)	(0.024)
TreatmentX2016	0.051	0.028	0.047	0.027	0.051	0.072	0.043
	(0.041)	(0.041)	(0.041)	(0.043)	(0.041)	(0.048)	(0.043)
TreatmentX2017	0.065	0.042	0.063	0.48	0.064	0.097	0.064
	(0.070)	(0.061)	(0.071)	(0.069)	(0.070)	(0.076)	(0.074)
				Cost			
TreatmentX2013	166.361	97.066	166.515	325.936	168.554	4.185	178.914
	(311.374)	(292.523)	(312.248)	(327.669)	(312.922)	(308.235)	(309.942)
TreatmentX2015	401.070**	389.884***	413.647**	494.454***		333.530*	392.676**
	(168.030)	(150.525)	(163.479)	(179.823)		(190.262)	(166.916)
TreatmentX2016	767.505***	674.316***	765.573***	754.196**	763.690***	736.137*	754.922***
	(279.849)	(245.650)	(279.401)	(306.425)	(279.478)	(303.416)	(284.309)
TreatmentX2017	913.826**	816.096**	922.486**	775.884*	908.670**	1164.348**	901.537*
	(463.406)	(407.139)	(462.925)	(463.229)	(463.121)	(464.579)	(465.464)
				Charge			
TreatmentX2013	-200.561	-736.035	-212.680	-362.822	-182.384	-484.347	-143.620
	(653.293)	(585.431)	(658.483)	(715.645)	(649.680)	(748.296)	(662.385)
TreatmentX2015	724.405	650.447	781.134	740.497		1241.302*	705.072
	(765.265)	(717.335)	(760.785)	(904.091)		(747.313)	(769.648)
TreatmentX2016	1462.808	1264.614	1408.477	1204.787	1456.781	2471.187*	1450.705
	(1510.935)	(1458.476)	(1512.855)	(1796.636)	(1509.121)	(1449.975)	(1531.467)
TreatmentX2017	1903.585	1642.674	1889.287	1488.181	1880.657	3529.995*	1883.537
	(1974.975)	(1920.729)	(1980.403)	(2210.473)	(1971.134)	(1833.930)	(1981.464)
N	305,873	379,426	302,266	271,195	243,369	277,686	303,060

NOTE: Table presents the results of robustness checking, which is the estimated marginal effects from equation (1), on three other outcomes and by targeted status, with error term clustered in MSA level. Column (1) presents the original spillover estimates. Column (2) extend to all Non-Medicare patients. Column (3) excludes patients with second payment as Medicare. Column (4) excludes patients being admitted to non-rehabilitation and non-LTC hospital. Column (5) excludes the samples in 2015. Column (6) excludes the patients from Arizona. Column (7) exclude patients identified as DRG 469.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table 7: Marginal effects of heterogeneity, four dimenions

	(1)	(2)	(3)	(4)
	HHC-SNF Penetration		LEJR Penetration	
	Medicare	Private	Medicare	Private
Home discharge	-0.014***	-0.016**	-0.000	-0.001
	(0.003)	(0.008)	(0.000)	(0.000)
SNF discharge	-0.004	-0.005	-0.001***	-0.001***
	(0.006)	(0.003)	(0.000)	(0.000)
HHC discharge	0.018**	0.021**	0.002***	0.002***
	(0.008)	(0.010)	(0.000)	(0.000)
Cost	-327.282**	115.949*	53.774***	47.673***
	(143.508)	(63.232)	(6.882)	(8.238)
N	608693	305882	608693	305882
	Medicare Penetration		LEJR-Medicare Penetration	
	Medicare	Private	Medicare	Private
Home discharge	-0.001**	-0.001*	-0.001**	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)
SNF discharge	0.001**	0.001*	0.003***	0.002***
	(0.001)	(0.000)	(0.000)	(0.000)
HHC discharge	-0.000	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Cost	-26.032***	-22.110***	-74.037***	-94.862***
	(6.813)	(7.956)	(18.917)	(35.571)
N	608693	305882	608693	305882

NOTE: Table presents the results of heterogeneity of CJR effects on Medicare and Private insured patients, which is the estimated marginal effects from equation (2), on four dimensions and with error term clustered in MSA level. Four dimensions of penetration include HHC-SNF penetration, which is the relative employment rate in given MSA between HHC and SNF before 2015, LEJR penetration, which is the share of LEJR patients by hospitals before 2015, Medicare penetration, which is the share of patients covered by Medicare by hospitals before 2015, and LEJR-Medicare penetration, which is the share of LEJR patients covered by Medicare by hospitals before 2015. The results of discharge location are estimated by Mlogit model and those of cost are estimated by GLM with gamma distribution and log-link.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table 8: CJR spillovers of other patients treated by CJR physicians, discharge location

	(1)	(2)	(3)	(4)
	MDC8		Other MDCs	
	Medicare	Private	Medicare	Private
	TreatmentX2013			
Home discharge	0.002	-0.002	-0.006	-0.006*
	(0.006)	(0.008)	(0.006)	(0.003)
SNF discharge	0.008	0.003	0.003	0.003
	(0.005)	(0.005)	(0.004)	(0.002)
HHC discharge	-0.010***	-0.001	0.003	0.002
	(0.003)	(0.005)	(0.004)	(0.002)
	TreatmentX2015			
Home discharge	-0.000	-0.014*	0.002	0.001
	(0.005)	(0.008)	(0.005)	(0.003)
SNF discharge	0.001	-0.001	-0.000	-0.001
	(0.005)	(0.005)	(0.002)	(0.002)
HHC discharge	-0.000	0.016***	-0.002	-0.000
	(0.005)	(0.006)	(0.004)	(0.003)
	TreatmentX2016			
Home discharge	-0.015***	-0.031***	-0.005	-0.003
	(0.004)	(0.008)	(0.008)	(0.004)
SNF discharge	0.003	0.003	0.005	0.002
	(0.007)	(0.005)	(0.005)	(0.003)
HHC discharge	0.012	0.029***	0.000	0.001
	(0.008)	(0.007)	(0.008)	(0.003)
	TreatmentX2017			
Home discharge	-0.017***	-0.052***	0.006	0.003
	(0.007)	(0.014)	(0.012)	(0.006)
SNF discharge	0.002	-0.005	-0.003	-0.004**
	(0.008)	(0.006)	(0.006)	(0.002)
HHC discharge	0.015**	0.057***	-0.003	0.001
	(0.007)	(0.011)	(0.007)	(0.005)
N	639932	249093	5781376	2288877

NOTE: Table presents the estimated marginal effects from equation (1) on non-CJR patients treated by CJR physicians, on discharge location and with error term clustered in MSA level. The included patients are those treated by the same physicians conducted CJR procedures. All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy. The results of discharge location are estimated by Mlogit model and those of cost are estimated by GLM with gamma distribution and log-link.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table 9: CJR spillovers of non-CJR patients undergone 81* procedures and of other DRGs, discharge location

	(1)	(2)	(3)	(4)
	Other Procedures		Other DRGs	
	Medicare	Private	Medicare	Private
	TreatmentX2013			
Home discharge	0.005	-0.008	-0.021*	-0.021*
	(0.034)	(0.029)	(0.012)	(0.011)
SNF or ICF discharge	-0.032	-0.003	0.005	0.010
	(0.028)	(0.023)	(0.014)	(0.010)
HHC discharge	0.028	0.011	0.016	0.011
	(0.026)	(0.030)	(0.014)	(0.011)
	TreatmentX2015			
Home discharge	-0.021	-0.045**	-0.008	-0.011
	(0.027)	(0.019)	(0.014)	(0.012)
SNF or ICF discharge	-0.003	0.015	-0.003	0.006
	(0.031)	(0.022)	(0.015)	(0.007)
HHC discharge	0.024	0.030	0.011	0.005
	(0.027)	(0.026)	(0.010)	(0.013)
	TreatmentX2016			
Home discharge	-0.036	-0.081***	-0.030**	-0.028*
	(0.033)	(0.025)	(0.013)	(0.015)
SNF or ICF discharge	-0.036	0.036	0.002	0.003
	(0.027)	(0.024)	(0.015)	(0.008)
HHC discharge	0.072**	0.045	0.027***	0.025*
	(0.035)	(0.035)	(0.010)	(0.013)
	TreatmentX2017			
Home discharge	-0.028	-0.076*	-0.038***	-0.037**
	(0.037)	(0.039)	(0.015)	(0.015)
SNF or ICF discharge	-0.063**	-0.006	0.008	0.001
	(0.029)	(0.026)	(0.016)	(0.008)
HHC discharge	0.091**	0.082*	0.030**	0.035**
	(0.042)	(0.043)	(0.012)	(0.018)
N	17137	15486	37546	49351

NOTE: Table presents the estimated marginal effects from equation (1) on non-CJR patients classified in related DRG or undergone 81* procedures with error term clustered in MSA level. The group of Other DRGs, column (1) and (2), include patients in three DRGs - DRG 483, Major Joint and Limb Reattachment Procedures of Upper Extremity, DRG 493, Lower Extremity and Humerus Procedures Except Hip, Foot, Femur with CC and DRG 494, Lower Extremity and Humerus Procedures Except Hip, Foot, Femur without CC/MCC. All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy. The results of discharge location are estimated by Mlogit model and those of cost are estimated by GLM with gamma distribution and log-link.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table 10: CJR spillovers of other patients treated by CJR physicians, other outcomes

	(1)	(2)	(3)	(4)
	MDC8		Other MDCs	
	Medicare	Private	Medicare	Private
		LOS		
TreatmentX2013	-0.022	0.036	0.032	0.121***
	(0.064)	(0.074)	(0.081)	(0.044)
TreatmentX2015	-0.031	0.024	-0.011	0.009
	(0.071)	(0.045)	(0.045)	(0.026)
TreatmentX2016	0.038	0.171**	0.053	0.143**
	(0.120)	(0.073)	(0.066)	(0.058)
TreatmentX2017	-0.054	0.080	-0.073	0.031
	(0.185)	(0.094)	(0.136)	(0.079)
		Cost		
TreatmentX2013	-22.602	160.953	150.378	396.853
	(243.411)	(253.393)	(204.138)	(258.145)
TreatmentX2015	-90.820	-23.198	29.918	134.029
	(177.764)	(318.107)	(77.103)	(99.958)
TreatmentX2016	-90.402	332.717	152.121	128.980
	(256.530)	(513.629)	(200.927)	(280.277)
TreatmentX2017	-8.564	79.479	89.714	243.126
	(261.267)	(320.568)	(244.630)	(234.707)
		Charge		
TreatmentX2013	-803.048	-1214.758	669.948	2066.551
	(1094.689)	(935.329)	(1427.266)	(1496.511)
TreatmentX2015	-2249.801***	-1109.989	-1147.785**	-443.491
	(780.961)	(1421.983)	(545.030)	(630.863)
TreatmentX2016	-2923.711**	-860.099	-1030.022	-596.916
	(1293.357)	(2289.618)	(1344.902)	(1952.009)
TreatmentX2017	-3288.781	-3551.313	-2073.158	-681.468
	(2028.583)	(2745.367)	(1633.818)	(1601.581)
N	639624	248932	5777346	2286967

NOTE: Table presents the estimated marginal effects from equation (1) on non-CJR patients treated by CJR physicians, and with error term clustered in MSA level. The included patients are those treated by the same physicians conducted CJR procedures. All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy. The results of LOS are estimated by Poisson regression while those of total charge and total cost are estimated by General Linear Model (GLM) with log link and gamma distribution.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table 11: CJR spillovers of other surgeries and DRGs, other outcomes

	(1)	(2)	(3)	(4)
	81* Procedures		other DRGs	
	LOS			
	Medicare	Private	Medicare	Private
TreatmentX2013	0.051	-0.129	-0.021	0.025
	(0.221)	(0.109)	(0.085)	(0.069)
TreatmentX2015	0.205	-0.155	0.035	0.086
	(0.161)	(0.128)	(0.079)	(0.063)
TreatmentX2016	0.283	0.156	0.136	-0.031
	(0.204)	(0.149)	(0.095)	(0.083)
TreatmentX2017	0.187	0.333**	0.121	0.124
	(0.220)	(0.140)	(0.090)	(0.078)
	Cost			
TreatmentX2013	315.816	-442.575	-73.767	-156.013
	(655.721)	(468.199)	(259.654)	(192.309)
TreatmentX2015	889.557	-563.949	354.911	45.461
	(675.965)	(472.100)	(279.827)	(229.073)
TreatmentX2016	209.644	318.817	207.624	-278.636
	(675.440)	(716.881)	(385.924)	(229.570)
TreatmentX2017	2166.559**	661.183	911.676**	505.898*
	(925.476)	(981.408)	(423.692)	(291.187)
	Charge			
TreatmentX2013	-5079.135	-5564.193***	-560.292	-1841.935**
	(4355.953)	(1978.166)	(1291.268)	(859.358)
TreatmentX2015	69.579	-3780.409	1005.272	-232.228
	(3897.746)	(2389.082)	(1305.643)	(1051.801)
TreatmentX2016	-2358.960	-1557.643	-1204.272	-2208.557**
	(4426.695)	(4381.942)	(1808.179)	(971.592)
TreatmentX2017	5273.233	1723.764	1146.859	-402.311
	(5403.299)	(5087.609)	(1914.047)	(1671.960)
N	17131	15481	37543	49344

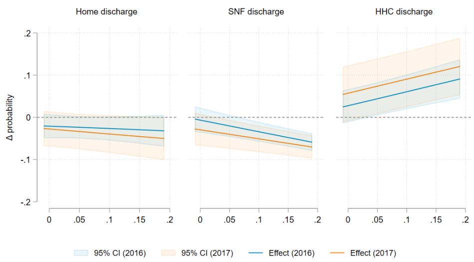
NOTE: Table presents the estimated marginal effects from equation (1) on non-CJR patients classified in related DRG or undergone 81* procedures with error term clustered in MSA level. The group of Other DRGs, column (1) and (2), include patients in three DRGs - DRG 483, Major Joint and Limb Reattachment Procedures of Upper Extremity, DRG 493, Lower Extremity and Humerus Procedures Except Hip, Foot, Femur with CC and DRG 494, Lower Extremity and Humerus Procedures Except Hip, Foot, Femur without CC/MCC. All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy. The results of LOS are estimated by Poisson regression while those of total charge and total cost are estimated by General Linear Model (GLM) with log link and gamma distribution.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table 12: 2SLS estimates of the functional form of Medicare policy effects on private-sector

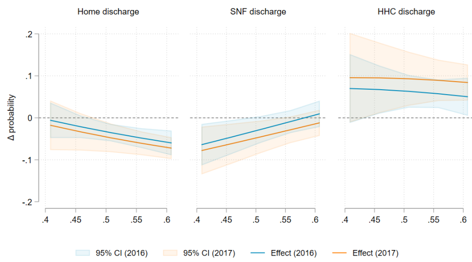
	1st stage	reduced form	IV
	(1)	(2)	(3)
	Cost		
Cost	0.864***	0.900***	0.938***
	(0.021)	(0.024)	(0.047)
N	253304	121412	121412
Home discharge			
Home discharge	0.597***	1.150***	0.835***
	(0.033)	(0.046)	(0.035)
SNF discharge	-0.100	-0.117	-0.081
	(0.101)	(0.078)	(0.065)
HHC discharge	-0.497***	-1.032***	-0.753***
	(0.084)	(0.066)	(0.048)
	258484	123232	123232
SNF discharge			
Home discharge	-0.379***	-0.495***	-0.510***
	(0.054)	(0.104)	(0.138)
SNF discharge	0.730***	0.489***	0.562***
	(0.039)	(0.031)	(0.046)
HHC discharge	-0.350***	0.006	-0.052
	(0.069)	(0.113)	(0.146)
	258484	123232	123232
HHC discharge			
Home discharge	-0.395***	-0.722***	-0.599***
	(0.051)	(0.107)	(0.078)
SNF discharge	-0.397***	-0.321***	-0.269***
	(0.080)	(0.058)	(0.057)
HHC discharge	0.792***	1.043***	0.867***
	(0.038)	(0.072)	(0.048)
N	258484	123232	123232

NOTE: Table presents the results of first stage, reduced form and IV estimates, which are described in the empircal strategy section. The first panel is for the total cost and the rest is for discharge. The results of total cost are estimated by General Linear Model (GLM) with log link and gamma distribution.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

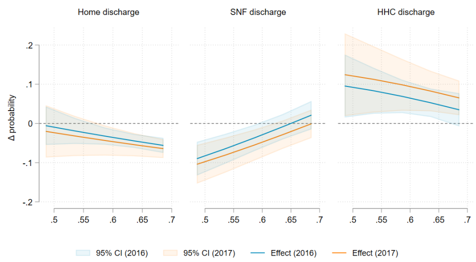
A Appendix 1



(a) LEJR penetration



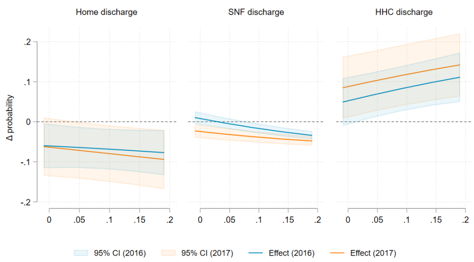
(b) Medicare penetration



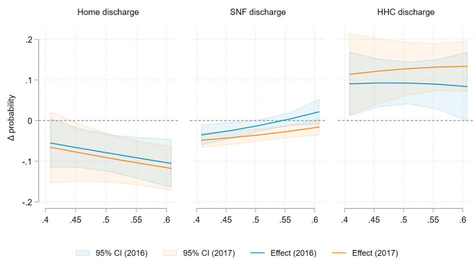
(c) LEJR-Medicare penetration

Figure A1: Heterogeneous effects of discharge on Medicare patients, episode charge

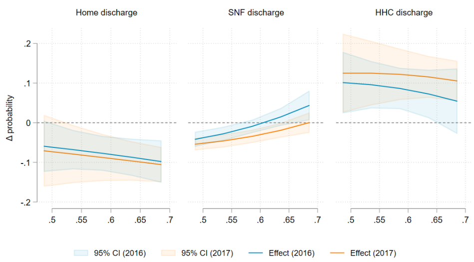
Figure presents the estimated marginal effects of heterogeneous CJR effects on discharge locations with 95 percent confidence interval by four dimensions. Four dimensions of penetration include HHC-SNF penetration, which is the relative employment rate in given MSA between HHC and SNF before 2015 (panel a), LEJR penetration, which is the share of LEJR patients by hospitals before 2015 (panel b), Medicare penetration, which is the share of patients covered by Medicare by hospitals before 2015 (panel c), and LEJR-Medicare penetration, which is the share of LEJR patients covered by Medicare by hospitals before 2015 (panel d). The results of discharge location are estimated by Mlogit model and those of cost are estimated by GLM with gamma distribution and log-link. After calculating three penetration variables and assigning them to each record, I regularize them by subtracting the mean.



(a) LEJR penetration



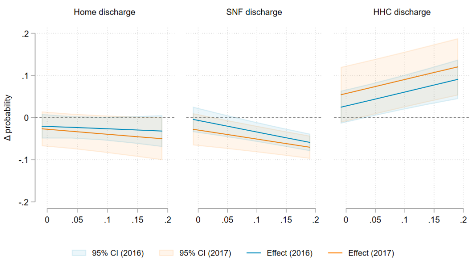
(b) Medicare penetration



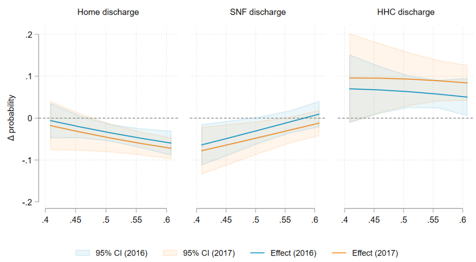
(c) LEJR-Medicare penetration

Figure A2: Heterogeneous effects of discharge on private insured patients, episode charge

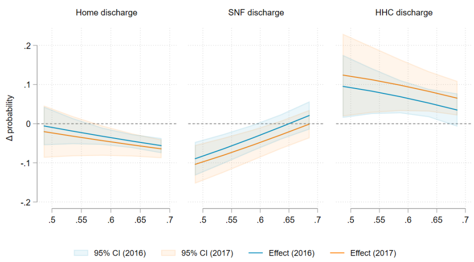
Figure presents the estimated marginal effects of heterogeneous CJR effects on discharge locations with 95 percent confidence interval by four dimensions. Four dimensions of penetration include HHC-SNF penetration, which is the relative employment rate in given MSA between HHC and SNF before 2015 (panel a), LEJR penetration, which is the share of LEJR patients by hospitals before 2015 (panel b), Medicare penetration, which is the share of patients covered by Medicare by hospitals before 2015 (panel c), and LEJR-Medicare penetration, which is the share of LEJR patients covered by Medicare by hospitals before 2015 (panel d). The results of discharge location are estimated by Mlogit model and those of cost are estimated by GLM with gamma distribution and log-link. After calculating three penetration variables and assigning them to each record, I regularize them by subtracting the mean.



(a) LEJR penetration



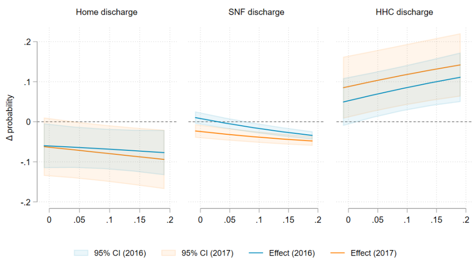
(b) Medicare penetration



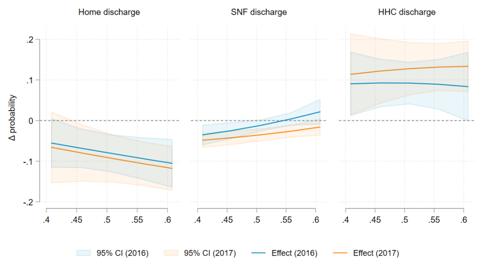
(c) LEJR-Medicare penetration

Figure A3: Heterogeneous effects of discharge on Medicare patients, episode cost

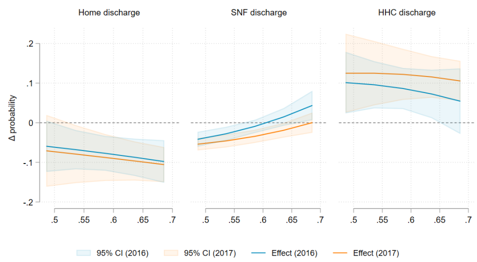
Figure presents the estimated marginal effects of heterogeneity on discharge locations with 95 percent confidence interval by targeted status. The penetrations are calculated using episode cost instead of episode number. Three dimensions of heterogeneity include LEJR penetration (total cost of LEJR divided by total cost in given hospital before 2015, panel (a)), Medicare penetration (share of Medicare cost to total cost in the hospital before 2015, panel (b)), LEJR-Medicare penetration (share of Medicare LEJR charge to total LEJR cost in the hospital before 2015, panel (c)). The estimated results is based on equation (2), with error term clustered in MSA level. The results of discharge locations are estimated by Mlogit model. After calculating three penetration variables and assigning them to each record, I regularize them by subtracting the mean.



(a) LEJR penetration



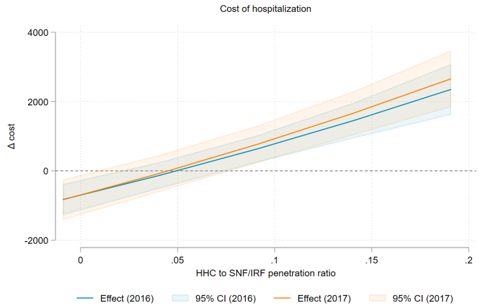
(b) Medicare penetration



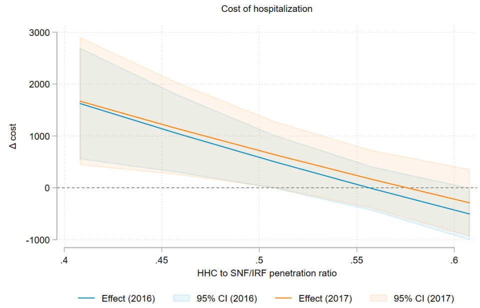
(c) LEJR-Medicare penetration

Figure A4: Heterogeneous effects of discharge on private insurance patients, episode cost

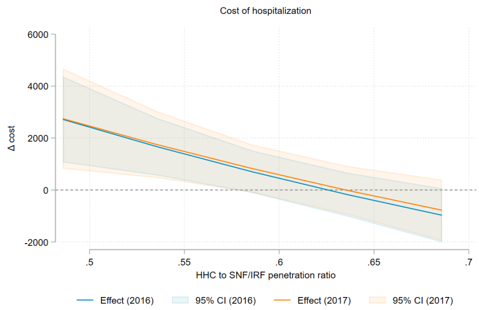
Figure presents the estimated marginal effects of heterogeneity on discharge locations with 95 percent confidence interval by targeted status. The penetrations are calculated using episode cost instead of episode number. Three dimensions of heterogeneity include LEJR penetration (total cost of LEJR divided by total cost in given hospital before 2015, panel (a)), Medicare penetration (share of Medicare cost to total cost in the hospital before 2015, panel (b)), LEJR-Medicare penetration (share of Medicare LEJR cost to total LEJR cost in the hospital before 2015, panel (c)). The estimated results is based on equation (2), with error term clustered in MSA level. The results of discharge locations are estimated by Mlogit model. After calculating three penetration variables and assigning them to each record, I regularize them by subtracting the mean.



(a) LEJR penetration



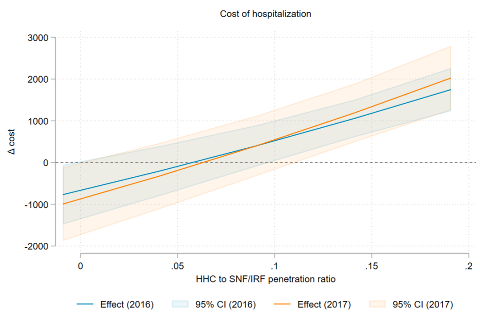
(b) Medicare penetration



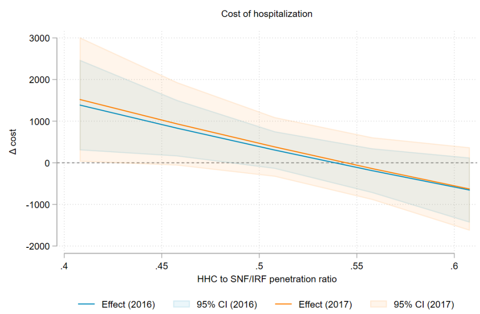
(c) LEJR-Medicare penetration

Figure A5: Heterogeneous effects of cost on Medicare patients, episode charge

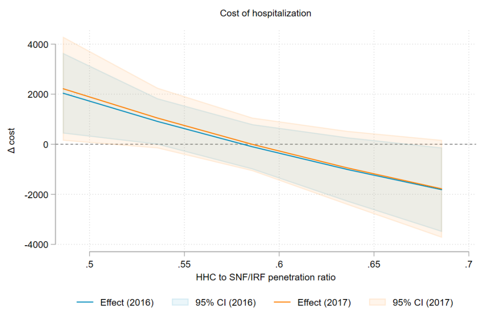
Figure presents the estimated marginal effects of heterogeneity on discharge locations with 95 percent confidence interval by targeted status. The penetrations are calculated using episode charge instead of episode number. Three dimensions of heterogeneity include LEJR penetration (total cost of LEJR divided by total cost in given hospital before 2015, panel (a)), Medicare penetration (share of Medicare cost to total cost in the hospital before 2015, panel (b)), LEJR-Medicare penetration (share of Medicare LEJR cost to total LEJR cost in the hospital before 2015, panel (c)). The estimated results is based on equation (2), with error term clustered in MSA level. The results of discharge locations are estimated by General Linear Model (GLM) with log link and gamma distribution model. After calculating three penetration variables and assigning them to each record, I regularize them by subtracting the mean.



(a) LEJR penetration



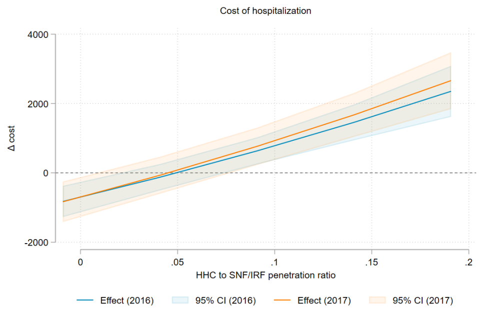
(b) Medicare penetration



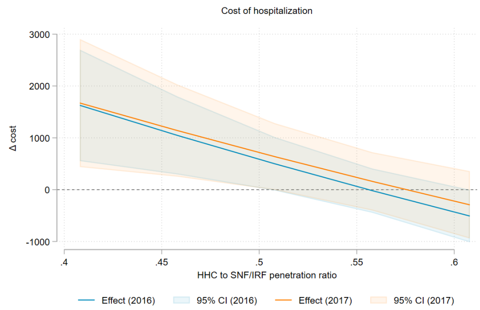
(c) LEJR-Medicare penetration

Figure A6: Heterogeneous effects of cost on private insurance patients, episode charge

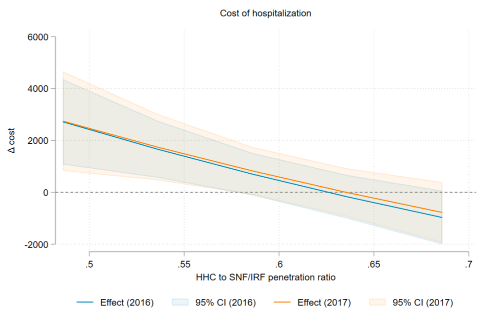
Figure presents the estimated marginal effects of heterogeneity on discharge locations with 95 percent confidence interval by targeted status. The penetrations are calculated using episode charge instead of episode number. Three dimensions of heterogeneity include LEJR penetration (total cost of LEJR divided by total cost in given hospital before 2015, panel (a)), Medicare penetration (share of Medicare cost to total cost in the hospital before 2015, panel (b)), LEJR-Medicare penetration (share of Medicare LEJR cost to total LEJR cost in the hospital before 2015, panel (c)). The estimated results is based on equation (2), with error term clustered in MSA level. The results of discharge locations are estimated by General Linear Model (GLM) with log link and gamma distribution model. After calculating three penetration variables and assigning them to each record, I regularize them by subtracting the mean.



(a) LEJR penetration



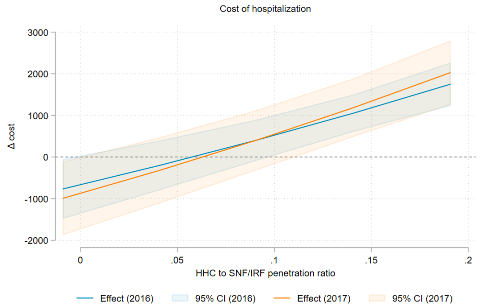
(b) Medicare penetration



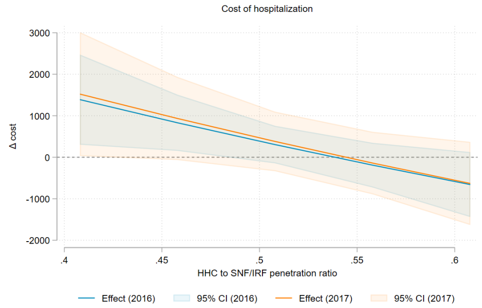
(c) LEJR-Medicare penetration

Figure A7: Heterogeneous effects of cost on Medicare patients, episode cost

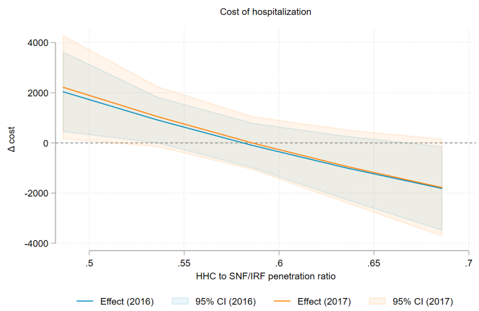
Figure presents the estimated marginal effects of heterogeneity on discharge locations with 95 percent confidence interval by targeted status. The penetrations are calculated using episode charge instead of episode number. Three dimensions of heterogeneity include LEJR penetration (total cost of LEJR divided by total cost in given hospital before 2015, panel (a)), Medicare penetration (share of Medicare cost to total cost in the hospital before 2015, panel (b)), LEJR-Medicare penetration (share of Medicare LEJR cost to total LEJR cost in the hospital before 2015, panel (c)). The estimated results is based on equation (2), with error term clustered in MSA level. The results of discharge locations are estimated by General Linear Model (GLM) with log link and gamma distribution model. After calculating three penetration variables and assigning them to each record, I regularize them by subtracting the mean.



(a) LEJR penetration



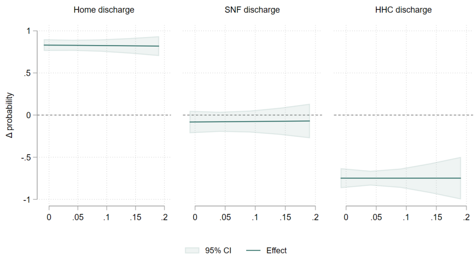
(b) Medicare penetration



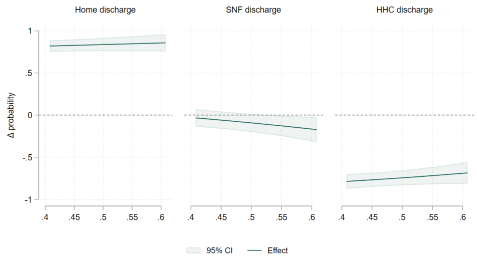
(c) LEJR-Medicare penetration

Figure A8: Heterogeneous effects of cost on private insurance patients, episode cost

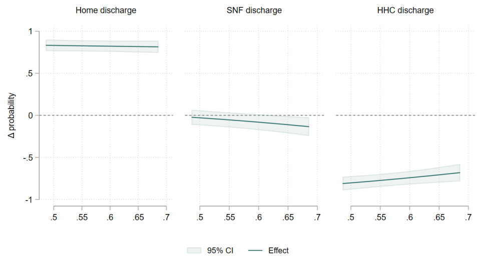
Figure presents the estimated marginal effects of heterogeneity on discharge locations with 95 percent confidence interval by targeted status. The penetrations are calculated using episode charge instead of episode number. Three dimensions of heterogeneity include LEJR penetration (total cost of LEJR divided by total cost in given hospital before 2015, panel (a)), Medicare penetration (share of Medicare cost to total cost in the hospital before 2015, panel (b)), LEJR-Medicare penetration (share of Medicare LEJR cost to total LEJR cost in the hospital before 2015, panel (c)). The estimated results is based on equation (2), with error term clustered in MSA level. The results of discharge locations are estimated by General Linear Model (GLM) with log link and gamma distribution model. After calculating three penetration variables and assigning them to each record, I regularize them by subtracting the mean.



(a) LEJR penetration



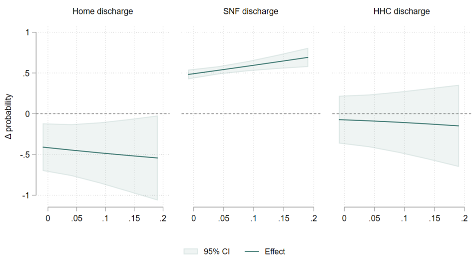
(b) Medicare penetration



(c) LEJR-Medicare penetration

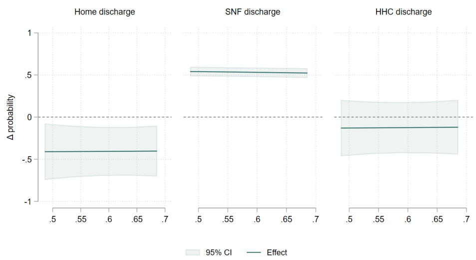
Figure A9: Heterogeneous effects of Medicare policy effects on private sector in Home discharge, Total Charge

Figure presents



(a) LEJR penetration

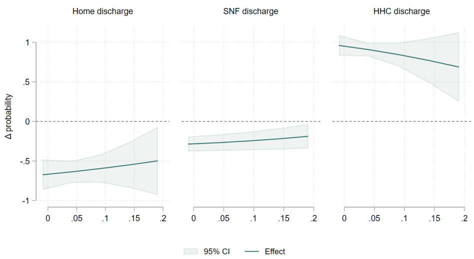
(b) Medicare penetration



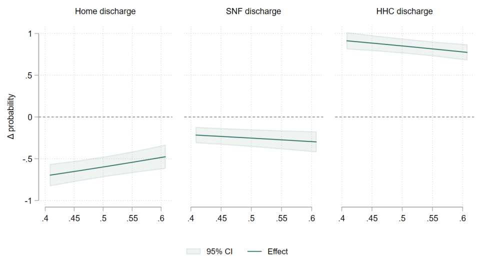
(c) LEJR-Medicare penetration

Figure A10: Heterogeneous effects of Medicare policy effects on private sector in SNF discharge, Total Charge

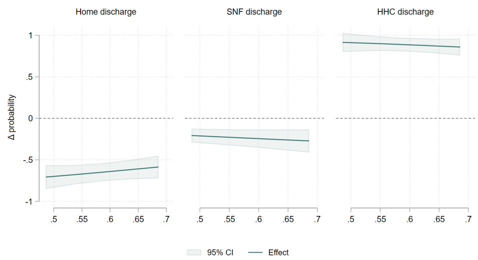
Figure presents



(a) LEJR penetration



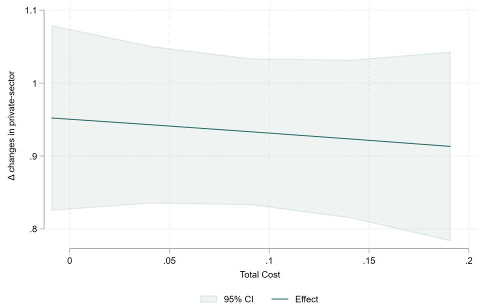
(b) Medicare penetration



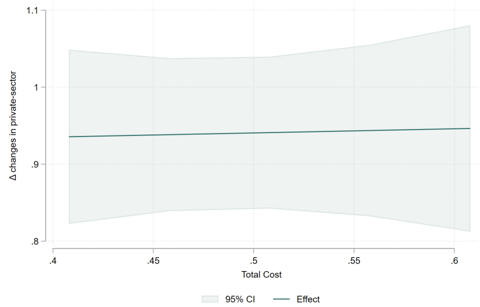
(c) LEJR-Medicare penetration

Figure A11: Heterogeneous effects of Medicare policy effects on private sector in HHC discharge, Total Charge

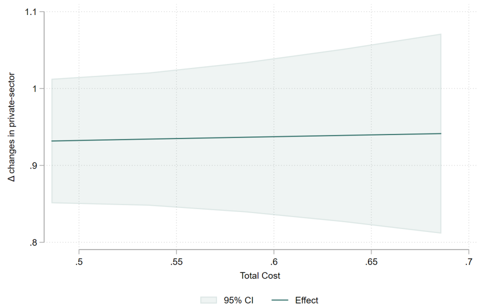
Figure presents the heterogeneous



(a) LEJR penetration



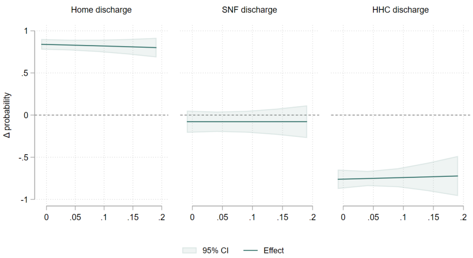
(b) Medicare penetration



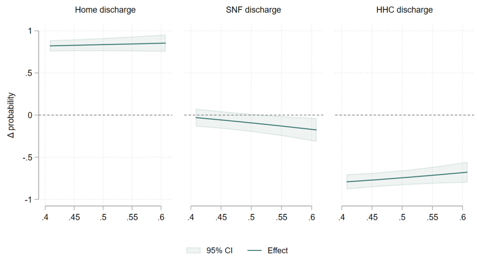
(c) LEJR-Medicare penetration

Figure A12: Heterogeneous effects of Medicare policy effects on private sector in other outcomes, Total Charge

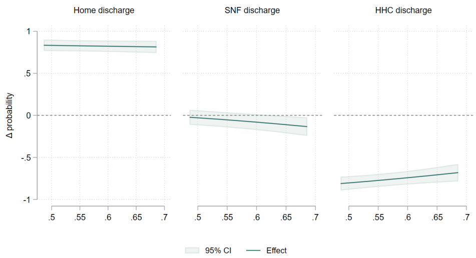
Figure presents



(a) LEJR penetration



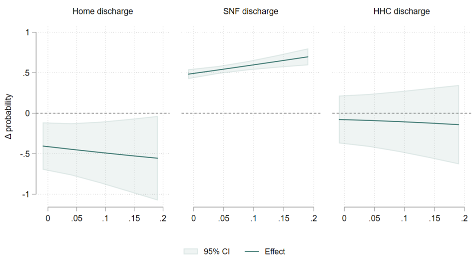
(b) Medicare penetration



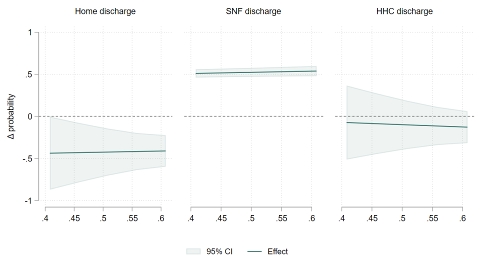
(c) LEJR-Medicare penetration

Figure A13: Heterogeneous effects of Medicare policy effects on private sector in Home discharge, Total Cost

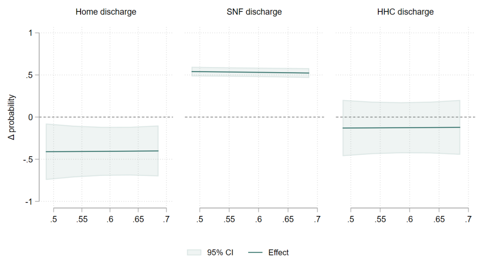
Figure presents



(a) LEJR penetration



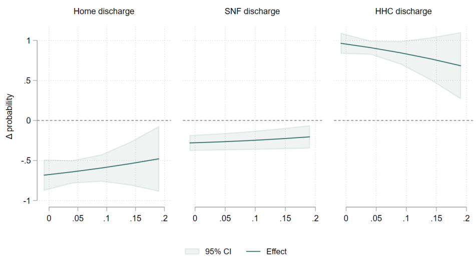
(b) Medicare penetration



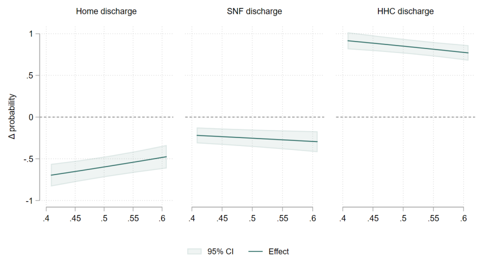
(c) LEJR-Medicare penetration

Figure A14: Heterogeneous effects of Medicare policy effects on private sector in SNF discharge, Total Cost

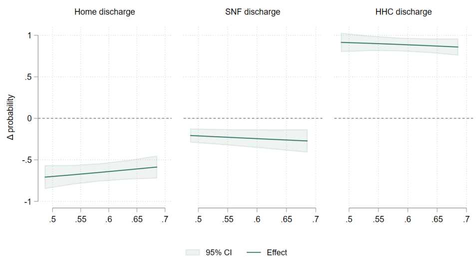
Figure presents



(a) LEJR penetration



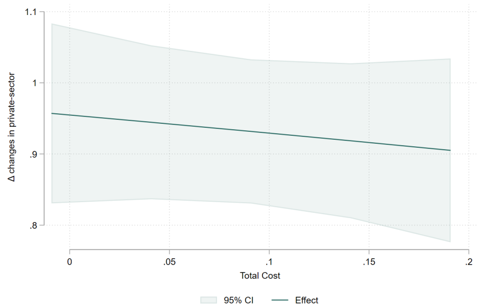
(b) Medicare penetration



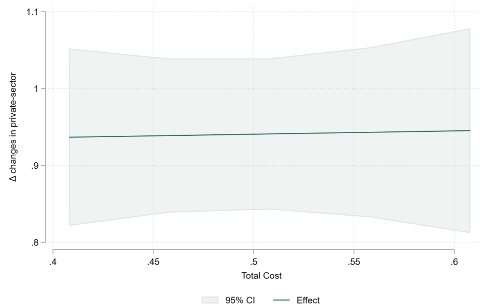
(c) LEJR-Medicare penetration

Figure A15: Heterogeneous effects of Medicare policy effects on private sector in HHC discharge, Total Cost

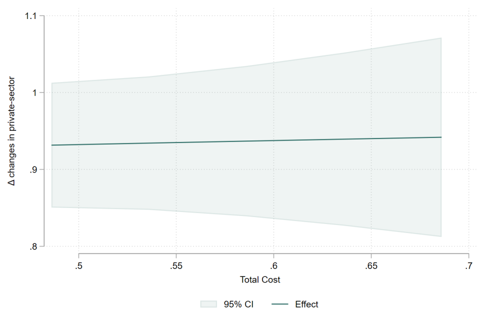
Figure presents the heterogeneous



(a) LEJR penetration



(b) Medicare penetration



(c) LEJR-Medicare penetration

Figure A16: Heterogeneous effects of Medicare policy effects on private sector in other outcomes, Total Cost

Figure presents

Table A1: Marginal effects of heterogeneity, Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	LEJR Charge		Medicare Charge		LEJR Cost	
	Medicare	Private	Medicare	Private	Medicare	Private
Home discharge	-0.000	-0.001	-0.001**	-0.001	-0.000	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
SNF discharge	-0.001***	-0.001***	0.002***	0.001**	-0.001***	-0.001***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
HHC discharge	0.002***	0.002***	-0.000	-0.000	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)
Cost	68.951***	61.569***	-46.962***	-55.437***	69.003***	61.616***
	(8.147)	(9.649)	(12.944)	(20.586)	(8.213)	(9.722)
N	608693	305882	608693	305882	608693	305882
	Medicare Cost		LEJR-Medicare Charge		LEJR-Medicare Cost	
	Medicare	Private	Medicare	Private	Medicare	Private
Home discharge	-0.001**	-0.001	-0.001**	-0.001	-0.001**	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
SNF discharge	0.002***	0.001**	0.003***	0.002***	0.003***	0.002***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
HHC discharge	-0.000	-0.000	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Cost	-47.021***	-55.502***	-78.014***	-102.097***	-77.960***	-102.052***
	(12.903)	(20.544)	(21.464)	(38.992)	(21.302)	(38.832)
N	608693	305882	608693	305882	608693	305882

NOTE: Table presents the results of heterogeneity of CJR effects and spillovers, which is the estimated marginal effects from equation (2), on three dimensions and two outcomes and by targeted status, with error term clustered in MSA level. HHC-SNF in column (1) indicates HHC-SNF penetration, which is the relative employment rate in given MSA between HHC and SNF. Medicare in column (2) indicates Medicare penetration, which is the share of Medicare covered patients to total LEJR patients. Column (3) indicates LEJR penetration in the hospital, which is the share of LEJR patients to total patients. All penetration variables are constructed using the patient record data before 2015. The results of discharge location are estimated by Mlogit model and those of cost are estimated by GLM with gamma distribution and log-link.
Sample: Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.

Table A2: Summary Statistics, non-CJR patients treated by CJR physicians MDC-8

	(1)	(2)	(3)	(4)
	Medicare		Private	
	Control	Treated	Control	Treated
Age	76.56	77.49	56.07	54.77
	(8.012)	(8.312)	(12.13)	(13.67)
Female	0.635	0.667	0.536	0.530
	(0.481)	(0.471)	(0.499)	(0.499)
White	0.910	0.780	0.842	0.702
	(0.287)	(0.415)	(0.364)	(0.457)
Black	0.0255	0.0623	0.0592	0.120
	(0.158)	(0.242)	(0.236)	(0.325)
Asian	0.0396	0.0956	0.0635	0.0986
	(0.195)	(0.294)	(0.244)	(0.298)
Other race	0.0254	0.0625	0.0349	0.0791
	(0.157)	(0.242)	(0.184)	(0.270)
Emergency	0.357	0.479	0.252	0.336
	(0.479)	(0.500)	(0.434)	(0.472)
Urgent	0.0641	0.0357	0.0579	0.0380
	(0.245)	(0.185)	(0.234)	(0.191)
Elective	0.579	0.485	0.690	0.626
	(0.494)	(0.500)	(0.463)	(0.484)
outcomes				
Home discharge	0.243	0.178	0.463	0.426
	(0.429)	(0.382)	(0.499)	(0.495)
SNF discharge	0.467	0.554	0.173	0.218
	(0.499)	(0.497)	(0.379)	(0.413)
HHC discharge	0.291	0.268	0.364	0.356
	(0.454)	(0.443)	(0.481)	(0.479)
LOS	3.637	4.233	3.116	3.556
	(3.317)	(3.854)	(3.529)	(4.030)
Total Charge	65871.2	70601.3	63144.1	71544.0
	(47102.6)	(53531.2)	(49693.9)	(57927.0)
Total Cost	13615.4	15026.7	14112.3	16565.0
	(8648.2)	(10996.6)	(9567.6)	(13252.0)
N	360409	676767	206335	461891

NOTE: Table presents the summary statistics on the control variables and outcome variables. All statistics are based on the HCUP SID 2013-2017 sample.

Table A3: Summary Statistics, non-CJR patients treated by CJR physicians MDC-8

	(1)	(2)	(3)	(4)
	Medicare		Private	
	Control	Treated	Control	Treated
Age	78.31	78.96	50.18	49.32
	(8.321)	(8.480)	(15.88)	(16.29)
Female	0.540	0.557	0.511	0.501
	(0.498)	(0.497)	(0.500)	(0.500)
White	0.859	0.677	0.747	0.580
	(0.349)	(0.468)	(0.434)	(0.494)
Black	0.0551	0.114	0.111	0.192
	(0.228)	(0.318)	(0.314)	(0.394)
Asian	0.0609	0.146	0.102	0.153
	(0.239)	(0.353)	(0.303)	(0.360)
Other race	0.0255	0.0631	0.0394	0.0744
	(0.158)	(0.243)	(0.195)	(0.262)
Emergency	0.852	0.926	0.811	0.878
	(0.355)	(0.262)	(0.392)	(0.327)
Urgent	0.109	0.0363	0.139	0.0685
	(0.312)	(0.187)	(0.346)	(0.253)
Elective	0.0390	0.0377	0.0504	0.0531
	(0.193)	(0.191)	(0.219)	(0.224)
Outcomes				
Home discharge	0.513	0.488	0.790	0.808
	(0.500)	(0.500)	(0.407)	(0.394)
SNF discharge	0.271	0.282	0.0980	0.0920
	(0.444)	(0.450)	(0.297)	(0.289)
HHC discharge	0.216	0.230	0.112	0.100
	(0.412)	(0.421)	(0.315)	(0.300)
LOS	4.911	5.258	4.658	4.697
	(5.064)	(5.525)	(5.769)	(6.209)
Total Charge	48929.9	56865.0	44531.9	49559.2
	(54647.4)	(67555.1)	(57065.5)	(71388.7)
Total Cost	9629.2	10985.2	9122.8	9802.5
	(10230.3)	(12772.1)	(11425.4)	(14169.0)
N	1528125	3475963	991156	2468917

NOTE: Table presents the summary statistics on the control variables and outcome variables. All statistics are based on the HCUP SID 2013-2017 sample.

Table A4: Summary Statistics, non-CJR patients with 81* procedures

	(1)	(2)	(3)	(4)
	Medicare		Private	
	Control	Treated	Control	Treated
Age	73.57	73.26	58.32	58.00
	(6.742)	(6.595)	(7.985)	(8.411)
Female	0.580	0.608	0.529	0.534
	(0.494)	(0.488)	(0.499)	(0.499)
White	0.911	0.816	0.863	0.765
	(0.285)	(0.387)	(0.344)	(0.424)
Black	0.0304	0.0577	0.0695	0.0995
	(0.172)	(0.233)	(0.254)	(0.299)
Asian	0.0313	0.0550	0.0355	0.0565
	(0.174)	(0.228)	(0.185)	(0.231)
Other race	0.0272	0.0708	0.0321	0.0789
	(0.163)	(0.257)	(0.176)	(0.270)
Emergency	0.129	0.123	0.0406	0.0385
	(0.335)	(0.329)	(0.197)	(0.192)
Urgent	0.0395	0.0307	0.0295	0.0273
	(0.195)	(0.173)	(0.169)	(0.163)
Elective	0.831	0.846	0.930	0.934
	(0.374)	(0.361)	(0.255)	(0.248)
Outcomes				
Home discharge	0.147	0.0967	0.255	0.174
	(0.355)	(0.296)	(0.436)	(0.379)
SNF discharge	0.602	0.681	0.387	0.504
	(0.489)	(0.466)	(0.487)	(0.500)
HHC discharge	0.250	0.223	0.358	0.322
	(0.433)	(0.416)	(0.480)	(0.467)
LOS	4.028	4.553	3.579	3.980
	(3.668)	(4.322)	(3.271)	(3.777)
Total Charge	107583.3	105590.2	98179.2	103589.7
	(62642.0)	(65297.4)	(52075.6)	(66522.9)
Total Cost	22416.9	24290.4	23562.0	26538.5
	(11455.1)	(13823.9)	(10802.1)	(16692.9)
N	5367	12887	5077	15102

NOTE: Table presents the summary statistics on the control variables and outcome variables. All statistics are based on the HCUP SID 2013-2017 sample.

Table A5: Summary Statistics, non-CJR patients in other DRG

	(1)	(2)	(3)	(4)
	Medicare		Private	
	Control	Treated	Control	Treated
Age	75.54	75.70	46.80	44.36
	(7.718)	(7.710)	(18.00)	(18.88)
Female	0.754	0.758	0.563	0.538
	(0.431)	(0.428)	(0.496)	(0.499)
White	0.908	0.784	0.822	0.658
	(0.288)	(0.412)	(0.383)	(0.474)
Black	0.0299	0.0542	0.0666	0.122
	(0.170)	(0.226)	(0.249)	(0.327)
Asian	0.0395	0.104	0.0701	0.120
	(0.195)	(0.306)	(0.255)	(0.325)
Other race	0.0222	0.0577	0.0413	0.100
	(0.147)	(0.233)	(0.199)	(0.301)
Emergency	0.616	0.694	0.639	0.669
	(0.486)	(0.461)	(0.480)	(0.470)
Urgent	0.0934	0.0590	0.0824	0.0569
	(0.291)	(0.236)	(0.275)	(0.232)
Elective	0.290	0.246	0.279	0.274
	(0.454)	(0.431)	(0.448)	(0.446)
Outcomes				
Home discharge	0.233	0.221	0.611	0.648
	(0.422)	(0.415)	(0.487)	(0.478)
SNF discharge	0.580	0.582	0.190	0.169
	(0.494)	(0.493)	(0.393)	(0.375)
HHC discharge	0.188	0.197	0.198	0.183
	(0.391)	(0.398)	(0.399)	(0.387)
LOS	3.831	4.292	3.307	3.569
	(3.122)	(3.315)	(3.427)	(3.547)
Total Charge	62519.6	70073.4	54641.7	64510.5
	(35458.2)	(39837.9)	(36828.3)	(44887.4)
Total Cost	13186.7	14690.0	12878.9	14835.1
	(5992.6)	(8008.8)	(6990.5)	(9799.8)
N	10698	22671	15273	42890

NOTE: Table presents the summary statistics on the control variables and outcome variables. All statistics are based on the HCUP SID 2013-2017 sample.

Table A6: 2SLS estimates of the functional form of Medicare policy effects on private-sector, Robustness

	1st stage (1)	reduced form (2)	IV (3)
		Cost	
Cost	0.886***	0.905***	0.886***
	(0.024)	(0.023)	(0.046)
N	150012	88600	88600
	Home discharge		
Home discharge	0.655***	0.961***	0.787***
	(0.031)	(0.035)	(0.036)
SNF discharge	-0.074	-0.096	-0.079
	(0.090)	(0.067)	(0.066)
HHC discharge	-0.581***	-0.865***	-0.708***
	(0.071)	(0.056)	(0.050)
N	152534	89866	89866
	SNF discharge		
Home discharge	-0.445***	-0.425***	-0.437***
	(0.118)	(0.132)	(0.142)
SNF discharge	0.783***	0.480***	0.533***
	(0.018)	(0.023)	(0.033)
HHC discharge	-0.338***	-0.055	-0.095
	(0.113)	(0.129)	(0.140)
N	152534	89866	89866
	HHC discharge		
Home discharge	-0.513***	-0.701***	-0.639***
	(0.039)	(0.066)	(0.062)
SNF discharge	-0.337***	-0.240***	-0.224***
	(0.069)	(0.051)	(0.059)
HHC discharge	0.850***	0.941***	0.864***
	(0.033)	(0.039)	(0.043)
N	152534	89866	89866

NOTE: Table presents the results of first stage, reduced form and IV estimates, which are described in the empirical strategy section. The first panel is for the total cost and the rest is for discharge. The results of total cost are estimated by General Linear Model (GLM) with log link and gamma distribution.
Sample: Data is restricted to those patients aged above 55 and less than 75. Patients in the HCUP SID 2013-2017, 5 States (Arizona, Florida, North Carolina, New Jersey, New York and Washington). All specifications include age, gender, race, DRG, hospital type dummy, year dummy and MSA dummy.