The Impact of Alternative Types of Elder Care Providers: Stratified IV Analysis with Machine Learning Using Nursing Home Exits

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Abstract

This paper develops the stratified instrumental variables (IV) with machine learning method to analyze elder care provider types. Despite an increasingly aging population, finding the appropriate elder care provider among various agencies and facilities is still difficult. For example, home health agencies, nursing homes, and inpatient rehabilitation facilities are all common providers, each with different care intensities, service categories, and cost burdens. With few medical guidelines, quality and cost comparisons of providers based on observational data are important, but the validity of results can be threatened by selection bias. In this paper, I focus on the analysis of post-acute care (care after hospital discharge) for the elderly, and overcome the empirical challenge by instrumenting provider type with hospital-nursing home vertical disintegration. Yet first stage results show that the exit of hospital-affiliated nursing homes increases the likelihood of both home health care and inpatient rehabilitation. To address the violation of monotonicity, I thus propose stratified IV with machine learning. I estimate the individual-specific first stage effects of instrument on treatment values with generalized random forest, use these estimates to stratify compliers along different response margins, and identify stratum-specific local average treatment effects. The analysis shows that the marginal elderly costs the government twice as much in inpatient rehabilitation facilities than nursing homes, without experiencing improvement in health outcomes. Meanwhile, for the elderly on another response margin, home health can provide care with quality and cost similar to nursing homes. These results can inform government policy on elder care financing and management, and the method is widely applicable to IV analysis in settings of multiple treatments.

*I am deeply grateful to Mark Duggan, Luigi Pistaferri, Caroline Hoxby, Susan Athey, Guido Imbens, and Raj Chetty for serving on my dissertation committee and providing me with invaluable support and guidance. I would also like to thank Emmanuel Saez, Patrick Kline, and David Chan for their extremely helpful advice and comments.

I Introduction

Population aging is an increasingly important global issue. In the U.S., the size of the population aged 65 plus is projected to more than double by 2050, and that of those aged 85 plus is projected to more than triple (Reaves and Musumeci, 2015). Meanwhile, the prevalence of chronic conditions is also on the rise especially among the elderly. For example, while 4.7 million people aged 65 plus lived with Alzheimer's in 2010, the number is projected to rise to 13.8 million by 2050 (The Alzheimer's Association, 2018).

Despite rapidly increasing demand for elder care driven by this demographic shift, finding the appropriate type of provider among various agencies and facilities can be challenging. For instance, home health agencies (HHAs), nursing homes (SNFs), and inpatient rehabilitation facilities (IRFs) are all common elder care providers in the U.S., each with different care intensities, service categories, and cost burdens. Since there are relatively few medical guidelines on how to meet the spectrum of elder care needs, quality and cost comparison of provider types based on observational data plays an important role in guiding government policies and informing consumers.

In this paper, I compare the quality and cost of elder care across different types of providers, focusing on post-acute care (PAC), defined as formal care that helps patients recover from an acute health shock. While post-acute and long-term care are the two main sources of revenue in most elder care providers, post-acute care encompasses better-defined needs and services, and thus fits well with the purpose of provider type comparison. It is a common form of care and important component of health care expenditure, as approximately 40% of Medicare-covered inpatient hospitalizations are followed with post-acute care, costing Medicare $58.9 billion (MedPAC, 2019a) in 2017. In general, patients with health conditions that require least intensive care tend to get PAC through home health services, while patients who need more intensive care tend to get admitted to inpatient rehabilitation facilities, and the nursing homes largely provide services for those in the middle[1]. Despite substantial overlap in patient characteristics, these providers are reimbursed at very different rates, making the utilization of PAC accountable for as much as over 70 percent of unexplained geographic variation in U.S. health care spending (Institute of Medicine, 2013). Meanwhile, rigorous comparison across different providers is limited by the concern of selection bias. For example, patients more prone to medical complications may be more likely to get PAC at inpatient rehab facilities than at nursing homes, confounding the estimated effects of IRFs in common OLS analysis.

Selection bias in multiple treatment settings as described above is a common issue in empirical analysis, and it can be challenging to address with econometric methods developed for binary treatment cases. For example, when the treatments are binary, instrumental variables (IV) can ensure causal identification as long as the assumptions of monotonicity, independence, exclusion, and first-stage hold. However, when the number of possible treatments is greater than two, standard IV analysis may not produce valid and interpretable results since the monotonicity assumption is often violated. Taking the elder care analysis as an example, I instrument a patient's elder care provider using vertical disintegration of hospitals and nursing homes to overcome selection bias[2]. Event study shows that the exit of hospital-affiliated nursing homes lowers the propensity of post-acute care at any nursing home and increases the likelihood of both home health care and inpatient rehab. Such heterogeneity in the first stage effect of instrument on possible treatments thus violates the monotonicity assumption, and deems standard IV unfit for causal identification in this setting. While such violation can arise in binary treatment settings as well, it is much more prevalent in cases where there are multiple treatment options or policy responses, such as elder care, education (Kline and Walters, 2016; Mountjoy, 2019), housing (van Dijk, 2019; Bergman et al., 2019), social insurance designs (Low and Pistaferri, 2015), and tax approximation models (Rees-Jones and

[1]Other less common post-acute care providers include long-term care hospitals and swing bed at rural and critical access hospitals.

[2]In 2000-2016, the number of hospital-affiliated nursing homes dropped by over a half, while the number of free-standing ones has remained relatively stable.

Taubinsky, 2019).

In a world where economists observe exactly how an instrument affects treatment selection for each individual, one can allow for violations of monotonicity in aggregate and separately identify LATE for compliers on different response margins. However, common nonparametric analysis of heterogeneous first stage effects can be severely constrained by the curse of dimensionality (Wasserman, 2006). For example, whether the instrument induces a patient to substitute PAC at nursing home with home care or inpatient rehab may be influenced by a large number of covariates and their interactions, such as the socio-economic status of the patient, diagnosis and severity of the health shock, vertical structure of hospitals and elder care providers, and availability of elder care agencies and facilities in the local health care market. Conventional heterogeneity analysis methods such as interacting instrument with these characteristic variables can quickly become intractable and prone to overfitting, and common nonparametric methods such as local maximum likelihood estimators can be infeasible as data points become increasingly sparse in higher dimensional covariate spaces. Meanwhile, parametric modeling of treatment selection usually relies on strong assumptions and may not adequately capture the complexity of underlying decision-making process. Existing methods often also require special properties of the instrument, which may not be readily applicable in empirical settings (Lee and Salanié, 2018).

Hence in this paper, I propose an advanced applied econometrics method named stratified IV with machine learning, harnessing machine learning's power in nonparametric estimation of heterogeneous treatment effects with high dimensional data. I apply recent developments in machine learning to estimate the individual-specific first stage effects, use these estimates to stratify compliers along different response margins, and identify stratum-specific local average treatment effects (LATEs). Specifically, I recast the treatment selection problem with potential outcomes framework, and estimate individual-specific conditional first stage effects of instrument on treatment values through generalized random forest. Adapting from classification and regression tree

(Breiman et al., 1984) and random forest (Breiman, 2001), generalized random forest (Athey et al., 2019) allows for accurate and flexible estimation of heterogeneous treatment effects by recursively partitioning the sample into leaves within which individuals experience similar treatment effects and across which the effects are as heterogeneous as possible. The partitioning (aka "tree growing") is repeated on different random subsamples and with random subsets of covariates, and the aggregation of trees forms a random forest. The treatment effects conditional on all observed covariates are then estimated through a local maximum likelihood estimator, where kernel weights are based on the frequency when each individual ends up in the same leaf as those with the covariates of interest. These individual-specific first stage effects thus allow for complier group stratification and stratum-specific LATE estimation, relaxing the monotonicity assumption in aggregate as long as it holds within a complier bucket. Therefore the proposed method – stratified IV with machine learning – effectively overcomes the curse of dimensionality and extends the application of IV without imposing strong functional form or behavioral assumptions.

I thus apply the stratified IV with machine learning method and use generalized random forest to estimate conditional first stage effects of the termination of hospital-affiliated nursing homes on the choice of PAC provider types, based on a wide range of observables such as patients' socio-demographic information, baseline health conditions, principal diagnosis codes, absolute and relative distance to nearest home health agency (HHA), inpatient rehabilitation facility (including hospital with IRF units), and long-term care hospital, and state-year average share of patients getting different types of PAC in a held-out sample [3]. To address concerns of potential overfitting, I randomly split the sample into two halves, one to build the random forest, and the other to predict the individual-specific first stage effects based on the random forest partitioning. Patients in the second subsample are then stratified into groups of nursing home to home care compliers and nursing home to inpatient rehab compliers according to the relative first stage estimates on home care

[3] Held out sample consists of inpatient hospitalizations at hospitals that do not have any affiliated SNF throughout 2001 - 2015, while satisfying all sample restrictions for the treatment and control samples.

and inpatient rehab propensities. Within each stratum, all standard IV assumptions (independence, exclusion, first stage, and monotonicity) should thus hold, and the stratum-specific local average treatment effects can be identified through two stage least squares.

The results show that patients who shift to inpatient rehab care after hospital-affiliated nursing home exits do not experience significant changes in mortality or inpatient readmission rates, but cost Medicare twice as much for the hospitalization and institutional post-acute care. Similarly, one cannot reject the null that the compliers shifting from nursing home to home care experience little change in health outcomes and utilizations. The results suggest that while inpatient rehab facilities could provide similar quality PAC when nursing homes become less available, the difference in care quality may not fully justify the higher cost. Meanwhile home health services could indeed prove to be a viable alternative to nursing home care with similar quality at no higher cost.

Empirically, this paper adds to the growing literature analyzing the impacts of elder care provider types on PAC quality and cost (Rahman et al., 2017; Werner et al., 2019; Rahman et al., 2013, 2016; Konetzka et al., 2018). The paper extends empirical strategy beyond common distance-based instruments in the literature to account for the concern that distance to PAC facilities may be confounded by other factors of the local health care market. More broadly, the paper contributes to the literature on vertical integration in the health care sector and the impact of institution ownership on health cost and outcomes (Gaynor et al., 2017; Brot-Goldberg and de Vaan, 2019; Duggan, 2000).

Methodologically, this paper contributes to the recent and growing literature on generalizing IV from binary to multiple treatment settings. Most of the literature still assumes monotonicity and develops methods to separately identify counterfactual-specific subLATEs (Kline and Walters, 2016; Feller et al., 2016; Kirkeboen et al., 2016; Hull, 2018; Mountjoy, 2019; Mogstad et al., 2019). Moving away from strict or ordered monotonicity assumption, Heckman and Pinto (2018) show conditions under which choice behaviors ensure unordered monotonicity, and characterize

IV estimators as weighted average of the margin-specific LATEs. Lee and Salanié (2018) fully relax the monotonicity assumption by modeling treatment selection as a vector of threshold-crossing rules, while highly model-specific and requiring enough continuous instruments. This paper relaxes the monotonicity constraint from aggregate to group-specific by applying machine learning to estimate individual-specific first stage effects, thereby allowing for identification of complier-specific LATEs in multiple treatment settings without strong model assumptions or special instrument properties. It is at the forefront of using machine learning to overcome bottleneck applied econometric challenges, and illustrates the applicability of the method to empirical analysis with high dimensional data in a natural experiment setting.

The rest of the paper proceeds as follows. Section 2 discusses the institutional background of post-acute care. Section 3 describes the data, summary statistics, and findings from average effect analysis. Section 4 develops the stratified IV with machine learning method, and Section 5 applies it to analyze the quality and cost of post-acute health care across different types of elder care providers. Section 6 concludes.

II Background of Post-Acute Care and Providers

II.1 Types of PAC Providers and Medicare Reimbursement Policies

Post-acute care (PAC), defined as formal care that helps patients recover from an acute health shock, is a common form of health care and one of the two main sources of revenue (the other being long-term care) for most elder care providers. The most important payer of PAC in the U.S. is Medicare[4], which is the largest payer of health care for the elderly. The total annual expenditure

[4]Note that all the policies discussed in this section and all analysis in this paper only pertain to original (fee-for-service) Medicare, as Medicare Advantage enrollees may face drastically different rules and may not have high quality data in the Medicare datasets used in this paper.

on all original Medicare (fee-for-service) PAC services is around $59 billion, following over 1 million inpatient hospitalizations (MedPAC, 2019a). From 2001 to 2013, Medicare payment to PAC providers more than doubled (MedPAC, 2015), as Chandra et al. (2013) identified PAC as the fastest growing major health care spending category in 1994 - 2009.

Importantly, the choice of PAC provider type and corresponding cost varies dramatically in the U.S. The most common elder care providers that offer PAC for Medicare beneficiaries are home health agencies (HHAs), nursing homes (skilled nursing facilities, aka SNFs), and inpatient rehabilitation facilities (IRFs). Among these, nursing homes have the largest share of PAC spending ($28.7 billion in 2017), followed by home health agencies ($18.0 billion), and inpatient rehab facilities ($7.9 billion) (MedPAC, 2019a). As shown in Table 1 and Figure 1, the share of patients getting PAC at each type of providers after an inpatient hospitalization also roughly follows this order. Partly due to a lack in definitive medical guidelines on optimal form of PAC, the choice of PAC provider type can be heavily influenced by non-clinical factors such as local practice patterns, availability in local health care market, patient preferences, financial incentives of providers, and vertical relations between hospital and elder care providers (MedPAC, 2015; Buntin et al., 2005). With such large differences in payment rates and utilization across PAC provider types, Institute of Medicine (2013) estimates that PAC alone could account for 73 percent of unexplained geographic variation in health care cost across the U.S. in 2013.

While Medicare pays for eligible PAC services at all certified providers, the reimbursement policies are different across provider types. Beneficiaries are eligible to get PAC at nursing homes if the stay follows an inpatient hospitalization of more than 3 days[5]. The reimbursement of nursing home care is on a per-diem basis. Medicare covers the full cost in the first 20 days of SNF stay, requires daily beneficiary coinsurance in the 21st - 100th day of the stay[6], and stops paying altogether after the first 100 days. The rates of reimbursement for the SNFs are determined by

[5]Except if readmitted to SNF within a Medicare benefit period

[6]For dual-eligibles, the copayment is usually paid for by Medicaid.

the resource utilization groups (RUGs) of the patients, which is based on the intensity of care and severity of health conditions (CMS, 2015, 2018). Home health agencies tend to provide post-acute care for patients with less intensive needs, and are reimbursed for each 60-day episode, regardless of the number of home health services provided during the episode[7]. Inpatient rehab facilities mainly target patients who need intensive rehabilitation therapy and careful coordination with a medical team. The IRFs receive higher reimbursement rates than SNFs and are thereby required to demonstrate that they are indeed providing services to patients who are in need of such intensive care. One important regulation is the "60 percent rule", which mandates that at least 60 percent of the total inpatient population at the IRF must need treatment for at least one of the 13 medical conditions such as stroke, spinal cord injury, amputation, hip fracture, brain injury, and neurological disorders[8]. The reimbursement is fixed for each IRF stay, adjusted for patient's clinical characteristics and expected resource uses, as well as other facility-level factors (CMS, 2019).

Besides the types discussed above, there are other providers of inpatient and outpatient PAC. For example, long-term care hospitals (LTCHs) began as a carve-out of hospital prospective payment system to provide care for patients whose average length of stay is 25 days or more. Gradually, LTCHs start providing PAC services that are arguably similar to those at SNFs (but get reimbursed at higher rates) (Einav et al., 2019). Conditions for patients receiving care at LTCHs are highly concentrated, with the top 25 MS-LTC-DRGs accounting for almost 70 percent of LTCH discharges and respiratory conditions alone accounting for over 35 percent of all LTCH cases (MedPAC, 2019a). Since LTCH is a relatively small share of total PAC observations in the Medicare data and is relatively less affected by the termination of hospital-affiliated nursing homes, I do not discuss it extensively in this paper. PAC can also be provided at swing beds in rural and critical access hospitals, which are designated hospital beds that can be used for either inpatient care or post-acute care. Swing bed PAC tends to be similar to those at SNFs, but accounts for a

[7]The episodes can be re-certified indefinitely as long as beneficiary could demonstrate medical need.

[8]The full list of the 13 conditions can be found in the appendix.

much smaller share of Medicare patients. To minimize confounds, I exclude all hospitals that have swing beds from the main analysis in this paper.

Despite the large variation in costs, evidence on care quality and health outcomes across different types of PAC providers has been scarce, largely focusing on a limited set of conditions (such as hip fracture and stroke) and often leading to contradicting conclusions. The lack of consistent quality measures and selection bias are the most important challenges for empirical analysis. For example, patients admitted to IRFs are expected to tolerate and benefit from intensive therapies[9], and thus may be healthier than those getting PAC at SNFs. On the other hand, patients more prone to medical complications may also be more likely to get PAC at inpatient rehab facilities than at nursing homes. Estimates of PAC provider effects in common OLS analysis are thus likely confounded by the patient and case mix. When comparing patient outcomes and Medicare spending between home health agencies and nursing homes, Werner et al. (2019) uses their relative distance as instruments to address selection bias, and finds that home health service saves significant cost but is associated with higher readmission rates. But the distance based IV can be hard to generalize to comparison between SNFs and IRFs. There are almost ten times as many SNFs than IRFs in the U.S., and thus patients living closer to an IRF may have access to a very different health care market than those living farther away.

Therefore, even though the Medicare payment advisory committee (MedPAC) has for years recommended Congress to unify PAC reimbursement, such attempts remain challenging without strong evidences on care quality across PAC provider types, potentially costing Medicare billions of dollars each year (MedPAC, 2019b; Einav et al., 2019). Meanwhile, with the rise of new payment systems such as bundled payment and accountable care organizations (ACOs), reducing PAC at institutional settings has become an increasingly common cost-saving measure (McWilliams et al., 2017; Werner et al., 2019). Although the literature does not find strong average effects of the

[9] The patients typically receive therapy for at least 3 hours per day, at least 5 days a week. (MedPAC, 2019a).

reduction of institutional PAC, average treatment effect may mask large heterogeneity in treatment effects and may ignore groups of individuals who are particularly vulnerable to the policy.

II.2 Trend of Vertical Integration

There has been a steady decline in the degree of vertical integration between hospitals and various types of elder care providers. The most stark trend is the massive terminations of hospital affiliated nursing homes in the last two decades. As shown in Table 2 and Figure 2, the number of hospital-affiliated SNFs in 2016 is less than half of the level in year 2000, while the number of free-standing SNFs has remained relatively stable. Prior literature and the industry has attributed the decline to the introduction of Medicare prospective payment system (PPS) for SNFs in 1998 which reimbursed hospital-owned SNFs at the same rate as free-standing ones, making them much less profitable than when paid at cost. However, Figure 2 and Figure 3 show that although the termination of hospital-affiliated SNFs started and peaked around the time of SNF PPS introduction, the trend has been steady and lasted for almost two decades. The trend of vertical disintegration is thus arguably unlikely to be a sharp response to a large policy change, but rather a gradual evolution that shapes current landscape of vertical relations between hospital and elder care providers.

The vertical disintegration is also happening for hospital IRF units. While the majority of inpatient rehabilitation facilities are still distinct units within a short-term hospital, the IRFs are slowly shifting towards more free-standing IRFs in the recent years (MedPAC, 2019a). As shown in Figure 3, there has been a wave of hospital IRF unit terminations since 2006, albeit smaller in magnitude compared to that of hospital-affiliated SNFs.

In this paper I focus on the termination of hospital-affiliated SNFs and exclude hospitals that experience concurrent changes in IRF unit status from the main analysis, since among hospitals that experienced termination of affiliated SNFs, there does not seem to be a stark pattern in IRF establishment or termination immediately preceding or following the SNF exit. Indeed, there are 250 terminations of hospital-affiliated SNFs in 2008 - 2014, among which only 22 had IRF unit establishment or closure up to 5 years prior to SNF termination[10] and 24 had IRF unit establishment or closure up to 5 years afterwards[11].

III Data and Summary Statistics

III.1 Data

The main source of data is the universe of fee-for-service Medicare claims for all inpatient hospitalizations and institutional post-acute care (aka MedPAR) in 2006-2015. MedPAR contains detailed medical information on each patient's health condition (admission and discharge dates, diagnoses, types of admission, etc.), institutional information on the name and type of health care facility, and financial information on Medicare reimbursement and patient coinsurance and deductible. Each year, there are around 3.3 million observations in the MedPAR data, of which around 2.5 million are for short-term inpatient hospital stays.

The MedPAR data is then complemented by the Medicare beneficiary summary files (MBSF) with demographic and socio-economic information (age, gender, race, dual-eligible status, Part-D low-income subsidy status, original type of eligibility), and baseline chronic health condition indicators.

Furthermore, I use CMS Provider of Service (POS) files in 2006 - 2015 for more detailed information on each health care facility (initial certification and termination dates, type, size, address) and the vertical relations among the providers. To illustrate the number of hospital-affiliated

[10] 9 are IRF unit establishments and 13 are terminations

[11] 9 are IRF unit establishments and 15 are terminations

vs. free-standing SNFs, I also use LTCFocus data compiled at Brown University School of Public Health from multiple sources (such as OSCAR/CASPER and MDS).

III.2 Sample Construction

The treatment group includes inpatient hospitalizations in 2007 - 2015 at short-term hospitals (excluding critical access hospitals and hospitals with swing beds) that experience termination of affiliated SNFs in 2008 - 2014 and do not have any change in IRF unit affiliation status or any other change in affiliated SNFs in 2001 - 2015. (The vertical structure of hospitals and PAC facilities are determined through the POS records.) The selection criteria makes sure that there are minimal confounds from changes in other types of medical-PAC integration during the analysis period. Moreover, patients who died during inpatient hospitalization are also excluded since they may confound the analysis of PAC's impact on mortality. Additionally, all samples are restricted to Medicare beneficiaries who are aged 67 and above and have enrolled in fee-for-service Medicare for at least 12 months prior to the inpatient hospitalization. The restriction allows constructing and controlling for baseline health condition for the analysis. Also note that in all samples, none of the inpatient hospitalizations include inpatient rehabilitations at short-term hospitals' IRF units. The analysis sample keeps observations from 3 years before the SNF termination to 3 years afterwards, and has 128 hospitals and 257,526 total observations in the treatment group.

The criteria for selecting control group is similar to that of the treatment group, except that the hospitals included in the control group have affiliated SNFs throughout 2001 - 2015. The analysis sample includes 285 hospitals and 632,985 observations for the control group.

To validate the accuracy of PAC type following each inpatient hospitalization and the affiliation status of SNF and IRF units with hospitals, I do two additional steps of data cleaning.

First, I check whether each inpatient hospitalization indeed has a corresponding PAC record according to the discharge destination field in the hospital MedPAR data. The hospital and PAC records are matched by the date of hospital discharge and institutional PAC facility admission. To ensure there is no systematic mis-coding around the termination of hospital-affiliated SNFs, I drop all individuals who've ever had discharge destination coded as institutional PAC but no corresponding MedPAR record, or who've had discharge destination coded as home/home care but matched with institutional PAC in MedPAR. Additionally, if the MedPAR record type or institution type does not agree with the discharge destination in the inpatient hospitalization record, I correct their destination code according to actual PAC type observed in the matched institutional PAC record.

Second, I check the validity of SNF and IRF unit affiliations in the POS files by merging them with the medical-PAC paired MedPAR sample. For the treatment group, I keep hospitals that have none-zero share of patients discharged to affiliated SNF each year prior to SNF termination and zero after the SNF termination. For the control group, I keep hospitals that have non-zero share of patients discharged to affiliated SNF each year in 2007 - 2015. For both groups, I keep hospitals that either have none-zero share of patients discharged to own IRF unit each year or zero each year in 2007 - 2015.

III.3 Summary Statistics

III.3.1 Characteristics of hospitals

Table 3 compares the characteristics of hospitals in the treatment and control groups of the analysis sample. Hospitals in the treatment group tend to be larger, more urban, and more likely to have IRF units within the hospital. SNFs affiliated with hospitals in the treatment group (aka those that got terminated in 2008 - 2014) tend to be smaller in size and slightly more likely to be in the same zip code as their parent hospitals, compared to the hospital-affiliated SNFs that stayed open throughout 2001 - 2015.

III.3.2 Characteristics of patients

Table 4 shows good balance of variables between the treatment and control groups. Patients in both groups are of similar age and have similar share of female, dual-eligible, and Part-D low income subsidy status, and equally likely to be originally eligible for Medicare through disability. They also experience similar mortality and readmission rates, and baseline number of chronic conditions and length of stay (LoS) at hospitals, although those in the treatment group have slightly higher cost for the hospital care and institutional PAC for Medicare. On average, patients in the two groups also have similar access to PAC providers as measured by distance from patient residence to the facility. Note that an average patient tends to live closer to their nearest home health agency (HHA) and SNF than IRF and LTCH, while around 23 or 25% of patients have IRF that are no farther away than the nearest HHA.

III.4 Average Treatment Effect from Event Study

To illustrate the plausibility of monotonicity and parallel trend assumptions, the following event study shows the impact of termination of hospital-affiliated SNFs on the type of post-acute care and health outcomes for patients receiving inpatient care at the corresponding hospital.

$$y_{isht} = \sum_{k=-3}^{k=3} \gamma_k (K_{it} = k) + \delta X_{it} + \alpha_{st} + \mu_h + \varepsilon_{isht} \tag{1}$$

Health outcome and utilization variables y_{isht} of patient i in state s, hospital h, and year t include mortality rates 30 and 90 days after discharge from hospital, inpatient readmission rate 30 days post discharge, LoS of hospitalization, and total Medicare reimbursement and beneficiary out-of-pocket payment for the hospitalization and subsequent institutional PAC.

The event study controls for state-by-year fixed effect and hospital fixed effect. To address differences in access to PAC facilities, I also include three-way interactions of quintile indicators for distance to the nearest HHA, IRF, and LTCH from the patient's residence[12], as well as an indicator for whether the nearest IRF is no farther away then the nearest HHA.

Additional control variables include demographic and socio-economic information such as age, gender, race, dual-eligible status, Part-D low-income subsidy status, and original Medicare eligibility status; baseline health condition such as number of chronic conditions[13] and indicators for each of the 27 chronic conditions recorded in Medicare beneficiary summary files by the end of the previous year; and information on type and severity of the health shock including principal diagnosis code, co-diagnosis codes, number of surgical procedures, principal procedure code, indicators for general and intermediate ICU and CCU use, indicators for type of inpatient admission (emergency, urgent, or elective), and indicator for whether any principal or co-diagnosis codes include diagnosis that is compliant with the IRF 60 percent rule[14].

The dynamic event study discussed above can also be summarized through a difference-in-difference framework below:

$$y_{isht} = \gamma W_{it} + \delta X_{it} + \alpha_{st} + \mu_h + \varepsilon_{isht} \tag{2}$$

where W_{it} are 0/1 indicators for whether the patient gets inpatient care at hospitals in the treatment group post termination of affiliated SNF, and γ is the diff-in-diff coefficient.

[12] Proxying actual address with centroids of zip codes.

[13] Acute Myocardial Infarction, Alzheimer's, Alzheimer's Disease and Related Disorders or Senile Dementia, Atrial Fibrillation, Cataract , Chronic Kidney Disease, Chronic Obstructive Pulmonary Disease, Heart Failure, Diabetes, Glaucoma, Hip/Pelvic Fracture, Ischemic Heart Disease, Depression, Osteoporosis, Rheumatoid Arthritis/Osteoarthritis, Stroke/Transient Ischemic Attack, Breast Cancer, Colorectal Cancer, Prostate Cancer, Lung Cancer, Endometrial Cancer, Anemia, Asthma, Hyperlipidemia, Benign Prostatic Hyperplasia, Hypertension, and Acquired Hypothyroidism.

[14] For details of the 60 percent rule, please refer to earlier discussions in section II.1

Figures 4 and 5 plot the coefficients from the event study as specified in equation (1). The graphs show little pre-trend in both PAC type and health outcomes prior to the SNF termination, which supports the validity of the diff-in-diff design and the interpretation of coefficients reported in Table 5.

Shown in both the diff-in-diff and the dynamic event study, the SNF termination has strong effects on the type of PAC patients receive post discharge. Patients are significantly less likely to get PAC at SNFs and are substituting SNF care with either less intensive home based care or more intensive rehab care at inpatient rehabilitation facilities.

However, despite the large changes in types of PAC providers, the average treatment effect of SNF termination on health outcomes seems small and not statistically different from zero. Meanwhile, the average Medicare expenditure and beneficiary out-of-pocket payment for the hospitalization and subsequent institutional PAC service increased significantly[15]. Without further analysis one cannot tell whether the null results for health outcomes are due to positive and negative impacts along different PAC switching margins canceling each other out, or whether one cannot reject the null even when examining patients switching from nursing home to home care or IRF separately. Both scenarios are plausible, but can lead to very different policy implications.

III.5 Heterogeneity Analysis with Triple-Difference

The average effects estimated in the event study above both show significant first stage effects of instrument on the likelihood of getting post-acute care through home health and inpatient rehabilitation, and illustrate violation of the monotonicity assumption which invalidates causal identification via standard IV. Before diving into the analysis of heterogeneous first stage effects with machine learning in the next sections, I first examine effect heterogeneity by the following

[15]The MedPAR data only contains claims for institutional health care, and thus the cost for any outpatient care such as home health service cannot be observed and assumed to be zero in calculations of Medicare expenditure

covariates with conventional methods.

One dimension of treatment effect variation may be socio-economic, such as whether the patient is eligible for both Medicare and Medicaid (henceforth dual-eligibles). Prior literature has shown that dual-eligibles tend to get care at lower-quality facilities (Sharma et al., 2019). Thus it is worthwhile to analyze whether dual-eligibles may experience different effects from the exit of hospital-affiliated SNFs. Heterogeneity may also arise from differences in access to HHA vs. IRF as an alternative to SNF. For example, patients at hospitals that have their own IRF units or patients who help an IRF meet the 60 percent rule may be more likely to substitute SNF with IRF care. To gauge such underlying heterogeneity, I start with the following triple-difference analysis that interacts treatment indicators with whether the patient is dual-eligible, has any diagnosis code compliant with the IRF 60 percent rule, or get inpatient care at a hospital that has its own IRF unit. The coefficients are shown in Tables 6, 7, and 8.

$$
\begin{aligned}
y_{isht} = & \sum_{k=-3}^{k=3} \gamma_k (K_{it} = k) + \sum_{k=-3}^{k=3} \gamma_k (K_{it} = k) \times \mathbb{1}(\text{Het-var} = 1) \\
& + \delta X_{it} + \alpha_{st} \times \mathbb{1}(\text{Het-var} = 1) + \mu_h + \varepsilon_{isht} \qquad (3)
\end{aligned}
$$

Table 6 shows dual-eligible patients are less likely to substitute SNF care with IRF care, but doesn't find significant effects of SNF termination on the health outcomes and utilizations for either the dual-eligibles or those eligible for Medicare only. Table 7 shows that patients who have at least one diagnosis code that is compliant with the IRF 60 percent rule are indeed more likely to substitute SNF with IRF care, though are substituting SNF with home care at similar rate as those without compliant diagnoses. Such difference in PAC provider choices does not lead to significant differences in health outcomes either. Table 8 shows that patients who go to hospitals with their own IRF units experience lower 30-day readmission rate than those at hospitals without own IRF units. They are, however, not more likely to substitute SNF care with IRF or home care. Hence the difference in readmission rate is likely driven by the care quality within a PAC provider type rather than differences across PAC provider types.

The analysis above shows that socio-economic, health, and institutional factors indeed have significant impact on how hospital-affiliated SNF exits affect patients' PAC provider choices and health outcomes. However, this method of analyzing treatment effect heterogeneity could quickly become intractable as more variables and their interactions get added to the list of potential factors driving treatment effects. Similarly, other standard nonparametric methods may also be constrained by the curse of dimensionality. Hence, in order to identify LATE for the SNF-to-home-care and SNF-to-IRF complier groups separately, I develop and apply the stratified IV with machine learning method in the following sections.

IV Stratified IV with Machine Learning

IV.1 Setup

Let Z_i and X_i denote the values or vectors of instrument and covariates for subject i. Suppose treatment W_i is discrete and can take on K different values, and denote the treatment as a binary vector

$$\mathbf{W}(Z_i,X_i) = [w_1(Z_i,X_i),\ w_2(Z_i,X_i),\ ...,\ w_K(Z_i,X_i)]' \tag{4}$$

where $w_k(Z_i,X_i) = 1$ if treatment takes on the kth value and $w_k(Z_i,X_i) = 0$ otherwise.

When the treatment is multi-valued, it is crucial to understand how the instrument can shift treatment from one value to another in order to estimate local average treatment effect along different response margins. Indeed, without clear recognition of the individual-specific instrument-induced changes in treatment propensity, instrumental variables need to rely on the monotonicity assumption even in the binary treatment setting.

To estimate how instruments shift the realized value of treatment for each individual, I recast this treatment selection problem through the potential outcomes framework. Assuming[16] $Z_i \in \{0,1\}$, each value of the treatment vector can be expressed as

$$\begin{aligned} w_k(Z_i, X_i) &= w_k(0, X_i) + (w_k(1, X_i) - w_k(0, X_i))Z_i \\ &= w_k(0, X_i) + \tau_{w_k}(X_i)Z_i \end{aligned} \tag{5}$$

Then each $\tau_{w_k}(X_i)$ for $k = 1, ..., K$ captures how the instrument affects w_k in the treatment vector. To distinguish from the more conventional use of the term "treatment effect" (that describes the effect of treatment on outcome variables), I call the $\tau_{w_k}(X_i)$ conditional first stage effects. The vector of such conditional first stage effects

$$\tau_{\mathbf{W}}(X_i) = [\tau_{w_1}(X_i),\ \tau_{w_2}(X_i),\ ...,\ \tau_{w_K}(X_i)]' \tag{6}$$

thus summarizes how the instrument induces any shift in treatment for all subjects with covariates X_i.

Note that the $\tau_{w_k}(X_i)$ is different from propensity score $\mathbb{E}[w_k|X_i]$, since the latter is a conditional mean while the former is a conditional treatment effect. An individual with high propensity of taking on the kth value of treatment may be very different from an individual who is highly likely to be induced to change their w_k propensity in response to a change in instrument value. While there are well-established methods to estimate propensity scores, such as probit and logit (sometimes with regularization through lasso, ridge, or elastic net), systematic estimations of heterogeneous (conditional) treatment effects have been challenging. Parametric analysis heavily relies on functional form assumptions, and non-parametric methods are constrained by the curse

[16] Assume binary instrument mainly for simplicity of notation.

of dimensionality[17]. Without detailed estimation of heterogeneity in first stage effects, monotonicity is a necessary yet untestable assumption and binary treatment is a necessary condition in the estimation of local average treatment effect through two stage least squares.

IV.2 Estimation of Conditional First Stage Effects

Recent developments in machine learning for causal inference has enabled flexible and accurate estimations of heterogeneous treatment effects. Thus in this section, I apply generalized random forest method to estimate the conditional first stage effects.

IV.2.1 Brief Background of Random Forest for Causal Inference

Classification and regression trees (Breiman et al., 1984) are popular nonparametric prediction methods in the machine learning literature. The method estimates detailed conditional mean of outcome variable by recursively partitioning the data into leaves of subjects with similar expected outcome, at each split making the subjects in different leaves as heterogeneous as possible and those in the same leaf as similar as possible. The resulting partition is usually referred to as the decision or regression tree. Yet a single tree may be biased and noisy, and too sensitive to the training data. The literature has thus developed boosting and bagging methods to improve the accuracy of tree-based classifications. Among those, random forest (Breiman, 2001) has become a leading method with its simple intuition and excellent empirical track record. The random forest is an ensemble of trees grown on randomly drawn subsamples with random subsets of covariates. It effectively addresses the bias and volatility of each decision tree by having an aggregation of trees

[17]For example, empiricists often interact terms of policy change with pre-specified characteristics to estimate the heterogeneity along margins of interest. However, such method can quickly become intractable as the dimension of interest grows large and may be prone to overfitting or overtesting. Wasserman (2006) explains both the computational and the statistical curse of dimensionality in non-parametric analysis, where one needs a sample size n that grows exponentially with dimension d since the neighborhood of an observation may contain very few data points due to sparsity under high dimensions.

to make the prediction.

While the classification and regression trees and random forests are mainly aimed at predicting conditional means, recent adaptation of these methods for causal inference has allowed for estimation of heterogeneous treatment effects. For example, Athey et al. (2019) adapt the random forest method to estimate any quantity that can be estimated by local moment conditions, including conditional treatment effect. They overcome the challenge of not observing the "ground truth" of treatment effect in the training process by modifying the tree splitting rules from minimizing simple mean squared errors to minimizing comparable values that can be feasibly estimated, during which process the heterogeneity in treatment effect across leaves is maximized and accuracy of conditional treatment effect is improved. They also show conditions that ensure consistency and asymptotic normality for valid statistical inference. I discuss the application of generalized random forest for conditional first stage estimation in the following section.

IV.2.2 Assumption

In order to estimate conditional first stage effect through generalized random forest, the following assumption is necessary.

A.1 Unconfoundedness

$$\{W_i(Z_i = 1), W_i(Z_i = 0)\} \perp\!\!\!\perp Z_i | X_i \tag{7}$$

The unconfoundedness assumption is that conditional on the covariates X_i, the instrument Z_i is as good as randomly assigned. It may be a result of random assignment in randomized controlled trials, or may be a reasonable assumption from a natural experiment. The unconfoundedness assumption is critical in the identification of treatment effects in the potential outcomes framework. Note that in the instrumental variables setting, the unconfoundedness of instrument assignment is part of the independence assumption which is necessary for the identification of local average treatment effects. Also note that there are additional assumptions to ensure the consistency and asymptotic normality for treatment effect estimates in generalized random forest, detailed in Athey et al. (2019).

IV.2.3 Application of Generalized Random Forest to Conditional First Stage Effect Estimation

The goal is to estimate the conditional first stage effect of instrument on each $w_k(X_i)$ for $k = 1,...,K$. Generalized random forest effectively enables non-parametric estimation of heterogeneous treatment effect through local maximum likelihood, where the kernel weights are derived from recursively partitioning subjects with similar treatment effects into leaves, done repeatedly on randomly drawn subsamples.

The τ_{w_k} from equation (5) can be estimated through $w_{ki} = \mu(X_i) + \tau_{w_k}(X_i)Z_i + \varepsilon_i$. Thus the moment function

$$\mathbb{E}[w_{ki} - \mu(X_i) - \tau_{w_k}(X_i)Z_i | X_i = X] = 0 \tag{8}$$

allows estimation through local maximum likelihood

$$(\hat{\tau}_{w_k}(X), \hat{\mu}(X)) \in \underset{\tau_{w_k},\mu}{\operatorname{argmin}} \{ \| \sum_{i=1}^{n} \alpha_i(X) \psi_{\tau_{w_k},\mu}(w_{ki}, Z_i) \|_2 \} \tag{9}$$

with the standard estimand

$$\psi_{\tau_{w_k}(X),\mu(X)}(w_{ki}, Z_i) = (w_{ki} - \tau_{w_k}(X)Z_i - \mu(X)) \left(1 \; Zi'\right)' \tag{10}$$

and $\alpha_i(X)$ as kernel weights that capture the proximity of each observation with those of covariates X.

Unlike the random forest for classification that makes each split to minimize in sample mean squared errors, generalized random forest does not observe the "ground truth" of treatment effect and thus cannot directly compute the mean squared errors. Hence in Athey et al. (2019), the splitting rule is modified in generalized random forest. As in standard random forest and regression trees, the partitioning start from parent node $P \subseteq \mathcal{X}$ and split it into two children nodes C_1 and C_2 to improve accuracy of $\hat{\tau}$ estimation. They rewrite the mean squared error as

$$err(C_1, C_2) = \sum_{j=1,2} \mathbb{P}[X \in C_j | X \in P] \mathbb{E}[(\hat{\tau}_{C_j}(\mathcal{J}) - \tau(X))^2 | X \in C_j] \tag{11}$$

$$= K(P) - \mathbb{E}[\Delta(C_1, C_2)] + o(r^2) \tag{12}$$

where the $K(P)$ term is specific only to parent node and not affected by the split of children nodes, and the $o(r^2)$ captures the variance. Hence the MSE-minimizing splitting rules can be rewritten as the maximization of

$$\Delta(C_1, C_2) := \frac{n_{C_1} n_{C_2}}{n_P^2} \left(\hat{\tau}_{C_1}(\mathcal{J}) - \hat{\tau}_{C_2}(\mathcal{J})\right)^2 \tag{13}$$

where $\hat{\tau}_{C_j}(\mathcal{J})$ is the solution to the estimating equation (given a sample of data $\mathcal{J}$)

$$\left(\hat{\tau}_{C_j}, \hat{\mu}_{C_j}\right)(\mathcal{J}) \in \underset{\tau,\mu}{\operatorname{argmin}} \{ \| \sum_{i \in \mathcal{J}: X_i \in C_j} \psi_{\tau,\mu}(w_{ki}, Z_i) \|_2 \} \tag{14}$$

The algorithm effectively increases the heterogeneity and improves the accuracy of $\hat{\tau}_{w_k}(X)$ at each split of the tree. Such trees are grown on repeatedly drawn random subsamples and random subsets of covariates to form a random forest. The kernel weights $\alpha_i(X)$ are computed from how often subject i is in the same leaf as those with covariates X, and the conditional first stage effects $\hat{\tau}_{w_k}(X)$ are then estimated through local MLE (equation (9)) with weights derived from the random forest.

Note that there has been extensive literature on local maximum likelihood and, more broadly, nonparametric regressions. However, the implementation in economic analysis has been constrained by the curse of dimensionality. The generalized random forest method addresses the issue through an intrinsic variable selection procedure, since the trees only make splits when the target estimation is improved. Thus instead of dividing the sample into neighborhoods by all variables and running into sparsity on the covariate space, the trees in the random forest can ensure enough number of observations within each leaf while still allow for complicated interactions among potentially large amount of covariates.

IV.3 Identification of Stratum-Specific Local Average Treatment Effect

IV.3.1 Stratification of Complier Groups

Define $W_{m\to n}$ compliers as all subjects with $w_m(Z_i = 0, X_i) = 1$ and $w_n(Z_i = 1, X_i) = 1$. The conditional first stage effects thus let us stratify complier groups based on the relative impact of instrument on all elements of the treatment vector. For example, an individual can be classified as a $W_{m\to n}$ complier if $\hat{\tau}_{w_m} \leq 0$, $\hat{\tau}_{w_n} \geq 0$, and $\hat{\tau}_{w_k} = 0\ \forall k \notin \{m,n\}$. Therefore, within each $W_{m\to n}$ stratum, the complier-specific local average treatment effect can be estimated with two stage least squares as long as the following standard IV assumptions hold.

IV.3.2 Additional Assumptions for IV

Let $Y_i(W_i, Z_i, X_i)$ denote the outcome variable for subject i with treatment W_i, instrument Z_i, and covariates X_i. For simplicity, denote $W_i(Z_i = 1)$ as W_{1i}, and $W_i(Z_i = 0)$ as W_{0i}. To identify local average treatment effect, the following assumptions are required.

A.2 Conditional Independence

$$\{Y_i(W_{1i}, 1), Y_i(W_{0i}, 0), W_{1i}, W_{0i}\} \perp\!\!\!\perp Z_i | X_i \tag{15}$$

Conditional on the covariates, the instrument assignment is as good as random. Note that $\{W_{1i}, W_{0i}\} \perp\!\!\!\perp Z_i | X_i$ carries through from assumption A.1 (unconfoundedness) in the estimation of conditional first stage effects.

A.3 General Exclusion

$$Y_i(W,0) = Y_i(W,1) \equiv Y_{W_i} \ \forall \ W_i \tag{16}$$

General exclusion restriction is that instrument Z_i affects outcome only through the value of treatment. Note the slight difference in terminology from the binary treatment setting. In the multiple treatment setting, if the researcher restricts the 2SLS analysis only to subjects with a treatment value of interest, instrument may affect estimated outcome by changing the sample composition[18].

A.4 First stage

$$\mathbb{E}[w_{m,1i} - w_{m,0i}] \neq 0 \tag{17}$$

$$\mathbb{E}[w_{n,1i} - w_{n,0i}] \neq 0 \tag{18}$$

IV estimations are valid only if the instrument can induce meaningful shifts in treatment value. Similarly, the complier-group-specific LATE for stratum $W_{m \to n}$ can only be estimated if there are compliers induced to switch from the mth to the nth treatment.

[18]For example, when using vertical relations between hospitals and nursing homes as instrument for types of post-acute care, suppose the researcher restricts the sample to patients getting post-acute care at inpatient rehab facilities and nursing homes, then the instrument could affect the outcome by changing the sample composition as some of the (counterfactual) nursing home patients may switch to home health in response to the instrument.

A.5 Monotonicity within Complier Stratum

$$w_{n,1i} - w_{n,0i} \geq 0 \ \forall i \in W_{m\to n} \tag{19}$$

$$w_{m,1i} - w_{m,0i} \leq 0 \ \forall i \in W_{m\to n} \tag{20}$$

$$w_{k,1i} - w_{k,0i} = 0 \ \forall k \notin \{m,n\}, i \in W_{m\to n} \tag{21}$$

By design of the stratification process, the $W_{m\to n}$ complier stratum should only consist of subjects who shift from the mth to the nth treatment in response to the change in instrument, according to the conditional first stage effects estimated by generalized random forest.

However, a caveat with the machine learning based method is that the within-stratum monotonicity assumption may be violated if there are selection on unobserved characteristics. Compared with methods that model selection by threshold crossing of latent variables, the machine learning method relies less on functional form and behavioral assumptions but inevitably lacks the ability to detect selection on unobserved characteristics. When the underlying selection process is complicated and involves multiple parties, the trade-off can be worthwhile. For example, where a patient gets post-acute care after inpatient hospitalization is a joint decision among the patient and their family, the doctor, and the provider organizations. They may each have different objective functions that interact with each other in ways more complicated than threshold crossing of latent values. Nevertheless, the accuracy of machine learning method relies on having large amount of data on a large array of covariates.

IV.3.3 Stratum-specific LATE through 2SLS

It follows from the original Imbens and Angrist (1994) results that with the above assumptions within each stratum, the local average treatment effect

$$\frac{\mathbb{E}[Y_i|Z_i=1]-\mathbb{E}[Y_i|Z_i=0]}{\mathbb{E}[w_{ni}|Z_i=1]-\mathbb{E}[w_{ni}|Z_i=0]}=\mathbb{E}[Y_{1i}-Y_{0i}|w_{n,1i}>w_{n,0i}] \tag{22}$$

for $W_{m\to n}$ compliers can be estimated from the following 2SLS.

$$w_{ni}=\alpha_0+\alpha_1 Z_i+\eta_i \tag{23}$$

$$Y_i=\beta_0+\beta_1\hat{w}_{ni}+\varepsilon_i \tag{24}$$

V Empirical Application of Stratified IV with Machine Learning

In this section, I apply the stratified IV with machine learning method to compare the quality and cost of different types of elder care providers that offer post-acute care, using the vertical disintegration of hospitals and nursing homes as instrument.

V.1 Estimation of Conditional First Stage Effects

Stratified IV is applicable whenever the instrument has differential impacts on the direction of first stage effects, which violates the monotonicity assumption and makes estimates from standard IV analysis uninterpretable for causal inference. In this case, first stage analysis of the full sample shows that the exit of hospital-affiliated nursing homes induces patients to substitute post-acute care at nursing homes both with home health and with inpatient rehab facilities. Standard IV results with full sample will thus be conflated by effects on the two different first stage compliance margins. Moreover, if one attempts to address the monotonicity issue by restricting the analysis sample, such action will violate the exclusion restriction and still not give valid causal identification. For example, if one only includes those *observed* getting post-acute care at nursing homes or inpatient rehab facilities, then even though all the compliers are on the same first stage response margin, the instrument will affect outcomes not only by inducing patients to shift from nursing home to inpatient rehab facilities, but also by changing the composition of nursing home patients relative to counterfactual as some patients substitute nursing home with home health care.

Hence to estimate local average treatment effects on each compliance margins in multiple treatment settings, the stratified IV method first estimates individual-specific first stage effects with machine learning in order to bucket the sample into different complier strata in subsequent steps. In this application, I first build two random forests to separately estimate conditional first stage effects of instrument on likelihood of getting PAC via home health and that of getting PAC at inpatient rehab facilities. Figure 6 shows examples of trees grown by recursively partitioning randomly drawn subsamples using random subsets of covariates, with each split maximizing heterogeneity in the treatment effect of hospital-affiliated SNF exit on the likelihood of getting PAC at IRFs. Zooming in closer on a random tree, Figure 7 shows more details of the splits and leaf sizes. Closer examination shows that patient socio-economic status, baseline health conditions, distance from residence to nearest different PAC facilities, and state-year average of PAC type shares are all important variables that the trees split on. Compared with baseline health and non-clinical factors, principal diagnosis of the current health shock gets relatively less weight, with more common conditions such as heart failure and hip fracture getting more weights.

To effectively form strata by likelihood of switching from SNF to home health care or IRF care, there needs to be meaningful differences in the estimated conditional first stage effects. Figure 8 shows that there are indeed substantial distinctions among individuals more likely to shift to home care or IRF following hospital-affiliated SNF exits. In Panel A of Figure 8, all individuals in the sample are divided into decile groups of $\hat{\tau}_{w_{IRF}}(X_i)$ (first stage effects of hospital-affiliated SNF exits on getting PAC at IRF). Each box then illustrates the min, 25th, 50th, 75th percentile, and max of the $\hat{\tau}_{w_{HC}}(X_i)$ for the individuals in each decile group. Panel B shows similar graph of $\hat{\tau}_{w_{IRF}}(X_i)$ distribution on the vertical axis by deciles of $\hat{\tau}_{w_{HC}}(X_i)$ on the horizontal axis. The graphs illustrate that individuals within deciles of higher $\hat{\tau}_{w_{IRF}}(X_i)$ tend to have lower $\hat{\tau}_{w_{HC}}(X_i)$ percentile, and vice versa.

Given the substantial differences in first stage estimates on each response margin, the last step before identifying complier-specific local average treatment effects is to bucket the sample into strata that satisfy the assumptions of monotonicity, independence, exclusion, and first-stage, according to the estimated conditional first stage effects. The stratification has to balance the representativeness of the complier bucket with the statistical power of local average treatment effect estimation. In other words, the stratum needs to exclude defiers, include as many compliers on the corresponding margin as possible, and maintain enough sample size for rigorous statistical inference.

To inform such decision, I plot the share of defiers and never-takers by different strata definitions in Figure 9, the share of compliers and always-takers in Figure 10, and the size of strata in Figure 11. For the SNF-to-HHA strata, the defiers and never-takers are those getting PAC at inpatient rehab facilities, and the compliers and always-takers are those getting PAC through home health agencies. Vice versa for the SNF-to-IRF strata. The strata are defined based on the percentile of the individual-specific first stage effects for home care and IRF care, and each panel shows a different scenario fixing the percentile cutoff of $\hat{\tau}_{w_{IRF}}(X_i)$ (or $\hat{\tau}_{w_{HC}}(X_i)$) and varying the percentile cutoff of $\hat{\tau}_{w_{HC}}(X_i)$ (or $\hat{\tau}_{w_{IRF}}(X_i)$). Figure 9 shows that the share of defiers and never-takers generally decreases as strata definition becomes more stringent and increases as strata definition becomes more relaxed, though the share can rise when the definition becomes too stringent for home care compliers, likely driven by outliers. Figure 10 shows that while the share of compliers and always-takers generally increases as IRF strata definition becomes more stringent and decreases as it gets more relaxed (with the exception of extremely stringent definitions), it tends to decrease if the home care strata definition gets either too stringent or too relaxed. Meanwhile, Figure 11 illustrates that strata definition can have substantial impact on the strata size, thereby affecting the power of statistical inference.

As illustrated by the figures discussed above, it is a reasonable stratification method in this case to group individuals with above median $\hat{\tau}_{w_{IRF}}(X_i)$ and below median $\hat{\tau}_{w_{HC}}(X_i)$ into the SNF-to-IRF compliance bucket, and individuals with below median $\hat{\tau}_{w_{IRF}}(X_i)$ and above median $\hat{\tau}_{w_{HC}}(X_i)$ into the SNF-to-HHA compliance bucket. Currently, the stratification rules need to be decided with reference to diagnostic graphs similar to Figures 9 - 11 for each specific empirical application of the stratified IV method, and future works on more consistent stratification methods and robustness checks will be worthwhile.

V.2 Identification of Stratum-Specific Local Average Treatment Effect

This section checks the validity of stratification by running first stage analysis separately for each stratum, and then estimates stratum-specific local average treatment effects with two stage least squares.

Figure 12 shows that the compliers in the SNF-to-HHA group indeed mostly switches from nursing home to home care, with much lower change in IRF likelihood than estimated in the full sample (Figure 4). There also seems to be little pre-trend in PAC provider type choices prior to SNF termination. Similarly, Figure 14 illustrates that the SNF-to-IRF compliers mainly switches from SNF to IRF. Table 9 compares the characteristics of the two complier groups. The home care compliers are more likely to be dual-eligibles and get Part-D low-income subsidy, and tend to have slightly fewer chronic conditions at baseline. Compared to the IRF compliers, the home care compliers live closer to the hospital they were admitted to for the inpatient hospitalization and the nearest HHA, but on average live farther away from the nearest IRF and are less likely to have an IRF that is in the same zip code or closer than the nearest HHA.

Turning to health outcomes and utilization, Figure 13 shows that there is little change in both health outcomes and Medicare spending following the SNF termination for the SNF-to-HHA complier group. Figure 15 shows that the switch results in significant increases in Medicare spending, while not showing large variations in health outcomes for the SNF-to-IRF compliers. Reassuringly, event study suggests that the parallel trend assumption still mostly holds.

The independence, monotonicity, and exclusion restrictions all hold within each complier stratum, and LATE is identified for each complier group with 2SLS. Table 10 illustrates that for patients who switch from nursing home to home health, there is no significant effect of the switch on either health outcomes or utilizations. When there is a reduction in SNF capacity, it seems that patients can still get access to PAC of similar quality without incurring higher cost through home health service, making the case for supporting home and community based PACs. On the other hand, Table 11 show that the compliers who switch from nursing home to inpatient rehab cost Medicare around twice as much for the hospitalization and subsequent institutional post-acute care, while not experiencing significant improvement in mortality or readmission rates. It shows that the quality difference may not fully justify the higher cost at IRFs, and that site-neutral PAC payment at least for certain health conditions could be a viable cost saving measure without hindering the recovery of patients.

VI Conclusion

Using machine learning, this paper extends the classic binary treatment IV analysis to cases of multiple treatments, where an instrument may induce shift across different treatment values and thus violate the strict monotonicity assumption. I develop stratified IV method which uses generalized random forest to group subjects into stratum within which the independence, monotonicity, and exclusion restrictions all hold, and separately identify LATE for each complier group with 2SLS. Applying the method to compare the quality and cost of different types of post-acute care providers, I show that when hospital-affiliated nursing home exit induces patients to get PAC through either home health service or inpatient rehabilitation facilities instead of nursing homes, the health outcomes measured by mortality and readmission rates remain unchanged, while those switching to IRF cost Medicare twice as much in expenditure.

These results are especially important as the government, insurance companies, and hospital groups are wrestling over site-neutral payment for comparable health services. Advocates for site-neutral payment argue that it can reduce substantial waste in health spending and curb anti-competitive vertical integration of hospital and physician groups (Gaynor et al., 2017). Yet without thorough analysis of effects on patient health outcomes, such proposals have been faced with fierce opposition from providers. While the current site-neutral debate spotlight has been on outpatient doctor visit and ambulatory surgery, rigorous analysis of care quality and cost differences across provider types in the post-acute care sector can be highly informative, especially as the sector has experienced massive vertical disintegration in the past two decades. Meanwhile, understanding the causal impact of shifting patients from nursing home to home health for post-acute care is also critical as new payment systems such as bundled payment and accountable care organizations (ACOs) increasingly adopt reduction in institutional PAC as common cost-saving measure (McWilliams et al., 2017; Werner et al., 2019). Note, however, that there may be differences in care quality (such as activities of daily living) that are not captured by mortality or readmission rates. Thus these additional dimensions of health outcomes are worth analyzing with more detailed and unified quality assessment data.

Methodologically, the stratified IV with machine learning method can be widely applied to settings wherever monotonicity is violated in aggregate while standard IV identification assumptions hold within complier strata. Future work which addresses the concern that machine learning only captures heterogeneity based on observables can further generalize the method to cases where selections on unobserved characteristics are crucial. It is also worthwhile to develop more systematic stratification techniques based on estimated conditional first stage effects in future analysis.

Tables

Table 1: Medicare Inpatient Hospitalization by Discharge Destination (in Thousands)

Year	Total	Home w/o care	Home care	Nursing home	Inpatient rehab	LTCH	Other	Died
2006	2,381	1,249	330	426	79	22	185	90
2008	2,551	1,304	390	479	81	26	178	93
2010	2,648	1,315	437	505	83	29	189	89
2012	2,594	1,273	436	499	85	28	190	84
2014	2,703	1,279	475	534	92	29	207	87

Notes: The table reports the number of inpatient hospitalizations by discharge destination for all Medicare fee-for-service beneficiaries in the MedPAR data. Home health service, nursing home, inpatient rehabilitation facility, and long-term care hospital are all common types of post-acute care providers. The "other" column mainly includes transfers to inpatient care at other hospitals and hospice.

Table 2: Number and Share of Nursing Homes Affiliated with Hospitals

Year	Total Number of Nursing Homes	Freestanding	Hospital-Affiliated	Share of Hospital Affiliated
2000	16,964	14,884	2,080	0.12
2004	16,181	14,674	1,507	0.09
2008	15,800	14,605	1,195	0.08
2012	15,551	14,632	919	0.06
2016	15,164	14,431	733	0.05

Notes: The table reports the total number of nursing homes in the US that are free-standing or affiliated with a hospital, and the share of hospital-affiliated nursing homes among all nursing homes. Data source is the LTCFocus dataset constructed at Brown University based on the characteristics of all nursing homes certified by Medicare or Medicaid.

Table 3: Characteristics of Hospitals and Affiliated Nursing Homes in Analysis Sample

Panel A:	Hospital Characteristics			
	Urban	Number of Beds	With IRF Units in Hospital	Number of IRF Beds
Treatment	0.76	283.45	0.33	10.24
Control	0.66	254.80	0.28	7.43

Panel B:	Hospital-Affiliated SNF Characteristics			
	Urban	Number of Beds	Same Zipcode as Hospital	Distance between Hospital and SNF
Treatment	0.76	35.53	0.81	1.00
Control	0.66	75.97	0.76	0.82

Notes: The table compares characteristics of hospitals and their affiliated nursing homes in the treatment and control groups of the analysis sample. The analysis sample is based on inpatient hospitalizations in 2007 - 2015 for Medicare fee-for-service beneficiaries who are aged 67+, discharged alive from hospital, and received inpatient hospitalizations at a treatment hospital (terminated affiliated nursing home in 2008 - 2014, no other change in nursing home or inpatient rehab unit through 2001 - 2015) or control hospital (with affiliated nursing home and no change in nursing home or inpatient rehab unit through 2001 - 2015).

Table 4: Summary Statistics of Patients in Analysis Sample

Panel A:	Socio-Demographic					
	Age	Female	Dual-Eligible	Part-D LIS	Disability	Chronic Conditions
Treatment	79.82	0.59	0.23	0.22	0.14	6.00
Control	79.94	0.59	0.24	0.23	0.14	6.06
Panel B:	**Health Outcomes and Utilization**					
	30 day mortality	90 day mortality	30 day readmission	Hospital LoS	Medicare Payment	Beneficiary Payment
Treatment	0.08	0.15	0.19	5.04	12369.53	1233.99
Control	0.08	0.15	0.19	4.99	11890.00	1240.55
Panel C:	**Distance to Nearest PAC Facilities**					
	To Hospital	Nearest HHA	Nearest SNF	Nearest IRF	Nearest LTCH	IRF Not Farther than HHA
Treatment	23.98	4.60	2.08	13.99	26.90	0.23
Control	25.57	4.83	2.15	13.75	32.43	0.25

Notes: The table compares the means of socio-demographic variables, health outcomes and utilization, and distances to admitted hospital and nearest post-acute care facilities (home health agency (HHA), nursing home (SNF), inpatient rehabilitation facility (IRF), long-term care hospital (LTCH)) for the patients in treatment and control groups of the analysis sample. The analysis sample is based on inpatient hospitalizations in 2007 - 2015 for Medicare fee-for-service beneficiaries who are aged 67+, discharged alive from hospital, and received inpatient hospitalizations at a treatment hospital (terminated affiliated nursing home in 2008 - 2014, no other change in nursing home or inpatient rehab unit through 2001 - 2015) or control hospital (with affiliated nursing home and no change in nursing home or inpatient rehab unit through 2001 - 2015).

Table 5: Effect of Hospital-Nursing Home Disintegration (Diff-in-Diff)

Panel A:	PAC Type					
	(1)	(2)	(3)	(4)	(5)	(6)
	Home w/o care	Home care	Nursing home	Inpatient rehab	LTCH	Other
SNF Termination	0.00745	0.0149***	-0.0308***	0.00613***	0.000501	0.00178
	(0.00457)	(0.00380)	(0.00365)	(0.00149)	(0.000642)	(0.00210)
Controls	Y	Y	Y	Y	Y	Y
Mean of Dep Var	0.461	0.173	0.242	0.0290	0.00975	0.0857
Observations	886219	886219	886219	886219	886219	886219

Panel B:	Health Outcomes and Utilization					
	(1)	(2)	(3)	(4)	(5)	(6)
	30 day mortality	90 day mortality	30 day readmission	Hospital LoS	Medicare Payment	Beneficiary Payment
SNF Termination	0.000154	-0.000824	0.00387	-0.0539	296.5***	42.30***
	(0.00161)	(0.00249)	(0.00259)	(0.0412)	(75.37)	(11.27)
Controls	Y	Y	Y	Y	Y	Y
Mean of Dep Var	0.0816	0.152	0.192	5.001	12028.9	1238.6
Observations	886219	886219	886219	886219	886219	886219

Notes: The table reports coefficients from diff-in-diff regressions analyzing the effect of terminations of hospital-affiliated nursing homes on types of post-acute care and health outcomes and utilizations for the full analysis sample. The analysis sample is based on inpatient hospitalizations in 2007 - 2015 for Medicare fee-for-service beneficiaries who are aged 67+, discharged alive from hospital, and received inpatient hospitalizations at a treatment hospital (terminated affiliated nursing home in 2008 - 2014, no other change in nursing home or inpatient rehab unit through 2001 - 2015) or control hospital (with affiliated nursing home and no change in nursing home or inpatient rehab unit through 2001 - 2015). Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state$\times$year FEs. Standard errors clustered at hospital level.

Table 6: Effect of Hospital-Nursing Home Disintegration by Dual-Eligibility Status

Panel A:	PAC Type					
	(1)	(2)	(3)	(4)	(5)	(6)
	Home w/o care	Home care	Nursing home	Inpatient rehab	LTCH	Other
SNF Termination	0.00674	0.0151***	-0.0314***	0.00693***	0.000418	0.00218
	(0.00454)	(0.00387)	(0.00373)	(0.00166)	(0.00110)	(0.00228)
Dual Eligible	-0.114***	-0.0147	0.140***	-0.0492***	0.00913***	0.0289
	(0.0241)	(0.0172)	(0.0289)	(0.00662)	(0.00293)	(0.0669)
Termination × Dual	0.000863	-0.00187	0.00434	-0.00345*	-0.0000592	0.000177
	(0.00586)	(0.00424)	(0.00551)	(0.00186)	(0.00288)	(0.00424)
Controls	Y	Y	Y	Y	Y	Y
Mean of Dep Var	0.461	0.173	0.242	0.0290	0.00975	0.0857
Observations	886219	886219	886219	886219	886219	886219

Panel B:	Health Outcomes and Utilization					
	(1)	(2)	(3)	(4)	(5)	(6)
	30 day mortality	90 day mortality	30 day readmission	Hospital LoS	Medicare Payment	Beneficiary Payment
SNF Termination	0.000988	0.000683	0.00302	-0.0403	324.2***	45.32***
	(0.00175)	(0.00253)	(0.00273)	(0.0402)	(80.02)	(11.40)
Dual Eligible	-0.0166	-0.0509**	0.0450***	0.359***	1100.2	783.9**
	(0.0110)	(0.0236)	(0.00671)	(0.120)	(1146.8)	(325.7)
Termination × Dual	-0.00201	-0.00423	0.00372	-0.0503	-105.3	-10.33
	(0.00240)	(0.00330)	(0.00337)	(0.0385)	(141.6)	(21.95)
Controls	Y	Y	Y	Y	Y	Y
Mean of Dep Var	0.0816	0.152	0.192	5.001	12028.9	1238.6
Observations	886219	886219	886219	886219	886219	886219

Notes: The table reports coefficients from triple-difference regressions interacting termination of hospital-affiliated nursing homes with indicator of whether the patient is dually eligible for Medicare and Medicaid. The analysis sample is based on inpatient hospitalizations in 2007 - 2015 for Medicare fee-for-service beneficiaries who are aged 67+, discharged alive from hospital, and received inpatient hospitalizations at a treatment hospital (terminated affiliated nursing home in 2008 - 2014, no other change in nursing home or inpatient rehab unit through 2001 - 2015) or control hospital (with affiliated nursing home and no change in nursing home or inpatient rehab unit through 2001 - 2015). Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state×year FEs. Standard errors clustered at hospital level.

Table 7: Effect of Hospital-Nursing Home Disintegration by Diagnosis Compliance

Panel A:	PAC Type					
	(1)	(2)	(3)	(4)	(5)	(6)
	Home w/o care	Home care	Nursing home	Inpatient rehab	LTCH	Other
SNF Termination	0.00642	0.0148***	-0.0285***	0.00448***	0.000404	0.00233
	(0.00464)	(0.00387)	(0.00356)	(0.00149)	(0.000716)	(0.00212)
Diag IRF Compliance	-0.213***	0.0247	0.0704	0.103**	-0.00816***	0.0237
	(0.0279)	(0.0295)	(0.0553)	(0.0465)	(0.00145)	(0.0337)
Termination × Compliance	0.00636	0.000647	-0.0146**	0.0116*	0.000664	-0.00471
	(0.00473)	(0.00402)	(0.00674)	(0.00599)	(0.00191)	(0.00356)
Controls	Y	Y	Y	Y	Y	Y
Mean of Dep Var	0.461	0.173	0.242	0.0290	0.00975	0.0857
Observations	886219	886219	886219	886219	886219	886219

Panel B:	Health Outcomes and Utilization					
	(1)	(2)	(3)	(4)	(5)	(6)
	30 day mortality	90 day mortality	30 day readmission	Hospital LoS	Medicare Payment	Beneficiary Payment
SNF Termination	0.000218	-0.000413	0.00376	-0.0599	238.1***	41.48***
	(0.00170)	(0.00256)	(0.00264)	(0.0418)	(80.16)	(11.15)
Diag IRF Compliance	0.0440	0.0740	0.0637	0.682***	5320.8***	466.8***
	(0.0445)	(0.0829)	(0.0387)	(0.165)	(244.6)	(98.44)
Termination × Compliance	-0.000587	-0.00325	0.000695	0.0373	406.5**	6.432
	(0.00307)	(0.00425)	(0.00370)	(0.0591)	(167.8)	(27.98)
Controls	Y	Y	Y	Y	Y	Y
Mean of Dep Var	0.0816	0.152	0.192	5.001	12028.9	1238.6
Observations	886219	886219	886219	886219	886219	886219

Notes: The table reports coefficients from triple-difference regressions interacting termination of hospital-affiliated nursing homes with indicator of whether the principal or co-diagnosis codes contain codes that are compliant with the inpatient rehabilitation facility 60% rule (i.e. health conditions that can benefit from intensive therapy such as stroke, brain and spinal cord injury, neurological disorders, amputation, ...). The analysis sample is based on inpatient hospitalizations in 2007 - 2015 for Medicare fee-for-service beneficiaries who are aged 67+, discharged alive from hospital, and received inpatient hospitalizations at a treatment hospital (terminated affiliated nursing home in 2008 - 2014, no other change in nursing home or inpatient rehab unit through 2001 - 2015) or control hospital (with affiliated nursing home and no change in nursing home or inpatient rehab unit through 2001 - 2015). Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule, quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state×year FEs. Standard errors clustered at hospital level.

Table 8: Effect of Hospital-Nursing Home Disintegration by Hospital Inpatient Rehab Status

Panel A:	PAC Type					
	(1)	(2)	(3)	(4)	(5)	(6)
	Home w/o care	Home care	Nursing home	Inpatient rehab	LTCH	Other
SNF Termination	0.00418	0.0199***	-0.0319***	0.00795***	0.000175	-0.000301
	(0.00652)	(0.00575)	(0.00452)	(0.00186)	(0.000613)	(0.00294)
Termination × Hospital IRF	0.00537	-0.00743	-0.00474	-0.00163	0.00253	0.00591
	(0.0100)	(0.00802)	(0.00750)	(0.00328)	(0.00162)	(0.00439)
Controls	Y	Y	Y	Y	Y	Y
Mean of Dep Var	0.461	0.173	0.242	0.0290	0.00975	0.0857
Observations	886219	886219	886219	886219	886219	886219

Panel B:	Health Outcomes and Utilization					
	(1)	(2)	(3)	(4)	(5)	(6)
	30 day mortality	90 day mortality	30 day readmission	Hospital LoS	Medicare Payment	Beneficiary Payment
SNF Termination	0.00121	-0.000223	0.00714*	-0.0285	367.9***	52.08***
	(0.00231)	(0.00350)	(0.00371)	(0.0427)	(72.84)	(14.53)
Termination × Hospital IRF	-0.00104	0.0000279	-0.00932*	0.0262	-23.19	-26.88
	(0.00311)	(0.00518)	(0.00554)	(0.0808)	(146.8)	(21.38)
Controls	Y	Y	Y	Y	Y	Y
Mean of Dep Var	0.0816	0.152	0.192	5.001	12028.9	1238.6
Observations	886219	886219	886219	886219	886219	886219

Notes: The table reports coefficient from triple-difference regressions interacting termination of hospital-affiliated nursing homes with indicator of whether the hospital has its own inpatient rehabilitation units. The analysis sample is based on inpatient hospitalizations in 2007 - 2015 for Medicare fee-for-service beneficiaries who are aged 67+, discharged alive from hospital, and received inpatient hospitalizations at a treatment hospital (terminated affiliated nursing home in 2008 - 2014, no other change in nursing home or inpatient rehab unit through 2001 - 2015) or control hospital (with affiliated nursing home and no change in nursing home or inpatient rehab unit through 2001 - 2015). Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability) baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state×year FEs. Standard errors clustered at hospital level.

Table 9: Summary Stats by Complier Strata in IV Analysis Sample

Panel A:	Socio-Demographic					
	Age	Female	Dual-Eligible	Part-D LIS	Disability	Chronic Conditions
SNF to Home Care Complier	80.28	0.58	0.27	0.25	0.14	5.92
SNF to IRF Complier	80.07	0.61	0.22	0.22	0.14	6.26

Panel B:	Distance to Nearest PAC Facilities					
	To Hospital	Nearest HHA	Nearest SNF	Nearest IRF	Nearest LTCH	IRF Not Farther than HHA
SNF to Home Care Complier	12.26	4.00	1.79	14.40	27.79	0.20
SNF to IRF Complier	13.39	5.10	2.34	12.46	34.17	0.30

Notes: The table compares the means of socio-demographic variables and distances to admitted hospital and nearest post-acute care facilities (home health agency (HHA), nursing home (SNF), inpatient rehabilitation facility (IRF), long-term care hospital (LTCH)) for the patients in the nursing home to home care complier group and those in the nursing home to inpatient rehab complier group of the IV analysis sample. The patients are stratified into complier groups based on the relative estimations of conditional first stage effects of hospital-nursing home vertical disintegration on the propensities of getting post-acute care through the respective providers. The conditional first stage effects are estimated through generalized random forest, which partitions the sample into leaves within which the first stage effects are as similar as possible and across which the first stage effects are as heterogeneous as possible. The full analysis sample is randomly split in half, one to grow random forest and form the partition, and the other to estimate conditional first stage effects using local maximum likelihood with kernel weights derived from the random forest and form the basis of IV analysis sample. An individual whose estimated first stage effect on home care propensity is above median and that on inpatient rehab is below median is grouped into the nursing home to home care complier stratum, and one whose estimated first stage effect on inpatient rehab is above median and that on home care is below median is in the nursing home to inpatient rehab complier stratum.

Table 10: IV Results for Nursing Home to Home Care Compliers

	Health Outcomes and Utilization					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Reduced Form and First Stage	30 day mortality	90 day mortality	30 day readmission	Hospital LoS	Log(Medicare Payment)	Log(60-day Medicare Payment)
SNF Termination	-0.00191	-0.00359	0.00236	0.0357	-0.000984	-0.00685
	(0.00329)	(0.00547)	(0.00494)	(0.0626)	(0.00991)	(0.0124)
Home Health Care	0.0389***	0.0389***	0.0389***	0.0389***	0.0389***	0.0389***
	(0.00736)	(0.00736)	(0.00736)	(0.00736)	(0.00736)	(0.00736)
Panel B: IV						
SNF Termination	-0.0491	-0.0923	0.0607	0.917	-0.0253	-0.176
	(0.0856)	(0.146)	(0.127)	(1.558)	(0.253)	(0.315)
Controls	Y	Y	Y	Y	Y	Y
Mean of Dep Var	0.0804	0.152	0.192	4.705	9.036	9.334
Observations	132559	132559	132559	132559	132559	132559
First-stage F-stat	27.92	27.92	27.92	27.92	27.92	27.92

Notes: The table reports coefficients from reduced form, first stage, and IV regressions for the nursing home to home care compliers, whose estimated first stage effect on home care propensity is above median and that on inpatient rehab is below median. The top panel estimates the reduced form effects of terminations of hospital-affiliated nursing homes on patient health outcomes and utilizations and the first stage effect on propensity of getting post-acute care through home care. The bottom panel estimates the local average treatment effect of getting post-acute care through home care on the health outcomes and utilizations for the compliers, using terminations of hospital-affiliated nursing homes as instrument. Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state×year FEs. Standard errors clustered at hospital level.

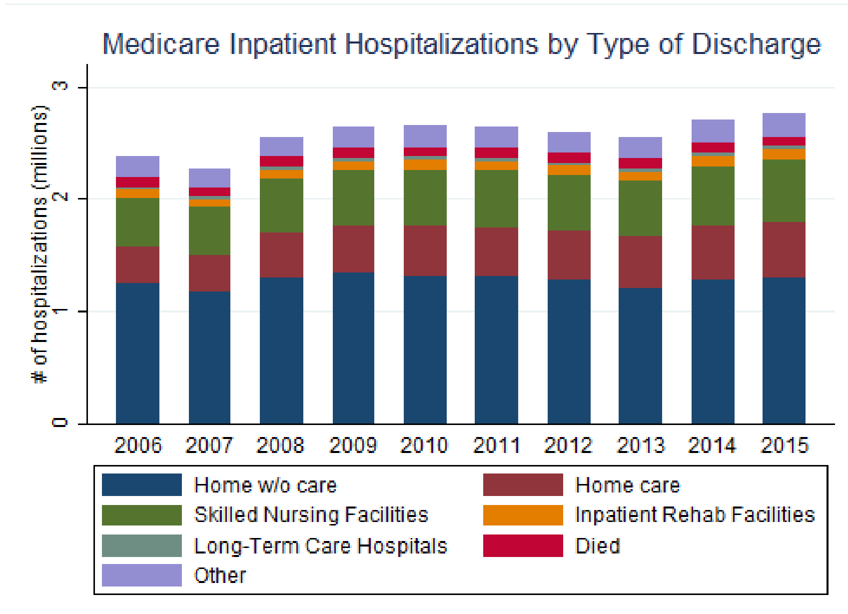
Table 11: IV Results for Nursing Home to Inpatient Rehab Compliers

	Health Outcomes and Utilization					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Reduced Form and First Stage	30 day mortality	90 day mortality	30 day readmission	Hospital LoS	Log(Medicare Payment)	Log(60-day Medicare Payment)
SNF Termination	0.00168	-0.00210	-0.00832	-0.107	0.0220**	0.0130
	(0.00407)	(0.00541)	(0.00595)	(0.0740)	(0.0100)	(0.0122)
IRF	0.0104***	0.0104***	0.0104***	0.0104***	0.0104***	0.0104***
	(0.00374)	(0.00374)	(0.00374)	(0.00374)	(0.00374)	(0.00374)
Panel B: IV						
SNF Termination	0.162	-0.202	-0.800	-10.30	2.115*	1.247
	(0.387)	(0.538)	(0.661)	(7.694)	(1.198)	(1.179)
Controls	Y	Y	Y	Y	Y	Y
Mean of Dep Var	0.0865	0.160	0.198	5.421	9.140	9.429
Observations	132862	132862	132862	132862	132862	132862
First-stage F-stat	7.732	7.732	7.732	7.732	7.732	7.732

Notes: The table reports coefficients from reduced form, first stage, and IV regressions for the nursing home to inpatient rehab compliers, whose estimated first stage effect on inpatient rehab propensity is above median and that on home care is below median. The top panel estimates the reduced form effects of terminations of hospital-affiliated nursing homes on patient health outcomes and utilizations, and the first stage effect on propensity of getting post-acute care through inpatient rehab. The bottom panel estimates the local average treatment effect of getting post-acute care through inpatient rehab on the health outcomes and utilizations for the compliers, using terminations of hospital-affiliated nursing homes as instrument. Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state$\times$year FEs. Standard errors clustered at hospital level.

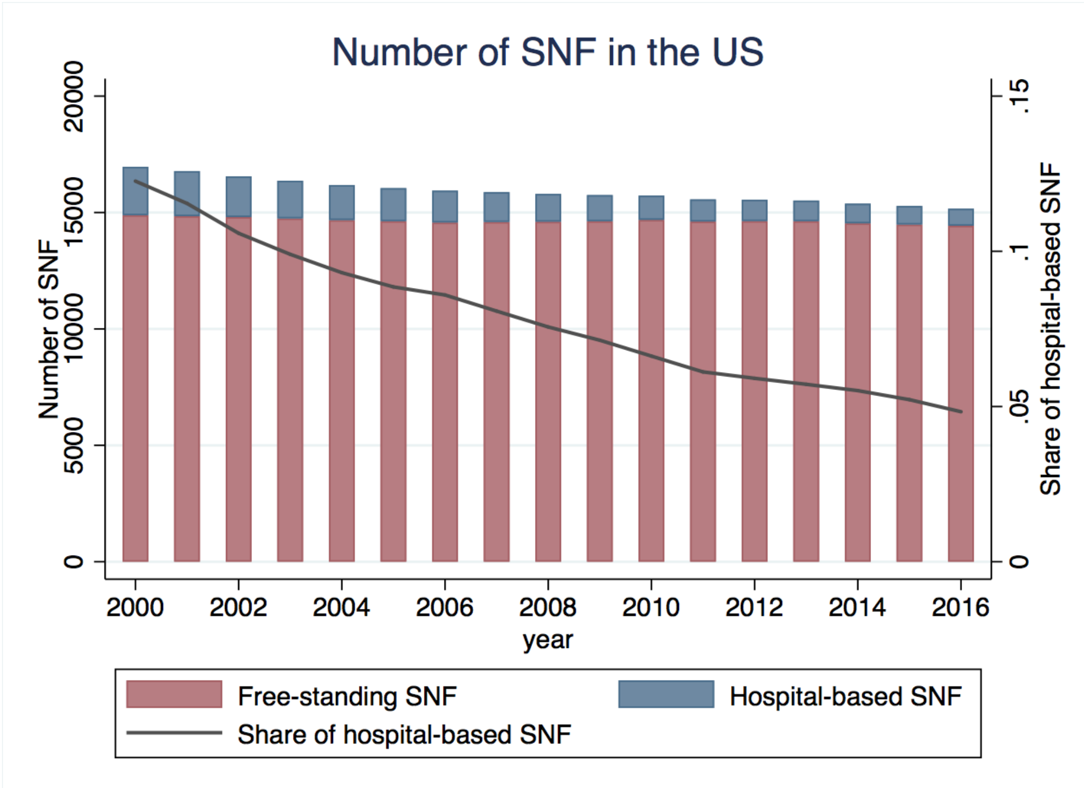
Figures

Figure 1: Medicare Inpatient Hospitalizations by Type of Discharge



Notes: The graph plots the number of inpatient hospitalizations by discharge destination for all Medicare fee-for-service beneficiaries in the MedPAR data. Home health service, nursing home, inpatient rehabilitation facility, and long-term care hospital are all common types of post-acute care providers. The "other" column mainly includes transfers to inpatient care at other hospitals and hospice.

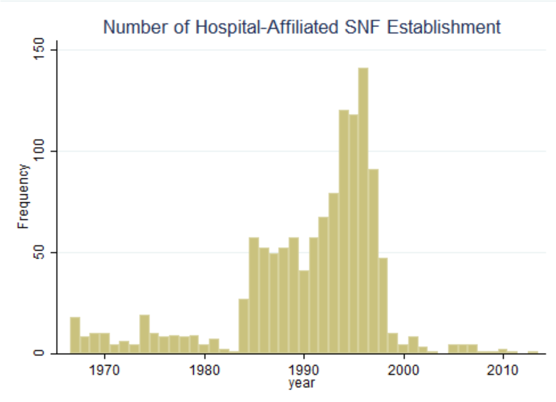
Figure 2: Number and Share of Nursing Homes Affiliated with Hospitals



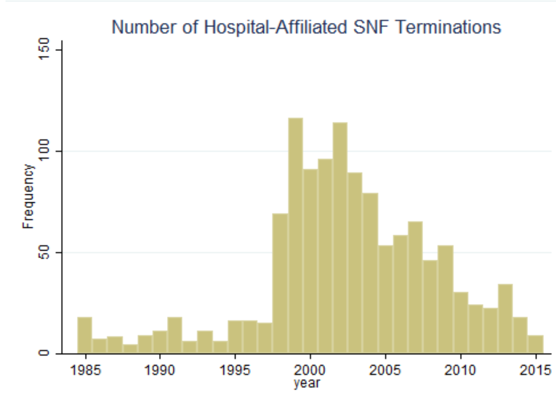
Notes: The graph plots the total number of nursing homes in the US that are free-standing or affiliated with a hospital, and the share of hospital-affiliated nursing homes among all nursing homes. Data source is the LTCFocus dataset constructed at Brown University based on the characteristics of all nursing homes certified by Medicare or Medicaid.

Figure 3: Establishment and Termination of Hospital-Affiliated Nursing Homes and Inpatient Rehab Units

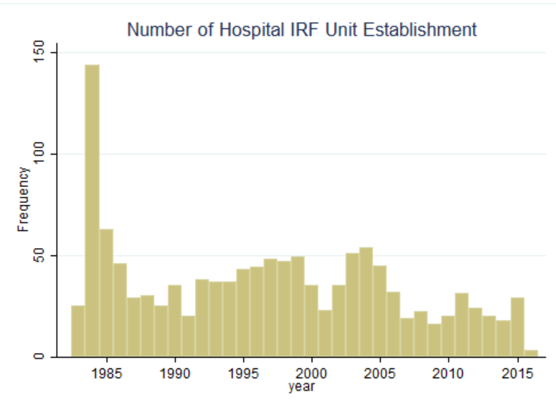
(a) Establishment of Hospital-Affiliated SNFs



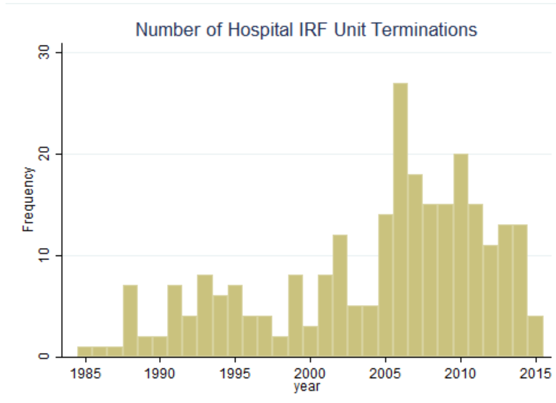
(b) Termination of Hospital-Affiliated SNFs



(c) Establishment of Hospital IRF Units



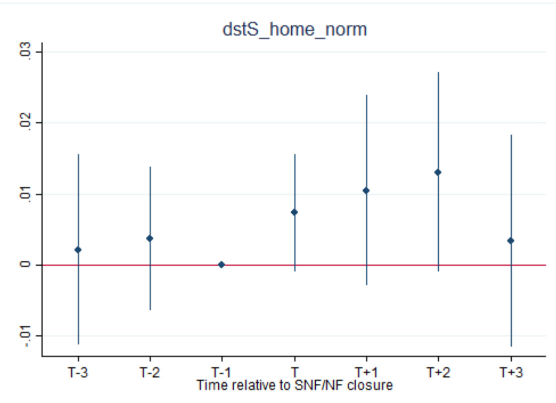
(d) Termination of Hospital IRF Units



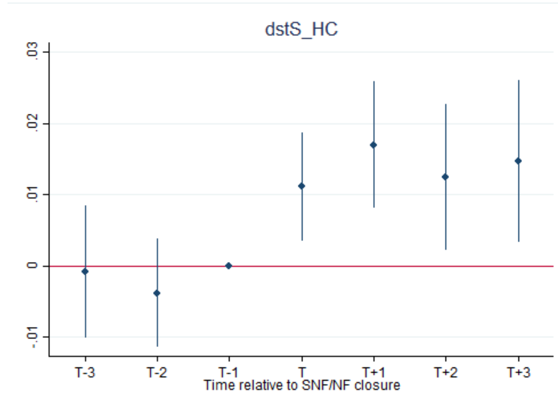
Notes: This graph plots the number of establishment and termination of all hospital-affiliated nursing homes and hospital inpatient rehabilitation units each year, excluding nursing home and inpatient rehab units terminated the same year as the hospital. Data source is CMS provider of service files that include information on all providers certified by Medicare or Medicaid.

Figure 4: Event Study around Termination of Hospital-Affiliated Nursing Homes – Types of Post-acute Care

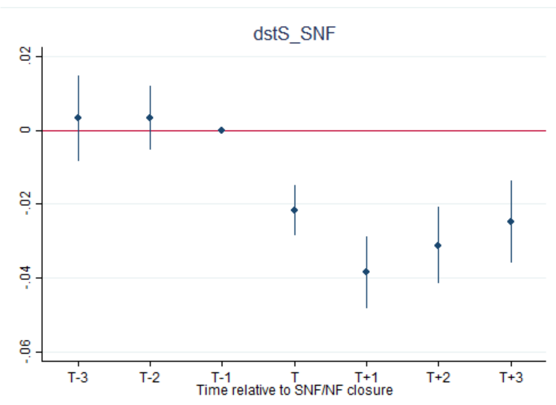
(a) Discharge to Home w/o PAC



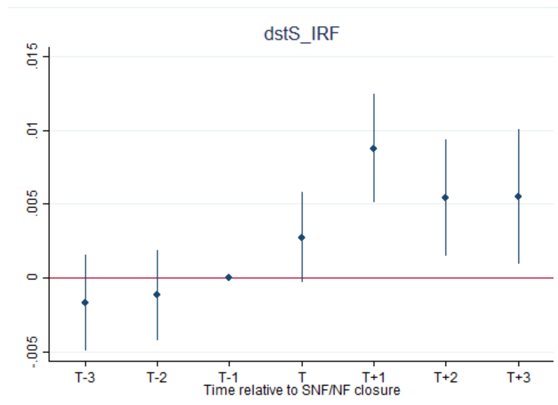
(b) Home Health Care



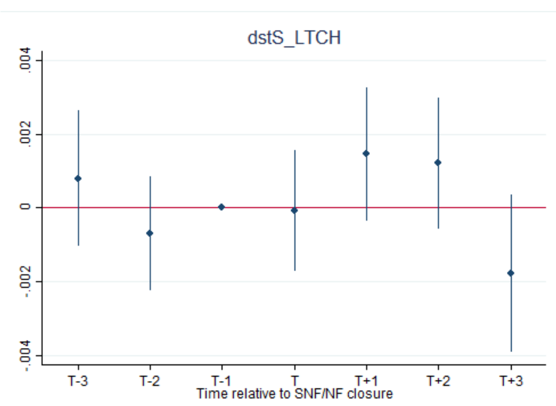
(c) Nursing Home Care



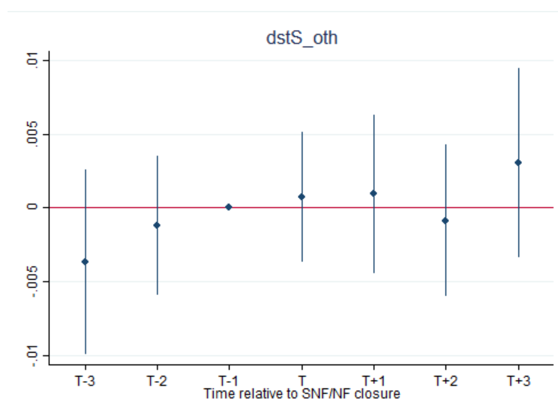
(d) Inpatient Rehab



(e) Long-term Care Hospital



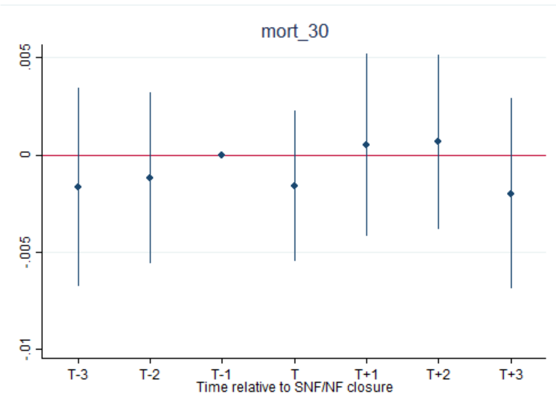
(f) Other



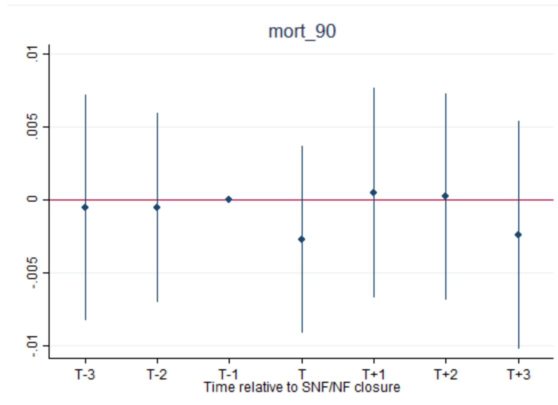
Notes: The graphs plot coefficients from event study regressions analyzing the effect of terminations of hospital-affiliated nursing homes on types of post-acute care for the full analysis sample. The analysis sample is based on inpatient hospitalizations in 2007 - 2015 for Medicare fee-for-service beneficiaries who are aged 67+, discharged alive from hospital, and received inpatient hospitalizations at a treatment hospital (terminated affiliated nursing home in 2008 - 2014, no other change in nursing home or inpatient rehab unit through 2001 - 2015) or control hospital (with affiliated nursing home and no change in nursing home or inpatient rehab unit through 2001 - 2015). Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state$\times$year FEs. Standard errors clustered at hospital level.

Figure 5: Event Study around Termination of Hospital-Affiliated Nursing Homes – Health Outcomes and Utilizations

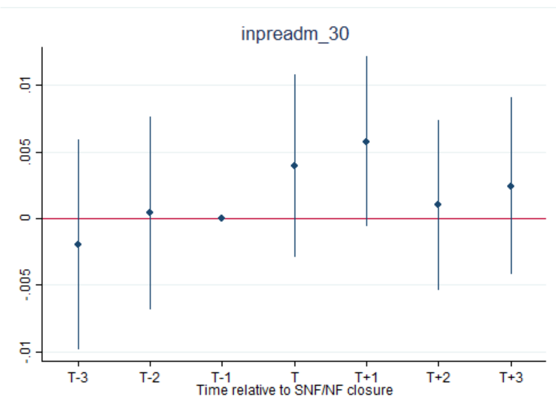
(a) 30 Day Mortality



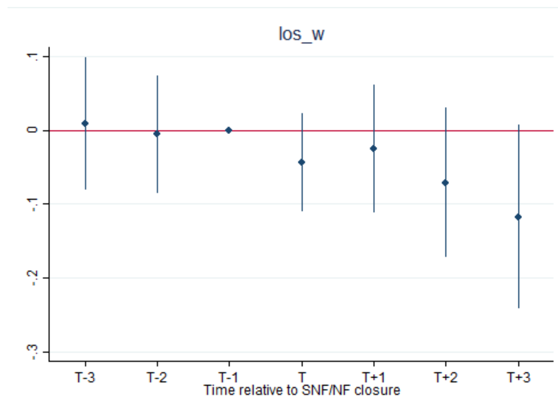
(b) 90 Day Mortality



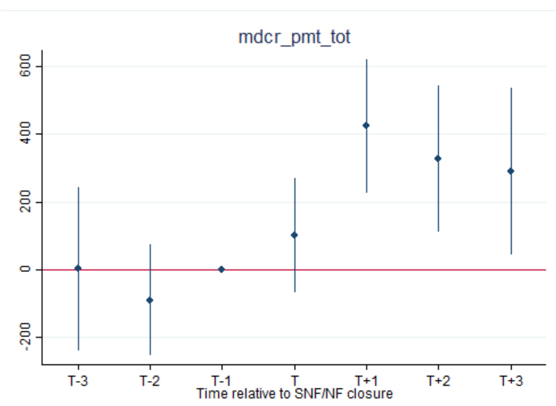
(c) 30 Day Readmission



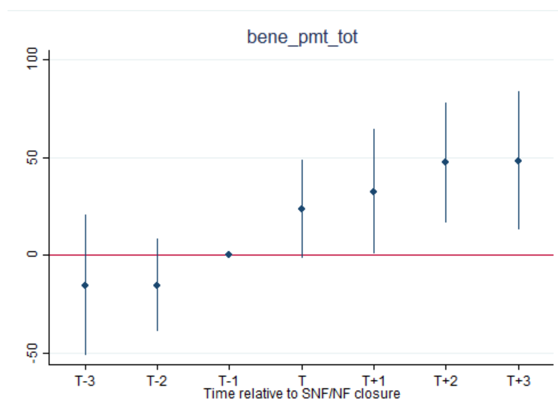
(d) LoS at Hospital



(e) Medicare Expenditure



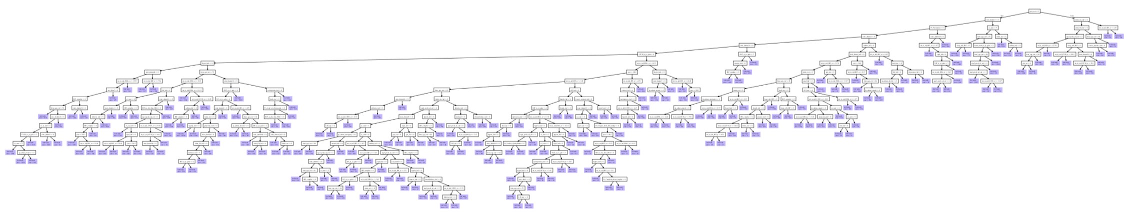
(f) Beneficiary Expenditure



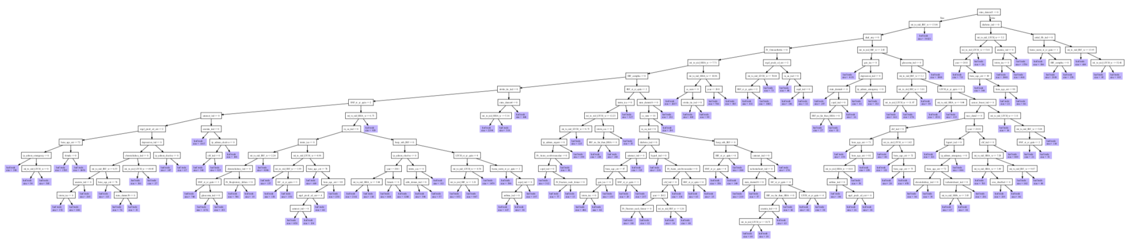
Notes: The graphs plot coefficients from event study regressions analyzing the effect of terminations of hospital-affiliated nursing homes on health outcomes and utilizations for the full analysis sample. The analysis sample is based on inpatient hospitalizations in 2007 - 2015 for Medicare fee-for-service beneficiaries who are aged 67+, discharged alive from hospital, and received inpatient hospitalizations at a treatment hospital (terminated affiliated nursing home in 2008 - 2014, no other change in nursing home or inpatient rehab unit through 2001 - 2015) or control hospital (with affiliated nursing home and no change in nursing home or inpatient rehab unit through 2001 - 2015). Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state×year FEs. Standard errors clustered at hospital level.

Figure 6: Example Trees from Random Forest for Conditional First Stage Effect Estimation

(a) Tree No. 500

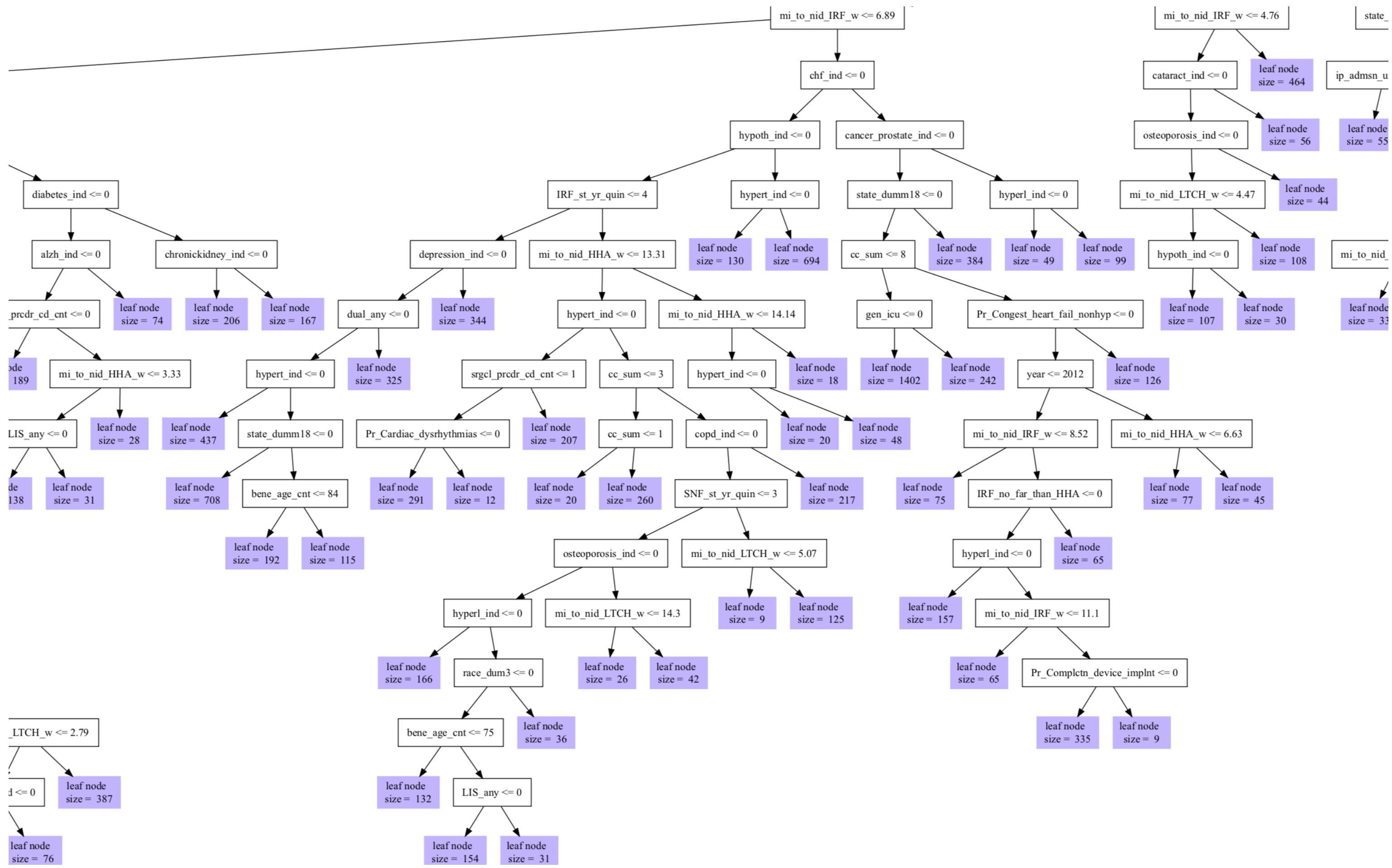


(b) Tree No. 1000



Notes: The graphs plot example trees from the generalized random forest estimating heterogeneous conditional first stage effects of terminations of hospital-affiliated nursing homes on propensity of getting post-acute care at inpatient rehabilitation facilities. The trees illustrate the recursive partitioning of the sample into leaves within which the first stage effects are as similar as possible and across which the first stage effects are as heterogeneous as possible. Each tree is grown on a random subsample with random subsets of covariates (and thus can make different branch splits and have different shapes), and an aggregation of trees form the random forest. The full analysis sample is randomly split in half, one to grow random forest and form the partition, and the other to estimate conditional first stage effects using local maximum likelihood with kernel weights derived from the random forest.

Figure 7: Example Tree from Random Forest – Detail

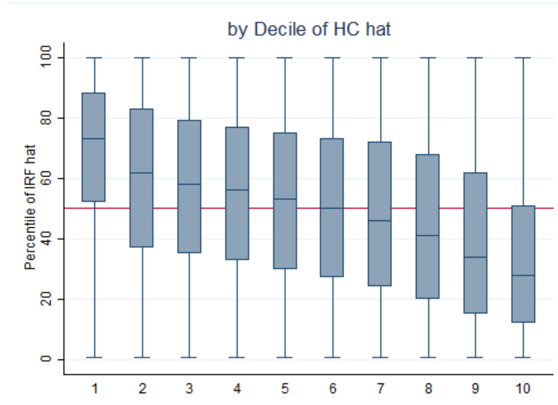


Notes: The graph zooms in on an example tree from the generalized random forest estimating heterogeneous conditional first stage effects of terminations of hospital-affiliated nursing homes on propensity of getting post-acute care at inpatient rehab. The trees illustrate the recursive partitioning of the sample into leaves within which the first stage effects are as similar as possible and across which the first stage effects are as heterogeneous as possible. The graph shows that common variables that the trees split on include distance to various post-acute care facilities, baseline chronic conditions, demographic and socio-economic variables, and principal diagnosis such as hip fracture and heart failure.

Figure 8: Distribution of Estimated Individual-Specific First Stage Effects

(a)

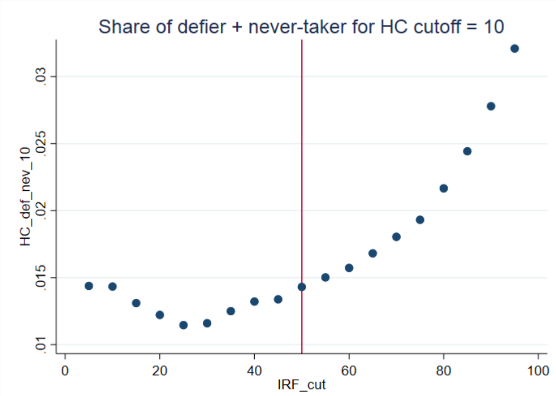
(b)



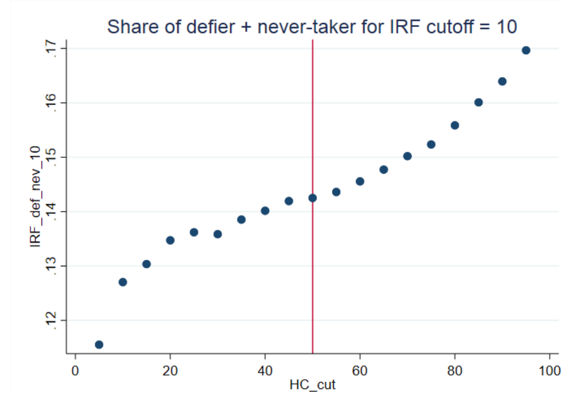
Notes: The graph plots the distribution (min, 25th percentile, 50th percentile, 75th percentile, max) of the percentile of estimated individual-specific first stage effects of hospital-nursing home vertical disintegration on propensity of getting post-acute care through home care, by the decile of the first stage effect on inpatient rehab in panel (a), and the distribution of percentile of first stage effect on propensity of inpatient rehab by the decile of first stage effect on home care in panel (b). The conditional first stage effects are estimated through generalized random forest, which partitions the sample into leaves within which the first stage effects are as similar as possible and across which the first stage effects are as heterogeneous as possible.

Figure 9: Share of Defier + Never-Taker by Strata Definition

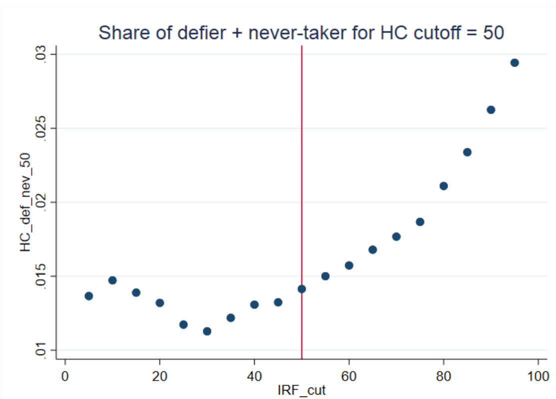
(a) Home Care Strata
$\hat{\tau}_{w_{HC}}(X_i) \geq$ 10th pctl, $\hat{\tau}_{w_{IRF}}(X_i) \leq$ nth pctl



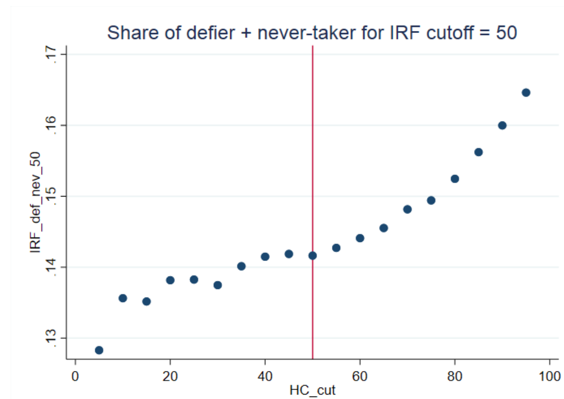
(b) IRF Strata
$\hat{\tau}_{w_{IRF}}(X_i) \geq$ 10th pctl, $\hat{\tau}_{w_{HC}}(X_i) \leq$ nth pctl



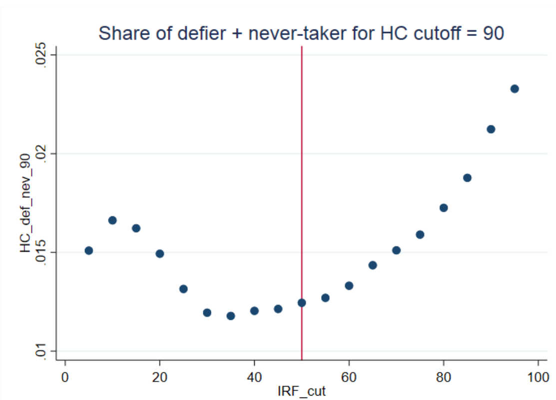
(c) Home Care Strata
$\hat{\tau}_{w_{HC}}(X_i) \geq$ 50th pctl, $\hat{\tau}_{w_{IRF}}(X_i) \leq$ nth pctl



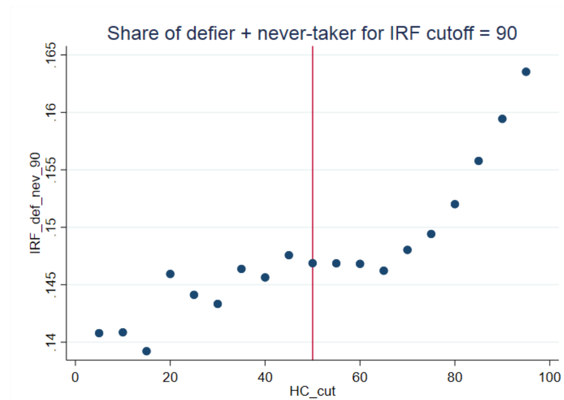
(d) IRF Strata
$\hat{\tau}_{w_{IRF}}(X_i) \geq$ 50th pctl, $\hat{\tau}_{w_{HC}}(X_i) \leq$ nth pctl



(e) Home Care Strata
$\hat{\tau}_{w_{HC}}(X_i) \geq$ 90th pctl, $\hat{\tau}_{w_{IRF}}(X_i) \leq$ nth pctl



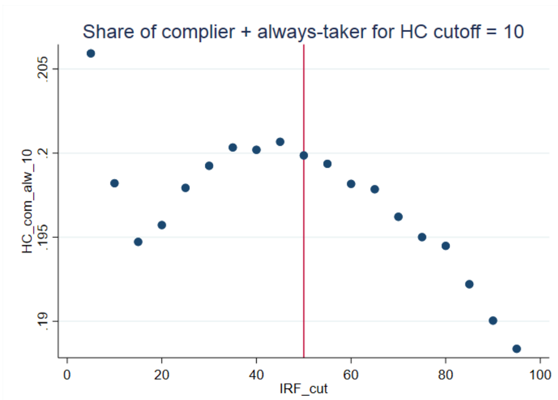
(f) IRF Strata
$\hat{\tau}_{w_{IRF}}(X_i) \geq$ 90th pctl, $\hat{\tau}_{w_{HC}}(X_i) \leq$ nth pctl



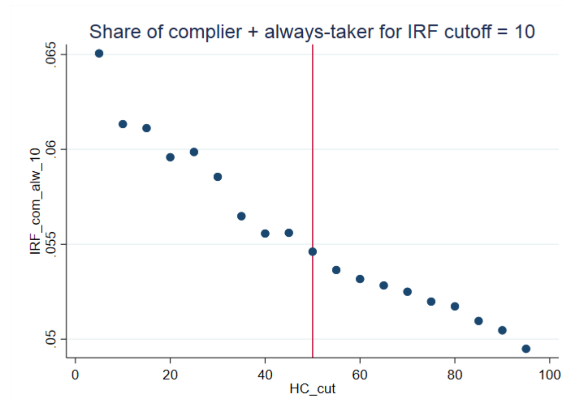
Notes: The graphs plot the share of defiers and never-takers by different strata definitions according to the estimated conditional first stage effects. The defiers and never-takers are those getting PAC at inpatient rehab facilities in the home care strata, and those getting PAC via home care in the IRF strata. Panels (a), (c), and (e) show the results for different home care strata, where the the cutoff of $\hat{\tau}_{w_{HC}}(X_i)$ is fixed at 10th, 50th, and 90th percentile respectively, and each point correspond to a stratum with $\hat{\tau}_{w_{IRF}}(X_i)$ cutoff according to the x-axis. Similarly, panels (b), (d), and (f) show the results for IRF strata, where the cutoff of $\hat{\tau}_{w_{IRF}}(X_i)$ is fixed at 10th, 50th, and 90th percentile respectively, and each point correspond to a stratum with $\hat{\tau}_{w_{HC}}(X_i)$ cutoff according to the x-axis. Conditional first stage effects are estimated through generalized random forest.

Figure 10: Share of Complier + Always-Taker by Strata Definition

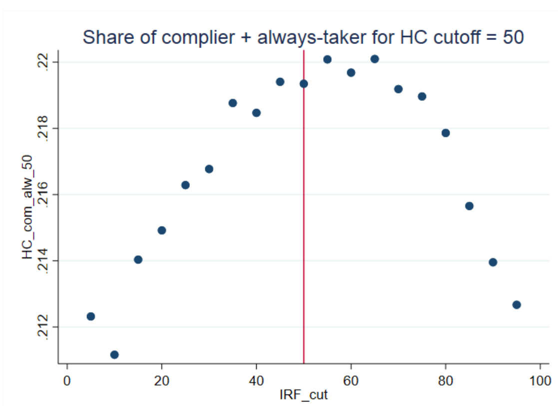
(a) Home Care Strata
$\hat{\tau}_{w_{HC}}(X_i) \geq$ 10th pctl, $\hat{\tau}_{w_{IRF}}(X_i) \leq$ nth pctl



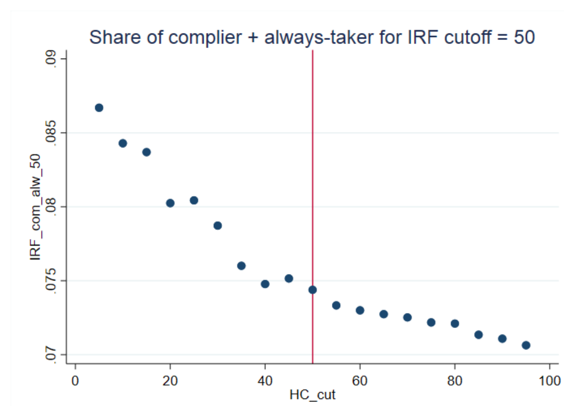
(b) IRF Strata
$\hat{\tau}_{w_{IRF}}(X_i) \geq$ 10th pctl, $\hat{\tau}_{w_{HC}}(X_i) \leq$ nth pctl



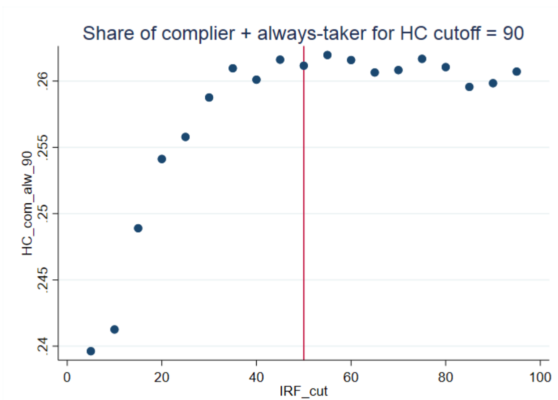
(c) Home Care Strata
$\hat{\tau}_{w_{HC}}(X_i) \geq$ 50th pctl, $\hat{\tau}_{w_{IRF}}(X_i) \leq$ nth pctl



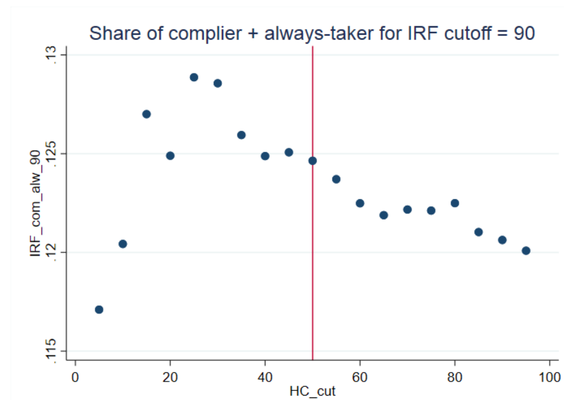
(d) IRF Strata
$\hat{\tau}_{w_{IRF}}(X_i) \geq$ 50th pctl, $\hat{\tau}_{w_{HC}}(X_i) \leq$ nth pctl



(e) Home Care Strata
$\hat{\tau}_{w_{HC}}(X_i) \geq$ 90th pctl, $\hat{\tau}_{w_{IRF}}(X_i) \leq$ nth pctl



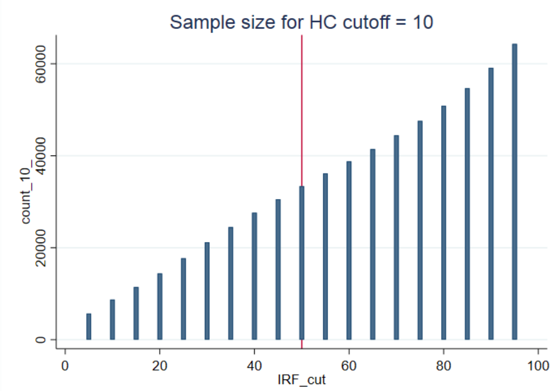
(f) IRF Strata
$\hat{\tau}_{w_{IRF}}(X_i) \geq$ 90th pctl, $\hat{\tau}_{w_{HC}}(X_i) \leq$ nth pctl



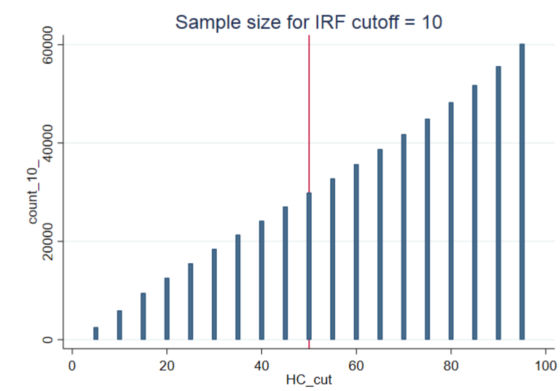
Notes: The graphs plot the share of compliers and always-takers by different strata definitions according to the estimated conditional first stage effects. The compliers and always-takers are those getting PAC via home care in the home care strata, and those getting PAC at inpatient rehab facilities in the IRF strata. Panels (a), (c), and (e) show the results for different home care strata, where the the cutoff of $\hat{\tau}_{w_{HC}}(X_i)$ is fixed at 10th, 50th, and 90th percentile respectively, and each point correspond to a stratum with $\hat{\tau}_{w_{IRF}}(X_i)$ cutoff according to the x-axis. Similarly, panels (b), (d), and (f) show the results for IRF strata, where the cutoff of $\hat{\tau}_{w_{IRF}}(X_i)$ is fixed at 10th, 50th, and 90th percentile respectively, and each point correspond to a stratum with $\hat{\tau}_{w_{HC}}(X_i)$ cutoff according to the x-axis. Conditional first stage effects are estimated through generalized random forest.

Figure 11: Size of Strata by Strata Definition

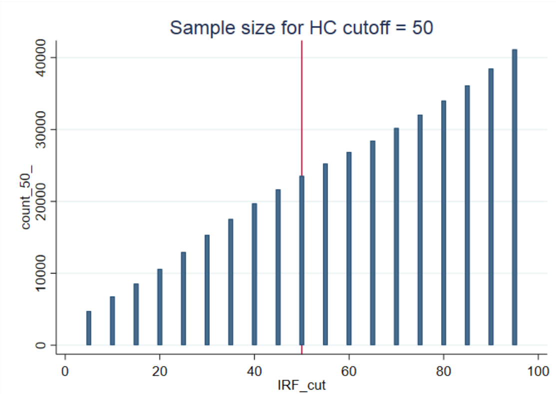
(a) Home Care Strata
$\hat{\tau}_{w_{HC}}(X_i) \geq$ 10th pctl, $\hat{\tau}_{w_{IRF}}(X_i) \leq$ nth pctl



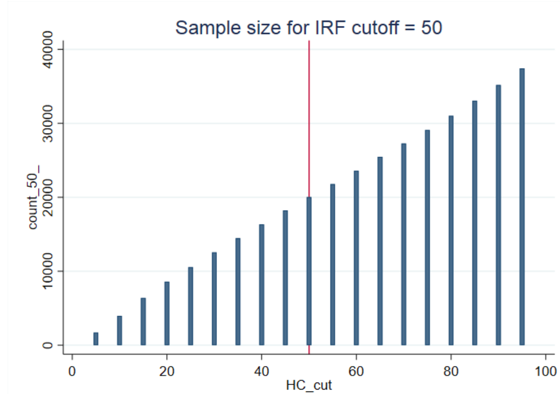
(b) IRF Strata
$\hat{\tau}_{w_{IRF}}(X_i) \geq$ 10th pctl, $\hat{\tau}_{w_{HC}}(X_i) \leq$ nth pctl



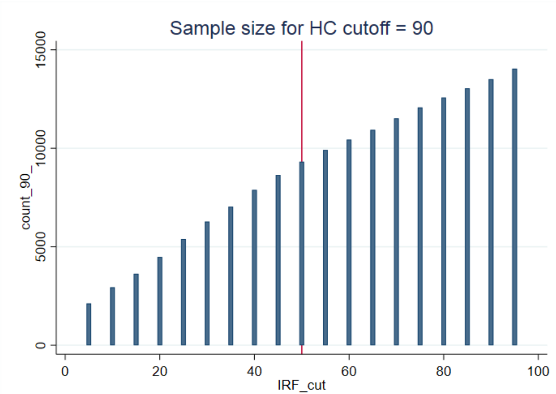
(c) Home Care Strata
$\hat{\tau}_{w_{HC}}(X_i) \geq$ 50th pctl, $\hat{\tau}_{w_{IRF}}(X_i) \leq$ nth pctl



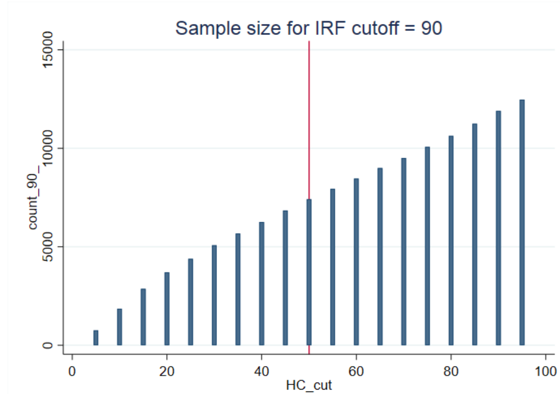
(d) IRF Strata
$\hat{\tau}_{w_{IRF}}(X_i) \geq$ 50th pctl, $\hat{\tau}_{w_{HC}}(X_i) \leq$ nth pctl



(e) Home Care Strata
$\hat{\tau}_{w_{HC}}(X_i) \geq$ 90th pctl, $\hat{\tau}_{w_{IRF}}(X_i) \leq$ nth pctl



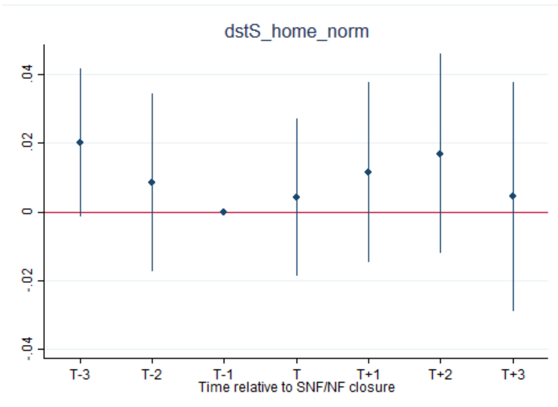
(f) IRF Strata
$\hat{\tau}_{w_{IRF}}(X_i) \geq$ 90th pctl, $\hat{\tau}_{w_{HC}}(X_i) \leq$ nth pctl



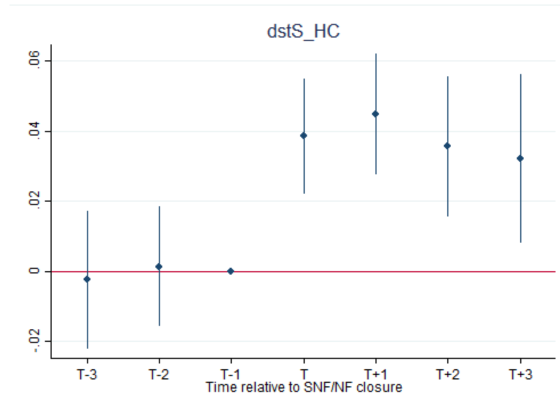
Notes: The graphs plot the strata size by different definitions according to the estimated conditional first stage effects. Panels (a), (c), and (e) show the results for different home care strata, where the the cutoff of $\hat{\tau}_{w_{HC}}(X_i)$ is fixed at 10th, 50th, and 90th percentile respectively, and each point correspond to a stratum with $\hat{\tau}_{w_{IRF}}(X_i)$ cutoff according to the x-axis. Similarly, panels (b), (d), and (f) show the results for IRF strata, where the cutoff of $\hat{\tau}_{w_{IRF}}(X_i)$ is fixed at 10th, 50th, and 90th percentile respectively, and each point correspond to a stratum with $\hat{\tau}_{w_{HC}}(X_i)$ cutoff according to the x-axis. Conditional first stage effects are estimated through generalized random forest.

Figure 12: Event Study for Home Health Compliers – Types of Post-Acute Care

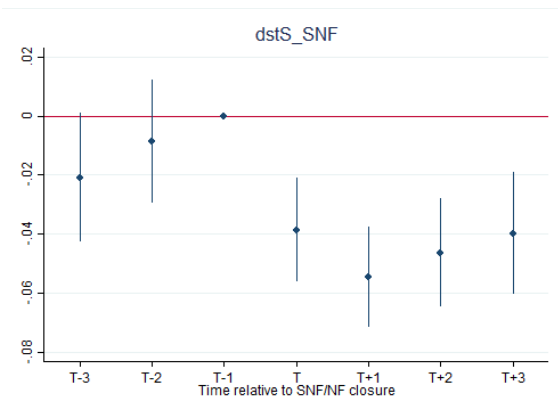
(a) Discharge to Home w/o PAC



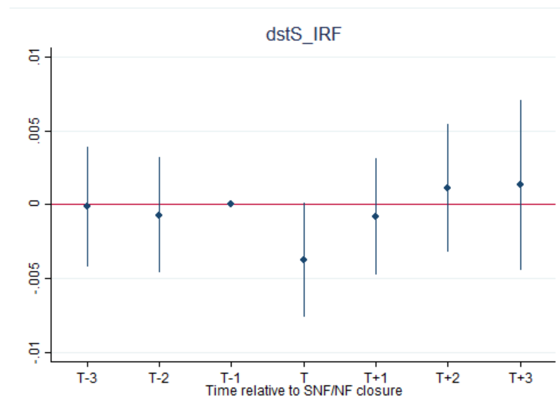
(b) Home Health Care



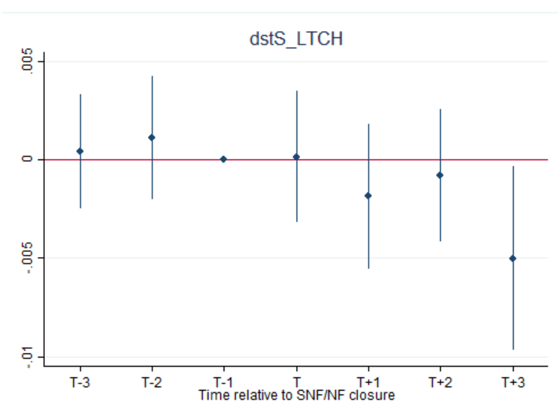
(c) SNF Care



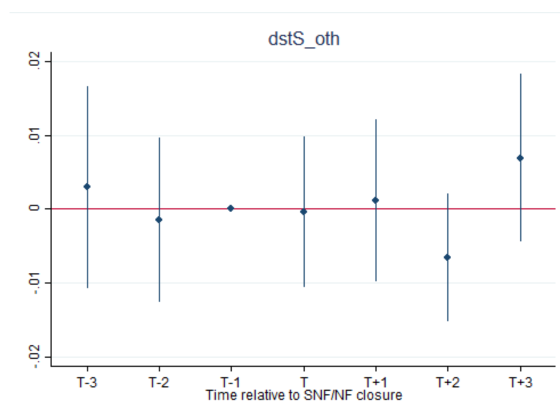
(d) IRF Care



(e) LTCH Care



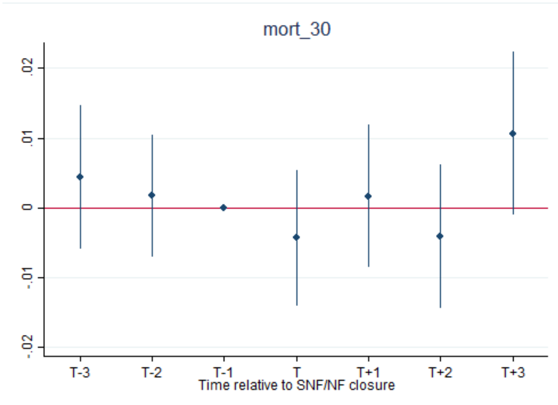
(f) Other



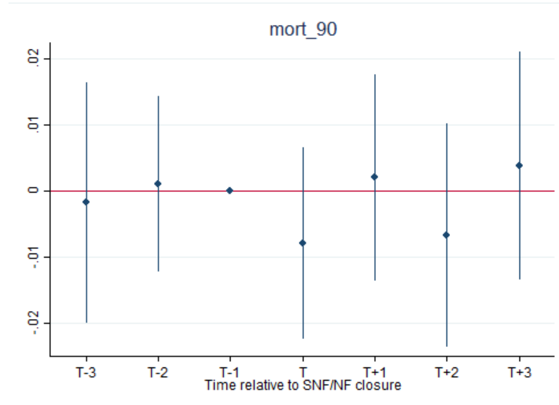
Notes: The graphs plot coefficients from reduced form event study of hospital-nursing home vertical disintegration on type of post-acute care for the nursing home to home care compliers, whose estimated first stage effect on home care propensity is above median and that on inpatient rehab is below median. Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state$\times$year FEs. Standard errors clustered at hospital level.

Figure 13: Event Study for Home Health Compliers – Health Outcomes and Utilizations

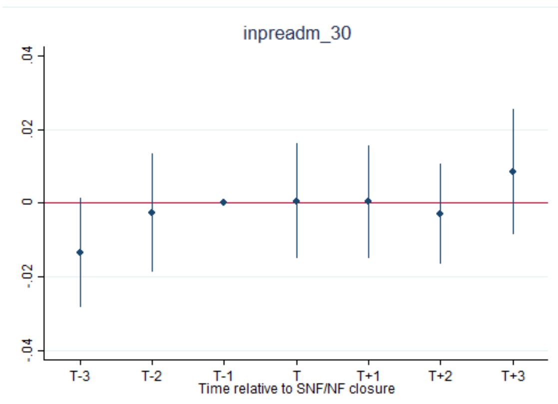
(a) 30 Day Mortality



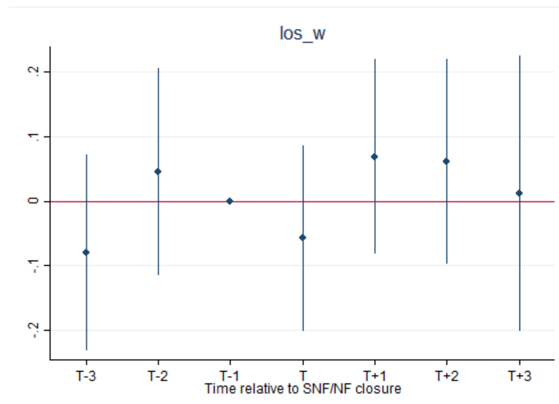
(b) 90 Day Mortality



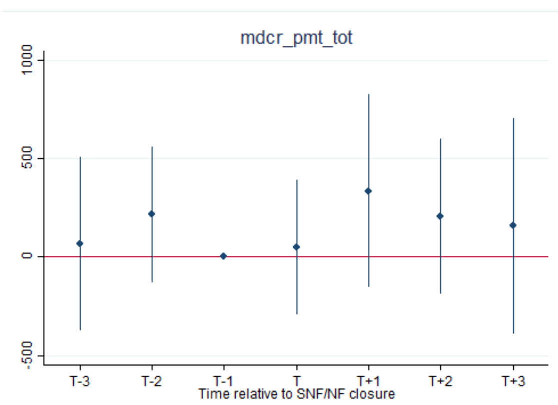
(c) 30 Day Readmission



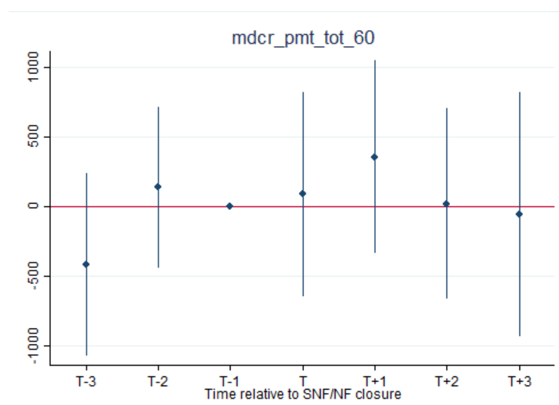
(d) LoS at Hospital



(e) Medicare Expenditure



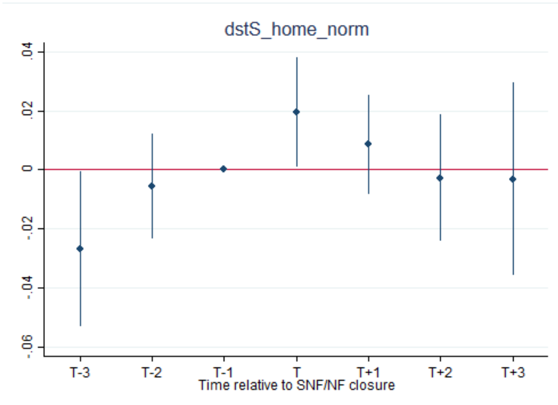
(f) 60-Day Medicare Expenditure



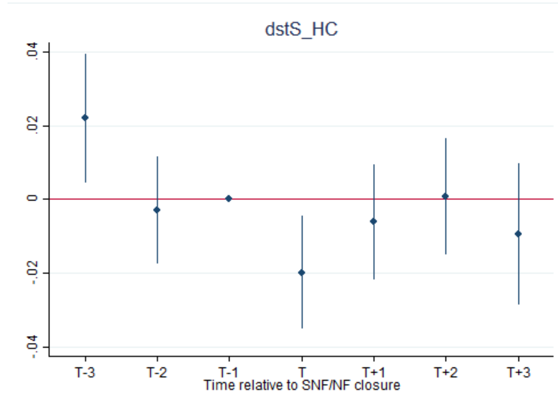
Notes: The graphs plot coefficients from reduced form event study of hospital-nursing home vertical disintegration on health outcomes and utilizations for the nursing home to home care compliers, whose estimated first stage effect on home care propensity is above median and that on inpatient rehab is below median. Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state$\times$year FEs. Standard errors clustered at hospital level.

Figure 14: Event Study for Inpatient Rehab Compliers – Types of Post-Acute Care

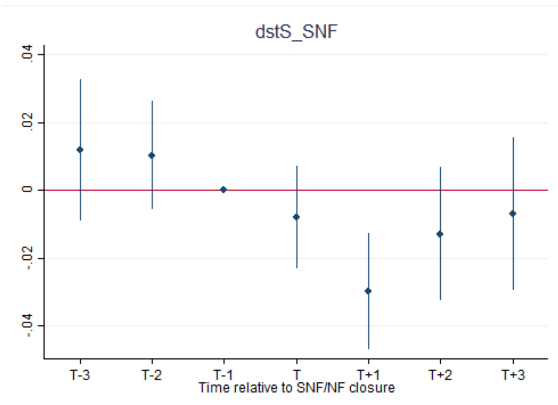
(a) Discharge to Home w/o PAC



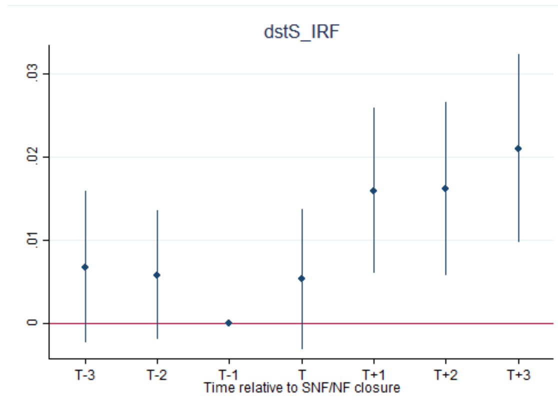
(b) Home Health Care



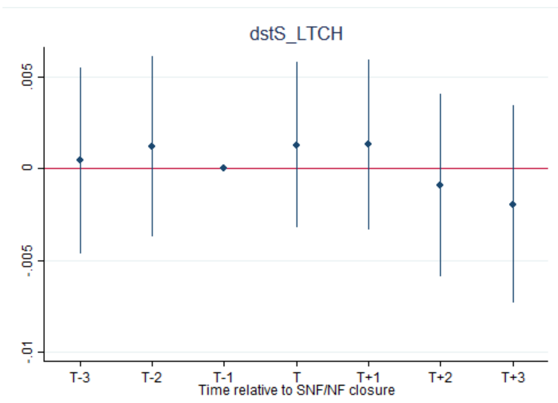
(c) SNF Care



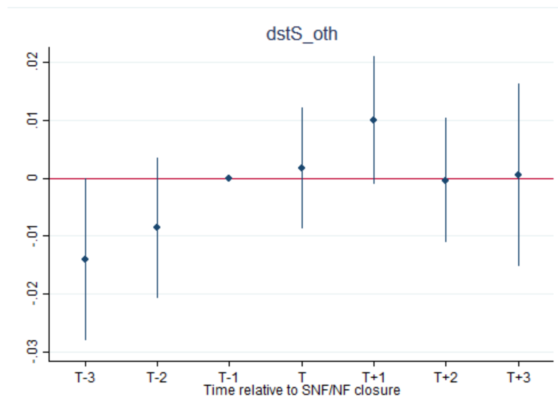
(d) IRF Care



(e) LTCH Care



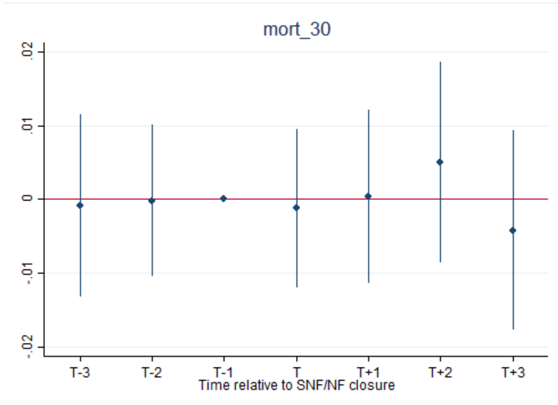
(f) Other



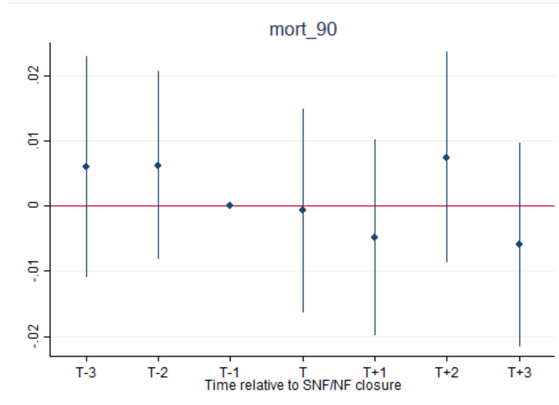
Notes: The graphs plot coefficients from reduced form event study of hospital-nursing home vertical disintegration on type of post-acute care for the nursing home to inpatient rehab compliers, whose estimated first stage effect on inpatient rehab propensity is above median and that on home care is below median. Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state$\times$year FEs. Standard errors clustered at hospital level.

Figure 15: Event Study for Inpatient Rehab Compliers – Health Outcomes and Utilizations

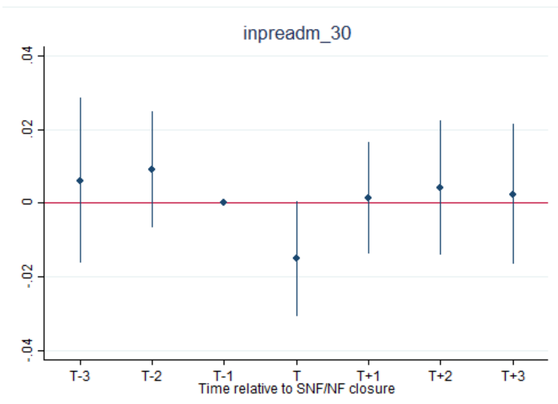
(a) 30 Day Mortality



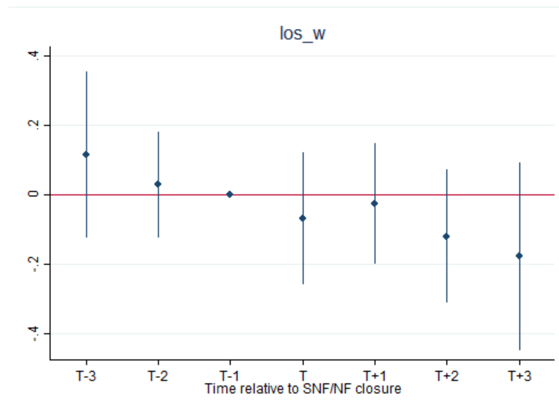
(b) 90 Day Mortality



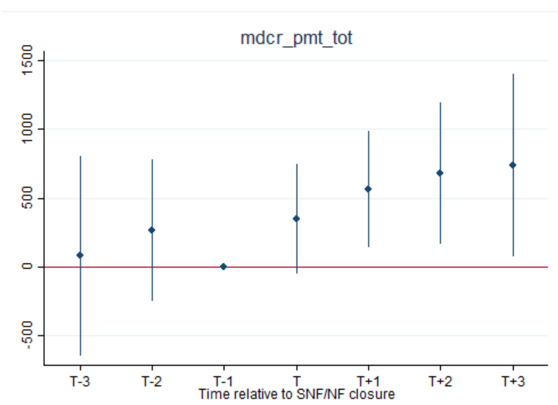
(c) 30 Day Readmission



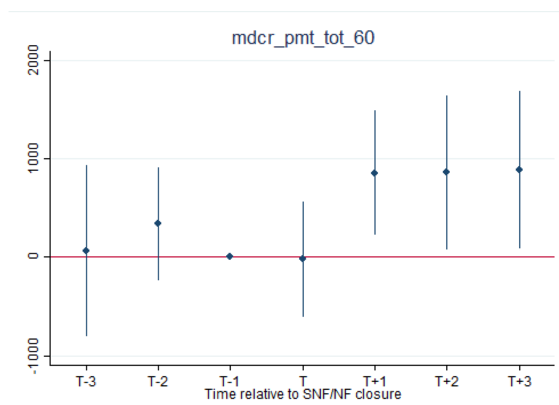
(d) LoS at Hospital



(e) Medicare Expenditure



(f) 60-Day Medicare Expenditure



Notes: The graphs plot coefficients from reduced form event study of hospital-nursing home vertical disintegration on health outcomes and utilizations for the nursing home to inpatient rehab compliers, whose estimated first stage effect on inpatient rehab propensity is above median and that on home care is below median. Control variables include individual demographics (age, gender, race), socio-economic variables (indicators for dual-eligibility, Medicare Part D low income subsidy, and original Medicare eligibility through disability), baseline chronic conditions, principal and co-diagnoses, number of surgical procedures, primary procedure, type of admission, ICU and CCU use, whether any diagnosis is compliant with inpatient rehab 60% rule (e.g. stroke, brain and spinal cord injury, ...), quintiles of distances to the nearest home health agency, inpatient rehab facility, and long-term care hospital, and indicator for whether the nearest inpatient rehab facility is no farther away to the patient than the nearest home health agency (all distances based on centroid of zip codes). Also controlling for hospital FEs and state×year FEs. Standard errors clustered at hospital level.

References

Athey, S., J. Tibshirani, and S. Wager (2019). Generalized Random Forests. *The Annals of Statistics 47*(2), 1148–1178.

Bergman, P., R. Chetty, S. DeLuca, N. Hendren, L. Katz, and C. Palmer (2019). Creating Moves to Opportunity: Experimental Evidence on Barriers to Neighborhood Choice. Working Paper No. 26164, National Bureau of Economic Research.

Breiman, L. (2001). Random Forests. *Machine Learning 45*(1), 5–32.

Breiman, L., J. Friedman, C. J. Stone, and R. Olshen (1984). *Classification and Regression Trees*. Belmont, CA: Wadsworth Advanced Books and Software.

Brot-Goldberg, Z. C. and M. de Vaan (2019). Intermediation and Vertical Integration in the Market for Surgeons. Working Paper.

Buntin, M. B., A. D. Garten, S. Paddock, D. Saliba, M. Totten, and J. J. Escarce (2005). How Much Is Postacute Care Use Affected by Its Availability? *Health Services Research 40*(2), 413–434.

Chandra, A., M. A. Dalton, and J. Holmes (2013). Large Increases In Spending On Postacute Care In Medicare Point To The Potential For Cost Savings In These Settings. *Health affairs (Project Hope) 32*(5), 864–872.

CMS (2015). Medicare Coverage of Skilled Nursing Facility Care. Technical Report CMS Product No. 10153.

CMS (2018). SNF Billing Reference. Technical Report ICN 006846.

CMS (2019). Inpatient Rehabilitation Facility Prospective Payment System. Technical Report ICN 006847.

Duggan, M. G. (2000). Hospital Ownership and Public Medical Spending. *The Quarterly Journal of Economics 115*(4), 1343–1373.

Einav, L., A. Finkelstein, and N. Mahoney (2019). Long-Term Care Hospitals: A Case Study in Waste. Working Paper No. 24946, National Bureau of Economic Research.

Feller, A., T. Grindal, L. Miratrix, and L. C. Page (2016). Compared to What? Variation in the Impacts of Early Childhood Education by Alternative Care Type. *The Annals of Applied Statistics 10*(3), 1245–1285.

Gaynor, M., F. Mostashari, and P. B. Ginsburg (2017). Making Health Care Markets Work: Competition Policy for Health Care. *JAMA 317*(13), 1313–1314.

Heckman, J. J. and R. Pinto (2018). Unordered Monotonicity. *Econometrica 86*(1), 1–35.

Hull, P. (2018). IsoLATEing: Identifying Counterfactual-Specific Treatment Effects with Cross-Stratum Comparisons. Working Paper.

Imbens, G. W. and J. D. Angrist (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica 62*(2), 467–475.

Institute of Medicine (2013). Variation in Health Care Spending: Target Decision Making, Not Geography. Technical report, National Academics Press.

Kirkeboen, L. J., E. Leuven, and M. Mogstad (2016). Field of Study, Earnings, and Self-Selection. *The Quarterly Journal of Economics 131*(3), 1057–1111.

Kline, P. and C. R. Walters (2016). Evaluating Public Programs with Close Substitutes: The Case of Head Start. *The Quarterly Journal of Economics 131*(4), 1795–1848.

Konetzka, R. T., E. A. Stuart, and R. M. Werner (2018). The Effect of Integration of Hospitals and Post-Acute Care Providers on Medicare Payment and Patient Outcomes. *Journal of Health Economics 61*, 244–258.

Lee, S. and B. Salanié (2018). Identifying Effects of Multivalued Treatments. *Econometrica 86*(6), 1939–1963.

Low, H. and L. Pistaferri (2015, October). Disability Insurance and the Dynamics of the Incentive Insurance Trade-Off. *American Economic Review 105*(10), 2986–3029.

McWilliams, J. M., L. G. Gilstrap, D. G. Stevenson, M. E. Chernew, H. A. Huskamp, and D. C. Grabowski (2017). Changes in Postacute Care in the Medicare Shared Savings Program. *JAMA Internal Medicine 177*(4), 518–526.

MedPAC (2015). Report to the Congress: Medicare Payment Policy. Technical report.

MedPAC (2019a). A Data Book: Health Care Spending and the Medicare Program. Technical report.

MedPAC (2019b). Report to the Congress: Medicare and the Health Care Delivery System. Technical report.

Mogstad, M., A. Torgovitsky, and C. Walters (2019). Identification of Causal Effects with Multiple Instruments: Problems and Some Solutions. Working Paper No. 25691, National Bureau of Economic Research.

Mountjoy, J. (2019). Community Colleges and Upward Mobility. Working Paper.

Rahman, M., J. McHugh, P. L. Gozalo, D. C. Ackerly, and V. Mor (2017). The Contribution of Skilled Nursing Facilities to Hospitals' Readmission Rate. *Health Services Research 52*(2), 656–675.

Rahman, M., E. C. Norton, and D. C. Grabowski (2016). Do Hospital-Owned Skilled Nursing Facilities Provide Better Post-Acute Care Quality? *Journal of Health Economics 50*, 36–46.

Rahman, M., J. S. Zinn, and V. Mor (2013). The Impact of Hospital-Based Skilled Nursing Facility Closures on Rehospitalizations. *Health Services Research 48*(2, Part 1), 499–518.

Reaves, E. L. and M. Musumeci (2015). Medicaid and Long-Term Services and Supports: A Primer. Technical report, Kaiser Family Foundation.

Rees-Jones, A. and D. Taubinsky (2019). Measuring "Schmeduling". *The Review of Economic Studies*. rdz045.

Sharma, H., M. C. Perraillon, R. M. Werner, D. C. Grabowski, and R. T. Konetzka (2019). Medicaid and Nursing Home Choice: Why Do Duals End Up in Low-Quality Facilities? *Journal of Applied Gerontology*, 1–20.

The Alzheimer's Association (2018). 2018 Alzheimer's Disease Facts and Figures. Technical report, The Alzheimer's Association.

van Dijk, W. (2019). The Socio-Economic Consequences of Housing Assistance. Working Paper.

Wasserman, L. (2006). *All of Nonparametric Statistics*. Springer Texts in Statistics. New York: Springer.

Werner, R. M., N. B. Coe, M. Qi, and R. T. Konetzka (2019). Patient Outcomes After Hospital Discharge to Home With Home Health Care vs to a Skilled Nursing Facility. *JAMA Internal Medicine 179*(5), 617–623.

A Appendix: Diagnoses that Satisfy the Inpatient Rehab Facility 60% Rule

The full list of the 13 conditions are: "1. stroke; 2. spinal cord injury; 3. congenital deformity; 4. amputation; 5. major multiple trauma; 6. fracture of femur (hip fracture); 7. brain injury; 8. neurological disorders, including multiple sclerosis, motor neuron diseases, ployneurapathy, muscular dystrophy, Parkinson's disease; 9. burns; 10 active, polyarticular rheumatoid arthritis, psoriatic arthritis, and seronegative arthropathies resulting in significant functional impairment of ambulation and other activities of daily living that have not improved after an appropriate, aggressive, and sustained course of outpatient therapy services or services in other less-intensive rehabilitation settings immediately preceding the inpatient rehabilitation admission or that result from a systemic disease activation immediately before admission, but have the potential to improve with more intensive rehabilitation; 11. systemic vasculitides with joint inflammation, resulting in significant functional impairment of ambulation and other activities of daily living that have not improved after an appropriate, aggressive, and sustained course of outpatient therapy services or services in other less-intensive rehabilitation settings immediately preceding the inpatient rehabilitation admission or that result from a systemic disease activation immediately before admission, but have the potential to improve with more intensive rehabilitation; 12. Severe or advanced osteoarthritis (osteoarthrosis or degenerative joint disease) involving two or more major weight bearing joints (elbow, shoulders, hips, or knees, but not counting a joint with a prosthesis) with joint deformity and substantial loss of range of motion, atrophy of muscles surrounding the joint, significant functional impairment of ambulation and other activities of daily living that have not improved after the patient has participated in an appropriate, aggressive, and sustained course of outpatient therapy services or services in other less-intensive rehabilitation settings immediately preceding the inpatient rehabilitation admission but have the potential to improve with more intensive rehabilitation (a joint replaced by a prosthesis no longer is considered to have osteoarthritis, or other arthritis, even though this condition was the reason for the joint replacement); 13. knee or hip joint replacement, or both, during an acute hospitalization immediately preceding the inpatient rehabilitation stay and meeting one or more of the following specific criteria: The patient underwent bilateral knee or bilateral hip joint replacement surgery during the acute hospital admission immediately preceding the IRF admission, The patient is extremely obese with a Body Mass Index of at least 50 at the time of admission to the IRF, The patient is age 85 or older at the time of admission to the IRF." (CMS, 2019)