

The Impact of Senior Living Facilities on Medicare Spending

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With the growing elderly population in the U.S., senior living facilities – residences that provide auxiliary services for seniors – have drastically expanded to serve the increasing needs of this population. These services are often much less intensive than those provided by skilled nursing facilities, yet they still have the potential to impact residents’ health outcomes and healthcare usage. Despite this potential, the literature lacks a clear understanding of the impact of senior living facilities on healthcare utilization among seniors. In this paper, we study the effects of senior living facilities on Medicare utilization by employing an instrumental variables approach on the entirety of Medicare fee-for-service claims data from 2011 to 2019. The analysis reveals that a higher density of senior living facilities in a Health Service Area (HSA) reduces admissions to, and payments for, skilled nursing facilities and home health services. Our estimates suggest that a one-standard-deviation increase (0.246) in senior living facilities per 1,000 Medicare beneficiaries leads to annual reductions in Medicare expenditures of \$27.623 million for skilled nursing care and \$17.958 million for home health services within an HSA. These results have important implications for policymakers seeking cost-effective strategies to manage Medicare spending amid rising enrollment pressures.

Key words: Senior living facility, Medicare, healthcare, chronic conditions, instrumental variable

1. Introduction

The U.S. has experienced rapid growth in its senior population, with those aged 65 and older projected to comprise 22% of the population by 2040 ([Administration on Aging 2022](#)). This growth and the increased prevalence of chronic diseases among this population have significantly increased spending for Medicare, the federal health insurance program for individuals aged 65 and older. Medicare’s spending totaled \$829 billion in 2021, accounting for 10% of the federal budget, and

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is expected to rise to 18% by 2032 ([Cubanski and Neuman 2023](#)). The Medicare Trustees estimate the Medicare Part A fund will be depleted in 2036 ([Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds 2024](#)). Consequently, there is a growing body of research dedicated to understanding how to effectively manage care and curb healthcare costs for the elderly. This paper considers a relatively less studied setting: senior living (SL) facilities.

This looming crisis for the Medicare Trust Fund has spurred intense research into strategies for managing and curtailing Medicare expenditures, with studies examining diverse factors like public vs. private Medicare spending ([Curto et al. 2019](#)), the impact of urgent care centers ([Currie et al. 2023](#)), and the role of long-term care hospitals ([Einav et al. 2023](#)). There have also been substantial works looking into the impact of Skilled Nursing Facilities (SNF), which offer 24-hour intensive nursing care and are covered by Medicare Part A based on certain eligibility requirements,¹ on healthcare consumption ([Mor et al. 2010](#), [Werner et al. 2019](#), [Rose 2020](#)). However, less attention has been on the impact of SL facilities on healthcare consumption.

SL facilities are assisted and independent living facilities that provide long-term residential care services for seniors and have the potential to significantly impact the well-being and health of their residents. Assisted living facilities provide long-term care for individuals who need help with everyday activities and some health care services but do not require 24-hour skilled nursing care services ([National Center for Assisted Living 2022](#)). Independent living facilities have less support available than assisted living facilities and are for seniors who do not need assistance with activities of daily living but are looking for a living environment that offers additional support, on-site amenities, and socializing opportunities and activities ([Lauretta 2024](#)). SL facilities provide housing in a community environment, often including services that span a wide range, from assistance with daily tasks such as bathing, dressing, housekeeping, and eating, to chronic disease management, which includes medication management, regular health check-ins, and customized diets ([Pearson et al. 2019](#)). Moreover, they often provide a rich array of social and recreational activities, as well as transportation services ([Brookdale Senior Living 2022](#), [Gatta 2024](#), [Trent-Gurbuz 2023](#), [Mountain Vista Health Park 2025](#)).

Similar to [Freedman and Spillman \(2014\)](#), [Lei et al. \(2023\)](#), we explicitly distinguish SL facilities from SNFs due to the difference in clinical staffing as well as reimbursement policies. Unlike SNFs, there is no Medicare coverage for SL facilities. While Medicaid covers the majority of nursing home residents ([Burns et al. 2025](#)), SL residents typically bear the full cost themselves, with Medicaid coverage being limited and subject to state-specific programs and substantial waiting lists ([Filbin 2023](#), [National Council on Aging 2025](#), [Burns et al. 2023](#), [Rau 2023](#)). In fact, federal

¹ See <https://www.medicare.gov/coverage/skilled-nursing-facility-care>.

law prohibits Medicaid from covering the room and board portion of these costs.² As policymakers consider expanding Medicaid’s Home- and Community-Based Services waiver programs to cover more services often provided in SL facilities (Filbin 2023, Chidambaram and Burns 2024, Paying For Senior Care 2024), understanding the fiscal impact of SL facilities becomes even more pressing.

SL facilities have expanded dramatically to meet the increasing demand for senior care. In fact, there are nearly twice as many SL facilities as SNFs.³ Despite this growth, the SL facility market is projected to be short over 360,000 new units to meet all demand by 2030.⁴ Despite the increasing number of SL facilities and seniors living in these facilities, it is still an open question as to the causal impact of SL facilities on senior healthcare utilization and spending. There has been some prior research examining the association between residing in assisted living facilities and healthcare consumption, e.g. as measured by emergency department (ED) visits and medication costs (Hua et al. 2021, Lei et al. 2023). Notably, prior work largely ignores the potential biases introduced by the non-random selection of SL facilities to develop and build in certain locations based on access to potential residents and health resources. Recently, Munevar et al. (2024) called for more research to estimate the impact of SL facilities on Medicare cost savings.

We use a comprehensive dataset on SL facilities in the U.S. provided by one of the largest SL facility real estate developers, together with the Centers for Medicare and Medicaid Services’ (CMS) Medicare insurance claims data for 100% traditional (fee-for-service) Medicare beneficiaries from 2011 to 2019. Our sample covers more than 100 million beneficiary-year observations across 145 Health Service Areas (HSAs) and nine years. Although we have granular data, analyzing the causal relationship with a naive regression will likely yield a biased estimate due to correlations between new SL facility developments and senior healthcare utilization. For example, more SL facilities may be built in an area with a healthier and wealthier senior population; alternatively, common factors such as senior welfare programs run by the local government may impact both the growth in SL facilities and senior healthcare expenditures. To address potential endogeneities, we use an instrumental variable (IV) approach with a novel IV motivated by the real estate economics literature.

We consider four different measures of healthcare utilization: SNF, inpatient hospital, home health, and ED visits. Our results show that SL facilities significantly decrease SNF and home health utilization among beneficiaries in the HSA. We estimate that a one-standard-deviation

² Social Security Act 1915(c)(1) [42 U.S.C. 1396n].

³ *New York Times*: Extra Fees Drive Assisted-Living Profits, by Jordan Rau. Nov 19, 2023. <https://www.nytimes.com/2023/11/19/health/long-term-care-assisted-living.html>.

⁴ *WSJ*: Aging Boomers Are About to Rekindle the Senior-Housing Market, by Peter Grant. Feb 11, 2025. <https://www.wsj.com/economy/housing/aging-boomers-are-about-to-rekindle-the-senior-housing-market-cd2ebbb5>

increase in SL facility density (0.246 additional facilities per 1,000 Medicare beneficiaries) leads to a reduction of \$339.57 in average SNF payments and \$220.76 in average home health payments per beneficiary within an HSA-year. We find no statistically significant effects of SL facilities on inpatient care or ED utilization. These results suggest that SL facilities decrease some Medicare care needs among seniors.

Given the estimated reduction in SNF and home health costs, there appear to be positive externalities of more SL facilities to the federal government (and the Medicare Trust). Notably, these beneficial effects amplify for seniors with multiple chronic conditions, suggesting that the chronic disease management services provided at SL facilities may decrease the need for healthcare utilization by improving the health condition of the residents. According to a report by the National Center for Health Statistics in 2024, 92% of SL facility residents have at least one chronic condition (Melekin et al. 2024). This suggests that senior living facilities could be pivotal in strategies aimed at managing and reducing Medicare expenditures. Moreover, our results suggest that there may be particular benefits in encouraging seniors with multiple chronic diseases to consider living in SL facilities. By doing so, we can potentially alleviate healthcare costs while simultaneously enhancing the quality of life for our aging population.

2. Related Literature

Our paper relates to several streams of literature, including the literature analyzing the relationship between senior living facilities and healthcare consumption and health outcomes, the literature evaluating the effects of healthcare organizations or policies on Medicare utilization, and the literature examining Medicare beneficiaries' healthcare consumption and health conditions.

First, our paper contributes to the literature on the relationship between senior living facilities and senior healthcare consumption or their health conditions. Hua et al. (2021), in a brief report, identify residents living in assisted living facilities and find that rates of ED use among community residents were lower than among assisted living residents. Sharpp and Young (2016) ascribe frequent ED visits among assisted living residents with dementia to falls based on the data from two assisted living facilities in California. Lei et al. (2023) analyze data from The National Health and Aging Trends Study and find that residents in assisted living facilities spend more on medications than residents in the community but less than those in nursing homes. These papers appear in medical journals and do not account for potential endogeneity issues in their analysis. For example, more SL facilities may enter an area where demand for such facilities is higher. Furthermore, previous studies focus only on assisted living facilities. In contrast, we consider both assisted and independent living facilities under the umbrella of SL facilities. We study their overall effects, as both facilities provide services that could improve their residents' health conditions.

Closer to our study, a series of technical, non-peer reviewed reports sponsored by The National Investment Center for Seniors Housing & Care analyze differences in health conditions between senior living residents and community-dwelling seniors. [Munevar and Gorman \(2023\)](#), [NORC \(2024\)](#), [Munevar et al. \(2024\)](#) find that those who live in senior living facilities are more frail, exhibit greater longevity, and are less likely to be admitted to the hospital from the ED than those who live in the community. In contrast to these reports, we consider a sample that spans a larger time horizon and explicitly account for the potential endogenous developments of senior living facilities by utilizing an IV approach to estimate the causal impact of senior living facilities on healthcare utilization.

This paper also relates to the growing literature on the impact of different healthcare organizations and policies on Medicare utilization. [Einav et al. \(2023\)](#) identify the effects of long-term care hospitals on Medicare spending and find that a discharge to a long-term care hospital increases Medicare spending by substituting discharge to skilled nursing facilities that are paid less than the former. Given the importance of these facilities for senior care, [Slaugh et al. \(2018\)](#), [Slaugh and Scheller-Wolf \(2023\)](#) consider stochastic models to guide staffing at long-term care facilities. [Currie et al. \(2023\)](#) study the impact of urgent care center entry on healthcare utilization among nearby Medicare beneficiaries and find that the urgent care center entries increase Medicare spending without significantly impacting mortality. [Gupta \(2021\)](#) finds that the Hospital Readmissions Reduction Program by CMS avoided annual hospital payments worth \$110 million by decreasing readmissions. [Jin et al. \(2022\)](#) examine the effects of the “three-day rule” that determines the amount of Medicare reimbursement for SNF care. They find that this rule led to the overuse of SNF care for patients discharged after the three-day cutoff and estimate that such overuse generated \$71 million to \$345 million per year in extra Medicare costs. [Shi \(2024\)](#) study the effects of Medicare’s Recovery Audit Contractor program on Medicare spending and find that monitoring reduced Medicare spending on admissions by \$9 billion from 2011 to 2015 without affecting the quality of patient care. More broadly, our paper is related to the literature that studies the healthcare consumption of Medicare beneficiaries and their health outcomes (e.g. [Card et al. \(2009\)](#), [Curto et al. \(2019\)](#)).

Lastly, in terms of methodology, our work is part of the healthcare research that uses an IV approach to address endogeneities (for example, [Gupta \(2021\)](#), [Einav et al. \(2023\)](#), [Shi \(2024\)](#)). As we explain later in [Section 4.2](#), our IV is motivated by the real estate economics literature, which uses housing supply elasticity, proxied by local land use regulations ([Gyourko et al. 2008, 2021](#)) or available land for new development in an area ([Saiz 2010](#)), to instrument real estate prices. [Gyourko et al. \(2008, 2021\)](#) measure the degree of residential land use regulation by surveying local residential land use regulatory regimes over 2,000 communities across the U.S. [Saiz \(2010\)](#)

uses satellite-generated data to estimate the amount of developable land in U.S. metropolitan areas and show that land-constrained cities have lower housing supply elasticities with respect to demand shocks. Chaney et al. (2012) use local housing supply elasticities provided in Saiz (2010) to instrument real estate prices and estimate their effects on corporate investment. Aladangady (2017) use both local land use regulation (Gyourko et al. 2008) and unavailable land (Saiz 2010) to instrument housing prices and study the effects of housing prices on household consumption.

3. Data, Sample, and Variables

3.1. Data

To estimate the impact of SL facilities on healthcare utilization, we leverage data from multiple sources. Three of these datasets are publicly available (free or through purchase): CMS, the American Hospital Association (AHA), and the U.S. Census Bureau. The fourth is a dataset on SL facilities provided by an industry partner who is a developer of SL facilities.

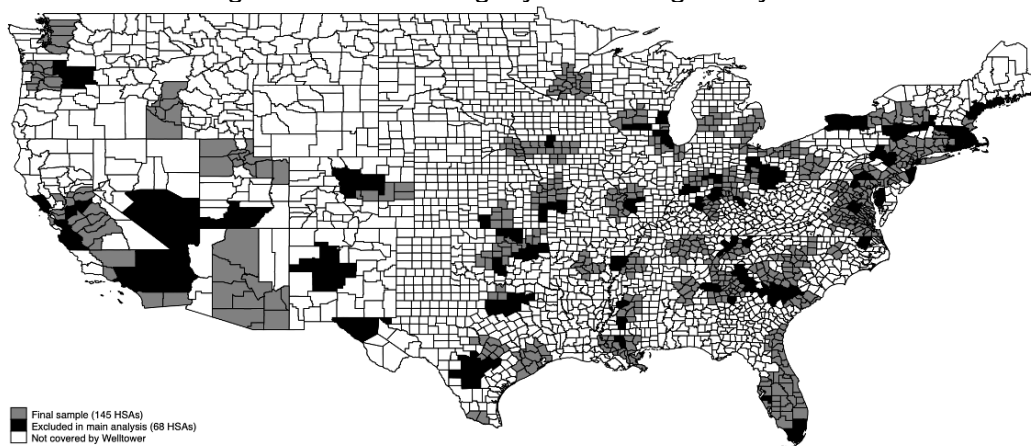
3.1.1. CMS Medicare Data Our primary data is the 100% Medicare Master Beneficiary Summary File (MBSF) Cost and Use segment⁵ from 2011 to 2019. The dataset contains the beneficiary-year-level summary of utilization and annual payments on all Medicare beneficiaries across SNFs, home health settings, and inpatient stays at both acute and non-acute care hospitals. The data files also include the number of visits to EDs.

We merge the MBSF Cost and Use segment with other CMS datasets. First, we use the MBSF Base segment that includes beneficiary enrollment information, such as enrollment date and whether a beneficiary is enrolled in fee-for-service Medicare or Medicare Advantage, and demographic information including age, sex, race, date of death (if applicable), county of residence. Second, we combine the MBSF Chronic Conditions segment that flags each beneficiary for the presence of 27 chronic conditions identified by the algorithms developed by Medicare. Chronic conditions include Alzheimer’s disease and related disorders, anemia, diabetes, depression, hypertension, hyperlipidemia, cancers (breast, colorectal, prostate, lung, endometrial), and others.

3.1.2. American Hospital Association To capture the amount of healthcare resources available to beneficiaries, we leverage the AHA annual survey data to determine the number of staffed inpatient beds in each HSA for each year from 2011 to 2019. The National Center for Health Statistics defines HSAs as one or more counties that are relatively self-contained with respect to the provision of routine hospital care (Makuc et al. 1991).

⁵ For details of the dataset including the list of variables, refer to <https://resdac.org/cms-data/files/mbsf-cost-and-use/data-documentation>.

Figure 1 HSA Coverage by Senior Living Facility Data



Notes. The shaded areas represent 213 HSAs at the county level covered by the data provided by Welltower Inc. Black-shaded areas are 68 HSAs (283 counties) that are excluded from our sample for various reasons explained in [Section 3.2](#). Gray-shaded areas are the 145 HSAs (651 counties) included in our final sample.

3.1.3. U.S. Census Bureau We obtain census characteristics data from the U.S. Census Bureau. We use its American Community Survey 5-year estimates to extract county-level variables, including education level (measured by the percent of people with a bachelor’s degree), income per capita, household size (the percent of household size over 3), housing prices (the distribution of house values and rent prices), changes in senior population, changes in percent of owner-occupied houses, changes in median senior household income, and changes in unemployment rates. We use County Business Patterns data to extract changes in the number of business establishments. We use levels for some of the control variables. As will be explained in [Section 4.2](#), some of the controls related to our IV will be included as changes. [Table OA.2](#) provides summary statistics of the variables.

We also use the U.S. Census Bureau Building Permits Survey, which provides statistics on new privately owned residential construction ([U.S. Census Bureau 2023a](#)) at the county level. From this source, we collect the annual number of single-family residential building permits and leverage this data to construct an IV. We discuss the details of our IV approach in [Section 4.2](#).

3.1.4. Senior Living Facility Data We obtain data on SL facilities from our industry partner, a leading real estate investment trust which invests in healthcare infrastructure, including SL facilities. The dataset provides information about all SL facilities within the U.S. at the HSA-year level, including, but not limited to, the total number of senior living facilities (assisted living and independent living) and their capacity as measured by the number of residential units for 213 HSAs (out of 952 total HSAs in the U.S.) from the year 2011 to 2019. [Figure 1](#) illustrates a map of 213 HSAs (shaded areas) covered by our SL facilities data. As [Figure 1](#) shows, the original dataset covers populated metropolitan areas. HSAs not included in the dataset either had too few or no

SL facilities (white-colored areas) and so were omitted by the data aggregator to avoid identifying specific SL facilities in those HSAs. The dataset also contains the number of nursing homes in each HSA and year. We use this information to control for the effect of nursing homes, which are traditional long-term care facilities, on healthcare utilization.

3.2. Sample

We identify the HSA-year sample through the following steps. Among the 213 HSAs provided by Welltower, we identify 192 HSAs with complete data on the numbers of assisted living facilities, independent living facilities, and nursing care properties for all years from 2011 to 2019. In addition, because our estimation relies on building permits as an IV, we exclude six HSAs that include counties not reporting building permits. This leaves 186 HSAs across the nine years. Next, we exclude 30 HSAs where at least one locality has a cap on building permits, as indicated in the 2018 survey of local residential land use regulatory regimes (Gyourko et al. 2021). We further exclude 11 HSAs for which it is unknown whether they have a cap on building permits because none of their localities participated in the land use survey. Our final sample thus includes 145 HSAs.

We aggregate variables from the beneficiary level to the HSA level by merging Medicare data with the senior living facility data and other datasets described in Section 3.1. Our initial sample covers fee-for-service Medicare beneficiaries aged 65 and older living in 145 HSAs from 2011 to 2019. Following prior works (e.g., Deryugina et al. 2019, Currie et al. 2023, Einav et al. 2023), we exclude Medicare Advantage enrollees because Medicare Advantage organizations do not submit all claims for healthcare utilization to CMS. We also exclude beneficiaries with missing basic demographic characteristics (sex and race). These steps yield 126,919,168 beneficiary-year observations.

We then remove beneficiary-year observations for beneficiaries who died in that year, dropping 5,317,120 observations. Furthermore, we exclude Medicare beneficiaries who moved to different HSAs during our study period because including them may invalidate the exogeneity condition of our IV approach. This step drops 15,441,528 beneficiary-year observations. In Section 5.5.5, as a robustness test, we add people who moved during our study period back to the analysis and find consistent results. The beneficiary-level sample now includes 106,160,520 beneficiary-year observations. We run a beneficiary-year-level analysis in Section 5.5.2.

Because our main unit of analysis is at the HSA and year level, we aggregate the variables to the HSA and year level. In aggregating the outcome variables, we exclude observations with extreme outcome values defined as those exceeding the 99th percentile of utilization within each HSA-year for each type of utilization. The resulting beneficiary-year sample sizes are 106,121,106 for SNF payments, 106,076,277 for home health payments, 106,016,619 for inpatient payments, and 105,951,655 for ED visits (see Table OA.15). Therefore, our final sample includes data aggregated

Table 1 Summary Statistics of Key Variables

	Mean	SD	Min	Max
Outcome variables				
<i>SNF utilization</i>				
Beneficiaries with SNF payments (%)	3.687	0.923	1.709	6.851
SNF payments per beneficiary				
Among those with payments	22,241.788	3,779.414	12,669.752	37,663.270
Among all beneficiaries	820.922	251.328	270.207	1,730.561
<i>Home health utilization</i>				
Beneficiaries with home health payments (%)	7.802	2.145	2.504	26.605
Home health payments per beneficiary				
Among those with payments	6,005.893	1,238.488	3,926.517	11,853.597
Among all beneficiaries	481.560	227.156	116.562	3,049.308
<i>Inpatient utilization</i>				
Beneficiaries with Inpatient payments (%)	13.750	1.957	8.493	20.620
Inpatient payments per beneficiary				
Among those with payments	21,280.705	3,032.834	16,032.086	36,494.375
Among all beneficiaries	2,902.282	450.270	1,948.809	4,627.315
<i>ED utilization</i>				
Beneficiaries with ED visits (%)	24.246	2.334	18.658	30.060
ED visits per beneficiary				
Among those with visits	1.749	0.067	1.569	1.958
Among all beneficiaries	0.425	0.052	0.315	0.575
Explanatory variables				
SLF density	0.446	0.246	0.027	1.679
SLF unit density	50.061	33.107	1.036	215.880
Instrumental variable				
Single-family permits density _{<i>t</i>-1}	28.407	24.332	1.848	216.123

Notes. $N = 1,305$. The unit of observation is HSA-year. Payment variables (SNF, inpatient, and home health) and income variables are in 2023 dollars. SNF: skilled nursing facility, ED: emergency department, SLF: senior living facility.

from the beneficiary level, consisting of fee-for-service Medicare beneficiaries aged 65 or older who have not moved and do not have extreme outcome values in 145 HSAs from 2011 to 2019. [Table 1](#) presents the summary statistics for the key variables of our sample.

Note that although our CMS data covers 100% of the Medicare sample, we do not have access to the exact residence information of each beneficiary nor do we have the exact addresses of the SL facilities. Therefore, we cannot identify which beneficiaries reside in a senior living facility. Leveraging our data on Medicare and senior living facilities, we estimate the causal effect of senior living facilities on the healthcare utilization of all seniors in a given geographic area (not just seniors living in senior living facilities). In effect, we are diluting the impact of senior living facilities by including people who are not living in senior living facilities. As such, our estimates should be interpreted as a lower bound of the effect of senior living facilities on healthcare utilization.

3.3. Variables

3.3.1. Outcome Variables The primary outcome variables are SNF, inpatient, home health, and ED utilization. We measure SNF and inpatient utilization by the annual payments made by both Medicare and beneficiaries, and home health utilization by the annual payments made by Medicare,⁶ collected from the MBSF Cost and Use segment. [Section 5.5.4](#) uses length of stay as an alternative outcome for utilization as a robustness test. For ED utilization, we use the annual number of ED visits for each beneficiary, also obtained from the MBSF Cost and Use segment. For all payment outcomes, we convert all dollar amounts to 2023 dollars to adjust for inflation.

We aggregate each outcome variable from the beneficiary level to the HSA-year level in three ways. First, we calculate the share of beneficiaries in each HSA-year who used a given healthcare service (i.e., were admitted to a SNF, received home health care, were admitted to an inpatient hospital, or visited the ED). Second, we calculate average utilization among beneficiaries who used the service. For SNF, home health, and inpatient care, this measure is the average payments among users; for ED care, it is the average number of ED visits among users. Third, we calculate average utilization (payments for SNF, home health, and inpatient, or visits for ED) among all beneficiaries in the sample, including those who did not utilize a given service. For this measure, beneficiaries without payments or visits are assigned a value of zero. Summary statistics of these outcomes are provided in [Table 1](#).

3.3.2. Explanatory Variables The main explanatory variable of interest is the density of SL facilities. We define this measure as the number of SL facilities per 1,000 Medicare beneficiaries in our sample in each HSA-year. The number of SL facilities is calculated as the sum of assisted living and independent living facilities in an HSA in each year. We combine assisted and independent living facilities because a single facility may contain both types of units. We scale the number of SL facilities by 1,000 Medicare beneficiaries because HSAs vary substantially in population size.

We obtain this variable from the data provided by our industry partner. On average, there are 35.41 senior living facilities in an HSA-year, with a minimum of 1 facility and a maximum of 179 facilities. By scaling the number of facilities per 1,000 beneficiaries, the average SL facility density is 0.446, with a minimum of 0.027 and a maximum of 1.679 (see [Table 1](#)). As the number of units per facility can vary quite a bit, we use the density of SL facility units instead of the density of facility properties to test the robustness of our results in [Section 5.5.3](#).

⁶ For Medicare-covered home health services, beneficiaries are not subject to cost-sharing requirements. Consequently, beneficiary payments for home health services are zero.

3.3.3. Control Variables We include an extensive set of control variables. First, we aggregate beneficiary characteristics at the HSA level. These include the average age, the share of female beneficiaries, the percentage of each racial group (racial composition), and the average number of chronic conditions among beneficiaries in each HSA-year. We identify the numbers of chronic conditions for each beneficiary using the MBSF Chronic Conditions data file.

Second, we measure the density of healthcare supply in the area. Healthcare supply includes the number of SNFs, nursing homes, and inpatient beds in each HSA and year. To define density, we scale these measures of healthcare supply by the number of 1,000 traditional Medicare beneficiaries in each HSA-year.

Third, we include census characteristics, including education level (% of people with a bachelor's degree), household size (% of families with more than three members), rent (% of housing with rent under \$500, % of housing with rent between \$500 and \$1500), and house values (% of housing values under \$50,000, % of housing values between \$50,000 and \$1 million), income per capita, change in the senior population (age ≥ 65), change in the percentage of owner-occupied housing units, change in the number of businesses, change in median senior household income, and change in unemployment rates.

We use levels for some control variables described above, since they could be determinants of beneficiaries' healthcare consumption. In addition, we also include changes of a subset of the control variables. These additional covariates control for the potential change in demand for SL facilities each year, as our instrumental variable approach exploits the change in supply of SL facilities due to new developments. We provide more details about these additional controls and the instrumental variable in [Section 4.2](#) and present summary statistics in [Table OA.2](#).

4. Empirical Strategy

To estimate the treatment effect of SL facilities on healthcare utilization, we begin with the following baseline two-way fixed effects model:

$$y_{ht} = \alpha_0 + \alpha_1 SLF_{ht} + \mathbf{X}'_{ht} \alpha_2 + \mathbf{W}'_{ht} \alpha_3 + \omega_h + \lambda_t + \varepsilon_{ht}, \quad (1)$$

where subscripts h and t indicate HSA and year, respectively. y_{ht} is the healthcare utilization measure of different types of care: SNF, inpatient, home health, and ED. SLF_{ht} is the main explanatory variable of interest, the density of senior living facilities in an HSA, h , at year t . $\mathbf{X}_{ht}$ is a vector of HSA-year-level Medicare beneficiary characteristics, including average age, proportion of females and different races, and the average number of chronic conditions among beneficiaries. $\mathbf{W}_{ht}$ is a vector of the HSA-year-level healthcare supply measures, including the density of inpatient beds, SNFs, and nursing homes, and census characteristics, including education level, household

size, and others. [Section 3.3.3](#) lists all control variables. We include HSA-fixed effects, ω_h , and year-fixed effects, λ_t . In [Section 5.5.2](#), we rerun the analysis at the beneficiary-year level to test the robustness of the results depending on the unit of analysis.

4.1. Endogeneity

Estimating [Equation \(1\)](#) could yield a biased estimate of α_1 due to potential endogeneity. Developers and operators of SL facilities are more likely to enter and expand into an area with greater underlying healthcare needs and stronger demand for senior care services. Such areas may have a sicker senior population and higher expected healthcare utilization. Consequently, unobserved demand factors are likely to be positively correlated with SLF_{ht} and healthcare expenditures, introducing bias in the estimation of α_1 .

In addition, other unobserved local characteristics, such as senior welfare programs run by the local government, may simultaneously influence both the growth of SL facilities and healthcare expenditures. Due to these unobserved factors, a naive estimate of [Equation \(1\)](#) is likely to result in a biased estimate of α_1 , the effect of senior living facility density on healthcare expenditure.

If SL facilities are more prevalent in areas with greater underlying health needs, and poorer health increases healthcare spending, omitting these demand-side factors will induce an upward bias in the OLS estimate of α_1 . The direction of the bias associated with senior welfare programs depends on their design and target population. For example, support programs that complement the offering of SL facilities may be positively correlated with the number of SL facilities. If these attract healthier (sicker) senior populations, this would lead to underestimated (overestimated) effects.

To address these potential endogeneity concerns, we employ an IV strategy.

4.2. Instrumental Variables Approach

To construct a valid IV, we leverage data from the U.S. Census Bureau Building Permits Survey ([U.S. Census Bureau 2023a](#)). Since 1980, the Census Bureau has collected the number of permits awarded for residential buildings across the country, along with breakdowns into whether the permit is for single-family or for multiple-family buildings ([Ferreira and Gyourko 2023](#)). This data has been used, for example, in [Barrot et al. \(2022\)](#) to show that an increase in mortgage debt is not associated with the construction of new housing; and in [Eichenbaum et al. \(2022\)](#) to analyze the changes in new building permits due to changes in interest rates. The survey includes the number of building permits issued by the jurisdictions that require permits for new privately owned residential construction. More than 99% of all privately owned residential buildings constructed are covered by this survey ([U.S. Census Bureau 2023b](#)). Each jurisdiction has distinct requirements for building permits and the permit review process. For instance, the District of Columbia requires compliance

with zoning regulations, mechanical/plumbing review, electric, fire, structural, and environmental review, among others (DC Department of Buildings 2025).

We instrument the density of SL facilities in an HSA-year, SLF_{ht} , using the density of single-family residential building permits issued in the HSA in the previous year, $Permits_{h,t-1}$. The density of building permits is defined as the number of single-family residential building permits per 1,000 senior traditional Medicare beneficiaries. The relevance of this instrument is based on supply-side housing market conditions, which affect both the growth of single-family residential buildings and multi-family residential buildings⁷ such as senior living facilities. For example, the available land for new development in an area (Saiz 2010) and local residential land use regulations (Gyourko et al. 2021) affect both the number of new single-family housing developments proxied by the approved building permits and the growth of senior living facilities. Moreover, time-varying local economic conditions, such as construction labor costs and materials costs, could impact both the growth of single-family buildings as well as senior living facilities. To strengthen the relevance condition, we exclude HSAs that have a cap on building permits in the main specification and conduct robustness analysis without dropping those HSAs. This excludes the possible cannibalization between the single-family and multi-family building permits. We use the single-family building permits awarded in the previous year because there are likely temporal lags from permit approval to new constructions.

The exclusion restriction of the IV, $Permits_{h,t-1}$, holds for the following reasons. First, $Permits_{h,t-1}$ measures the density of single-family building permits instead of multi-family building permits. National Association of Realtors (2020) finds that 19.06% of single-family houses – newly constructed and existing – were purchased by those 65+. Since those in the senior population are not the primary buyers of new single-family homes, the IV is unlikely to be correlated with senior population specific characteristics conditional on general demographic characteristics in that HSA. As a result, $Permits_{h,t-1}$ is also unlikely to be correlated with the senior population’s healthcare expenditure. We assess this exclusion restriction condition below in Figure 2(b).

In addition, we exclude from our sample beneficiaries who moved across HSAs to rule out demand-side housing market conditions which can affect both the growth of single-family and multi-family buildings and senior’s healthcare expenditure. In particular, this excludes the possible scenario of healthier seniors moving into HSAs with more attractive living conditions and more senior living facilities which could drive down the average healthcare expenditure in those HSAs.⁸

⁷ Following Ferreira and Gyourko (2023), we define multi-family buildings as the sum of buildings permitted in 2-unit, 3-4 unit, and 5+ unit structures.

⁸ We conduct robustness analysis by including the movers in our sample. Our findings are qualitatively the same. See Table OA.20.

Finally, since the IV's relevance condition operates through new developments aimed at addressing new or unmet demand for SL facilities, we use additional covariates to control for factors related to changes in demand for SL facilities. Specifically, we control for change in senior population, change in percentage of owner-occupied housing units, change in the number of businesses, change in median senior household income, and change in unemployment rates.

With the IV, we specify the full model, including the first stage of the estimation, as follows:

- First stage:

$$SLF_{ht} = \theta_0 + \theta_1 Permits_{h,t-1} + \mathbf{X}'_{ht} \boldsymbol{\theta}_2 + \mathbf{W}'_{ht} \boldsymbol{\theta}_3 + \mu_h + \tau_t + \xi_{ht}, \quad (2)$$

- Second stage:

$$y_{ht} = \beta_0 + \beta_1 \widehat{SLF}_{ht} + \mathbf{X}'_{ht} \boldsymbol{\beta}_2 + \mathbf{W}'_{ht} \boldsymbol{\beta}_3 + \gamma_h + \delta_t + \zeta_{ht}. \quad (3)$$

4.3. Validity of the Instrumental Variable

We verify empirically that the instrument variable strongly predicts SLF_{ht} . [Figure 2\(a\)](#) provides a graphical representation of the first-stage regression, [Equation \(2\)](#). Specifically, it plots a binned scatterplot of the residualized explanatory variable, SLF_{ht} , on the y-axis and residualized IV, $Permits_{h,t-1}$, on the x-axis. Residualization removes the effects of all control variables and fixed effects included in [Equation \(2\)](#). The figure shows a strong positive relationship between SLF_{ht} and $Permits_{h,t-1}$, consistent with the first-stage results (coefficient = 0.0010, SE = 0.0003). In addition, [Online Appendix Figure OA.1](#) illustrates the positive relationship between the two variables for each of the sample years from 2011 to 2019. For brevity, we present the detailed first-stage regression results and robustness tests in [Table OA.3](#).

To assess the exclusion restriction of the IV, we test whether $Permits_{h,t-1}$ is correlated with determinants of Medicare spending. Following [Chan et al. \(2023\)](#)'s approach, we construct a predicted outcome, $\hat{y}_{ht}$ (average SNF payments), using observable beneficiary, census, and healthcare supply characteristics, excluding the treatment variable SLF_{ht} . We then estimate the relationship between $\hat{y}_{ht}$ and $Permits_{h,t-1}$ using the same right-hand-side specification as in [Equation \(3\)](#) except $\widehat{SLF}_{ht}$. In [Figure 2\(b\)](#), the hollow circles show no significant relationship between $\hat{y}_{ht}$ and $Permits_{h,t-1}$ (coefficient = $-3.3e - 10$, $p = 0.549$), suggesting that the instrument is not correlated with observable predictors of the outcome. In contrast, the solid circles show a negative reduced-form relationship between the actual outcome y_{ht} and the instrument $Permits_{h,t-1}$ estimated using the following equation:

$$y_{ht} = \beta_0^r + \beta_1^r Permits_{ht} + \mathbf{X}'_{ht} \boldsymbol{\beta}_2^r + \mathbf{W}'_{ht} \boldsymbol{\beta}_3^r + \gamma_h^r + \delta_t^r + \zeta_{ht}^r. \quad (4)$$

We find a significant negative relationship between y_{ht} and $Permits_{h,t-1}$ ($\beta_1^r = -0.0021$, $p < 0.001$). These results represented in [Figure 2\(b\)](#), together with the strong first-stage relationship, support the identifying assumption that the instrument affects Medicare payments⁹ primarily through its effect on the explanatory variable, SL facility density.

Furthermore, we directly test whether the instrument is correlated with additional proxies for market attractiveness that are not included in our main specifications, following [Aladangady \(2017\)](#)'s approach. Specifically, using data from the American Community Survey, we construct measures of (i) the number of households with retirement income, (ii) the number of seniors with self-care, ambulatory, and independent living disabilities, and (iii) the number of seniors with at least one type of disability. These variables capture local economic conditions and the health-related demand for supportive living arrangements, both of which are likely relevant for SL entry decisions. Specifically, we regress each of these proxies on the instrument while controlling for the full set of covariates and fixed effects used in our baseline specification in [Equation \(2\)](#). We report the results in [Online Appendix Table OA.4](#), in which we find no statistically significant relationship between the instrument and any of these measures, including independent living disability, which is plausibly among the most relevant demand-side factors for SL facilities. These results provide additional evidence supporting the validity of our IV.

5. Results

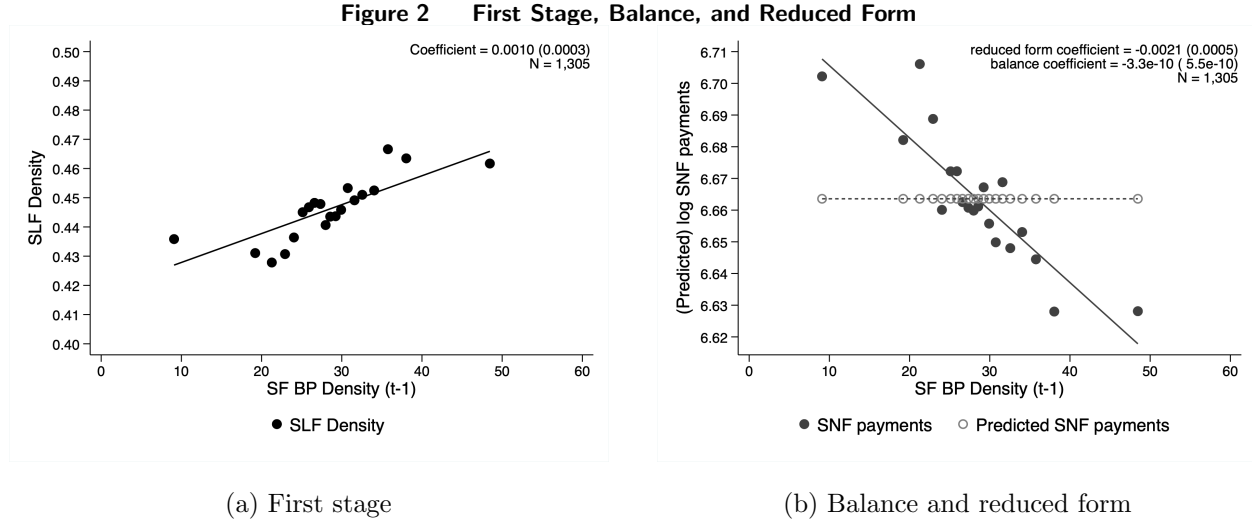
5.1. Effects of Senior Living Facilities on Medicare Utilization

We present the effects of SL facility density on Medicare utilization using the IV approach described in [Section 4](#). We begin by discussing the estimation results of the first-stage model, [Equation \(2\)](#), in [Table OA.3](#). We find that single-family residential building permits in the previous year have a strong positive relationship with SL facility density in the current year ($\theta_1 = 0.001$, $p < 0.001$, column (1)). This estimate implies that a one-unit increase in single-family building permit density is associated with a 0.001 increase in SL facility density in the following year. This result suggests that the new single-family residential development and the development of SL facilities are shaped by common local supply-side housing market conditions. The first-stage F statistics exceeds the conventional rule-of-thumb threshold of 10.¹⁰ Overall, these results indicate that the instrumental variable is both relevant and strong.

[Table 2](#) presents the second-stage model results for SNF (Panel A), home health (Panel B), inpatient (Panel C) and ED utilization (Panel D). Columns (1) to (3) report ordinary least squares

⁹ Due to space limit, we present the results using SNF payments here, but we find consistent results for other Medicare payments.

¹⁰ Because we have one endogenous variable and one IV, our robust F-statistic is identical to the effective F-statistic of [Olea and Pflueger \(2013\)](#). In this setting, [Andrews et al. \(2019\)](#) suggest that the effective F-statistic can be compared to the rule-of-thumb value of 10 as a test for weak instruments. (p. 14).



Notes. Panel (a) plots a binned scatterplot of the residualized density of senior living facilities per 1,000 Medicare beneficiaries (SLF density) against the residualized density of single-family residential building permits per 1,000 Medicare beneficiaries (SF BP density) in the previous year at HSA-year level. This figure provides a graphical representation of the first-stage relationship, and the reported coefficient corresponds to the estimated effect of lagged SF BP density on SLF density, controlling for all covariates and fixed effects in Equation (2). Panel (b) plots a binned scatterplot of log average total SNF payments against SF BP density at HSA-year level. Solid circles show bin averages of actual SNF payments, while hollow circles show bin averages of predicted payments based on observable characteristics. The relationship between the instrument and predicted payments provides a balance test (balance coeff), while the relationship with actual payments represents the reduced-form effect (red. form coeff). All relationships control for the same covariates and fixed effects as in Equation (3). In both panels, two-way clustered standard errors at the HSA and year levels are reported in parentheses. The figure is produced using replication code from Chan et al. (2023).

(OLS) estimates without the IV, whereas columns (4) to (6) report two-stage least squares (2SLS) estimates using the IV approach. Columns (1) and (4) examine the share of beneficiaries with positive utilization, columns (2) and (5) examine average payments conditional on positive utilization, and columns (3) and (6) examine average payments across all Medicare beneficiaries. For most outcomes, the OLS estimates differ substantially from the 2SLS estimates, suggesting that treating SL facility density as exogenous may introduce significant endogeneity bias. These differences underscore the importance of addressing potential endogeneity using the proposed IV strategy.

For SNF utilization (Panel A of Table 2), we find that greater SL facility density significantly reduces both the likelihood of SNF admission and average spending among Medicare beneficiaries within the HSA. Specifically, the coefficient reported in column (4) is negative and statistically significant (coefficient = -4.975 , $p < 0.05$), implying that a one-standard-deviation increase in SL facility density, corresponding to 0.246 additional facilities per 1,000 Medicare beneficiaries, reduces the share of beneficiaries with positive SNF utilization by 1.22 percentage points. In contrast, we do not find a statistically significant effect on SNF spending conditional on utilization in column (5) (coefficient = -0.402 , $p = 0.197$). For unconditional average SNF spending across all Medicare beneficiaries, column (6) reports a statistically significant negative effect (coefficient = -2.170 ,

$p < 0.001$). This estimate implies that a one-standard-deviation increase in SL facility density reduces average SNF spending per beneficiary by 41.36%,¹¹ corresponding to a \$339.57 reduction in average SNF payments. Aggregated across the average number of beneficiaries within an HSA, this corresponds to approximately \$27.623 million lower SNF spending per HSA-year. Taken together, these findings indicate that the reduction in SNF spending is driven primarily by decreases in the probability of SNF admission rather than by reductions in spending conditional on SNF admission.

This pattern on the extensive margin is likely driven by two complementary mechanisms. First, the long-term, supportive environment of SL facilities may improve seniors' baseline health – a dynamic we explore further in Section 5.2 – thereby preventing the physical decline that necessitates post-acute care. Second, for seniors who do experience an acute health event, SL facilities likely act as an acuity-based substitute at the point of hospital discharge. We emphasize that SL facilities and SNFs are generally different types of institutions: SL facilities are long-term, residential living options (with median stays often exceeding two years) that provide assistance with activities of daily living, whereas SNFs provide temporary, intensive medical care following an injury or illness (with average stays of roughly 22 days)([American Health Care Association and National Center for Assisted Living 2026](#), [Montgomery 2025](#), [Byrd et al. 2025](#)). Because our baseline results show significant reductions in SNF admissions but no significant reductions in overall inpatient hospitalizations, they suggest that hospital discharge planners may be diverting lower-acuity patients away from unnecessary, short-term SNF stays and into supported SL environments. While our data do not allow us to directly observe discharge pathways, this interpretation aligns with the clinical reality of these facilities: SL facilities act as a residential alternative that reduces the need for institutional care for less severe cases ([Grabowski et al. 2012](#), [Cornell et al. 2020](#)), but they do not serve as clinical substitutes for highly acute patients who genuinely require intensive medical care.

Next, we analyze the effects of SL facility density on home health utilization. As shown in Panel B of [Table 2](#), greater SL facility density significantly reduces the likelihood of home health utilization (column (4)), average payment among beneficiaries with home health utilization (column (5)), and the average payment among all beneficiaries (column (6)). Specifically, the coefficient reported in column (4) is negative and statistically significant (coefficient = -9.635 , $p < 0.01$), implying that a one-standard-deviation increase in SL facility density reduces the share of beneficiaries with home health utilization by 2.37 percentage points. Given that the average home health payment among beneficiaries with utilization is \$6,005.89, a 2.37 percentage point reduction corresponds to a decrease of \$142.34 per beneficiary in the HSA-year. The coefficient reported in column (5) is

¹¹ = $[\exp(-2.170 \times 0.246) - 1] \times 100\%$.

Table 2 Effects of Senior Living Facility Density on Medicare Utilization

Model	Without IV (OLS)			With IV (2SLS)		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	% Pos. Pay	Avg. Pos.	Total Avg.	% Pos. Pay	Avg. Pos.	Total Avg.
<i>Panel A. SNF Payments</i>						
SLF density	-0.755* (0.30)	0.013 (0.08)	-0.171 (0.13)	-4.975* (2.32)	-0.402 (0.31)	-2.170*** (0.62)
<i>Panel B. Home Health Payments</i>						
SLF density	0.034 (0.84)	-0.084 (0.11)	-0.149 (0.18)	-9.635** (3.58)	-1.044** (0.36)	-2.493*** (0.70)
<i>Panel C. Inpatient Payments</i>						
SLF density	-0.461 (0.53)	0.032 (0.05)	-0.006 (0.04)	-4.091 (3.22)	0.141 (0.27)	-0.122 (0.22)
<i>Panel D. ED Visits</i>						
SLF density	0.047 (0.77)	0.018 (0.02)	0.013 (0.05)	-2.734 (3.38)	-0.171* (0.08)	-0.273 (0.20)
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	145	145	145	145	145	145
Years	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019
Observations	1,305	1,305	1,305	1,305	1,305	1,305

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density is the number of senior living facilities per 1,000 Medicare beneficiaries and is instrumented using the prior-year density of single-family building permits in Columns (4)–(6). Columns (1) and (4) examine the share of beneficiaries with positive payments; (2) and (5) the average payments among beneficiaries with positive payments; and (3) and (6) the average payments among all living Medicare beneficiaries. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (density of nursing care properties, SNF organizations, and inpatient beds). ED: emergency department, HSA: health service area, IV: instrumental variable, OLS: ordinary least squares, SLF: senior living facility, SNF: skilled nursing facility, 2SLS: two-stage least squares. ⁺ $p < 0.1$, ^{*} $p < 0.05$, ^{**} $p < 0.01$, ^{***} $p < 0.001$.

also negative and statistically significant (coefficient = -1.044 , $p < 0.01$), suggesting that a one-standard-deviation increase in SL facility density reduces average payments among beneficiaries with home health utilization by 22.65%, corresponding to a \$1,360.33 reduction among beneficiaries who use home health services. Column (6) reports a statistically significant negative effect on unconditional average home health spending (coefficient = -2.493 , $p < 0.001$). This estimate suggests that a one-standard-deviation increase in SL facility density reduces average home health spending per beneficiary by 45.84%, corresponding to a \$220.76 reduction in payments. Aggregated across the average number of beneficiaries within an HSA, this corresponds to approximately \$17.958 million lower home health spending per HSA-year. Taken together, these findings indicate that the reduction in home health spending is driven by both decreases in the probability of home health utilization and reductions in spending conditional on utilization.

For inpatient utilization, we do not find significant effects of SL facilities (Panel C of [Table 2](#)). For ED utilization, we find a statistically significant negative effect on the number of ED visits conditional on having any ED visit (column (5), Panel D of [Table 2](#)), with a coefficient of -0.171 ($p < 0.05$). This implies that a one-standard-deviation increase in SL facility density reduces the average number of ED visits among beneficiaries with any ED visit by 4.12%, corresponding to a decrease of 0.072 visits. However, we do not find statistically significant effects on the share of beneficiaries visiting the ED (column (4)) or on the average number of ED visits across all beneficiaries in the HSA-year (column (6)).

Overall, our findings suggest that SL facilities have statistically significant negative effects on SNF and home health utilization. For SNF utilization, the reduction is driven primarily by a lower likelihood of admission. For home health utilization, the reduction is driven by both a lower probability of use and lower payments conditional on use. In contrast, we do not find significant effects of SL facilities on other types of healthcare utilization, including inpatient care and ED visits. Importantly, the effect sizes estimated in our analyses are likely smaller than the true effects on SL facility residents because our analysis examines the effects of SL facility density on all Medicare beneficiaries in the area, rather than only on beneficiaries residing in SL facilities, as discussed in [Section 3.2](#).

5.2. Potential Mechanism: Care for Chronic Conditions

We now explore a potential mechanism of the effect of SL facilities on healthcare utilization: the resources and support that SL facilities provide for beneficiaries with chronic conditions. One of the conspicuous characteristics of SL facility residents is that they have numerous chronic conditions. According to the report by the National Center for Health Statistics in 2024, 55% of the SL facility residents have 2-3 chronic conditions, and 17.8% of the residents have 4-10 chronic conditions, while only 8% of the residents have zero chronic conditions ([Melekin et al. 2024](#)). As such, most SL facilities provide support and resources for chronic disease management, including, but not limited to, regular health check-ins, customized diets tailored to specific conditions (e.g., low-sodium meals for heart disease or anti-inflammatory diet for arthritis), memory care for people with Alzheimer’s disease and dementia, daily medication management, and exercise programs ([Brookdale Senior Living 2022](#), [Mountain Vista Health Park 2025](#)).

We hypothesize that the chronic disease management provided by SL facilities decreases the need for healthcare utilization by improving the health condition of their residents. If this were true, the effects of SL facility density on healthcare utilization would be more pronounced among seniors with more chronic conditions. We test our hypothesis by analyzing the effects of SL facilities on healthcare utilization stratified by the number of chronic conditions that Medicare beneficiaries

have. Because the median number of chronic conditions per beneficiary in the beneficiary level sample is 3 (mean = 3.32, sd = 2.92), we analyze the effects among people with more than three chronic conditions and up to 7 conditions (the 90th percentile).

Figure 3 summarizes the results of the analysis by the number of chronic conditions. Detailed results are reported in Online Appendix Tables **OA.9 - OA.12**. **Figure 3(a)** presents the effects of SL facility density on the total average utilization. For both SNF and home health services, the estimated effects become increasingly negative as the number of chronic conditions increases (y-axis), suggesting that the impact of SL facility density is more pronounced among beneficiaries with more chronic conditions. This pattern appears to be driven primarily by changes in the share of beneficiaries with utilization (**Figure 3(b)**) rather than changes in average utilization conditional on use (**Figure 3(c)**).

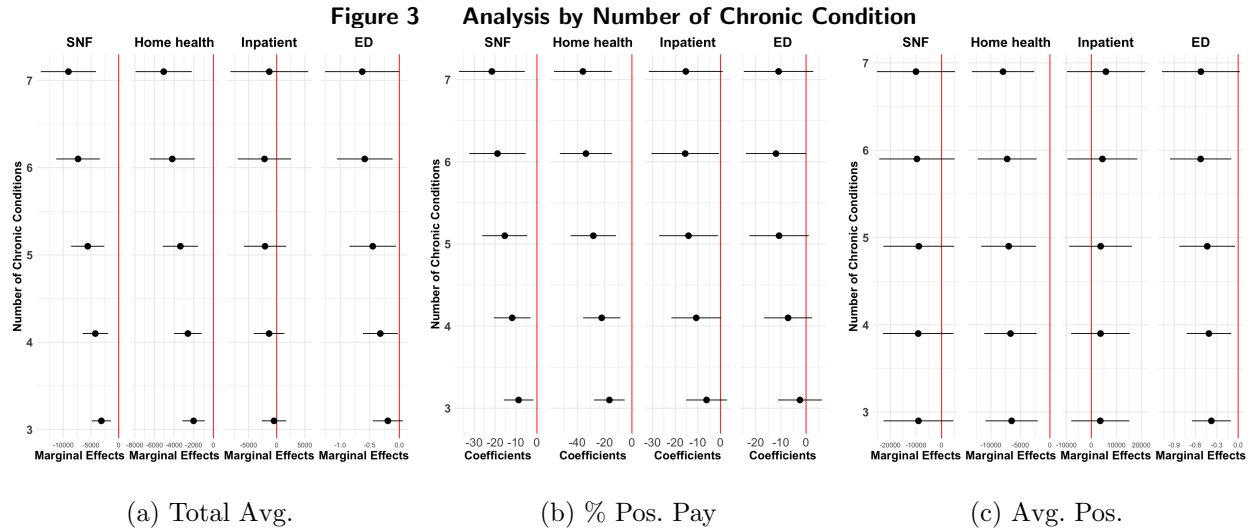
For inpatient utilization, the estimated effects on the share of beneficiaries with positive utilization (**Figure 3(b)**) are statistically significant for beneficiaries with at least four ($p < 0.1$), five, six ($p < 0.05$), and seven ($p < 0.1$) chronic conditions. In contrast, we do not find statistically significant effects for either total average inpatient utilization or utilization conditional on use. For ED utilization, the coefficients for total average visits are statistically significant among beneficiaries with at least 4 chronic conditions (**Figure 3(a)**). As shown in **Figure 3(c)**, this effect is driven by reductions in average ED visits among beneficiaries with positive utilization.

Overall, these findings are consistent with our hypothesis about chronic disease management. The significant reduction in inpatient admissions for highly morbid beneficiaries (**Figure 3(b)**) provides direct support for the health-improvement mechanism discussed in Section 5.1: by effectively managing chronic conditions, SL facilities help the sickest patients avoid acute health shocks entirely, rather than merely diverting them at hospital discharge. However, we must note that since we cannot link beneficiaries directly to SL facilities, nor do we have information on what support resources each SL facility has, our results can best be interpreted as suggestive evidence that chronic disease management provided at these facilities may be driving the reduction in healthcare utilization.

Our results are consistent with the findings of [Kim et al. \(2016\)](#), that, in a systematic review of 67 medical articles, document some benefits of community-based chronic disease management. Although this paper does not focus on SL facilities, they find that chronic disease management interventions by community-based health workers could be effective for certain health conditions, such as high blood pressure, diabetes, and cardiovascular disease.

5.3. Nonlinear and Heterogeneous Effects of SL Facilities

In this section, we examine whether the effect of SL facility density is nonlinear and whether there are heterogeneous effects based on density of alternative healthcare facilities. These results are reported in [Online Appendix E](#).



Notes. Each subfigure plots the effects of SLF density (number of senior living facilities per 1,000 beneficiaries) on total average utilization (a), share of beneficiaries with utilization (b), and positive average utilization (c) by the number of chronic conditions (y-axis) and by type of care: SNF, home health, inpatient, and ED. The error bars represent 95% confidence intervals.

The marginal impact of additional SL facilities may diminish as market penetration increases. For example, an additional SL facility in a market with low SL facility density may have a larger effect on healthcare utilization than an additional facility in a market where SL facilities are already abundant. To investigate this possibility, we estimate a quadratic specification by augmenting Equation (3) with a squared treatment term, SLF_{ht}^2 . Because SLF_{ht} enters the specification nonlinearly through both its level and squared term and is endogenous, we employ a control-function approach, which is well suited for nonlinear models with endogenous regressors (Wooldridge 2015). Specifically, we include both the first-stage residual, $\hat{\xi}_{ht}$, and its square, $\hat{\xi}_{ht}^2$, as additional controls in the second-stage equation.

Table OA.5 reports the results. We focus on SNF utilization (columns (1)–(3)) and home health utilization (columns (4)–(6)), the outcomes for which we find significant effects of SL facility density in Section 5.1. To facilitate interpretation, we report the implied marginal effects of SL facility density evaluated at the 25th, 50th, and 75th percentiles of the SL facility density distribution.

For SNF utilization, we find no evidence of a statistically significant nonlinear relationship. In contrast, for home health utilization, the coefficient on the squared term is positive and statistically significant, indicating diminishing marginal effects. Specifically, the negative effect of SL facility density on home health utilization is strongest in markets with relatively low SLF density and becomes progressively smaller as SL facility density increases.¹² This pattern is observed across all

¹² The differences in the estimated marginal effects across 25th, 50th, and 75th percentiles of the SL facility density are statistically different at the 5% significance level.

three home health outcomes, including the share of utilization, average utilization conditional on use, and unconditional average utilization.

Next, we examine whether the effects of SL facility density vary with the access to different healthcare facilities, including SNFs and inpatient hospital beds. To do so, we augment [Equation \(3\)](#) with an interaction term, $SLF_{ht} \times D_{ht}$, where D_{ht} denotes either SNF density or inpatient bed density. Following the control function approach, we include the first-stage residual, $\hat{\xi}_{ht}$, and its interaction with D_{ht} as additional controls in the second-stage equation.

We find that significant heterogeneous effects appear only for SNF utilization: the effect of SL facility density becomes more negative as SNF density ([Table OA.6](#) columns (1) and (3)) and inpatient bed density ([Table OA.7](#) column (3)) increases.¹³ In contrast, we find little evidence that the effects of SL facility density on home health utilization vary systematically with local healthcare capacity. These results suggest that the effects of SL facility density are more pronounced in HSAs with greater acute-care and post-acute-care capacity. At first glance, one might expect that when institutional beds are scarce, the effect of SL facilities would be largest due to substitution effects. However, this capacity-moderated result actually highlights that substitution is likely only plausible for lower acuity patients, but insufficient for high acuity patients, reinforcing the acuity-based diversion mechanism introduced in [Section 5.1](#). In markets with constrained SNF capacity, scarce beds are likely strictly rationed for the highest-acuity patients who require intensive skilled nursing. For these highly acute patients, SL facilities are simply not clinical substitutes, so their presence barely alters SNF utilization. Conversely, in markets with abundant SNF capacity, some institutional beds could be filled by marginal, lower-acuity patients. When SL facilities become available, they offer a viable residential alternative that diverts these “not too sick” patients away from unnecessary SNF stays.

5.4. Multiple Hypothesis Testing

As we examine multiple outcomes and measures, we address concerns related to multiple hypothesis testing using two complementary approaches. First, following [Anderson \(2008\)](#), we construct a summary measure – total Medicare payments – that aggregates across SNF, inpatient, and home health utilization, which we examine in [Table 3](#). Second, in [Online Appendix F](#), we report adjusted p -values for the full set of outcome-specific tests. Specifically, we report sharpened q -values that control the false discovery rate (the expected proportion of rejections that are type I errors) following the procedure in ([Anderson 2008](#), p.1487).

¹³ For SNF density, the estimated marginal effects evaluated at the 25th, 50th, and 75th percentiles differ significantly from one another in columns (1) and (3) of [Table OA.6](#) (all $p < 0.01$). Similarly, for inpatient bed density, the estimated marginal effects evaluated at the 25th, 50th, and 75th percentiles differ significantly in column (3) of [Table OA.7](#) ($p < 0.05$).

Table 3 Effects of SLF Density on Aggregated Medicare Utilization

	Aggregated Payments		
	(1) % Pos. Pay (2.62)	(2) Avg. Pos. (0.33)	(3) Total Avg. (0.72)
SLF density	-5.23*	-0.41	-2.29**
Fixed effects	HSA Year	HSA Year	HSA Year
Controls	Yes	Yes	Yes
Number of HSAs	145	145	145
Years	2011-2019	2011-2019	2011-2019
Observations	1,305	1,305	1,305

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density is instrumented by the prior-year density of single-family building permits in all models. Column (1) reports the effect on the percentage of beneficiaries with positive payments; Column (2) reports the effect on average payments among beneficiaries with payments; Column (3) reports the effect on average payments among all Medicare beneficiaries. Outcomes in columns (2) and (3) are log- transformed. Control variables are the same as those in [Table 2](#). SLF: senior living facility, SNF: skilled nursing facility. ⁺ $p < 0.1$, ^{*} $p < 0.05$, ^{**} $p < 0.01$, ^{***} $p < 0.001$.

In [Table 3](#), we find a consistent result that increases in SL facility density significantly reduce total average Medicare payments, primarily through a reduction in the likelihood of Medicare utilization. Our estimate indicates that a one standard deviation increase in SL facility density reduces average Medicare payments by 43.07%, corresponding to \$1,810.82 per beneficiary. While this aggregate analysis provides a valuable overall measure of cost impacts, it does not allow us to distinguish which types of Medicare services drive the reduction in spending. We therefore complement this analysis with outcome-specific tests using false discovery rate adjusted inference in [Online Appendix F](#) Tables [OA.8](#) to [OA.12](#).¹⁴

Overall, our primary findings that increases in SL facility density significantly reduce SNF and home health utilization, with effects becoming stronger as the number of chronic conditions increases, remain robust after accounting for multiple hypothesis testing.

5.5. Robustness Analyses

We conduct multiple sets of additional analyses to examine the robustness of our results. We present the result tables in [Online Appendix G](#).

5.5.1. Specification Tests We examine the sensitivity of our first- and second-stage estimates to the inclusion of alternative sets of covariates. [Table OA.13](#) reports the results of these

¹⁴ For the main analysis in [Table OA.8](#), we treat all 12 specifications (4 types of Medicare services $\times$ 3 outcomes) as a single family of tests. For the subsample analyses by the number of chronic conditions in [Tables OA.9](#) to [OA.12](#), we take a conservative approach and treat all 60 specifications (4 services $\times$ 3 outcomes $\times$ 5 subsamples) as a single family of tests.

specification tests. The results show that both the first- and second-stage coefficient estimates remain stable across specifications, indicating that our findings are not sensitive to the inclusion of different sets of covariates.

Additionally, we assess the robustness of our results when using one-way clustering at the HSA level instead of our baseline two-way clustering at the HSA and year levels. We report the second-stage results in [Online Appendix Table OA.14](#) and the first-stage result in [Table OA.3](#) column (2). We find that the estimated standard errors do not change much under one-way clustered standard errors at the HSA-level, suggesting that our findings are robust to this alternative clustering structure.

5.5.2. Beneficiary-Year Level Analysis Although CMS Medicare Data record healthcare utilization and annual payments at the beneficiary-year level, our primary analysis is conducted at the aggregated HSA-year level, which corresponds to the level at which the treatment variable varies. As a robustness check, we also estimate the models at the beneficiary-year level, which allows us to control for beneficiary-level characteristics that could drive healthcare consumption. [Online Appendix G.2](#) discusses the beneficiary-level specification and reports the corresponding results.

Specifically, we use a two-part model that accounts for the large mass at zero and the highly skewed distribution of healthcare expenditure data ([Newhouse and Phelps 1976](#), [Deb and Norton 2018](#)) together with the IV approach. The beneficiary-level results are qualitatively consistent with our main HSA-level findings. Greater SL facility density is associated with significant reductions in SNF and home health utilization, while having no statistically significant effect on inpatient hospitalizations or ED visits. These findings indicate that our conclusions are robust to estimating the model at a more disaggregated beneficiary-year level despite the treatment varying at the HSA-year level.

5.5.3. Alternative Explanatory Variable The main analysis uses the density of SL facilities in an HSA-year as the explanatory variable. Here, we rerun our analysis using the density of SL facility units instead of SL facility properties. This alternative measure accounts for differences in facility capacity, as a larger number of SL facilities does not necessarily imply a greater number of available units within an HSA.

[Table OA.16](#) presents the results. Overall, the results using SL facility unit density closely mirror those from our baseline specification, indicating that our findings are robust to measuring SL capacity using either the number of facilities or the number of available units.

Because total SL facility units include both assisted living and independent living units, we conduct an additional robustness check by separately examining the effects of assisted living unit

density and independent living unit density. [Table OA.17](#) and [Table OA.18](#) report the results for assisted living unit density and independent living unit density, respectively. We find that both measures yield results that are consistent with our main findings. Specifically, higher assisted living unit density and higher independent living unit density each cause statistically significant reductions in SNF payments and home health payments. These findings suggest that our results are not driven solely by one type of senior living facility and are robust across both assisted living and independent living settings.

5.5.4. Alternative Outcome Variable We also analyze length of stay (LOS) as an alternative measure of healthcare utilization in place of Medicare spending. We collect the annual LOS in SNFs and inpatient hospitals from the CMS MBSF Cost and Use data files. [Table OA.19](#) displays the results. For SNF utilization, the findings are consistent with our main results. Specifically, a one-standard-deviation increase in SL facility density reduces annual average SNF LOS per beneficiary by 36.8% ($p < 0.01$) and decreases the probability of SNF utilization by 1.2 percentage points ($p < 0.05$). These findings suggest that greater availability of SL facilities is associated with lower SNF utilization regardless of whether utilization is measured in terms of spending or length of stay. For inpatient utilization, we find no statistically significant effect of SL facility density on LOS, which is also consistent with our main findings. Overall, these results indicate that our conclusions are robust to using LOS as an alternative measure of healthcare utilization.

5.5.5. Including Beneficiaries Who Move As we describe in [Section 3.2](#), we exclude Medicare beneficiaries who move to different HSAs during our study period due to potential violation of the exogeneity condition of our IV; the relocation decisions by the movers may be influenced by the new residential buildings as well as healthcare utilization in the area where they are moving to. For example, beneficiaries may choose to move to areas experiencing greater residential development, which could also be associated with changes in healthcare utilization. However, excluding them removes a substantial number of observations. To double-check if this exclusion significantly alters our results, we report the results with a sample that includes the beneficiaries who move. This increases the number of beneficiaries (in SNF analysis) to 121,580,671.

[Table OA.20](#) presents the analysis results with movers in the sample. The results are consistent with our main analysis. For SNF, the estimated effect on average SNF payments is -1.867 ($p < 0.01$), which is slightly smaller in magnitude than the corresponding estimate in our main analysis (-2.170 , $p < 0.001$). Similarly, for home health utilization, the estimated effect on average payments is -2.102 ($p < 0.001$), compared with -2.493 ($p < 0.001$) in the main analysis. With these analyses, we confirm that our results do not change significantly by using a different sample (including movers); still, because of the potential threat to the exogeneity condition of the IV, we exclude the beneficiaries who moved during our study period from our main sample.

5.5.6. Including HSAs with caps on permits or not included in land use survey

As discussed in [Section 3.2](#), we exclude HSAs that either impose caps on the number of building permits or are not covered by the land use survey and therefore have unknown permit-cap status. These exclusions are motivated by our instrumental variable strategy, which relies on variation in single-family residential building permits as a proxy for local housing supply conditions. In markets where permit issuance is subject to binding caps, or where regulatory constraints cannot be observed, the relationship between building permits and housing supply may differ substantially from that in unconstrained markets, potentially weakening the relevance of the instrument.

To assess the sensitivity of our findings to these sample restrictions, we re-estimate the models using alternative samples that include the previously excluded HSAs. The results for SNF payments and home health payments are reported in [Table OA.21](#) and [Table OA.22](#), respectively. Columns (1)–(3) include all HSAs excluded for either reason, columns (4)–(6) include HSAs not covered by the land-use survey, and columns (7)–(9) include HSAs with permit caps. Across all specifications, the estimated coefficients remain similar in magnitude and retain their statistical significance. These findings indicate that our results are not sensitive to the exclusion of HSAs with permit caps or unknown permit-cap status, providing additional support for the robustness of our empirical findings.

6. Conclusions and Discussion

Our study examines the effects of SL facilities on healthcare utilization and Medicare spending among Medicare beneficiaries in the area. Using an IV approach on the entirety of Medicare fee-for-service claims data, we find that greater SL facility density significantly decreases SNF admissions and Medicare payments for SNF care. In addition, we find that greater SL facility density significantly reduces home health utilization and associated Medicare spending, indicating that SL facility services could reduce home-based medical care.

Additional analyses show that the beneficial effects of SL facilities become more pronounced among beneficiaries with more chronic conditions as SL facilities provide specialized services for chronic disease care. We further find evidence of heterogeneous effects across markets: the effects of SL facility density are strongest in areas with low SL penetration and in markets with greater acute-care and post-acute-care capacity, suggesting that both market saturation and the availability of alternative care settings influence the impact of SL facilities on Medicare utilization. Our findings are robust across a wide range of sensitivity analyses, including adjustments for multiple hypothesis testing, alternative measures of SL facility and healthcare utilization, and alternative model specifications and sample definitions.

This paper contributes to a growing literature examining the effects of SL facilities on healthcare utilization among older adults ([McGrail et al. 2013](#), [Sharpp and Young 2016](#), [Bartley et al. 2018](#),

Hua et al. 2021, Lei et al. 2023, NORC 2024, Munevar et al. 2024). Prior studies report mixed evidence on healthcare use. Some find that SL residents experience fewer adverse events and reduced use of certain post-acute services, such as SNF stays (NORC 2024), or reduced use of outpatient care after transitioning into assisted living (McGrail et al. 2013). Our findings are consistent with this line of work: we document significant reductions in SNF and home health utilization associated with greater SL facility availability. At the same time, prior evidence on inpatient hospitalizations and ED visits is mixed. Some studies find that SL residents have fewer hospitalizations for injuries (Munevar and Gorman 2023), while others report higher or repeated ED use relative to community-dwelling seniors (Sharpp and Young 2016, Bartley et al. 2018), or lower ED use (Hua et al. 2021). In contrast, we find no significant effects of SL facility density on hospitalizations or ED visits.

One potential explanation for these differences is that prior studies typically compare SL residents to community-dwelling seniors, whereas our analysis captures market-level effects of SL facility availability across all Medicare beneficiaries. As a result, our estimates reflect system-wide changes in healthcare utilization across all beneficiaries, incorporating how patients and providers adjust to the availability of SL facilities, rather than isolating individual-level differences in care settings. Additionally, our IV approach provides a causal, rather than associative, look at these relationships.

6.1. Implications of the Findings

Our findings are important for Medicare and policymakers for several reasons. First, while prior literature provides some evidence that SL facilities can substitute for traditional nursing homes among patients with low acuity levels (Grabowski et al. 2012, Cornell et al. 2020), there has historically been no comprehensive understanding of their causal effects on senior health conditions and systemic healthcare expenditure. Our findings help fill this gap by demonstrating that these acuity-based substitution effects scale to the market level. Second, as Medicare faces financial challenges due to the increasing enrollment of seniors (Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds 2024, Cubanski and Neuman 2023), it is essential to study ways to manage and reduce Medicare spending. Our findings suggest that SL facilities could be helpful in reducing Medicare spending. Our estimates indicate that a one-standard-deviation increase in SL facility density could reduce aggregate Medicare spending among beneficiaries in the area by \$27.623 million per year for SNF, and \$17.958 million per year for home health spending. These estimates suggest that increasing SL facility density by 0.0052, which is the average annual increase in SL facility density during our sample period, in each HSA across the U.S. (952 HSAs in total) would reduce Medicare and beneficiary payments on SNF by \$713.4 million per year (2.5% of total annual Medicare spending on SNF) and home health by \$480.3 million (3.0% of total Medicare spending on home health¹⁵).

¹⁵ In 2023, the total Medicare fee-for-service expenditure on SNF and home health were \$28.5 billions and \$16 billions, respectively (Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds 2024).

At the same time, we note that greater availability of SL facilities is accompanied by higher private expenditures, as Medicare generally does not cover room, board, or personal care services provided in SL facilities. For example, the average monthly rent of SL facilities in our sample is \$3,558, compared with an average local housing cost of \$1,389.¹⁶ For an average HSA with 81,349 Medicare beneficiaries, a one-standard-deviation increase in SL facility density, assuming the associated additional capacity is occupied, would imply approximately \$66.68 million in additional housing expenditures per HSA-year. By comparison, our estimates suggest that a one-standard-deviation increase in SL facility density would reduce Medicare spending by approximately \$45.58 million per HSA-year. Although these figures are not directly comparable because they do not account for differences in services, housing size, or amenities provided by SL facilities, the comparison illustrates a shift in financial burden from public insurance programs to individuals.

Crucially, however, this should not be interpreted merely as a zero-sum transfer of costs. From an overall societal welfare perspective, the marginal senior who chooses to transition into an SL facility possesses a willingness-to-pay that matches the incremental private housing cost. Because the individual fully internalizes the private cost of the SL facility, the substantial Medicare cost savings generated by their transition represent a positive externality. Therefore, from a societal point of view, our findings suggest that the expansion of SL capacity could yield an overall societal welfare improvement. Furthermore, this implies that if policymakers were to provide a marginal subsidy to seniors whose willingness-to-pay is just below the SL rental cost, they would willingly incur the remaining cost to reside in the facility, while Medicare would continue to realize significant savings.

Lastly, this welfare implication is highly relevant to ongoing policy discussions. With the increasing number of residents in SL facilities, policymakers are considering expanding Medicaid's Home- and Community-Based Services waiver programs to cover care services in SL facilities (Filbin 2023). Currently, only 18% of SL facility residents use Medicaid as a payer source, while 62% of nursing home residents are covered by Medicaid (Sengupta et al. 2022). Our findings on the positive externalities and societal welfare improvements associated with SL facilities provide a strong economic rationale for such targeted subsidies and can actively inform this policy discussion.

6.2. Limitations and Future Research

This paper has a few limitations. Although our dataset covers 100% of traditional Medicare beneficiaries, it does not include Medicare Advantage beneficiaries. Therefore, we cannot project the potential impact of additional SL facilities on Medicare Advantage beneficiaries. As enrollment

¹⁶ Measured as the household-weighted average of median housing costs across counties within each HSA.

to Medicare Advantage plans has been increasing (Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds 2024), future research could try to estimate the total effects of SL facilities on Medicare spending, including both traditional (fee-for-service) and Medicare Advantage beneficiaries. Secondly, our data cannot identify Medicare beneficiaries living in the SL facilities, as explained in Section 3.2. Therefore, our estimands pertain to the effects of SL facilities on Medicare spending of Medicare beneficiaries living in the area (not living in SL facilities). Our estimates are useful for evaluating the implications of SL facilities for Medicare spending at the market level. However, they likely underestimate the effects of SL facilities on the healthcare spending of residents living in these facilities because the estimated effects are diluted by averaging outcomes across all Medicare beneficiaries residing in the area rather than only those living in SL facilities. This limitation also prevents us from directly examining the mechanisms underlying our findings. In particular, we cannot determine whether patients are diverted to SL facilities following hospital discharge, which may be one pathway through which greater SL facility availability reduces SNF utilization and spending. Future research could use the Medicare Carrier File to obtain the 9-digit Zip codes of beneficiaries, a comprehensive dataset on all SL facility addresses and capacity, and the Thomas et al. (2018) approach to identify SL facility residents and examine the effects of SL facilities on their residents. To the best of our knowledge, such dataset on SL facilities does not exist yet. Third, while our back-of-the-envelope calculation in Section 6.1 suggests that the positive externalities of SL facilities may yield an overall societal welfare improvement, our data do not permit a formal structural welfare analysis. Future research should formally quantify these exact consumer surpluses and the broader social welfare implications of SL facilities. Finally, although the SL sector in the U.S. experienced substantial growth during our sample period, new SL facility construction slowed considerably following the COVID-19 pandemic. While the occupancy rates have since recovered toward the pre-pandemic levels, development activity remains below historical trends.¹⁷ Future research should examine how these post-pandemic changes in the supply of SL facilities affect senior health outcomes, healthcare utilization, and Medicare spending.

References

- Administration on Aging (2022) 2021 profile of older Americans. Report, Administration for Community Living, U.S. Department of Human Services, Washington, DC.
- Aladangady A (2017) Housing wealth and consumption: Evidence from geographically linked microdata. *American Economic Review* 107(11):3415–3446.
- American Health Care Association, National Center for Assisted Living (2026) Assisted living facts and figures Accessed 6 April 2026, <https://www.ahcancal.org/Assisted-Living/Facts-and-Figures/Pages/default.aspx>.

¹⁷ <https://www.nic.org/blog/senior-housing-occupancy-continues-climbing-in-first-quarter-2025/>.

- Anderson ML (2008) Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association* 103(484):1481–1495.
- Andrews I, Stock JH, Sun L (2019) Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics* 11:727–753.
- Barrot JN, Loualiche E, Plosser M, Sauvagnat J (2022) Import competition and household debt. *The Journal of Finance* 77(6):3037–3091.
- Bartley MM, Quigg SM, Chandra A, Takahashi PY (2018) Health outcomes from assisted living facilities: a cohort study of a primary care practice. *Journal of the American Medical Directors Association* 19(3):B26.
- Brookdale Senior Living (2022) How Brookdale helps manage the top 10 chronic conditions for seniors. Retrieved January 17, 2025, <https://www.brookdale.com/en/healthcare-professionals/blogs/2022/how-brookdale-helps-manages-the-top-10-chronic-conditions-for-se.html>.
- Burns A, Hinton E, Rudowitz R, Mohamed M (2025) 10 things to know about Medicaid. *KFF* (February 18), <https://www.kff.org/medicaid/issue-brief/10-things-to-know-about-medicaid/>.
- Burns A, Mohamed M, Watts MO (2023) A look at waiting lists for Medicaid home- and community-based services from 2016 to 2023. *KFF* (November 29), <https://www.kff.org/medicaid/issue-brief/a-look-at-waiting-lists-for-medicaid-home-and-community-based-services-from-2016-to-2023/>.
- Byrd MC, Stark A, Head J, Su CL, Gibson K, Salzman E, Mody L, Foxman B (2025) Skilled nursing facility population characteristics and length of stay: A prospective cohort study. *Journal of the American Medical Directors Association* 26(11):105853.
- Card D, Dobkin C, Maestas N (2009) Does Medicare save lives? *The Quarterly Journal of Economics* 124(2):597–636.
- Chan DC, Card D, Taylor L (2023) Is there a VA advantage? Evidence from dually eligible veterans. *American Economic Review* 113(11):3003–43.
- Chaney T, Sraer D, Thesmar D (2012) The collateral channel: How real estate shocks affect corporate investment. *American Economic Review* 102(6):2381–2409.
- Chidambaram P, Burns A (2024) 10 things about long-term services and supports (LTSS). *KFF* (July 2024), <https://www.kff.org/medicaid/issue-brief/10-things-about-long-term-services-and-supports-ltss/>.
- Cornell PY, Zhang W, Thomas KS (2020) Changes in long-term care markets: assisted living supply and the prevalence of low-care residents in nursing homes. *Journal of the American Medical Directors Association* 21(8):1161–1165.e4.
- Cubanski J, Neuman T (2023) What to know about Medicare spending and financing. *KFF* (January 19), <https://www.kff.org/medicare/issue-brief/what-to-know-about-medicare-spending-and-financing/>.

- Currie J, Karpova A, Zeltzer D (2023) Do urgent care centers reduce Medicare spending? *Journal of Health Economics* 89:102753.
- Curto V, Einav L, Finkelstein A, Levin J, Bhattacharya J (2019) Health care spending and utilization in public and private Medicare. *American Economic Journal: Applied Economics* 11(2):302–332.
- DC Department of Buildings (2025) Overview of permitting process. Retrieved January 14, <https://dob.dc.gov/page/overview-permitting-process-0>.
- Deb P, Norton EC (2018) Modeling health care expenditures and use. *Annual Review of Public Health* 39:489–505.
- Deryugina T, Heutel G, Miller NH, Molitor D, Reif J (2019) The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review* 109(12):4178–4219.
- Eichenbaum M, Rebelo S, Wong A (2022) State-dependent effects of monetary policy: The refinancing channel. *American Economic Review* 112(3):721–761.
- Einav L, Finkelstein A, Mahoney N (2023) Long-term care hospitals: A case study in waste. *The Review of Economics and Statistics* 105(4):745–765.
- Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds (2024) 2024 Annual report of the Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds. Report, The Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds, Washington, DC.
- Ferreira FV, Gyourko J (2023) Does political partisanship affect housing supply? Evidence from US cities. Working Paper 31966, National Bureau of Economic Research.
- Filbin P (2023) New legislation offers hope for expanding HCBS across more states. *Home Health Care News* (October 24), <https://homehealthcarenews.com/2023/10/new-legislation-offers-hope-for-expanding-hcbs-across-more-states/>.
- Freedman VA, Spillman BC (2014) The residential continuum from home to nursing home: Size, characteristics and unmet needs of older adults. *The Journals of Gerontology: Series B* 69(Suppl.1):S42–S50.
- Gatta F (2024) Types of senior living communities: What to know. *Forbes* (February 7), <https://www.forbes.com/health/senior-living/types-of-senior-living-communities/>.
- Grabowski DC, Stevenson DG, Cornell PY (2012) Assisted living expansion and the market for nursing home care. *Health Services Research* 47(6):2296–2315.
- Gupta A (2021) Impacts of performance pay for hospitals: The readmissions reduction program. *American Economic Review* 111(4):1241–1283.
- Gyourko J, Hartley JS, Krimmel J (2021) The local residential land use regulatory environment across U.S. housing markets: Evidence from a new Wharton index. *Journal of Urban Economics* 124:103337.
- Gyourko J, Saiz A, Summers A (2008) A new measure of the local regulatory environment for housing markets: The Wharton Residential Land Use Regulatory Index. *Urban Studies* 45(3):693–729.

- Hua CL, Zhang W, Cornell PY, Rahman M, Dosa DM, Thomas KS (2021) Characterizing emergency department use in assisted living. *Journal of the American Medical Directors Association* 22(4):913–917.e2.
- Jin GZ, Lee A, Lu SF (2022) Patient routing to skilled nursing facilities: The consequences of the Medicare reimbursement rule. *Management Science* 68(12):8722–8740.
- Kim K, Choi JS, Choi E, Nieman CL, Joo JH, Lin FR, Gitlin LN, Han HR (2016) Effects of community-based health worker interventions to improve chronic disease management and care among vulnerable populations: A systematic review. *American Journal of Public Health* 106(4):e3–e28.
- Lauretta A (2024) What is independent living? Benefits, types, and costs. *Forbes* (February 5), <https://www.forbes.com/health/senior-living/independent-living/>.
- Lei L, Samus QM, Thomas KS, Maust DT (2023) Medication costs and use of older Americans in assisted living settings: A nationally representative cross-sectional study. *Journal of General Internal Medicine* 38(2):294–301.
- Makuc DM, Haglund B, Ingram DD, Kleinman JC, Feldman JJ (1991) Health service areas for the United States. *Vital and Health Statistics. Series 2, Data Evaluation and Methods Research* 112:1–102.
- McGrail KM, Lilly MB, McGregor MJ, Broemeling AM, Salomons K, Peterson S, McKendry R, Barer ML (2013) Health care services use in assisted living: A time series analysis. *Canadian Journal on Aging/La Revue canadienne du vieillissement* 32(2):173–183.
- Melekin A, Sengupta M, Caffrey C (2024) Residential care community resident characteristics: United States, 2022. *NCHS Data Brief* No. 506.
- Montgomery A (2025) Inside the dynamics driving senior living unit turnover, length of stay. *Senior Housing News* Accessed 6 April 2026, <https://seniorhousingnews.com/2025/03/21/inside-the-dynamics-driving-senior-living-unit-turnover-length-of-stay/>.
- Mor V, Intrator O, Feng Z, Grabowski DC (2010) The revolving door of rehospitalization from skilled nursing facilities. *Health Affairs* 29(1):57–64.
- Mountain Vista Health Park (2025) How assisted living can help with chronic disease management. Retrieved June 20, <https://mtvistahealth.com/how-assisted-living-helps-chronic-disease-management/>.
- Munevar D, Gorman C (2023) Vulnerability to adverse health outcomes amongst senior housing residents. Report, NORC at the University of Chicago, Chicago, IL, <https://www.norc.org/content/dam/norc-org/pdfs/20230922.NIC>.
- Munevar D, Hartzman A, Oberlander T, Gorman C (2024) An analysis of health outcomes among senior housing residents. Report, NORC at the University of Chicago, Chicago, IL, <https://www.norc.org/content/dam/norc-org/pdf2024/nic-outcomes-report-revised-2024.pdf>.
- National Association of Realtors (2020) 2020 Home buyers and sellers generational trends report. Report, Research Group, National Association of Realtors, Chicago, IL, <https://www.nar.realtor/sites/default/files/documents/2020-generational-trends-report-03-05-2020.pdf>.

- National Center for Assisted Living (2022) Assisted living state regulatory review. Report, National Center for Assisted Living, Washington, DC, https://www.ahcancal.org/Assisted-Living/Policy/Documents/2022_reg_review.pdf.
- National Council on Aging (2025) Does Medicaid pay for assisted living? Retrieved June 20, <https://www.ncoa.org/article/does-medicaid-pay-for-assisted-living/>.
- Newhouse JP, Phelps CE (1976) New estimates of price and income elasticities of medical care services. Rosett RN, ed., *The Role of Health Insurance in the Health Services Sector*, 261–320 (New York: National Bureau of Economic Research; distributed by Neale Watson Academic Publications).
- NORC (2024) An analysis of longevity among senior housing residents. Final report, NORC at the University of Chicago, Chicago, IL, <https://www.norc.org/content/dam/norc-org/pdf2024/longevity-final-report-2024.pdf>.
- Olea JLM, Pflueger C (2013) A robust test for weak instruments. *Journal of Business & Economic Statistics* 31(3):358–369.
- Paying For Senior Care (2024) Medicaid & assisted living: State by state benefits & eligibility. Retrieved June 20, 2025, <https://www.payingforseniorcare.com/medicaid-waivers/assisted-living>.
- Pearson CF, Quinn CC, Loganathan S, Datta AR, Mace BB, Grabowski DC (2019) The forgotten middle: Many middle-income seniors will have insufficient resources for housing and health care. *Health Affairs* 38(5):851–859.
- Rau J (2023) Extra fees drive assisted-living profits. *The New York Times* (November 19), <https://www.nytimes.com/2023/11/19/health/long-term-care-assisted-living.html>.
- Rose L (2020) The effects of skilled nursing facility care: Regression discontinuity evidence from Medicare. *American Journal of Health Economics* 6(1):39–71.
- Saiz A (2010) The geographic determinants of housing supply. *The Quarterly Journal of Economics* 125(3):1253–1296.
- Sengupta M, Lendon JP, Caffrey C, Melekin A, Singh P (2022) Post-acute and long-term care providers and services users in the United States, 2017–2018. *Vital and Health Statistics. Series 3, Analytical and Epidemiological Studies* (47):1–93.
- Sharpp TJ, Young HM (2016) Experiences of frequent visits to the emergency department by residents with dementia in assisted living. *Geriatric Nursing* 37(1):30–35.
- Shi M (2024) Monitoring for waste: Evidence from Medicare audits. *The Quarterly Journal of Economics* 139(2):993–1049.
- Slaugh VW, Scheller-Wolf AA (2023) Flexibility and consistency in long-term care rostering. *Manufacturing & Service Operations Management* 25(2):719–736.
- Slaugh VW, Scheller-Wolf AA, Tayur SR (2018) Consistent staffing for long-term care through on-call pools. *Production and Operations Management* 27(12):2144–2161.

- Thomas KS, Dosa D, Gozalo PL, Grabowski DC, Nazareno J, Makineni R, Mor V (2018) A methodology to identify a cohort of Medicare beneficiaries residing in large assisted living facilities using administrative data. *Medical Care* 56(2):e10–e15.
- Trent-Gurbuz CJ (2023) What type of senior living is best for you? *U. S. News*. Retrieved May 3, <https://health.usnews.com/best-senior-living>.
- US Census Bureau (2023a) ASCII files by state, CBSA, county or place. *Building Permits Survey*. Retrieved September 26, <https://www2.census.gov/econ/bps/>.
- US Census Bureau (2023b) Building permits survey methodology. Retrieved September 26, <https://www.census.gov/construction/bps/methodology.html>.
- Werner RM, Coe NB, Qi M, Konetzka RT (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.
- Wooldridge JM (2015) Control function methods in applied econometrics. *Journal of Human resources* 50(2):420–445.

Online Appendices

Online Appendix A: Data and Variables

Table OA.1 Data and Variables

Data	Variable ¹	Variation ²	Year
Medicare Master Beneficiary Summary File (MBSF) Base	Age, sex, race, mortality status, county of residence	Beneficiary-year	2005–2019 ³
MBSF Cost and Use	Inpatient length of stay (LOS), inpatient payment, skilled nursing facility (SNF) LOS, SNF payment, home health payment, number of emergency department visits	Beneficiary-year	2005–2019 ³
MBSF 27 Chronic Conditions	Number of chronic conditions	Beneficiary-year	2005–2019 ³
Medicare Provider Analysis and Review file	Number of SNF organizations	Claim	2005–2019 ³
Welltower Senior Living Community Dataset	Number of assisted/independent living facilities/units, number of nursing care properties/units	Health service area (HSA)-quarter	2008–2019 ³
American Hospital Association	Number of inpatient beds	Organization-year	2011–2021 ³
U.S. Census Bureau Building Permits Survey	Single-family building permits	County-year	2010–2019 ⁴
U.S. Census Bureau American Community Survey	Family size, education, housing rent/value distribution, income per capita, senior population, owner-occupied units, senior income, unemployment rates	County-year	2010–2019 ⁴
U.S. Census Bureau County Business Patterns	Number of establishments	County-year	2010–2019 ⁴

Notes. ¹ The variables in the analysis that are derived from each dataset.

² The variation provided by the original data. All variables are aggregated at the HSA-year level for analysis.

³ The years of data to which we have access.

⁴ The years of data included in the analysis.

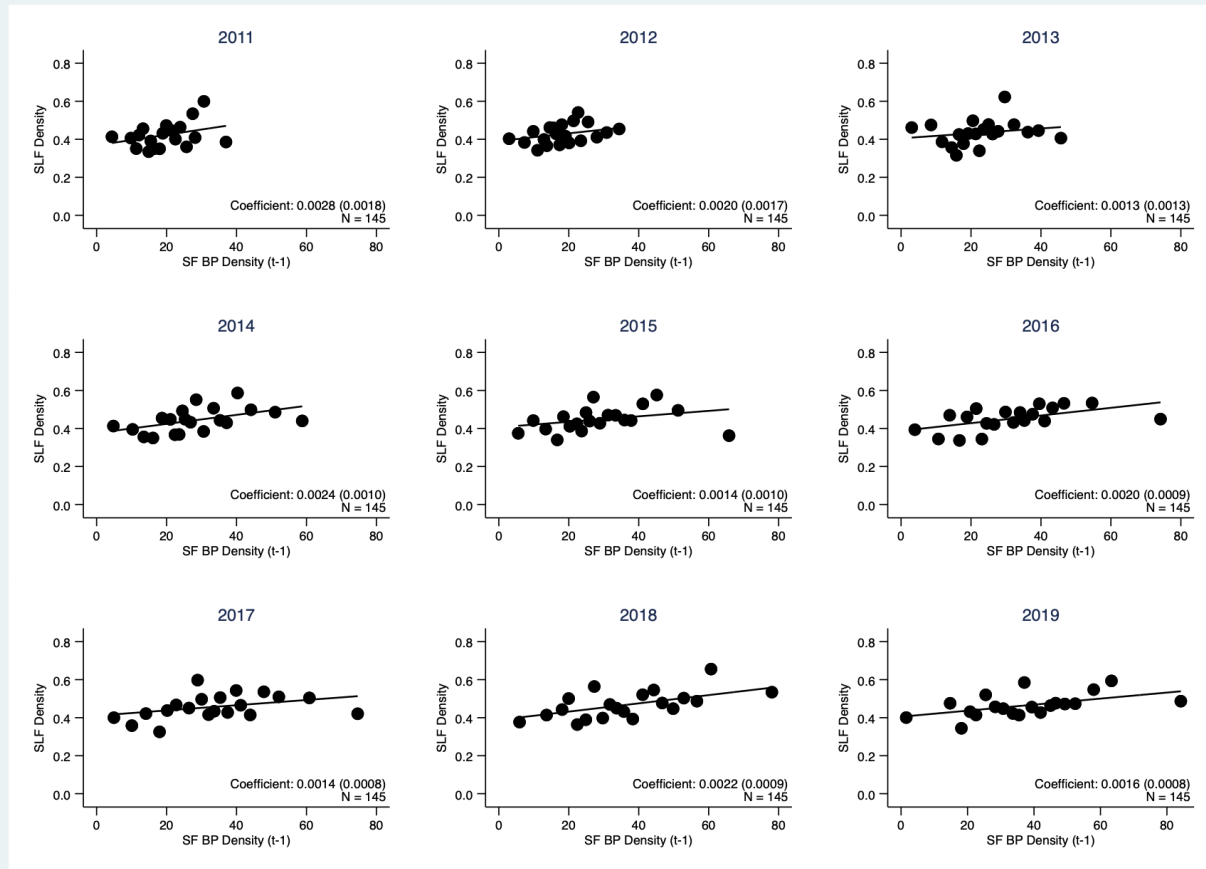
Table OA.2 Summary Statistics: Control Variables

	Mean	SD	Min	Max
Age	74.254	0.682	72.554	76.448
Sex: Female (%)	54.822	1.545	46.701	58.505
Number of chronic conditions	3.294	0.386	2.119	4.590
Race				
White (%)	86.939	9.158	49.496	99.395
Black (%)	8.376	7.765	0.099	38.838
Asian (%)	1.577	2.740	0.024	24.276
Hispanic (%)	1.372	2.610	0.000	24.662
North American Native (%)	0.318	1.156	0.000	10.110
Others (%)	1.419	1.403	0.210	10.503
Nursing care facility density	0.335	0.168	0.016	0.923
SNF density	0.559	0.248	0.172	2.109
Inpatient beds density	28.255	12.304	4.946	72.506
Household size over 3 (%)	56.313	5.080	34.205	73.607
People with bachelor's degree (%)	27.139	7.930	11.196	59.666
Rent price under \$500 (%)	11.659	5.957	1.785	36.935
Rent price \$500–\$1,500 (%)	75.621	10.430	20.268	90.302
House value under \$50K (%)	7.547	4.634	0.837	30.987
House value \$50K–\$1M (%)	90.682	4.925	42.132	97.484
Income per capita (\$1,000)	36.965	7.853	17.650	76.198
Change in establishments (1,000)	0.236	0.532	-6.827	3.802
Change in senior income (\$1,000)	0.956	0.927	-3.775	4.518
Change in owner-occupied houses (%)	-0.278	0.498	-2.275	1.893
Change in unemployment rates (%)	-0.238	0.672	-2.403	2.027
Change in senior population (1,000)	4.613	4.957	-0.197	38.161

Notes. $N = 1,305$. The unit of observation is HSA-year.

Online Appendix B: Senior Living Facilities and Single-family Residential Building Permits

Figure OA.1 Growth of Senior Living Facility Density and Single-family Building Permit Density



Notes. The figure plots binned scatterplots of the growth of the density of senior living facility properties (y-axis) and the density of single-family residential building permits in the previous year (x-axis) for each HSA in each year. Each graph reports the coefficient of the density of single-family building permits in the previous year on the SL facility density, controlling for beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). Clustered standard errors at the HSA level are reported in parentheses. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SF BP density: number of single-family residential building permits per 1,000 Medicare beneficiaries.

Online Appendix C: First-stage Results**Table OA.3 First-stage Results and Robustness Tests**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model	Main	Robustness Checks							
		HSA	Alternative			Including	HSAs with permit cap		
		cluster	Endogenous Variables			movers	(8)+(9)	unk. cap	w. cap
	See Section	5.5.1	5.5.3	5.5.3	5.5.3	5.5.5	5.5.6	5.5.6	5.5.6
Dependent	SLF density	SLF density	SL units density	AL units density	IL units density	SLF density	SLF density	SLF density	SLF density
SF BP _{t-1} density	0.001* (0.0003)	0.001*** (0.0003)	0.135** (0.0300)	0.064* (0.0214)	0.071** (0.0212)	0.001* (0.0003)	0.001** (0.0003)	0.001* (0.0003)	0.001** (0.0003)
Observations	1,305	1,305	1,305	1,305	1,305	1,305	1,674	1,404	1,575
K-P F-statistics	10.63	11.95	21.65	8.65	13.97	9.50	11.32	10.65	11.37
SE Clustering	two-way	one-way	two-way	two-way	two-way	two-way	two-way	two-way	two-way

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses for Columns (1), (3)–(9). One-way clustered standard error at the HSA level is reported in parentheses for Column (2). Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (density of nursing care properties for Columns (1), (2), (6)–(9) or units for Columns (3)–(5), SNF organizations and inpatient beds). Columns 7 adds the sample of HSAs with unknown permit cap regulations and HSAs with permit caps. Column 8 adds the sample of HSAs with unknown permit cap regulations. Column 9 adds the sample of HSAs with permit caps. SLF: senior living facility. SL: senior living. AL: assisted living. IL: independent living. SF BP: single-family building permit. K-P F-statistics: Kleibergen-Paap F-statistics. SE: standard error. ⁺ $p < 0.1$, ^{*} $p < 0.05$, ^{**} $p < 0.01$, ^{***} $p < 0.001$.

Online Appendix D: Analysis of the Effects of Excluded Instrument on Senior Economic and Health Variables

Table OA.4 Effects of Instrument on Proxies of Senior Economic and Health Conditions

Dependent variable	(1) Households with retirement income	(2) Seniors with self-care disability	(3) Seniors with ambulatory disability	(4) Seniors with independent living disability	(5) Seniors with at least one disability type
SF BP density _{<i>t</i>-1}	4.347 (23.59)	-6.741 (4.96)	9.497 (6.53)	9.028 (7.50)	21.108 (13.11)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year
Observations	1,305	1,305	1,305	1,305	1,305
Partial Correlation	0.0120	-0.0500	0.0524	0.0389	0.0637

Notes. Each column represents a separate regression of the dependent variable on the instrumental variable, HSA and year fixed effects, and control variables. Control variables include all controls in [Equation \(3\)](#). Two-way clustered standard errors at the HSA and year levels are reported in parentheses. HSA: health service area, SNF: skilled nursing facility. ⁺ $p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Online Appendix E: Nonlinear and Heterogeneous Treatment Effects**Table OA.5 Nonlinear Effects of SLF Density on SNF and Home Health Utilization**

	SNF payments			Home health payments		
	(1) % Pos. Pay	(2) Avg. Pos.	(3) Total Avg.	(4) % Pos. Pay	(5) Avg. Pos.	(6) Total Avg.
SLF density	-5.01*	-0.48	-2.24**	-13.74*	-1.44**	-3.28**
	(2.32)	(0.45)	(0.82)	(5.43)	(0.53)	(1.03)
(SLF density) ²	0.02	0.06	0.05	3.02*	0.29*	0.57*
	(0.38)	(0.08)	(0.13)	(1.18)	(0.12)	(0.22)
<i>Marginal Effects of SLF density</i>						
At 25 th percentile	-5.00*	-0.45	-2.21**	-11.95*	-1.27*	-2.94**
(SLF density = 0.30)	(2.36)	(0.44)	(0.80)	(5.28)	(0.50)	(0.97)
At 50 th percentile	-4.99*	-0.43	-2.20**	-11.33*	-1.21*	-2.82**
(SLF density = 0.40)	(2.38)	(0.43)	(0.80)	(5.25)	(0.49)	(0.96)
At 75 th percentile	-4.99*	-0.41	-2.18**	-10.39*	-1.12*	-2.64**
(SLF density = 0.55)	(2.41)	(0.43)	(0.80)	(5.23)	(0.48)	(0.94)
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	145	145	145	145	145	145
Years	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019
Observations	1,305	1,305	1,305	1,305	1,305	1,305

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density: number of SL properties per 1,000 living Medicare beneficiaries. All models are estimated using the control function approach. The Kleibergen–Paap F-statistic for the first stage of each model is 10.63. Columns (1) and (4) examine the share of beneficiaries with positive payments; (2) and (5) the average payments among beneficiaries with positive payments; and (3) and (6) the average payments among all living Medicare beneficiaries. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. Control variables include all the controls included in main specification. HSA: health service area, SLF: senior living facility, SNF: skilled nursing facility. ⁺ $p < 0.1$, $*$ $p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table OA.6 Effects of SLF Density and SNF Density Interactions

	SNF payments			Home health payments		
	(1) % Pos. Pay	(2) Avg. Pos.	(3) Total Avg.	(4) % Pos. Pay	(5) Avg. Pos.	(6) Total Avg.
SLF density	-3.24 (2.34)	-0.36 (0.44)	-1.74* (0.82)	-12.12* (5.59)	-1.17* (0.53)	-2.80* (1.09)
SLF density × SNF density	-2.83** (0.91)	-0.08 (0.19)	-0.72** (0.24)	3.84 (2.66)	0.19 (0.24)	0.46 (0.45)
SNF density	2.69*** (0.73)	-0.07 (0.13)	0.58* (0.25)	-2.73 (1.71)	-0.05 (0.13)	-0.21 (0.27)
Marginal Effects of SLF density						
At 25 th pctl. of SNF density (= 0.38)	-4.31 ⁺ (2.32)	-0.39 (0.44)	-2.01* (0.80)	-10.67* (5.35)	-1.10* (0.50)	-2.63** (1.00)
At 50 th pctl. of SNF density (= 0.52)	-4.72* (2.33)	-0.40 (0.43)	-2.11** (0.79)	-10.12 ⁺ (5.31)	-1.07* (0.48)	-2.56** (0.97)
At 75 th pctl. of SNF density (= 0.67)	-5.14* (2.34)	-0.41 (0.43)	-2.22** (0.79)	-9.56 ⁺ (5.29)	-1.05* (0.47)	-2.49** (0.94)
Fixed effects	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	145	145	145	145	145	145
Years	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019
Observations	1,305	1,305	1,305	1,305	1,305	1,305

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. All models are estimated using the control function approach. The Kleibergen–Paap F-statistic for the first stage of each model is 10.63. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SLF density is instrumented by the density of single-family building permits in all models. Columns (1) and (4) report the effects on the percentage of beneficiaries with positive payments; Columns (2) and (5) report the effects on average payments among beneficiaries with payments; Columns (3) and (6) report the effects on average payments among all Medicare beneficiaries. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. Control variables include all the controls included in main specification. SLF: senior living facility, SNF: skilled nursing facility. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table OA.7 Effects of SLF Density and Inpatient Bed Density Interactions

	SNF payments			Home health payments		
	(1) % Pos. Pay	(2) Avg. Pos.	(3) Total Avg.	(4) % Pos. Pay	(5) Avg. Pos.	(6) Total Avg.
SLF density	-4.59 ⁺ (2.41)	-0.33 (0.44)	-2.00* (0.83)	-9.72 ⁺ (5.08)	-0.90* (0.46)	-2.32* (0.94)
SLF density × Bed density	-0.25 (0.17)	-0.05 (0.04)	-0.11* (0.05)	0.002 (0.49)	-0.09 ⁺ (0.05)	-0.11 (0.08)
Bed density	0.18 ⁺ (0.12)	0.003 (0.02)	0.05 (0.04)	0.09 (0.26)	0.06** (0.02)	0.08* (0.04)
Marginal Effects of SLF density						
At 25 th pctl. of bed density (= 1.98)	-5.09* (2.46)	-0.43 (0.44)	-2.22** (0.83)	-9.72 ⁺ (5.48)	-1.07* (0.48)	-2.53** (0.98)
At 50 th pctl. of bed density (= 2.65)	-5.25* (2.48)	-0.46 (0.44)	-2.29** (0.83)	-9.71 ⁺ (5.64)	-1.13* (0.50)	-2.60** (0.99)
At 75 th pctl. of bed density (= 3.43)	-5.45* (2.52)	-0.50 (0.44)	-2.37** (0.84)	-9.71 ⁺ (5.85)	-1.20* (0.51)	-2.69** (1.02)
Fixed effects	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	145	145	145	145	145	145
Years	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019
Observations	1,305	1,305	1,305	1,305	1,305	1,305

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. All models are estimated using the control function approach. The Kleibergen–Paap F-statistic for the first stage of each model is 10.63. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SLF density is instrumented by the density of single-family building permits in all models. Columns (1) and (4) report the effects on the percentage of beneficiaries with positive payments; Columns (2) and (5) report the effects on average payments among beneficiaries with payments; Columns (3) and (6) report the effects on average payments among all Medicare beneficiaries. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). SLF: senior living facility, SNF: skilled nursing facility. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Online Appendix F: Multiple Hypothesis Testing Adjusted p -values**Table OA.8 Effects of SLF Density on Utilization with Adjusted P -values**

Outcome	SNF payments			Home health payments		
	(1)	(2)	(3)	(4)	(5)	(6)
	% Pos. Pay	Avg. Pos.	Total Avg.	% Pos. Pay	Avg. Pos.	Total Avg.
SLF density	-4.975* (2.32)	-0.402 (0.31)	-2.170*** (0.62)	-9.635** (3.58)	-1.044** (0.36)	-2.493*** (0.70)
P -value	0.0321*	0.1974	0.0005***	0.0071**	0.0042**	0.0003***
Adjusted p -value	0.0650 ⁺	0.2720	0.0040**	0.0220*	0.0170*	0.0040**

Outcome	Inpatient payments			ED visits		
	(1)	(2)	(3)	(4)	(5)	(6)
	% Pos. Pay	Avg. Pos.	Total Avg.	% Pos. Pay	Avg. Pos.	Total Avg.
SLF density	-4.091 (3.22)	0.141 (0.27)	-0.122 (0.22)	-2.734 (3.38)	-0.171* (0.08)	-0.273 (0.20)
P -value	0.2033	0.6012	0.5757	0.4186	0.0286*	0.1746
Adjusted p -value	0.2720	0.6020	0.6020	0.5030	0.0650 ⁺	0.2720

Notes. Observations: 1,305. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SLF density is instrumented by the density of single-family building permits in all models. Columns (1) and (4) examine the share of beneficiaries with positive payments; (2) and (5) the average payments among beneficiaries with payments; and (3) and (6) the average payments among all Medicare beneficiaries. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). Adjusted p -values are sharpened q -values calculated following the procedure in [Anderson \(2008\)](#) to account for multiple hypothesis testing. SLF: senior living facility, SNF: skilled nursing facility, ED: emergency department. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table OA.9 Effects of SLF Density on SNF by Number of Chronic Conditions with Adjusted *P*-values

Outcome	Share (%) of beneficiaries with utilization				
	(1)	(2)	(3)	(4)	(5)
Sample with at least	3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density	-8.76* (3.61)	-11.84** (4.48)	-15.38** (5.50)	-18.86** (6.87)	-21.56** (8.02)
<i>P</i> -value	0.0153*	0.0083**	0.0051**	0.0061**	0.0072**
Adjusted <i>p</i> -value	0.0330*	0.0200*	0.0150*	0.0160*	0.0190*
Outcome	Average payments among beneficiaries with utilization (log-transformed)				
	(6)	(7)	(8)	(9)	(10)
Sample with at least	3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density	-0.40 (0.31)	-0.40 (0.31)	-0.39 (0.31)	-0.41 (0.32)	-0.42 (0.32)
<i>P</i> -value	0.1934	0.1937	0.2068	0.1994	0.1967
Adjusted <i>p</i> -value	0.2500	0.2500	0.2540	0.2500	0.2500
Outcome	Average payments among all beneficiaries (log-transformed)				
	(11)	(12)	(13)	(14)	(15)
Sample with at least	3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density	-2.14*** (0.60)	-2.26*** (0.63)	-2.24*** (0.61)	-2.15*** (0.59)	-1.96*** (0.54)
<i>P</i> -value	0.0004***	0.0003***	0.0002***	0.0002***	0.0003***
Adjusted <i>p</i> -value	0.0030**	0.0030**	0.0030**	0.0030**	0.0030**

Notes. Observations: 1,305. Adjusted *p*-values are sharpened *q*-values calculated following the procedure in [Anderson \(2008\)](#) to account for multiple hypothesis testing. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SLF density is instrumented by the density of single-family building permits in all models. Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). SLF: senior living facility, SNF: skilled nursing facility. ⁺*p* < 0.1, **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

Table OA.10 Effects of SLF Density on Home Health Payments by Number of Chronic Conditions with Adjusted *P*-values

Outcome	Share (%) of beneficiaries with utilization				
	(1)	(2)	(3)	(4)	(5)
Sample with at least	3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density	-16.50** (5.71)	-22.09** (6.91)	-28.22*** (8.44)	-33.60*** (9.71)	-35.84*** (10.80)
<i>P</i> -value	0.0039**	0.0014**	0.0008***	0.0005***	0.0009***
Adjusted <i>p</i> -value	0.0130*	0.0070**	0.0050**	0.0030**	0.0050**

Outcome	Average payments among beneficiaries with utilization (log-transformed)				
	(6)	(7)	(8)	(9)	(10)
Sample with at least	3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density	-1.07** (0.37)	-1.09** (0.37)	-1.11** (0.38)	-1.12** (0.39)	-1.19** (0.40)
<i>P</i> -value	0.0039**	0.0032**	0.0032**	0.0043**	0.0030**
Adjusted <i>p</i> -value	0.0130*	0.0120*	0.0120*	0.0140*	0.0120*

Outcome	Average payments among living beneficiaries (log-transformed)				
	(11)	(12)	(13)	(14)	(15)
Sample with at least	3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density	-2.43*** (0.69)	-2.54*** (0.69)	-2.57*** (0.69)	-2.48*** (0.68)	-2.35*** (0.67)
<i>P</i> -value	0.0004***	0.0002***	0.0002***	0.0003***	0.0005***
Adjusted <i>p</i> -value	0.0030**	0.0030**	0.0030**	0.0030**	0.0030**

Notes. Observations: 1,305. Adjusted *p*-values are sharpened *q*-values calculated following the procedure in [Anderson \(2008\)](#) to account for multiple hypothesis testing. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SLF density is instrumented by the density of single-family building permits in all models. Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). SLF: senior living facility, SNF: skilled nursing facility. ⁺*p* < 0.1, **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

Table OA.11 Effects of SLF Density on Inpatient Payments by Number of Chronic Conditions with Adjusted *P*-values

Outcome		Share (%) of beneficiaries with utilization				
		(1)	(2)	(3)	(4)	(5)
Sample with at least		3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density		-6.15 (4.59)	-10.72 ⁺ (5.58)	-14.11* (6.61)	-15.59* (7.61)	-15.32 ⁺ (8.31)
<i>P</i> -value		0.1806	0.0548 ⁺	0.0327*	0.0404*	0.0653 ⁺
Adjusted <i>p</i> -value		0.2470	0.0890 ⁺	0.0620 ⁺	0.0720 ⁺	0.1010
Outcome		Average payments among beneficiaries with utilization (log-transformed)				
		(6)	(7)	(8)	(9)	(10)
Sample with at least		3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density		0.16 (0.27)	0.16 (0.27)	0.16 (0.27)	0.18 (0.29)	0.22 (0.30)
<i>P</i> -value		0.5454	0.5370	0.5609	0.5324	0.4625
Adjusted <i>p</i> -value		0.5850	0.5850	0.5910	0.5850	0.5240
Outcome		Average payments among living beneficiaries (log-transformed)				
		(11)	(12)	(13)	(14)	(15)
Sample with at least		3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density		-0.09 (0.22)	-0.22 (0.22)	-0.26 (0.24)	-0.20 (0.23)	-0.10 (0.26)
<i>P</i> -value		0.6704	0.3304	0.2780	0.3706	0.7094
Adjusted <i>p</i> -value		0.6820	0.3890	0.3340	0.4280	0.7100

Notes. Observations: 1,305. Adjusted *p*-values are sharpened *q*-values calculated following the procedure in [Anderson \(2008\)](#) to account for multiple hypothesis testing. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SLF density is instrumented by the density of single-family building permits in all models. Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). SLF: senior living facility, SNF: skilled nursing facility. ⁺*p* < 0.1, **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

Table OA.12 Effects of SLF Density on ED Visits by Number of Chronic Conditions with Adjusted *P*-values

Outcome	Share (%) of beneficiaries with utilization				
	(1)	(2)	(3)	(4)	(5)
Sample with at least	3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density	-2.43 (4.45)	-7.15 (4.88)	-10.73 ⁺ (6.01)	-11.94 ⁺ (6.11)	-10.91 (7.03)
<i>P</i> -value	0.5843	0.1430	0.0745 ⁺	0.0508 ⁺	0.1206
Adjusted <i>p</i> -value	0.6050	0.2000	0.1120	0.0850 ⁺	0.1770
Outcome	Average payments among beneficiaries with utilization (log-transformed)				
	(6)	(7)	(8)	(9)	(10)
Sample with at least	3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density	-0.20** (0.07)	-0.21* (0.09)	-0.22* (0.10)	-0.24* (0.10)	-0.22 ⁺ (0.12)
<i>P</i> -value	0.0061**	0.0124*	0.0275*	0.0168*	0.0615 ⁺
Adjusted <i>p</i> -value	0.0160*	0.0290*	0.0550 ⁺	0.0350*	0.0980 ⁺
Outcome	Average payments among living beneficiaries (log-transformed)				
	(11)	(12)	(13)	(14)	(15)
Sample with at least	3 conditions	4 conditions	5 conditions	6 conditions	7 conditions
SLF density	-0.28 (0.18)	-0.39* (0.19)	-0.45* (0.21)	-0.47* (0.19)	-0.41* (0.21)
<i>P</i> -value	0.1233	0.0362*	0.0282*	0.0149*	0.0476*
Adjusted <i>p</i> -value	0.1770	0.0660 ⁺	0.0550 ⁺	0.0330*	0.0820 ⁺

Notes. Observations: 1,305. Adjusted *p*-values are sharpened *q*-values calculated following the procedure in [Anderson \(2008\)](#) to account for multiple hypothesis testing. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SLF density is instrumented by the density of single-family building permits in all models. Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). SLF: senior living facility, SNF: skilled nursing facility, ED: emergency department. ⁺*p* < 0.1, **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

Online Appendix G: Results of Robustness Tests

G.1. Specification Tests

We examine the sensitivity of our first- and second-stage estimates to the inclusion of alternative sets of covariates. **Table OA.13** reports the results of these specification tests. Column (1) includes only the HSA- and year-fixed effects without any control variables. Column (2) adds healthcare supply controls, including the densities of nursing home facilities, SNF organizations, and inpatient beds, as well as census characteristics such as family size, education attainment, housing rent and value, and income per capita. Column (3) further adds changes in local demographic and economic characteristics, including the senior population, owner-occupied housing units, the number of businesses, senior income, and unemployment rates. Finally, column (4) includes beneficiary characteristics such as average age, the share of female beneficiaries, racial composition, and the prevalence of chronic conditions.

The results show that both the first- and second-stage coefficient estimates remain stable across specifications, indicating that our findings are not sensitive to the inclusion of different sets of covariates. Although the first-stage F-statistics are smaller in columns (1) and (2), they increase after additional controls are introduced in columns (3) and (4). This pattern suggests that conditioning on local demographic and economic characteristics strengthens the partial relationships between the instrument and SL facility density.

Table OA.13 Specification Tests: Effects of SLF Density on SNF and Home Health Utilization

Outcome	Total Average Payments			
	(1)	(2)	(3)	(4)
<i>Panel A. SNF Payments</i>				
SLF density	-1.839* (0.83)	-2.011* (0.79)	-2.090** (0.76)	-2.170*** (0.62)
<i>Panel B. Home Health Payments</i>				
SLF density	-2.451* (0.96)	-2.364** (0.86)	-2.536** (0.84)	-2.493*** (0.70)
First stage results				
SF BP density _{t-1}	0.0010** (0.0003)	0.0009** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)
F-statistics	7.87	9.43	10.55	10.63
Controls				
Census at levels	No	Yes	Yes	Yes
Health supply	No	Yes	Yes	Yes
Census in changes	No	No	Yes	Yes
Beneficiary	No	No	No	Yes
Fixed effects	HSA	HSA	HSA	HSA
	Year	Year	Year	Year
Number of HSAs	145	145	145	145
Years	2011-2019	2011-2019	2011-2019	2011-2019
Observations	1,305	1,305	1,305	1,305

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density is instrumented by the density of single-family building permits. Census at levels include census characteristics in measured in levels, including family size, education level, housing rent and value distributions, and income per capita. Healthcare supply characteristics include densities of nursing home facilities, SNF organizations, and inpatient beds. Census characteristics in changes include changes in senior population, owner-occupied housing units, number of businesses, senior income, and unemployment rates. Beneficiary characteristics include average age, the proportion of female beneficiaries, race composition, and the prevalence chronic conditions. HSA: health service area, SLF: senior living facility, SNF: skilled nursing facility. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table OA.14 Estimations Using One-Way Clustered Standard Errors

Outcome	SNF payments			Home health payments		
	2SLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
	% Pos. Pay	Avg. Pos.	Total Avg.	% Pos. Pay	Avg. Pos.	Total Avg.
SLF density	-4.975 ⁺ (2.58)	-0.402 (0.37)	-2.170** (0.74)	-9.635** (3.57)	-1.044** (0.37)	-2.493*** (0.70)
Observations	1,305	1,305	1,305	1,305	1,305	1,305
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	145	145	145	145	145	145
Years	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019

Notes. Clustered standard errors at the HSA are reported in parentheses. SLF density is instrumented by the density of single-family building permits in all models. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. SLF: senior living facility, SNF: skilled nursing facility, HSA: health service area, 2SLS: two-stage least squares. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

G.2. Beneficiary-Level Analysis

In this robustness check, we rerun our analysis at the beneficiary-year level. As with other healthcare expenditure data, our data have a substantial point mass at zero and a highly right-skewed distribution. For such data, linear regression models using ordinary least squares may not fit the data well (Buntin and Zaslavsky 2004, Belotti et al. 2015). Therefore, we employ a two-part model that has been widely used in the health economics literature to better fit the data (Newhouse and Phelps 1976, Mihaylova et al. 2011, Deb and Norton 2018). The main idea of the method is that the overall mean of the outcome can be written as the product of the expectations from two separate parts. That is, $E(y|x) = P(y > 0|x) \times E(y|y > 0, x)$. Since the two parts of the model are additively separable in the log-likelihood function, they can be estimated separately. In addition to better fit, another advantage of the two-part model compared to a single-equation model is that it allows a better understanding of the effects by separately analyzing the likelihood of positive healthcare consumption and the expected amount of expenditure given a positive consumption.

The first part uses a probit model for the likelihood of having a positive value for the outcome of interest; the second uses a log-linear model for the positive quantity of the outcome. Specifically, we estimate the following models with the IV at the beneficiary-year level.

- First stage:

$$SLF_{h_i t} = \theta_0 + \theta_1 Permits_{h_i, t-1} + \mathbf{X}'_{it} \theta_2 + \mathbf{W}'_{h_i t} \theta_3 + \mathbf{Z}'_{z_i t} \theta_4 + \omega_{h_i} + \lambda_t + \varepsilon_{it}, \quad (\text{OA.1})$$

- Second stage:

— 1st part:

$$Pr(y_{it} > 0) = \Phi(\pi_0 + \pi_1 SLF_{h_i t} + \mathbf{X}'_{it} \pi_2 + \mathbf{W}'_{h_i t} \pi_3 + \mathbf{Z}'_{z_i t} \pi_4 + \omega_{h_i}^1 + \lambda_t^1 + \hat{\varepsilon}_{it}), \quad \text{for } \forall y_{it} \quad (\text{OA.2})$$

— 2nd part:

$$\ln y_{it} = \delta_0 + \delta_1 \widehat{SLF}_{h_i t} + \mathbf{X}'_{it} \delta_2 + \mathbf{W}'_{h_i t} \delta_3 + \mathbf{Z}'_{z_i t} \delta_4 + \omega_{h_i}^2 + \lambda_t^2 + \zeta_{it}, \quad \text{for } y_{it} > 0, \quad (\text{OA.3})$$

where subscripts i , h_i , z_i , and t indicate beneficiary, HSA, county, and year, respectively. y_{it} is the healthcare utilization measure of different types of care: SNF, home health, inpatient, and ED. $SLF_{h_i t}$ is the main explanatory variable of interest, the density of senior living facilities in an HSA, h_i , at year t . $\mathbf{X}_{it}$ is a vector of beneficiary characteristics, including age, gender, race, and indicators for 26 chronic conditions. $\mathbf{W}_{h_i t}$ is a vector of the HSA-year-level healthcare supply measures, including the density of inpatient beds, SNFs, and nursing homes. $\mathbf{Z}_{z_i t}$ is a vector of county-year-level census characteristics, including the senior population, income, education level, household size, and all others listed in Section 3.3.3. We include HSA-fixed effects, $\omega_{h_i}^1$ and $\omega_{h_i}^2$, and year-fixed effects, λ_t^1 and λ_t^2 in both equations.

Equation (OA.2) is the first part probit model that analyzes the likelihood of positive expenditure of a care type in a year (i.e., $Pr(y_{it} > 0)$) for all observations, and Equation (OA.3) is the second part that analyzes the expenditure amount conditional on positive expenditure in a year. Equation (OA.1) is the first stage regression in which $Permits_{h_i, t-1}$ is the density of new single-family residential building permits in an HSA in the previous year. We estimate π_1 using a control function approach where we include $\hat{\varepsilon}$, the residual from

the first stage regression, in Equation (OA.2).¹⁸ We estimate δ_1 by two-stage least squares with the fitted $\widehat{SLF}_{izht}$ from the first stage, Equation (OA.1).

Table OA.15 reports the results of the estimation. The odd-numbered columns report the first-part (probit) results in which the outcome is binary (i.e., $\mathbb{1}(\text{Payment} > 0)$), and the even-numbered columns present the second-part results for the continuous outcomes (conditional on the outcome being positive). We find consistent results with our main analysis. We find significant negative effects of SL facility density on SNF payments and home health payments, but not for inpatient payments and ED visits.

For SNF, we find that larger SL facility density significantly decreases the likelihood of SNF admissions among beneficiaries in the area (column (1), coefficient = -0.65 , $p < 0.01$), as well as the average spending conditional on admission (column (2), coefficient = -0.50 , $p < 0.05$). Similarly, for home health, SL facility density has a significant negative impact on both the likelihood of utilization (column (3), coefficient = -1.01 , $p < 0.001$) and the average spending conditional on utilization (column (4), coefficient = -1.08 , $p < 0.001$). We confirm again that the IV is significantly positively correlated with the explanatory variable in all our estimations.

Based on columns (1) and (3), a one-standard-deviation (0.246) increase in SL facility density leads to a 0.798 ($p < 0.01$) percentage point decrease in the probability of SNF admission and a 2.532 ($p < 0.001$) percentage point decrease in the probability of home health admission. Based on columns (2) and (4), a one-standard-deviation (0.246) increase in SL facility density leads to an 11.57%, or \$2,639.52, decrease in SNF payments and a 23.33%, or \$1,436.85, decrease in home health payments, conditional on SNF and home health admission, respectively.

By combining the first- and second-part results, we estimate that a one-standard-deviation increase (0.246) in SL facility density reduces annual SNF spending by \$115.32 per beneficiary and annual home health spending by \$88.58 per beneficiary. Because both the first- and second-part results for SNF and home health utilization are statistically significant, the reductions in utilization are driven by decreases in both the likelihood of admission and spending conditional on admission.

In Section 5.1, where we use HSA-year level specification, we find that a one-standard-deviation increase in SL facility density leads to a \$339.57 reduction in average SNF payments and a \$220.76 reduction in average home health payments per beneficiary. The corresponding estimates from the beneficiary-level model are qualitatively similar but smaller in magnitude, amounting to less than half of the HSA-level estimates. A likely explanation for the smaller beneficiary-level estimates is that SL facility density varies at the HSA-year level, whereas outcomes are measured at the beneficiary level. Consequently, the estimated effect is averaged across all Medicare beneficiaries within an HSA, many of whom may not be directly affected by changes in SL facility availability. Since the effects of SL facilities are concentrated among a subset of beneficiaries who reside in the facilities, averaging across the broader beneficiary population attenuates the estimated effect at the beneficiary level relative to the HSA-level estimates. Nevertheless, the consistency in sign and statistical

¹⁸ We assume the error terms in the first stage and 1st part of second stage are bivariate normal with mean zero, and independent of exogenous variables (Wooldridge 2010, p.585)

significance across the two specifications provides reassurance that our main conclusions are not sensitive to the level of aggregation used in the analysis.

Next, we analyze the effects of SL facilities on inpatient and ED utilization. We find no evidence that SL facilities reduce the likelihood of hospital admission (column (5), coefficient = -0.023 , $p > 0.1$), the inpatient spending conditional on admission (column (6), 0.063 , $p > 0.1$), the likelihood of ED admission (column (7), coefficient = -0.009 , $p > 0.1$), or the number of ED visits conditional on admission (column (8), coefficient = 0.007 , $p > 0.1$).

Overall, our finding suggests that SL facilities have statistically significant negative effects on SNF and home health utilization by decreasing both the likelihood of having admissions and the amount of payments. On the other hand, we do not find significant effects of SL facilities on other healthcare utilization, including inpatient utilization and ED visits.

Table OA.15 Effects of SLF Density at Beneficiary-Year Level

Outcome	SNF payments		Home health payments		Inpatient payments		ED visits	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	IV Probit	2SLS	IV Probit	2SLS	IV Probit	2SLS	IV Probit	2SLS
SLF density	-0.65** (0.23)	-0.50* (0.23)	-1.01*** (0.29)	-1.08*** (0.32)	-0.023 (0.13)	0.063 (0.20)	-0.009 (0.09)	0.007 (0.04)
Observations	106,121,106	3,970,987	106,076,277	8,404,213	106,016,619	14,311,044	105,951,655	25,093,315
First stage results								
SF BP density _{t-1}	0.0016*** (0.0003)	0.0016*** (0.0003)	0.0016*** (0.0003)	0.0015*** (0.0003)	0.0016*** (0.0003)	0.0015*** (0.0003)	0.0016*** (0.0003)	0.0015*** (0.0003)
K-P F statistics	34.9	30.5	34.9	32.0	34.9	31.1	39.31	33.01
Number of HSAs	145	145	145	145	145	145	145	145
Years	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. Columns (1), (3), (5), and (7) report the effects on the probability of having utilization. Columns (2), (4), (6), and (8) report the effects on the log-transformed utilization amount for beneficiaries with utilization. All models include HSA fixed effects, year fixed effects, and the following control variables: beneficiary-level (age, sex, race, 26 chronic conditions), county-level census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and HSA-level healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). SLF: senior living facility, SNF: skilled nursing facility, ED: emergency department, HSA: health service area, IV: instrumental variable, 2SLS: two-stage least squares, SF: single-family, BP: building permit, K-P: Kleibergen-Paap. ⁺ $p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

G.3. Analyses with Alternative Variables**Table OA.16 Estimations Using an Alternative Explanatory Variable: SL Units**

Outcome Model	SNF payments			Home health payments		
	2SLS			2SLS		
	(1) % Pos. Pay	(2) Avg. Pos.	(3) Total Avg.	(4) % Pos. Pay	(5) Avg. Pos.	(6) Total Avg.
SLF unit density	-0.038** (0.013)	-0.003 (0.003)	-0.017*** (0.003)	-0.072* (0.031)	-0.008** (0.003)	-0.019*** (0.005)
Observations	1,305	1,305	1,305	1,305	1,305	1,305
Fixed effects	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs Years	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF unit density is instrumented by the prior-year density of single-family building permits in all models. Columns (1) and (4) report the effects on the percentage of beneficiaries with positive payments; Columns (2) and (5) report the effects on average payments among beneficiaries with payments; Columns (3) and (6) report the effects on average payments among all Medicare beneficiaries. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. SLF: senior living facility, SNF: skilled nursing facility, HSA: health service area, 2SLS: two-stage least squares. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table OA.17 Estimations Using an Alternative Explanatory Variable: Assisted Living Units

Outcome Model	SNF payments			Home health payments		
	2SLS			2SLS		
	(1) % Pos. Pay	(2) Avg. Pos.	(3) Total Avg.	(4) % Pos. Pay	(5) Avg. Pos.	(6) Total Avg.
AL unit density	-0.080 ⁺ (0.041)	-0.007 (0.005)	-0.035** (0.011)	-0.152* (0.061)	-0.017** (0.006)	-0.040** (0.013)
Observations	1,305	1,305	1,305	1,305	1,305	1,305
Fixed effects	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs Years	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. AL unit density: number of assisted living units per 1,000 Medicare beneficiaries. AL unit density is instrumented by the density of single-family building permits in all models. Columns (1) and (4) report the effects on the percentage of beneficiaries with positive payments; Columns (2) and (5) report the effects on average payments among beneficiaries with payments; Columns (3) and (6) report the effects on average payments among all Medicare beneficiaries. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. AL: assisted living, SNF: skilled nursing facility, HSA: health service area, 2SLS: two-stage least squares. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table OA.18 Estimations Using an Alternative Explanatory Variable: Independent Living Units

Outcome Model	SNF payments			Home health payments		
	2SLS			2SLS		
	(1) % Pos. Pay	(2) Avg. Pos.	(3) Total Avg.	(4) % Pos. Pay	(5) Avg. Pos.	(6) Total Avg.
IL unit density	-0.072*** (0.016)	-0.006 (0.005)	-0.031*** (0.005)	-0.136+ (0.072)	-0.015* (0.006)	-0.035** (0.013)
Observations	1,305	1,305	1,305	1,305	1,305	1,305
Fixed effects	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs Years	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. IL unit density: number of independent living units per 1,000 Medicare beneficiaries. IL unit density is instrumented by the density of single-family building permits in all models. Columns (1) and (4) report the effects on the percentage of beneficiaries with positive payments; Columns (2) and (5) report the effects on average payments among beneficiaries with payments; Columns (3) and (6) report the effects on average payments among all Medicare beneficiaries. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. IL: independent living, SNF: skilled nursing facility, HSA: health service area, 2SLS: two-stage least squares. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table OA.19 Estimations Using an Alternative Outcome Variable: Length of Stay

Outcome Model	SNF LOS			Inpatient LOS		
	2SLS			2SLS		
	(1) % Pos. Pay	(2) Avg. Pos.	(3) Total Avg.	(4) % Pos. Pay	(5) Avg. Pos.	(6) Total Avg.
SLF density	-4.974* (2.32)	-0.100 (0.28)	-1.868** (0.58)	-3.892 (2.95)	0.329 (0.31)	0.056 (0.23)
Observations	1,305	1,305	1,305	1,305	1,305	1,305
Fixed effects	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs Years	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019	145 2011-2019

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density is instrumented by the density of single-family building permits in all models. Columns (1) and (4) report the effects on the percentage of beneficiaries with positive payments; Columns (2) and (5) report the effects on average payments among beneficiaries with payments; Columns (3) and (6) report the effects on average payments among all Medicare beneficiaries. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. SLF: senior living facility, SNF: skilled nursing facility, HSA: health service area, 2SLS: two-stage least squares, LOS: length of stay. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

G.4. Analyses with Alternative Sample**Table OA.20 Analysis with Movers in the Sample**

Outcome Model	SNF payments			Home health payments		
	2SLS			2SLS		
	(1) % Pos. Pay	(2) Avg. Pos.	(3) Total Avg.	(4) % Pos. Pay	(5) Avg. Pos.	(6) Total Avg.
SLF density	-4.646* (2.27)	-0.492 ⁺ (0.29)	-1.867** (0.63)	-7.989* (3.22)	-0.873* (0.35)	-2.102*** (0.63)
Observations	1,305	1,305	1,305	1,305	1,305	1,305
Fixed effects	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	145	145	145	145	145	145
Years	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SLF density is instrumented by the density of single-family building permits in all models. Columns (1) and (4) report the effects on the percentage of beneficiaries with positive payments; Columns (2) and (5) report the effects on average payments among beneficiaries with payments; Columns (3) and (6) report the effects on average payments among all Medicare beneficiaries. Outcomes in Columns (2), (3), (5), and (6) are log-transformed. Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). SLF: senior living facility, SNF: skilled nursing facility, HSA: health service area, 2SLS: two-stage least squares. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table OA.21 Analysis of HSAs with Permit Cap: SNF Payments

Outcome	SNF payments			SNF payments			SNF payments		
	HSAs with permits cap and unknown cap			HSAs with unknown permits cap			HSAs with permits cap		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	% Pos.	Avg. Pos.	Total Avg.	% Pos.	Avg. Pos.	Total Avg.	% Pos.	Avg. Pos.	Total Avg.
SLF density	-4.68*	-0.37	-2.16***	-4.92*	-0.42	-2.21***	-4.76*	-0.36	-2.13***
	(2.36)	(0.29)	(0.64)	(2.33)	(0.30)	(0.64)	(2.35)	(0.29)	(0.63)
Observations	1,674	1,674	1,674	1,404	1,404	1,404	1,575	1,575	1,575
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	186	186	186	156	156	156	175	175	175
	2011-	2011-	2011-	2011-	2011-	2011-	2011-	2011-	2011-
	2019	2019	2019	2019	2019	2019	2019	2019	2019

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SLF density is instrumented by the density of single-family building permits in all models. Columns (1), (4), and (7) report the effects on the percentage of beneficiaries with positive payments; Columns (2), (5), and (8) report the effects on average payments among beneficiaries with payments; Columns (3), (6), and (9) report the effects on average payments among all Medicare beneficiaries. Outcomes in Columns (2), (3), (5), (6), (7), and (8) are log-transformed. Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). SLF: senior living facility, SNF: skilled nursing facility, HSA: health service area. ⁺ $p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table OA.22 Analysis of HSAs with Permit Cap: Home Health Payments

Outcome	Home health payments			Home health payments			Home health payments		
	HSAs with permits cap and unknown cap			HSAs with unknown permits cap			HSAs with permits cap		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	% Pos.	Avg. Pos.	Total Avg.	% Pos.	Avg. Pos.	Total Avg.	% Pos.	Avg. Pos.	Total Avg.
SLF density	-11.27**	-1.17**	-2.84***	-10.45**	-1.01**	-2.53***	-10.65**	-1.21**	-2.82***
	(3.64)	(0.40)	(0.77)	(3.50)	(0.37)	(0.70)	(3.68)	(0.40)	(0.77)
Observations	1,674	1,674	1,674	1,404	1,404	1,404	1,575	1,575	1,575
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	186	186	186	156	156	156	175	175	175
	2011-	2011-	2011-	2011-	2011-	2011-	2011-	2011-	2011-
	2019	2019	2019	2019	2019	2019	2019	2019	2019

Notes. Two-way clustered standard errors at the HSA and year levels are reported in parentheses. SLF density: number of senior living facilities per 1,000 Medicare beneficiaries. SLF density is instrumented by the density of single-family building permits in all models. Columns (1), (4), and (7) report the effects on the percentage of beneficiaries with positive payments; Columns (2), (5), and (8) report the effects on average payments among beneficiaries with payments; Columns (3), (6), and (9) report the effects on average payments among all Medicare beneficiaries. Outcomes in Columns (2), (3), (5), (6), (7), and (8) are log-transformed. Control variables include: beneficiary (age, sex, race, chronic conditions), census (family size, education, housing rent/value distribution, income per capita, and changes in senior population, owner-occupied units, businesses, senior income, and unemployment rates), and healthcare supply characteristics (nursing care properties, SNF organizations, inpatient beds). SLF: senior living facility, SNF: skilled nursing facility, HSA: health service area. ⁺ $p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

References

- Anderson ML (2008) Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association* 103(484): 1481–1495.
- Belotti F, Deb P, Manning WG, Norton EC (2015) Twopm: Two-part models. *The Stata Journal* 15(1):3–20.
- Buntin MB, Zaslavsky AM (2004) Too much ado about two-part models and transformation? Comparing methods of modeling Medicare expenditures. *Journal of Health Economics* 23(3):525–542.
- Deb P, Norton EC (2018) Modeling health care expenditures and use. *Annual Review of Public Health* 39:489–505.
- Mihaylova B, Briggs A, O’Hagan A, Thompson SG (2011) Review of statistical methods for analysing healthcare resources and costs. *Health Economics* 20(8):897–916.
- Newhouse JP, Phelps CE (1976) New estimates of price and income elasticities of medical care services. In *The Role of Health Insurance in the Health Services Sector*, ed. RN Rosett, 261–320. Cambridge, MA: National Bureau of Economic Research.
- Wooldridge JM (2010) *Econometric analysis of cross section and panel data* (Cambridge, MA: MIT Press), second edition.