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 number of senior living facilities in a Health Service Area (HSA) reduces admissions to skilled nursing facilities and inpatient hospitals. Our estimates suggest that adding one senior living facility to each of the 952 HSAs nationwide could lead to annual reductions in Medicare expenditures of \$151.3 million for skilled nursing care and \$272.8 million for inpatient hospitalizations. 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 2028 (Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds 2022). 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 senior living facilities on Medicare cost savings.

We use a comprehensive dataset on senior living 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. 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: skilled nursing facility (SNF), inpatient hospital, home health, and emergency department (ED) visits. Our results show that SL facilities significantly decrease SNF utilization among beneficiaries in the health service area (HSA). We estimate that one more SL facility will reduce SNF spending by $1.994 per beneficiary

[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 Rekindlethe 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

per year or \$158,882.01 per HSA per year. For inpatient care, we find a marginally ($p < 0.1$) significant decrease in the probability of admission. The estimated overall impact suggests that one SL facility leads to a \$3.601 decrease in inpatient hospital spending per beneficiary per year or \$286,606.63 per HSA per year. These results suggest that SL facilities decrease some Medicare care needs among seniors. We do not find significant causal effects of SL facilities on home health care or ED visits.

Given the estimated reduction in skilled nursing facilities and inpatient hospitalization 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 grappling 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.

The paper proceeds as follows. In Section 2, we discuss related literature, and in Section 3, we describe the data, sample, and variables used in our analysis. Section 4 explains the empirical challenges of our study and the econometric approach to address them. Section 5 presents the results of the main analysis, additional analysis to explore potential mechanisms, and various robustness checks. Section 6 concludes the paper by discussing the contribution and implications of our findings and directions for future research.

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, use a method developed by Thomas et al. (2018) to 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 the 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 Senior Living (SL) facilities on healthcare utilization, we leverage data from multiple sources. Three of these datasets are publicly available (free or through purchase): the Centers for Medicare and Medicaid Services (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 segment[5] from 2011 to 2019. The dataset contains the beneficiary-year-level summary of utilization and total annual payments on all Medicare beneficiary inpatient stays at acute and non-acute care hospitals and SNFs, as well as visits to home health care. The data files also include the number of visits to EDs, and the summary of Medicare Part D (prescription drug coverage) payments, events, and prescription fills.

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), ZIP code, and others.

[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`.

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.

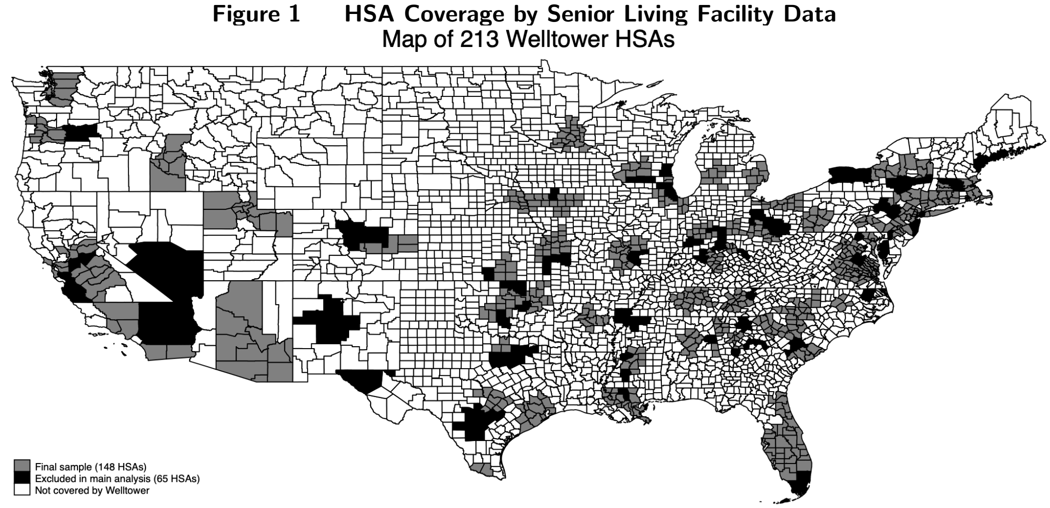
3.1.2. American Hospital Association To capture the amount of healthcare resources available to beneficiaries, we leverage the AHA annual survey data to determine the number of staffed inpatient beds in each health service area (HSA) for each year from 2011 to 2019. The National Center for Health Statistics 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).

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 ZIP code-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, and changes in percent of owner-occupied houses; a county-level variable: changes in median senior household income. Also, we use ZIP Codes Business Patterns data to extract changes in the number of business establishments. We use levels for most of the control variables. As will be explained in more detail in Section 4.2 when we introduce our IV, some of the controls related to our IV will be included as changes. Table 1 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). From this source, we collect the annual number of single-family residential building permits in each HSA 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 and their capacity 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.

Figure 1 HSA Coverage by Senior Living Facility Data



Notes. The shaded areas represent 213 health service areas (HSAs) at the county level covered by the data provided by Welltower Inc. Black-shaded areas are 65 HSAs (232 counties) that are excluded from our sample for various reasons. Gray-shaded areas are the 148 HSAs (600 counties) included in our final sample.

3.2. Sample

We construct our sample 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 211 HSAs (out of 213 HSAs covered by the Welltower dataset; two HSAs are excluded as they have no Medicare beneficiaries residing there) from 2011 to 2019. Similar to 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 (Research Data Assistance Center 2021). We also exclude beneficiaries whose basic characteristics (sex and race) are unknown in the data and those living in zip codes without available census characteristics data. These steps leave us with 169,517,129 beneficiary-year observations.

We then exclude 17 HSAs without any assisted living or independent living facilities and two HSAs without AHA data, dropping 1,908,853 beneficiary-year observations. In addition, because our estimation relies on building permits as an IV, we exclude six HSAs that include counties that do not report building permits. Next, we exclude 12 HSAs because it is unknown if they have a cap on building permits as they do not participate in the survey of local residential land use regulatory regimes which reports building caps (Gyourko et al. 2021). We then exclude 26 HSAs with a cap on building permits as indicated in the land use survey. Excluding these 44 $(= 6 + 12 + 26)$ HSAs drops 40,676,522 beneficiary-year observations.

We also 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 15,935,915 beneficiary-year observations. In Section 5.3.4, as a robustness test, we add people who moved during our study period back to the analysis and find consistent results. Furthermore, we remove beneficiary-year observations for beneficiaries who died in that year, dropping 4,830,599 observations. The sample now includes 20,593,435 unique beneficiaries with 106,165,240 beneficiary-year observations. Lastly, in the analysis, we exclude observations that exhibit extreme outcome values (e.g., payments exceeding the 99th percentile). Therefore, our final sample includes fee-for-service Medicare beneficiaries aged 65 or older who have not moved and do not have extreme outcome values in 148 HSAs from 2011 to 2019. Table 1 presents the summary statistics of our sample.

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, collected from the MBSF Cost and Use segment. Section 5.3.2 uses length of stay as an alternative outcome for utilization as a robustness test. For the ED, we measure the utilization by the number of visits to the ED in a year for each beneficiary, collected from the MBSF Cost and Use segment. In the analysis of each outcome, we exclude samples with outcome values bigger than the 99th percentile. For the payment outcomes, we convert all dollar payments to 2023 dollars to adjust for inflation.

We analyze a binary outcome, whether the beneficiary utilized the healthcare service (i.e., having admission to a SNF or an inpatient hospital, or visiting home health or having a visit to ED), as well as the continuous outcome variable given that the beneficiary utilized the care. As Table 1 shows, 13% of Medicare beneficiaries have at least one inpatient admission in a year with an average of $3,022 annual spending (including zeros), and 3.8% of beneficiaries have at least one SNF admission, with an average of $886.5 spending. For home health, 8.3% of beneficiaries have at least one visit per year, with $531.8 average spending per year. For the ED, 24% of beneficiaries have at least one ED visit annually, with an average of 0.41 visits.

3.3.2. Explanatory Variables The main explanatory variable of interest is the number of SL facilities. This is the sum of assisted living and independent living facilities in an HSA per year. We combine assisted and independent living because a single facility can include both types of units.We obtain this variable from the data provided by our industry partner. As Table 1 presents, there are 75 senior living facilities in an HSA, on average, with a minimum of 1 facility and a maximum of 313 facilities. As the number of units per facility can vary quite a bit, we use the number of SL facility units instead of the number of facilities to test the robustness of our results in Section 5.3.1.

Table 1 Summary Statistics

Variable	Mean	SD	Min	Max	N
Outcome Variables					
SNF utilization					
$\mathbb{1}$(SNF payment > 0)	0.038	0.19	0	1	106,124,564
SNF payments (including 0)	886.5	5,809.2	0	91,385.1	106,124,564
SNF payments (> 0)	23,362.8	19,085.0	0.012	91,385.1	4,027,022
Inpatient hospital utilization					
$\mathbb{1}$(Inpatient payment > 0)	0.13	0.34	0	1	106,020,795
Inpatient payments (including 0)	3,022.0	10,959.2	0	142,915.0	106,020,795
Inpatient payments (> 0)	22,404.8	21,358.2	0.026	142,915.0	14,300,130
Home health utilization					
$\mathbb{1}$(Home health payment > 0)	0.083	0.28	0	1	106,075,919
Home health payments (including 0)	531.8	2,267.2	0	27,505.4	106,075,919
Home health payments (> 0)	6,379.8	4,934.8	0.012	27,505.4	8,842,825
ED utilization					
$\mathbb{1}$(Number of ED visit > 0)	0.24	0.42	0	1	105,951,642
Number of ED visits (including 0)	0.41	0.96	0	8	105,951,642
Number of ED visits (> 0)	1.75	1.24	1	8	24,973,815
Explanatory Variables					
Number of senior living facilities	74.6	69.1	1	313	106,124,564
Number of senior living facility units	9,534.3	8,766.1	38	35,233	106,124,564
Instrumental Variable					
Single-family building permits$_{t-1}$	3,754.9	4,806.3	0	28,737	106,124,564
Control Variables					
Age	74.4	7.80	65	100	106,124,564
Male	0.45	0.50	0	1	106,124,564
Race					
White	0.84	0.37	0	1	106,124,564
Black	0.087	0.28	0	1	106,124,564
Asian	0.029	0.17	0	1	106,124,564
Hispanic	0.020	0.14	0	1	106,124,564
North American Native	0.0031	0.055	0	1	106,124,564
Others	0.022	0.15	0	1	106,124,564
Number of inpatient beds	6,366.5	5,855.2	35	25,966	106,124,564
Number of nursing homes	67.7	74.5	1	358	106,124,564
Number of SNFs	86.4	76.6	1	365	106,124,564
Senior population (number of people)	4,340.1	3,056.0	0	45,684	106,124,564
Household size over 3 (%)	38.7	10.9	0	100	106,124,564
People with bachelor's degree (%)	20.04	9.11	0	81.9	106,124,564
Rent price under \$500 (%)	8.91	9.43	0	100	106,124,564
Rent price \$500-\$1,500 (%)	68.7	20.24	0	100	106,124,564
House value under \$50K (%)	6.27	7.97	0	100	106,124,564
House value \$50K-\$1M (%)	90.0	11.6	0	100	106,124,564
Change in number of business entities	7.53	22.1	-687	676	106,124,564
Income per capita (thousand \$)	34.7	15.2	1.98	279.4	106,124,564
Change in median senior income (\$)	760.4	1,872.8	-59,195.0	62,483.2	106,124,564
Change in owner-occupied houses (%)	-0.29	1.85	-92.0	77.8	106,124,564

Notes. The unit of observation is beneficiary-year. Outcome variables exclude extreme values exceeding the 99th percentile. Payment variables (SNF, inpatient, and home health) are in 2023 dollars. Summary statistics of variables other than outcome variables include the sample consistent with the SNF utilization outcomes.

3.3.3. Control Variables We include an extensive set of control variables. First, we have beneficiary characteristics, such as age, sex, race, and chronic conditions (e.g., anemia, hyperlipidemia, hypertension, diabetes). We define the indicators for chronic conditions following the MBSF Chronic Conditions data file. Second, we have the healthcare supply in the area, including the number of SNFs, the number of nursing homes, and the number of inpatient beds in each HSA and year. Lastly, we include zip code- and year-level 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 $50k, % of housing values between $50k and $1 million), income per capita, change in the senior population (age $\geq$ 65), change in percentage of owner-occupied housing units, change in the number of businesses, and change in median senior household income. We use levels for the 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.

4. Empirical Strategy

We now introduce our empirical model to estimate the treatment effect of SL facilities on healthcare utilization. In doing so, we must address a number of empirical challenges that arises from data limitations.

4.1. Empirical Challenges

4.1.1. Lack of Residence Information 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.

We note that Thomas et al. (2018) matches the 9-digit Zip code of Medicare beneficiaries to that of assisted living facilities in their dataset. Unfortunately, we cannot take this approach because we only have the 5-digit Zip code, not the 9-digit Zip code, of each beneficiary, and we do not have the address of each senior living facility. While Thomas et al. (2018)'s data is more detailed than our approach in terms of beneficiary residence, we analyze more comprehensive data covering 100% Medicare beneficiaries and both types of SL facilities (assisted and independent living facilities) in sampled HSAs from 2011 to 2019. We also analyze different measures of healthcare utilization by looking at ED, inpatient, SNF, and home health claims. In contrast, Thomas et al. (2018) focuses on assisted living facilities and a 20% random sample of Medicare Part B claims from 2007 to 2009 for validation purposes, but they do not explore the differences in utilization between assisted living residents and those not in assisted living facilities.

4.1.2. Large Mass at Zero 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 equation 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 at the beneficiary-year level.

$$Pr(y_{it} > 0) = \Phi\big(\pi_0 + \pi_1 SLF_{h_i t} + \boldsymbol{X}'_{it}\pi_2 + \boldsymbol{W}'_{h_i t}\pi_3 + \boldsymbol{Z}'_{z_i t}\pi_4 + \omega^1_{h_i} + \lambda^1_t\big), \quad \text{for } \forall\ y_{it} \tag{1}$$

$$\ln y_{it} = \delta_0 + \delta_1 SLF_{h_i t} + \boldsymbol{X}'_{it}\delta_2 + \boldsymbol{W}'_{h_i t}\delta_3 + \boldsymbol{Z}'_{z_i t}\delta_4 + \omega^2_{h_i} + \lambda^2_t + \zeta_{it}, \quad \text{for } y_{it} > 0, \tag{2}$$

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

$\omega^1_{h_i}$ and $\omega^2_{h_i}$, and year-fixed effects, λ^1_t and λ^2_t in both equations. Equation (1) 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 (2) is the second part that analyzes the expenditure amount conditional on positive expenditure in a year.

4.1.3. Endogeneity The third empirical challenge is the potential endogeneity problem in the estimation of π_1 and δ_1. Developers and operators of SL facilities are more likely to enter and expand into an area with a healthier and wealthier senior population as the area will likely correspond to higher demand for SL facilities. As a result, such unobserved demand factors will be correlated with SLF_{h_it} and healthcare expenditures, introducing bias in the estimation of π_1 and δ_1. In addition, other unobserved factors such as senior welfare programs run by the local government, may impact the growth in senior living facilities and healthcare expenditure jointly. Due to these unobserved factors, a naive estimate of Equation (1) and Equation (2) is likely to result in biased estimates of π_1 and δ_1, the effects of senior living facilities on the likelihood and amount of healthcare expenditure, respectively. Since healthier senior population is positively correlated with the number of SL facilities and negatively correlated with the likelihood and amount of healthcare expenditure, the bias is likely to be negative–i.e., the impact of SL facilities on the likelihood and amount of healthcare expenditure is likely underestimated in magnitude. The bias introduced by senior welfare programs may depend on the type of senior welfare programs introduced and their target users. 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 the potential endogeneity issue, we use an instrumental variable (IV) approach.

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 increase in mortgage debt is not related to 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 number of senior living facilities in an HSA, using the previous year's number of single-family residential building permits issued in the HSA. 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 buildings[6] 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. In Section 5.3.3, we use the number of building permits approved two years before as a robustness test.

The exclusion restriction of the IV, $Permits_{h,t-1}$, holds for the following reasons. First, $Permits_{h,t-1}$ measures the number of single-family building permits instead of multi-family building permits. Since those in the senior population are not the primary buyers of new single-family homes (National Association of Realtor (2020) finds that 19.06% of single-family houses – newly constructed and not – were purchased by those 65+) 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. 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 where healthier seniors moving into HSAs with more attractive living conditions and more senior living facilities which drives down the average healthcare expenditure in those HSAs[7]. 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

[6] 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.

[7] We conduct robustness analysis by including the movers in our sample. Our findings qualitatively the same. See Table OA.6

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, and change in median senior household income.

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

- First stage:

$$SLF_{h_it} = \theta_0 + \theta_1 Permits_{h_i,t-1} + \boldsymbol{X}'_{it}\theta_2 + \boldsymbol{W}'_{h_it}\theta_3 + \boldsymbol{Z}'_{z_it}\theta_4 + \omega_{h_i} + \lambda_t + \varepsilon_{it}, \tag{3}$$

- Second stage:

  — 1st part:

$$Pr(y_{it} > 0) = \Phi\big(\pi_0 + \pi_1 SLF_{h_it} + \boldsymbol{X}'_{it}\pi_2 + \boldsymbol{W}'_{ht}\pi_3 + \boldsymbol{Z}'_{z_it}\pi_4 + \omega^1_{h_i} + \lambda^1_t + \hat{\varepsilon}_{it}\big), \quad \text{for } \forall\ y_{it} \tag{4}$$

  — 2nd part:

$$\ln y_{it} = \delta_0 + \delta_1 \widehat{SLF}_{h_it} + \boldsymbol{X}'_{it}\delta_2 + \boldsymbol{W}'_{h_it}\delta_3 + \boldsymbol{Z}'_{z_it}\delta_4 + \omega^2_{h_i} + \lambda^2_t + \zeta_{it}, \quad \text{for } y_{it} > 0, \tag{5}$$

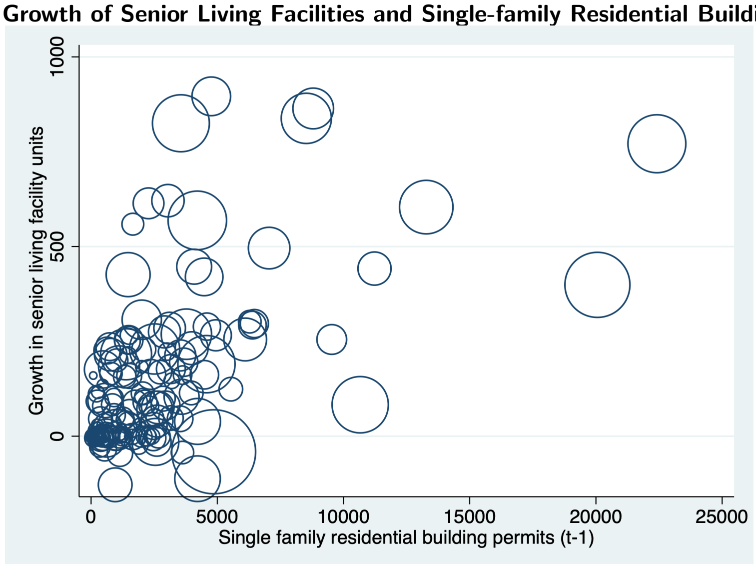
where Equation (3) is the first stage regression in which $Permits_{h,t-1}$ is the previous year's new single-family residential building permits in an HSA. We estimate π_1 using a control function approach where we include $\hat{\varepsilon}$, the residual from the first stage regression, in Equation (4)[8]. We estimate δ_1 by two-stage least squares with the fitted $\widehat{SLF}_{izht}$ from the first stage, Equation (3). All the other variables are defined as in Equation (1) and Equation (2).

We verify empirically that the instrument variable strongly predicts SLF_{ht}. Figure 2 shows the positive relationship between the growth of senior living facility units and the previous year's single-family residential building permits in 2017. Online Appendix Figure OA.1 illustrates the positive relationship between the two variables for all sample years from 2011 to 2019. We present the first-stage regression results from estimating Equation (3) in every estimation with the IV. We find that single-family residential building permits in the previous year have a strong positive relationship with the number of SL facilities in the current year in all our estimations with the IV. For example, in the analysis of SNF utilization in Table 2, a one-unit increase in single-family building permits is associated with a 0.0019 increase ($p < 0.001$) in SL facilities in the following year. This result supports that the new development of single-family residential buildings in an area is positively related to the development of senior living facilities due to common supply-side housing market conditions in the area. The first-stage F statistics is above the rule-of-thumb value of 10 in all the estimations with the IV.[9] Overall, the results suggest that the instrument variable is relevant and strong.

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

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

Figure 2 **Growth of Senior Living Facilities and Single-family Residential Building Permits**



Notes. The figure plots the growth of the number of senior living facility units (y-axis) and single-family residential building permits in the previous year (x-axis) for each HSA in 2017. The size of each bubble is proportional to the senior population in the HSA.

5. Results

5.1. Effects of Senior Living Facilities on Medicare Utilization

We analyze the effects of SL facilities on Medicare utilization using the two-part models with an IV described in Section 4. We consider four measures of Medicare utilization: SNF, inpatient, home health, and ED.

Table 2 presents the results of the analysis of SNF and inpatient utilization, and Table 3 presents the results for home health and ED utilization. The odd-numbered columns report the first-part (probit) results in which the outcome is binary (i.e., $\mathbb{1}(Payment > 0)$), and the even-numbered columns present the second-part results for the continuous outcomes (conditional on the outcome being positive). In Table 2 and Table 3, we include both the results with and without using the IV. When we report the results with the IV, we present the first-stage results together with the first-stage F statistics. We confirm that the IV is significantly positively correlated with the explanatory variable in all our estimations with the IV. For most outcomes, we see that the estimates without the IV are different from the estimates with the IV, suggesting that there may be significant biases in the estimates without accounting for endogeneities. Therefore, it is important to address the potential endogeneities using the IV, as we discuss in Section 4.1.3 and Section 4.2.

For SNF utilization, we find that more SL facilities significantly decrease the likelihood of SNF admissions among Medicare beneficiaries in the area. The coefficient of interest from the first-part (IV probit) in column 3 shows a significant negative estimate (-0.0019, $p < 0.05$). On the other hand, we do not find a significant effect (-0.00024, $p > 0.1$) in column 4 on the SNF spending, conditional on admission. By combining the first- and second-part results, we estimate that one additional SL facility reduces the annual SNF spending by \$1.994 ($p < 0.05$) per beneficiary. Aggregating over the average number of beneficiaries per HSA, this effect amounts to \$158,882.01 less spending per HSA-year. This decrease in SNF utilization is driven by a decrease in the likelihood of SNF admission rather than the reduction in spending when admitted to an SNF.

Next, we analyze the effects of SL facilities on inpatient utilization. We find weak evidence of that SL facilities reduce the likelihood of hospital admission, as suggested by a marginally significant negative estimate (-0.0014, $p < 0.1$) in column 7. In the analysis of inpatient spending conditional on admission, we find no significant effect of SL facilities ($0.00041, p > 0.1$) in column 8. Overall, we find that SL facilities have a marginally significant negative impact on inpatient utilization by decreasing annual inpatient spending by \$3.601 ($p < 0.1$) per beneficiary. We estimate the aggregate impact of \$286,606.63 less spending per HSA-year, on average.

For home health utilization and ED, we do not find significant effects of SL facilities (Table 3). Both in the first- and the second-part results in columns 3, 4, 7, and 8, we find no statistically significant estimates, suggesting that SL facilities, on average, have no significant impact on home health or ED utilization of Medicare beneficiaries living in the area.

Overall, our finding suggests that SL facilities have statistically significant negative effects on SNF and inpatient utilization by decreasing the likelihood of having admissions to SNFs and inpatient hospitals. On the other hand, we do not find significant effects of SL facilities on other healthcare utilization, including home health and ED visits. These results suggest that SL facilities decrease the need for medicare care among Medicare beneficiaries in the area for certain types of care, such as SNFs and inpatient hospital, but not for home health and EDs. Note here that the effect sizes that we estimate from our data will likely be smaller than the actual effect of SL facilities on their residents because we are analyzing the effects of SL facilities on Medicare beneficiaries in the area, not the beneficiaries residing in the SL facilities, as we explained in Section 4.1.1.

Table 2 **Effects of Senior Living Facilities on SNF and Inpatient Utilization**

Outcome	SNF payments				Inpatient payments			
Model	Without IV		With IV		Without IV		With IV	
	(1) Probit	(2) OLS	(3) IVProbit	(4) 2SLS	(5) Probit	(6) OLS	(7) IVProbit	(8) 2SLS
SL facilities	-0.00012	-0.00075	-0.0019*	-0.00024	0.00026	0.00033	-0.0014+	0.00041
	(0.00070)	(0.0010)	(0.00086)	(0.00091)	(0.00048)	(0.00036)	(0.00078)	(0.00050)
1st stage results								
Single-family building permits$_{t-1}$	-	-	0.0019***	0.0019***	-	-	0.0019***	0.0019***
			(0.0000)	(0.0002)			(0.0000)	(0.0002)
Kleibergen-Paap F-statistics	-	-	125.9	136.7	-	-	126.0	135.3
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148	148	148	148	148
Years	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019
Observations	106,124,564	4,027,022	106,124,564	4,027,022	106,020,795	14,300,130	106,020,795	14,300,130

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under $500, percentage of housing with rent between $500 and $1500, percentage of housing values under $50k, percentage of housing values between $50k and $1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, ED: emergency department, HSA: health service area, IV: instrumental variable, OLS: ordinary least squares, 2SLS: 2-stage least squares. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 3 Effects of Senior Living Facilities on Home Health and ED Utilization

Outcome	Home health payments				ED visits			
Model	Without IV		With IV		Without IV		With IV	
	(1) Probit	(2) OLS	(3) IVProbit	(4) 2SLS	(5) Probit	(6) OLS	(7) IVProbit	(8) 2SLS
SL facilities	-0.0012^{+}	-0.00084	-0.0012	0.00040	-0.00035	-0.00018	-0.00044	-0.000064
	(0.00060)	(0.00076)	(0.0011)	(0.0021)	(0.00035)	(0.00010)	(0.00054)	(0.00021)
1st stage results								
Single-family building permits$_{t-1}$	-	-	0.0019***	0.0018***	-	-	0.0019***	0.0019***
			(0.0000)	(0.0002)			(0.0000)	(0.0002)
Kleibergen-Paap F statistics	-	-	126.1	138.3	-	-	125.9	140.6
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148	148	148	148	148
Years	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019
Observations	106,075,919	8,842,825	106,075,919	8,842,825	105,951,642	24,973,815	105,951,642	24,973,815

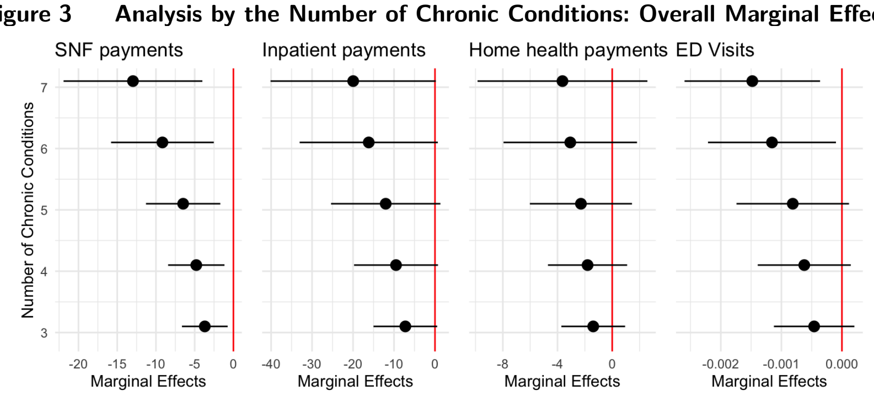
Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under $500, percentage of housing with rent between $500 and $1500, percentage of housing values under $50k, percentage of housing values between $50k and $1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, ED: emergency department, HSA: health service area, IV: instrumental variable, OLS: ordinary least squares, 2SLS: 2-stage least squares. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

5.2. Potential Mechanism: Care for Chronic Conditions

In this section, we 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. The top ten chronic conditions amongst SL facility residents are hypertension (57%), Alzheimer's disease and other dementias (42%), heart disease (34%), depression (28%), arthritis (27%), osteoporosis (21%), diabetes (17%), chronic obstructive pulmonary disease (15%), cancer (11%), and stroke (11%) (Khatutsky et al. 2016). 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 facilities 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 our 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 **Analysis by the Number of Chronic Conditions: Overall Marginal Effects**



Notes. The overall marginal effects (point) of SL facilities on healthcare utilization by type of care (each subfigure) and by the number of chronic conditions (y-axis). The black error bar represents the 95% confidence interval.

Figures 3 and 4 summarize the results of the analysis by the number of chronic conditions. Detailed results are presented in Online Appendix Tables OA.2 - OA.5. Figure 3 presents the estimates of the overall marginal effects of SL facilities on SNF, inpatient, home health, and ED care, which are calculated by combining both the first- and second-part analyses results. We find that as the number of chronic conditions that a beneficiary has increases (y-axis), the marginal effects of SL facilities on healthcare utilization become more negative, suggesting that the effects of SL facilities on SNF and inpatient utilization become more pronounced.

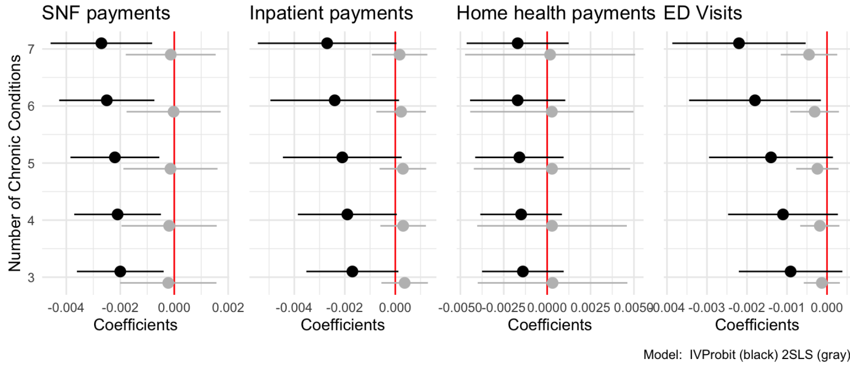
The estimated marginal effects for SNF utilization are all statistically significant ($p < 0.5$), and for inpatient utilization, the estimates are marginally significant ($p < 0.1$). For home health, the estimates do not show statistical significance. For ED visits, the marginal effects are not significantly different from 0 for beneficiaries with 3 or 4 chronic conditions, but for the beneficiaries with 5, 6, and 7 chronic conditions, the estimates show statistical significance at 10%, 5%, and 1% levels, respectively.

The increasing negative marginal effects in the number of chronic conditions shown in Figure 3 are driven by the increasing negative effects on the likelihood of using healthcare services. As Figure 4 shows, we find that the coefficients from the first-part (IV probit) results become more negative as the number of chronic conditions increases, but the coefficients from the second part (2SLS) do not show a similar pattern and are not statistically significant. Our results demonstrate that the more chronic diseases a beneficiary has, the larger the impact of increased SL facilities on reducing healthcare utilization. Such findings are consistent with our hypothesis about chronic disease management. 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 that chronic disease management provided at these facilities may be driving the reduction in healthcare utilization. Our results are consistent with those of Kim et al. (2016), that, in a systematic review of 67 medical articles, document some benefits of chronic disease management by community-based health workers.Although this paper does not focus on SL facilities, they document 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. Robustness Analyses

In this section, we conduct multiple sets of additional analyses to examine the robustness of our results.

Figure 4 Analysis by the Number of Chronic Conditions: Two Part Results



Notes. Each panel shows the analysis results of the two part models, first-part IV probit (black) and second-part 2SLS (gray), by the number of chronic conditions (y-axis) and by the type of care: SNF, inpatient, home health, and ED. The error bar represents the 95% confidence interval.

5.3.1. Alternative Explanatory Variable The main analysis uses the number of SL facilities in an HSA-year as the explanatory variable. Here, we rerun our analysis using the number of SL facility units instead of the number of SL facilities because each SL facility has a different capacity (i.e., units), and a larger number of SL facilities does not necessarily correspond to a larger number of SL facility units in an HSA. However, we chose the number of SL facilities as our main explanatory variable because it shows a stronger relationship with the IV, $Permits_{i,t-1}$, as we find in the first-stage regression results.

Table 4 presents the results using SL facility units as the explanatory variable. First, we find consistent findings for SNF utilization as we find a statistically significant negative marginal effect (estimate $= -0.018$, $p < 0.05$) with a significant negative coefficient in the first part, the analysis of the likelihood of having an SNF admission (estimate $= -0.000017$, $p < 0.05$). Because the values of the number of SL facility units are much bigger than the SL facilities, the estimates in Table 4 are much smaller than those in Table 2. However, when looking at the marginal effects, when we consider adding another average-sized SL facility (128 units), the total dollars saved in an HSA-year is \$181,050.88, which is a similar order of magnitude with our main results of \$158,882.01 in SNF savings in an HSA-year.

When using SL facility units as the explanatory variable for the analysis of inpatient utilization, the estimated effect of one SL facility unit marginally significant (estimate $= -0.034$, $p < 0.1$). When we consider adding another average-sized SL facility (128 units), the total inpatient dollars saved in an HSA-year is \$343,032.32. Similar to our main results, the effect is driven by reductions in inpatient admissions, but there is no statistically significant effect on inpatient spending, conditional on admission.

As SL facility units include both assisted living and independent living units, we conduct an additional robustness check using only assisted living units as the explanatory variable, given that

Table 4 **Estimations Using an Alternative Explanatory Variable: SL Units**

Outcome	SNF payments		Inpatient payments	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS
SL units	-0.000017*	-0.0000026	-0.000013+	0.0000056
	(0.0000075)	(0.0000086)	(0.0000074)	(0.0000045)
1st stage results				
Single-family building permits$_{t-1}$	0.1999***	0.1954***	0.1999***	0.1982***
	(0.0000)	(0.0276)	(0.0000)	(0.0274)
Kleibergen-Paap F-statistics	69.2	60.5	69.2	67.0
Fixed effects	HSA	HSA	HSA	HSA
	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148
Years	2011–2019	2011–2019	2011–2019	2011–2019
Observations	106,124,564	4,027,022	106,020,795	14,300,130

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under $500, percentage of housing with rent between $500 and $1500, percentage of housing values under $50k, percentage of housing values between $50k and $1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care units, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^+p<0.1$, $^*p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

prior literature on residents' health in senior living facilities primarily focuses on assisted living settings. Table OA.12 presents the effects of assisted living units on SNF and inpatient payments. The significance levels are the same as those observed for SL facility units, and we find even larger effects for assisted living units, with marginal effects of -0.026 on SNF payments and -0.049 on inpatient payments.

5.3.2. Alternative Outcome Variable We also analyze LOS as an alternative measure of healthcare utilization instead of dollar spending. We collect the annual LOS in SNFs and inpatient hospitals from the CMS MBSF Cost and Use data files. Table 5 displays the results. We find consistent results for both the SNF and inpatient utilization. For the SNF, we find that one additional SL facility decreases the annual LOS by 0.003 days ($p < 0.05$) per beneficiary. This marginal effect aggregates to 244.67 fewer SNF days per HSA (columns 1 and 2).

For inpatient utilization, we find a statistically significant effect of -0.001 days ($p<0.05$) per beneficiary per year, which sums to 82.11 fewer annual hospital days per HSA (columns 3 and 4). Unlike the main result, the second-part analysis (positive outcome) of inpatient LOS in column 4 shows a statistically significant *positive* coefficient (estimate = 0.00088, $p < 0.05$). However, because the SL facility decreases the likelihood of admissions significantly (estimate = -0.0014, $p < 0.05$), the overall marginal effect on inpatient LOS becomes negative. This result may also suggest that the people who are getting admitted to the hospital really need to be there and have

Table 5 **Estimations Using an Alternative Outcome Variable: Length of Stay**

Outcome	SNF LOS		Inpatient LOS	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS
SL facilities	-0.0020*	0.0016	-0.0014*	0.00088*
	(0.00084)	(0.00095)	(0.00064)	(0.00043)
1st stage results				
Single-family building permits$_{t-1}$	0.0019***	0.0019***	0.0019***	0.0019***
	(0.0000)	(0.0002)	(0.0000)	(0.0002)
Kleibergen-Paap F-statistics	125.9	136.7	126.1	138.0
Fixed effects	HSA	HSA	HSA	HSA
	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148
Years	2011–2019	2011–2019	2011–2019	2011–2019
Observations	106,124,931	4,027,359	106,031,487	13,844,778

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under \$500, percentage of housing with rent between \$500 and \$1500, percentage of housing values under \$50k, percentage of housing values between \$50k and \$1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, LOS: length of stay, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

severe conditions, so the inpatient LOS increases. One potential explanation is that the resources available at SL facilities – including, but not limited to, regular health check-ins – may result in better triage of which individuals should be referred to the hospital versus those who could be managed outside of the hospital at their facility. Hence, fewer patients are being admitted to the hospital, but those that are, are sicker and stay slightly longer.

5.3.3. Alternative Instrumental Variable As we explain in Section 4.2, we use the single-family residential building permits in an HSA in the previous year, $Permits_{h,t-1}$, as the IV. We use a one-period lagged variable to account for the time delay from the permit approval to the completion of the building construction. Because the delays may be longer than one year, we use the two-year lagged single-family residential building permits, $Permits_{h,t-2}$, as a robustness test.

Table 6 presents the results of the analysis using $Permits_{h,t-2}$ as the IV. First, when using a two-year lagged IV, the first-stage F statistics become smaller than when using $Permits_{h,t-1}$ as the IV. For example, in column 1, the first-stage F statistic is 72.7, whereas the corresponding analysis in Table 2 yields a larger first-stage F statistic, 125.9. With this caution of weaker first-stage result, we find consistent estimates for the SNF utilization in columns 1 and 2, but for the inpatient utilization in columns 3 and 4, the first-part as well as the marginal effect shows statistically insignificant results. This could be because of the weaker first-stage results and statistically weaker effects of SL facilities on inpatient utilization that we find in Table 2.

Table 6 Estimations Using an Alternative Instrumental Variable: Single-family building permits$_{t-2}$

Outcome	SNF payments		Inpatient payments	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS
SL facilities	-0.0017^{+}	-0.00053	-0.0012	0.00037
	(0.00088)	(0.00097)	(0.00080)	(0.00041)
1st stage results				
Single-family building permits$_{t-2}$	0.0022***	0.0022***	0.0022***	0.0022***
	(0.0000)	(0.0003)	(0.0000)	(0.0003)
Kleibergen-Paap F-statistics	72.7	81.0	72.8	76.5
Fixed effects	HSA	HSA	HSA	HSA
	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148
Years	2011–2019	2011–2019	2011–2019	2011–2019
Observations	106,124,564	4,027,022	106,020,795	14,300,130

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under \$500, percentage of housing with rent between \$500 and \$1500, percentage of housing values under \$50k, percentage of housing values between \$50k and \$1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

5.3.4. 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 moving decision by the movers, as well as healthcare utilization, may be influenced by the new residential buildings in the area where they are moving to. However, excluding them results in removing a substantial number of observations, as we describe in Section 3.2. 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 observations (in SNF analysis) to 121,580,671.

Table OA.6 presents the analysis results with movers in the sample. The results are consistent for SNF utilization. For SNF, we estimate the marginal effect of -2.092 ($p < 0.05$) , slightly larger in magnitude than that in our main analysis (-1.994, $p < 0.05$). Therefore, the results suggest that our main analysis without movers yields a conservative estimate for SNF. For inpatient care, the marginal effect, -3.440, is slightly smaller in magnitude compared to the main analysis (-3.601) and is marginally significant ($p < 0.1$). With this analysis, 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.

5.3.5. Including HSAs with caps on permits or not included in land use survey As noted in Section 3.2, we exclude beneficiaries in HSAs which have a cap on the number of building permits or which it is unknown whether they have a cap because they are not included in the land use survey. These exclusions are because the relevance of our IV is based on supply-side housing market conditions, which are proxied by the number of single-family residential building permits issued in the HSA. We run robustness checks including these beneficiary-years. The results for SNF payments are reported in Table OA.7 and those for inpatient payments in Table OA.8. These magnitude and sign of these results are largely consistent with our main results, though the significance is impacted. We can see that the results which include just the HSAs with unknown permits cap are largely consistent with our main results, thought the results are marginally significant ($p < 0.10$). When including HSAs with permit cap, the marginal significance is mostly lost. This is likely due to the fact that the IV is weaker as we include these additional HSAs. This is not surprising due to the fact that caps on building permits would jeopardize the validity of the IV. However, this impact is mitigated when only adding HSAs with unknown cap, because while some of these may have constraints on the total number of building permits, others may not and the IV will still work in a subset of these added HSAs.

5.3.6. One-way Clustered Standard Errors In our analysis so far, we use two-way clustering at the HSA and year level to account for potential correlation within the clusters, as the treatment variable (i.e., the number of senior living facilities) varies at HSA-year levels (Abadie et al. 2023). To test the robustness of our results using different clustered standard errors, we rerun our analysis using HSA clustered standard errors instead of the two-way clustering. We present the results in Online Appendix Table OA.9.

We find that for the analysis of SNF, the standard errors of the IV probit model become slightly smaller when using HSA-level clustering than the two-way clustering in our main analysis. The coefficient of SL facilities in the first-part is -0.0019 ($p < 0.05$) with standard error of 0.00079. The standard errors in the second-part (2SLS), 0.0012, remain unchanged compared to using two-way standard errors. For inpatient analysis, the standard errors become slightly larger in the IV probit model than the two-way clustered standard errors. The coefficient of SL facilities is -0.0014 ($p > 0.1$), with standard errors of 0.00088, while in the main result, the coefficient is marginally significant ($p < 0.1$), with standard errors of 0.00078. Overall, our results do not change significantly when using one-way clustered standard errors at the HSA-level.

5.3.7. Alternative Specifications for Control Variables Our primary specification includes controls related to our IV as change variables, while others are included as level variables. We conduct robustness checks by controlling for all census characteristics as changes and in levels, as shown in Table OA.10 (for SNF payments) and Table OA.11 (for inpatient payments). The results for SNF payments remain consistent with the main specification (Table 2), and controlling for changes in all census characteristics makes the effect on inpatient payments significant at the 5% level.

6. Conclusion

6.1. Summary

Our study examines the effects of SL facilities on healthcare utilization and Medicare spending among beneficiaries in the area. Using an IV approach on the entirety of Medicare fee-for-service claims data, we find that SL facilities significantly decrease SNF admissions, suggesting that SL facilities could effectively reduce the need for post-acute care after hospital discharges. In addition, we find SL facilities weakly (i.e., marginal statistical significance at the 10% level) reduce inpatient admissions, indicating that SL facility services could improve senior health conditions. This is further supported by additional analyses that show that the beneficial effects of SL facilities become larger for seniors with more chronic conditions as SL facilities provide specialized services for chronic disease care. Our findings remain consistent with several robustness tests, including using alternative explanatory, outcome, or IV and different specifications and samples.

6.2. Contribution to the Literature

This paper is one of the early works that examine the effects of SL facilities on senior health conditions and healthcare utilization (Hua et al. 2021, Sharpp and Young 2016, Lei et al. 2023, NORC 2024, Munevar et al. 2024). Previous research relies on rudimentary analyses such as group comparisons between SL facility residents and community-dwelling seniors (Hua et al. 2021, Lei et al. 2023, NORC 2024, Munevar et al. 2024), or case studies (Sharpp and Young 2016). We attempt to yield a rigorous causal estimate by using an IV approach. In addition, our empirical findings are novel and contribute to the literature by first analyzing the effects of SL facilities on Medicare expenditure and also examining different types of health care by differentiating the likelihood of healthcare consumption and the expected expenditure conditional on a positive consumption using a two-part model. Previous works have not examined expenditure in monetary values nor employed two-part models. Specifically, we are the first to examine the effects of SL facilities on SNF expenditure. Second, we examine the effects of SL facilities that include both assisted and independent living facilities, while previous papers focused more on assisted living facilities (Hua et al. 2021, Sharpp and Young 2016, Lei et al. 2023). Third, we use comprehensive data that includes 100% Medicare fee-for-service beneficiaries spanning a longer period from 2011 to 2019. Other papers use cross-sectional analyses or cover a limited time frame. Unlike others, we use a panel regression method accounting for HSA-fixed and year-fixed effects.

6.3. Implications of the Findings

Our findings are important for Medicare and policymakers for several reasons. First, there is some evidence that SL facilities have been used as substitutes for nursing homes, which are more traditional long-term care providers, for patients with low acuity levels (Grabowski et al. 2012, Cornell et al. 2020), yet there is no comprehensive understanding of their effects on senior health conditions and healthcare expenditure. Our findings help fill this gap. Second, as Medicare faces financial challenges due to the increasing enrollment of seniors (Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds 2022, Cubanski and Neuman 2023), it is essential to study ways to manage and reduce Medicare spending. Our findings suggest that new residential environment for seniors that provide long-term care, SL facilities, could be helpful to reduce Medicare spending. Our analysis estimate that one additional SL facility in an HSA could reduce aggregate Medicare spending among beneficiaries in the area by \$158,882.01 per year for SNF, and \$286,606.63 per year for inpatient hospital care. These estimates suggest that adding one SL facility in each HSA across the U.S. (952 HSAs in total) would reduce Medicare and beneficiary payments on SNF by \$151.3 million (0.53% of total Medicare spending on SNF) and inpatient hospitalizations by \$272.8 million (0.19% of total Medicare spending on inpatient hospital[10]). Lastly, with increasing number of residents in SL facilities, there are ongoing discussions about 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 results showing the effectiveness of SL facilities in decreasing healthcare spending (SNF and inpatient) could be useful for policymakers in this discussion.

6.4. 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 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 4.1.1. Therefore, our estimands pertain to the effects of SL facilities on Medicare spending of Medicare beneficiaries living in the area (not living in SL

[10] In 2023, the total Medicare fee-for-service expenditure on SNF and inpatient hospital were \$28.5 billion and \$144.4 billion, respectively (Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds 2024).

facilities). Our estimates are useful for assessing SL facilities' effects on Medicare's expenditure. However, they would underestimate the effects of SL facilities on the healthcare spending of the residents living in these facilities as we dilute the magnitude of the estimates by including all Medicare beneficiaries living in the area. 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.

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Online Appendices

Online Appendix A: Data and Variables

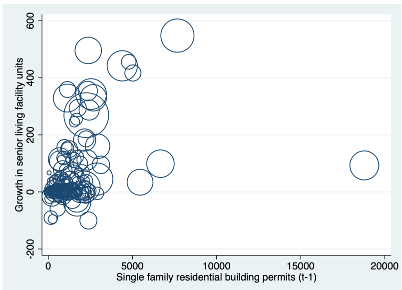
Table OA.1 Data and Variables

Data	Variable	Variation	Year[1]
Medicare Master Beneficiary Summary File (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, number of SNF organizations	beneficiary-year	2011 – 2019
MBSF Base	Age, sex, race, date of death (if any), ZIP code, county code	beneficiary-year	2011 – 2019
MBSF 27 Chronic Conditions	Chronic conditions	beneficiary-year	2011 – 2019
Welltower Senior Living Community Dataset	Number of senior living community units, number of nursing home units	Health service area (HSA)-quarter level	2008 – 2019
American Hospital Association	Number of inpatient beds	HSA-year level	2011 – 2019
U.S. Census Bureau	Education level, household size, rent, house values, income, population, number of businesses	ZIP code-year level	2011 – 2019

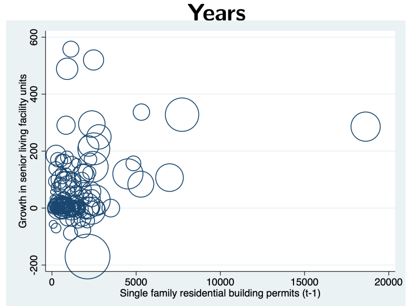
Notes. [1] The years of data that we have access to.

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

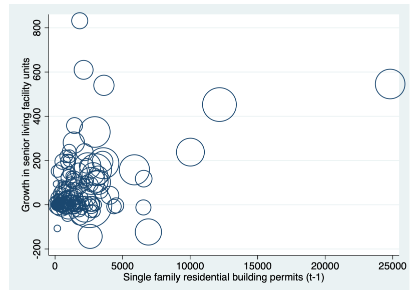
Figure OA.1 Growth of Senior Living Facilities and Single-family Residential Building Permits for All Sample Years



(a) Year: 2011

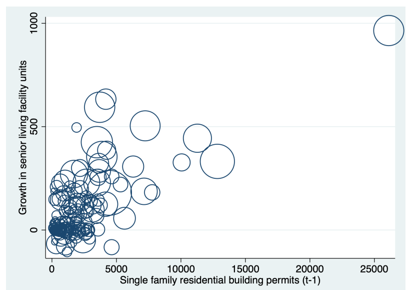


(b) Year: 2012

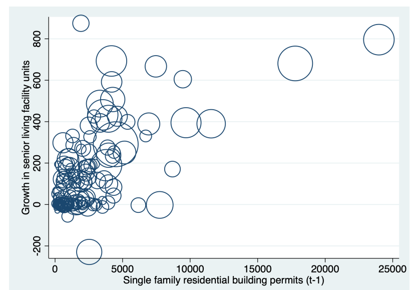


(c) Year: 2013

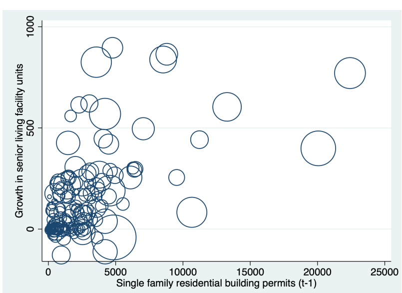
(d) Year: 2014



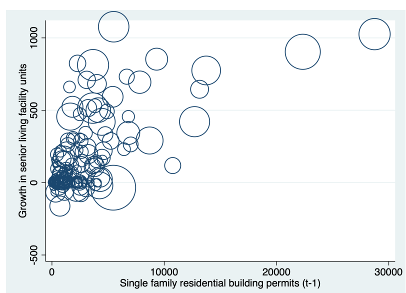
(e) Year: 2015



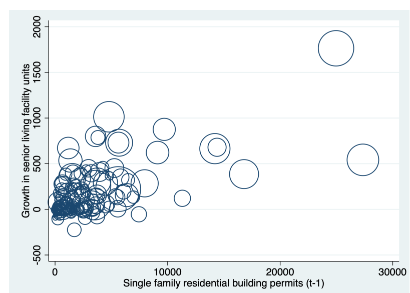
(f) Year: 2016



(g) Year: 2017



(h) Year: 2018



(i) Year: 2019

Notes. Each figure plots the growth of the number of senior living facility units (y-axis) and single-family residential building permits in the previous year (x-axis) for each HSA. The size of each bubble is proportional to the senior population in the HSA.

Online Appendix C: Analysis by Number of Chronic Conditions

Table OA.2 Effects of SL Facilities on SNF Utilization by Number of Chronic Conditions

Outcome	SNF payments									
Sample: Number of chronic conditions	3 conditions		4 conditions		5 conditions		6 conditions		7 conditions	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS	(5) IVProbit	(6) 2SLS	(7) IVProbit	(8) 2SLS	(9) IVProbit	(10) 2SLS
SL facilities	-0.0020*	-0.00022	-0.0021**	-0.00019	-0.0022**	-0.00014	-0.0025**	-0.000023	-0.0027**	-0.00013
	(0.00082)	(0.00091)	(0.00082)	(0.00090)	(0.00084)	(0.00089)	(0.00090)	(0.00089)	(0.00096)	(0.00085)
1st stage results										
Single-family building permits$_{t-1}$	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***
	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)
Kleibergen-Paap F-statistics	149.1	136.5	153.2	136.2	157.3	136.1	161.9	136.7	163.3	135.5
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148	148	148	148	148	148	148
Observations	58,983,845	3,969,339	46,100,666	3,868,059	33,719,017	3,674,274	23,418,231	3,363,625	15,597,794	2,936,978

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. All estimations include HSA- and year-fixed effects. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under \$500, percentage of housing with rent between \$500 and \$1500, percentage of housing values under \$50k, percentage of housing values between \$50k and \$1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table OA.3 Effects of SL Facilities on Inpatient Utilization by Number of Chronic Conditions

Outcome	Inpatient payments									
Sample: Number of chronic conditions	3 conditions		4 conditions		5 conditions		6 conditions		7 conditions	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS	(5) IVProbit	(6) 2SLS	(7) IVProbit	(8) 2SLS	(9) IVProbit	(10) 2SLS
SL facilities	-0.0017^{+}	0.00037	-0.0019^{+}	0.00031	-0.0021^{+}	0.00030	-0.0024^{+}	0.00023	-0.0027*	0.00017
	(0.00093)	(0.00047)	(0.0010)	(0.00046)	(0.0012)	(0.00047)	(0.0013)	(0.00050)	(0.0014)	(0.00056)
1st stage results										
Single-family building permits$_{t-1}$	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***
	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)
Kleibergen-Paap F statistics	149.4	136.3	153.7	137.0	157.9	138.7	162.6	141.0	164.2	142.1
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148	148	148	148	148	148	148
Observations	58,887,138	13,543,314	46,011,748	12,670,954	33,641,400	11,358,312	23,354,490	9,674,033	15,548,840	7,783,424

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under \$500, percentage of housing with rent between \$500 and \$1500, percentage of housing values under \$50k, percentage of housing values between \$50k and \$1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table OA.4 Effects of SL Facilities on Home Health Utilization by Number of Chronic Conditions

Outcome	Home health payments									
Sample: Number of chronic conditions	3 conditions		4 conditions		5 conditions		6 conditions		7 conditions	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS	(5) IVProbit	(6) 2SLS	(7) IVProbit	(8) 2SLS	(9) IVProbit	(10) 2SLS
SL facilities	-0.0014	0.00031	-0.0015	0.00028	-0.0016	0.00028	-0.0017	0.00027	-0.0017	0.00017
	(0.0012)	(0.0022)	(0.0012)	(0.0022)	(0.0013)	(0.0023)	(0.0014)	(0.0024)	(0.0015)	(0.0025)
1st stage results										
Single-family building permits$_{t-1}$	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***
	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)
Kleibergen-Paap F statistics	149.6	137.9	153.8	138.0	158.0	138.1	162.7	139.3	164.2	140.1
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148	148	148	148	148	148	148
Observations	58,938,296	8,478,703	46,058,865	8,006,410	33,682,710	7,268,624	23,388,662	6,291,033	15,575,406	5,153,404

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under \$500, percentage of housing with rent between \$500 and \$1500, percentage of housing values under \$50k, percentage of housing values between \$50k and \$1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table OA.5 Effects of SL Facilities on ED Utilization by Number of Chronic Conditions

Outcome	ED visits									
Sample: Number of chronic conditions	3 conditions		4 conditions		5 conditions		6 conditions		7 conditions	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS	(5) IVProbit	(6) 2SLS	(7) IVProbit	(8) 2SLS	(9) IVProbit	(10) 2SLS
SL facilities	-0.00091	-0.00013	-0.0011	-0.00018	-0.0014^{+}	-0.00024	-0.0018*	-0.00031	-0.0022**	-0.00045
	(0.00066)	(0.00023)	(0.00070)	(0.00025)	(0.00079)	(0.00027)	(0.00084)	(0.00031)	(0.00085)	(0.00036)
1st stage results										
Single-family building permits$_{t-1}$	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***
	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0002)
Kleibergen-Paap F statistics	149.2	145.2	153.4	147.3	157.5	150.1	162.1	152.5	163.6	153.1
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148	148	148	148	148	148	148
Observations	58,813,617	21,426,934	45,997,129	18,997,939	33,617,755	15,964,374	23,358,195	12,782,044	15,539,613	9,687,712

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under \$500, percentage of housing with rent between \$500 and \$1500, percentage of housing values under \$50k, percentage of housing values between \$50k and \$1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, ED: emergency department, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Online Appendix D: Results of Robustness Tests

Table OA.6 Analysis with Movers in the Sample

Outcome	SNF payments		Inpatient payments	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS
SL facilities	-0.0020*	-0.00011	-0.0014+	0.00065
	(0.00079)	(0.00088)	(0.00077)	(0.00046)
Fixed effects	HSA	HSA	HSA	HSA
	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148
Years	2011–2019	2011–2019	2011–2019	2011–2019
Observations	121,580,671	4,794,943	121,461,032	16,639,163

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under $500, percentage of housing with rent between $500 and $1500, percentage of housing values under $50k, percentage of housing values between $50k and $1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table OA.7 Analysis of HSAs with Permit Cap: SNF Payments

Outcome	SNF payments		SNF payments		SNF payments	
Additions to Main Sample	HSAs with permits cap and unknown cap		HSAs with unknown permits cap		HSAs with permits cap	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS	(5) IVProbit	(6) 2SLS
SL facilities	-0.00100	-0.000025	-0.0015+	-0.00034	-0.0014+	-0.000087
	(0.00075)	(0.00096)	(0.00082)	(0.00086)	(0.00075)	(0.0010)
1st stage results						
Single-family building permits$_{t-1}$	0.0020***	0.0020***	0.0020***	0.0019***	0.0020***	0.0020***
	(0.0000)	(0.0003)	(0.0000)	(0.0002)	(0.0000)	(0.0003)
Kleibergen-Paap F-statistics	73.4	71.1	138.6	148.0	64.7	62.3
Fixed effects	HSA	HSA	HSA	HSA	HSA	HSA
	Year	Year	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	186	186	160	160	174	174
Years	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019
Observations	137,034,083	5,215,295	113,045,879	4,283,971	130,112,767	4,958,345

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under $500, percentage of housing with rent between $500 and $1500, percentage of housing values under $50k, percentage of housing values between $50k and $1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table OA.8 Analysis of HSAs with Permit Cap: Inpatient Payments

Outcome	Inpatient payments		Inpatient payments		Inpatient payments	
Additions to Main Sample	HSAs with permits cap and unknown cap		HSAs with unknown permits cap		HSAs with permits cap	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS	(5) IVProbit	(6) 2SLS
SL facilities	-0.0010	0.00058	-0.0013^{+}	0.00046	-0.0011	0.00049
	(0.00090)	(0.00040)	(0.00075)	(0.00045)	(0.00092)	(0.00043)
1st stage results						
Single-family building permits$_{t-1}$	0.0020^{***}	0.0020^{***}	0.0020^{***}	0.0019^{***}	0.0020^{***}	0.0020^{***}
	(0.0000)	(0.0003)	(0.0000)	(0.0002)	(0.0000)	(0.0003)
Kleibergen-Paap F-statistics	73.4	73.4	138.8	148.1	64.8	63.3
Fixed effects	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year	HSA Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of HSAs	186	186	160	160	174	174
Years	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019	2011–2019
Observations	136,900,506	18,439,419	112,935,258	15,235,471	129,986,043	17,504,078

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under \$500, percentage of housing with rent between \$500 and \$1500, percentage of housing values under \$50k, percentage of housing values between \$50k and \$1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

Table OA.9 Estimations Using One-Way Clustered Standard Errors

Outcome	SNF payments		Inpatient payments	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS
SL facilities	-0.0019^{*}	-0.00024	-0.0014	0.00041
	(0.00079)	(0.0012)	(0.00088)	(0.00056)
Fixed effects	HSA Year	HSA Year	HSA Year	HSA Year
Controls	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148
Years	2011–2019	2011–2019	2011–2019	2011–2019
Observations	106,124,564	4,027,022	106,020,795	14,300,130

Notes. Clustered standard errors at the HSA are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under \$500, percentage of housing with rent between \$500 and \$1500, percentage of housing values under \$50k, percentage of housing values between \$50k and \$1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

Table OA.10 Estimations Using All Changes or All Levels Census Control Variables on SNF Payments

Outcome	SNF payments		SNF payments	
Control	All Changes Census		All Levels Census	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS
SL facilities	-0.0020*	0.000060	-0.0020*	-0.00027
	(0.00088)	(0.00095)	(0.00084)	(0.00093)
Fixed effects	HSA	HSA	HSA	HSA
	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148
Years	2011–2019	2011–2019	2011–2019	2011–2019
Observations	106,027,091	4,022,941	106,124,564	4,027,022

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (for columns (1) and (2): percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under $500, percentage of housing with rent between $500 and $1500, percentage of housing values under $50k, percentage of housing values between $50k and $1 million, income per capita, senior population, percentage of owner-occupied housing units, the number of businesses, median senior household income; for columns (3) and (4): change in percentage of families with more than three members, change in percentage of people with at least a bachelor's degree, change in percentage of housing with rent under $500, change in percentage of housing with rent between $500 and $1500, change in percentage of housing values under $50k, change in percentage of housing values between $50k and $1 million, change in income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

Table OA.11 Estimations Using All Changes or All Levels Census Control Variables on Inpatient Payments

Outcome	Inpatient payments		Inpatient payments	
Control	All Changes Census		All Levels Census	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS
SL facilities	-0.0015*	0.00037	-0.0013	0.00035
	(0.00077)	(0.00050)	(0.00081)	(0.00050)
Fixed effects	HSA	HSA	HSA	HSA
	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148
Years	2011–2019	2011–2019	2011–2019	2011–2019
Observations	105,923,434	14,284,972	106,020,795	14,300,130

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (for columns (1) and (2): percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under $500, percentage of housing with rent between $500 and $1500, percentage of housing values under $50k, percentage of housing values between $50k and $1 million, income per capita, senior population, percentage of owner-occupied housing units, the number of businesses, median senior household income; for columns (3) and (4): change in percentage of families with more than three members, change in percentage of people with at least a bachelor's degree, change in percentage of housing with rent under $500, change in percentage of housing with rent between $500 and $1500, change in percentage of housing values under $50k, change in percentage of housing values between $50k and $1 million, change in income per capita, 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 (4) HSA-level healthcare supply (number of nursing care properties, number of SNF organizations, number of inpatient beds). SL: senior living, SNF: skilled nursing facility, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

Table OA.12 Estimations Using an Alternative Explanatory Variable: Assisted Living Units

Outcome	SNF payments		Inpatient payments	
Model	(1) IVProbit	(2) 2SLS	(3) IVProbit	(4) 2SLS
AL units	-0.000025*	-0.0000038	-0.000019^{+}	0.0000080
	(0.000011)	(0.000012)	(0.000011)	(0.0000065)
1st stage results				
Single-family building permits$_{t-1}$	0.1375***	0.1377***	0.1375***	0.1376***
	(0.0000)	(0.0166)	(0.0000)	(0.0166)
Kleibergen-Paap F-statistics	82.1	81.0	82.1	83.8
Fixed effects	HSA	HSA	HSA	HSA
	Year	Year	Year	Year
Controls	Yes	Yes	Yes	Yes
Number of HSAs	148	148	148	148
Years	2011–2019	2011–2019	2011–2019	2011–2019
Observations	106,124,564	4,027,022	106,020,795	14,300,130

Notes. Two-way clustered standard errors at the HSA and year are reported in parentheses. Control variables include: (1) patient characteristics (age, sex, race); (2) 26 chronic condition indicators; (3) zipcode-level census characteristics (percentage of families with more than three members, percentage of people with at least a bachelor's degree, percentage of housing with rent under $500, percentage of housing with rent between $500 and $1500, percentage of housing values under $50k, percentage of housing values between $50k and $1 million, income per capita, 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 (4) HSA-level healthcare supply (number of nursing care units, number of SNF organizations, number of inpatient beds). AL: assisted living, SNF: skilled nursing facility, HSA: health service area, IV: instrumental variable, 2SLS: 2-stage least squares. $^{+}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.