Policy Determinants of Medicaid Nursing Home Use in Pennsylvania, 2013-2019

by

Damian Ramon Da Costa

B.A., Yale College, 1998

M.A., CUNY Graduate Center, 2006

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This dissertation was presented

by

Damian Ramon Da Costa

It was defended on

December 15, 2022

and approved by

Eric T. Roberts, Assistant Professor, Health Policy and Management,
School of Public Health, University of Pittsburgh

Steven M. Albert, Professor, Behavioral and Community Health Sciences,
School of Public Health, University of Pittsburgh

Marc Cohen, Clinical Professor, Department of Gerontology,
McCormack Graduate School, University of Massachusetts, Boston

Dissertation Director: Howard B. Degenholtz, Professor, Health Policy and Management,
School of Public Health, University of Pittsburgh

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Damian Ramon Da Costa, PhD

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This dissertation applies statistical modeling techniques to estimate the impact of policy determinants on nursing home use in the Medicaid-covered population in Pennsylvania during the years 2013-2019. Using difference-in-difference analysis, the first essay exploits Pennsylvania's staggered implementation of mandatory managed care to investigate whether longstay (>100 day) nursing home residents in counties that moved to managed care were more likely to be successfully discharged to a community setting within six months of longstay incidence. The second essay models the association between regional subsidized housing access and discharge to a community setting among longstay nursing facility residents. The third essay uses probabilistic matching to assign HUD program status (public housing, Section 8 project-based, and Section 202) to a population of waiver-eligible Pennsylvania Medicaid enrollees. Time-to-event analysis is applied to compare hazard of nursing home admission among these three housing-defined Medicaid populations.

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Dedication

To Hilary, Mattie, and Ellie

1.0 Introduction

Each of the empirical studies presented in this dissertation seeks to evaluate the impact of some aspect of the current policy environment on the critical population-health objective put forth in the US Supreme Court's Olmstead decision of 1999: to deliver the benefits and services due to all US people in the most integrated setting possible (McCormick et al., 2019). The programs taken as main effects in these essays each have the potential to influence events at one critical juncture in the progression from community to institution and back again for the elderly Medicaid population. The first essay, exploring the association between residence in HUD Supportive Housing for the Elderly and time-to-nursing home admission, asks the question of whether a longstanding federally subsidized housing program is associated with the delay or prevention of nursing home admission. The second essay moves the focus to another program intervention--Medicaid Managed Care—assessed for its effect on Medicaid beneficiaries inside nursing facilities who have resided there for at least 100 days. The third and final essay considers the viability of subsidized housing supply in the community beyond the nursing facility for Medicaid longstay residents who have the potential to move back into an integrated community setting.

The results of all three studies expose the trade-offs inherent in *program* evaluation, as opposed to the evaluation of more discrete policy interventions. *"HUD program status and hazard of nursing home admission in the Pennsylvania Medicaid population, 2013-2019"* finds a strong and significant independent association between reduced risk of nursing home admission and residence in Section 202 housing—a seeming confirmation that supportive services for the elderly are doing their job, helping vulnerable elderly populations remain in the integrated community settings envisioned in the Olmstead decision. This interpretation is brought into question, however, by a similarly strong and significant independent association observed between risk of nursing home admission and Section 8 project-based housing—a housing program that commonly serves the at-risk Medicaid population as a consequence of its income eligibility rules (targeting households that earn less than 30% Area Median Income), but is not geared toward nursing home diversion as a primary goal.

On the other hand, *"Changes in successful discharge to the community for longstay nursing home residents associated with Medicaid managed care adoption in Pennsylvania, 2014-2019,"* which sets out to evaluate the causal effect of the introduction Mandatory Managed Care on the rate of community transitions for longstay nursing home residents, detects no intervention effect. As the paper's discussion indicates, however, the impact of program effects for such a low-frequency outcome may be highly sensitive both to model specification and to identification of the appropriate study population.

Finally, *"Association between county-level HUD housing density and discharge to the community among Medicaid longstay nursing home residents in Pennsylvania, 2015-2017"* attempts to lend some empirical scaffolding to the claim, made often in the literature around nursing home transition, that a primary barrier to moving longstay nursing home residents back into the community for care is lack of available affordable housing (Irvin, 2017; Lipson et al., 2011). While studies of targeted voucher programs have shown effectiveness in promoting nursing home transition (e.g. (D. Hoffman et al., 2017)), little work has been done to establish whether a systematic relationship exists between *existing and established* affordable housing, which, even in the marginal presence of targeted housing-affordability interventions, will always constitute the majority of housing supply available to nursing home residents. The challenge to program evaluation posed by this study is: what is the best summary measure for "access to affordable housing”? Three paths present themselves: a maximalist measure that seeks to identify and sum all subsidized housing resources local to a region; a highly targeted measure that identifies the housing types most obviously suitable for longstay nursing home residents, such as HUD Section 202 housing; or a third type of measure—the type selected by our study—that aims to broadly capture historical levels of housing subsidy in a region. Along each path, construct error looms—there are so many types of housing subsidy, acting through so many channels, that it is unlikely a maximal measure will be complete. Selecting only population-targeted housing will likewise exclude really available options for transitioners. The compromise measure favored in the present study—density of HUD project-based housing, which represents the oldest type of federally subsidized housing stock—is justified by its intuitive appeal, but limited in its practical implications for policy.

Taken together, these studies seek to lay the empirical groundwork for an understanding of the community-dwelling Medicaid population that is as detailed and granular as our understanding of this population as it moves through institutional settings. The background belief that motivates this work is that the community dwelling Medicaid enrollee is profoundly under-observed in comparison to what is possible given the clustering of this population among subsidized housing developments for which rich data are available, and which may offer us the key to measuring exogenous program effects in environments and situations where it would have seemed impossible before. As a greater proportion of long-term care moves into dispersed community environments, the ability to accurately assess whether state and federal policies can enact the goals embraced by the Olmstead decision—for older adults and people with disabilities to have the freedom to choose where to live, and that public programs should support delivery of care and services in the most integrated community setting—will only grow in urgency.

2.0 Association Between HUD Program Status and Hazard of Nursing Home Admission in The Pennsylvania Medicaid Population, 2013-2019

2.1 Abstract

Pennsylvania Medicaid enrollees that were either dually-eligible for Medicare and Medicaid or eligible for HCBS waivers during the years 2013-2019 were assigned probable HUD program status using nine-digit zip-code matching. I developed time-to-event and restricted mean survival time models to observe the association between HUD-program status and time-to-nursing-home admission. Compared with residence in Public Housing (PH), residence in Section 202 housing is associated with a 21% reduction in hazard of nursing home admission (HR: 0.79, p=0.01) in a model adjusted for enrollee-level measures of demography, health, and function, and for development-level measures of service coordination and household structure. Section 8 Project-based housing, which includes a mix of housing with and without supportive services, is associated with a 20% reduction in hazard of nursing home admission in the adjusted model (HR: 0.80, p<0.01).

2.2 Background

Federal policymakers in the United States are prioritizing efforts to use housing-oriented policy to impact health outcomes (Butler, 2022). Examples include the proposal of reforms that would expand and innovate the role of debt subsidy by the US Department of Housing and Urban

Development (HUD) to aid in financing CMS-certified Skilled Nursing Facilities, and for Medicaid funding to subsidize the cost of supportive housing for people with behavioral health disorders (Crossley, 2018; Esworthy et al., 2022). Recent research indicates that housing subsidy in the form of targeted vouchers for nursing home residents improves post-discharge outcomes, and there is indication that data sharing and policy coordination between state housing and Medicaid agencies can increase subsidy effectiveness while also reducing cost(Cole et al., 2022; D. Hoffman et al., 2017; Miles et al., 2017). Using a linkage between National Health Interview Survey (NCHS) results and HUD administrative data, researcher have begun to document the health and disability status of people who live in HUD-assisted housing (Brucker et al., 2018; Brucker & Helms, 2019; Fenelon et al., 2017, 2018; Helms et al., 2017; A. E. Simon et al., 2017).

The Housing and Urban Development Section 202 Supportive Housing for Elderly program was established by the Housing Act of 1959 (P.L. 86-372) to incentivize development of housing for the moderate-income elderly population that didn't qualify for public housing but couldn't afford market-rate housing. Since that time, the program's financing arrangements and tenant-income requirements have passed through several changes. From the program's inception until 1962, HUD made direct low-interest loans to developers of housing for the elderly that allowed them rent units to elderly households at affordable rents. In 1962, HUD instituted tenant-income requirements adjusted to local conditions to ensure units remained affordable to middle-income households. In 1968 HUD revised the income requirement to 135% of Public Housing limits or 80% of area median income. In 1974 HUD made project-based Section 8 rental assistance available to Section 202 owners. This marked the program's shift toward serving predominantly low-income elderly tenants, a policy goal that was formalized with the Omnibus Budget Reconciliation Act of 1981. This law required that the large majority of future units built using

Section 202 financing be occupied by households earning at or below 50% Area Median Income. After it was found in 1990 that Section 202 development owners redirected Section 8 funds intended for rent subsidy toward paying down debt service on HUD 202 loans, HUD converted the 202 financing from direct loans accompanied by Section 8 rental subsidy to capital grants with no interest or repayment accompanied by flexible, development-specific rental assistance contracts (PRACs). PRACs were untethered from the Section 8 Fair Market Rent formula, which capped rental subsidies at low levels in regional markets with low market rate rents (Vandawalker et al., 2020). The case-by-case funding arrangement was designed to facilitate negotiation between HUD and developers for subsidies that would allow developers to better meet the supportive housing needs of specific elderly populations. Since 2000, Section 202 developers have additionally had access to Low-Income Housing Tax Credits (LIHTC) as incentive to produce affordable units (Perl, 2010).

HUD has estimated that adults aged 62 and above occupy at least 1.3 million of the units it administers, spread over Public Housing, private-owner Multi-Family Housing (which includes Section 202-assisted properties and project-based Section 8 properties), and the Housing Choice Voucher Program. About 20 percent these are Section 202 units. Open to any very-low income household with at least one resident aged 62 or above at the time of program entry, Section 202 Supportive Housing for Elderly is the only program that exclusively targets the elderly population and requires as a condition of financing that developers commit to making supportive services accessible to residents (Perl, 2010). Supportive services associated with Section 202 housing, which vary by development and are determined according the specific development contract, can include on-premise service coordination, congregate meals, transportation, and personal assistance. The purpose of these services is to enable residents to live independently and to prevent or delay institutionalization. (*Section 202 Supportive Housing for the Elderly: Program Status and Performance Measurement*, 2008) To my knowledge, however, there has been no quantitative evaluation of the extent to which the Section 202 program has met its objective of preventing or delaying institutionalization among its population.

2.3 Study Objectives

The first objective of this study to characterize the population of dual-eligible Medicaid residents who reside across three HUD programs: Public Housing, which includes no universal programmatic features to address the need of this population, Section 202 housing, which is programmatically geared toward addressing the needs of this population through provision of supportive services, and Section 8 Project-base Rental Assistance. Section 8 Project-based rental subsidy is distributed by HUD to rental property owners that make a maximum of 25% of their units available to low-income renters, defined as having a household income not more that 80% of area median income adjusted for household size. Property owners can in some instances increase their allotment of subsidized units by making them available to vulnerable populations such as veterans, people with disabilities, and older adults, with the accompanying provision of supportive services (*Multifamily Housing - Section 8 Background Information - HUD*, 2022).

The second objective of this study is to observe whether residence in Section 202 or Section 8 Project-based housing is associated with reduced risk of nursing home admission by estimating the association between time-to-nursing home admission and HUD program status. In this study, Section 8 project-based housing, which includes a compositionally diverse population and a mix of developments with and without supportive services, serves as a secondary comparison group to aid interpretation of the main Section 202 results. Section 202 and Project-based Section 8 are both evaluated with reference to the combined population of dual-eligible and HCBS-waiver eligible Medicaid enrollees who reside in Public Housing, which has no programmatic services and supports element.

2.4 Data and Methods

2.4.1 Study Population

I analyzed a sample of 2013 through 2019 waiver-eligible Pennsylvania Medicaid enrollees whose enrollment records indicated residence in one of three types of housing development administered by HUD: Public Housing (PH), Project-based Section 8, or Section 202. I construct models to test differences between time-to-nursing home admission during the observation period. I excluded enrollees whose waiver status indicated they were long-term residents of a nursing facility.

Medicaid/Medicare dual-eligibility and HCBS waiver-eligibility was determined from monthly Medicaid Enrollment for the state of Pennsylvania. Chronic conditions are measured using Medicaid and Medicare claims data based on definitions from the Chronic Conditions Warehouse, including Alzheimer's or dementia-related disorders (*CCW Medicaid Data White Papers - Chronic Conditions Data Warehouse*, 2022). The presence or absence of a total of 72 chronic conditions are observed in the analytic dataset for each enrollee. I used the publicly available HUD Inventories of Public Housing (PH) and Multifamily (MF) housing to determine

HUD program status and HUD development-level characteristics (*Multifamily Properties - Assisted*, n.d.; *Public Housing Buildings*, 2022).

2.4.2 HUD Matching and Sample Selection

Community-resident waiver-eligible Medicaid enrollees were matched to probable HUD program status using nine-digit zip codes obtained from their Medicaid enrollment. Two HUD data sources were used for program-status matching: an inventory of Public Housing developments and an inventory of Multifamily Housing developments. HUD's Inventory of Public Housing Developments designates one nine-digit zip code per building. A single nine-digit zip code typically localizes to several floors of apartments within a public housing development. A public housing development yields a nine-digit zip code for each building, so each development yielded several nine-digit zip codes for matching.

HUD's Inventory of Multifamily Housing Developments (which includes Project-based Section 8 and Section 202 developments) only includes development-level information, and thus yields one nine-digit zip code per development. The study population comprises all community-resident Medicaid enrollees either dually-eligible for Medicaid and Medicare or eligible for Medicaid HCBS waivers from 2013-2019 who matched to a nine-digit zip code in either the HUD Inventory of Public Housing, or a Project-based Section 8 or Section 202 development in the HUD Inventory of Multifamily Housing (Figure 3).

2.4.3 Probability Weights

Individuals in different HUD developments had different probabilities of selection because population numbers varied by development. Using HUD-reported data on the total number of residents per development, I weighted the data for analysis using development as the primary sampling unit, given as:

$$wt_{ij} = (\frac{n_j}{N_j})/(\frac{o_j}{O_j})$$

where n_j is the HUD-reported number of residents in the development, N_j is the total number of HUD-reported residents in all developments represented in the study sample, o_i is the number of observations for the development in the sample, and O_j is the total number of observations among all developments in the sample.

2.4.4 Medicaid Enrollee Covariates

From Medicaid enrollment records, I determined the enrollee's age, sex, and race/ethnicity. I used the Enterprise Data Warehouse file to determine the enrollee's residence in a community setting (as opposed to in a skilled-nursing-facility) and whether the enrollee received home-and-community-based services as part of waiver eligibility. I used the Chronic Conditions Warehouse (CCW) to determine whether the enrollee had a diagnosis of Alzheimer's or dementia-related disorder, and whether the enrollee had >=6 chronic conditions. Multiple chronic conditions have been shown to increase of health care utilization and costs(Lehnert et al., 2011). I arrived at 6 conditions as a cut-off empirically. From the HUD Inventory files, I determined whether the enrollee lived in a HUD development that contracted with a service coordinator, and whether the mean household size for the development was >=2.

I categorized enrollee age to reflect the HUD age requirement for application to Section 202 (at least one member of the household must be >=62 years old) and the intrinsically heightened risk of nursing home admission at age 85 and above (Jaul & Barron, 2017; Murtaugh, Christopher M. et al., 1997). I included indicators for HCBS use, Alzheimer's and dementia-related disorders, and multiple chronic conditions because these are established risk factors for nursing home admission (Gaugler et al., 2007; Gorges et al., 2019; Jaul & Barron, 2017; Nihtilä et al., 2008; Park et al., 2020). I included development-level presence of service coordination and mean household size because the literature indicates that these factors are protective from nursing home admission(Carrier, 2012; Freedman, 1996; Onder et al., 2007; Rudberg et al., 1996). Service coordination can take diverse forms across different HUD program types. I assign a dummy variable to each HUD development based on whether the HUD property inventory indicates the development has a contract with a service coordinator. All covariates are observed once, during the first monthly period of observation, and are assumed to remain constant throughout the observation period.

2.4.5 Outcome and Observation Period

The outcome for this study is time-to-nursing home admission, with admission determined from MDS 3.0 records. The period of observation for each subject begins on date of entry into the sample. Entry into the sample is dated to the first day of the first month that a HUD-matched community-resident waiver-eligible Medicaid enrollee is observed in monthly enrollment data during the 2013-2019 study period. Age at entry, nursing home admission, or censoring is determined from the enrollee's date of birth as recorded in the Medicaid enrollment file, and, as in the case of some censored observations, date of death, as recorded in Medicaid enrollment. Each enrollee appears once in the data, for a single observation period.

2.4.6 Right Censoring

There are several ways an observation can be right-censored. An observation is right-censored when consecutive months of Medicaid enrollment end or are interrupted; when the study period ends (on December 31, 2019); or when the study subject dies. While there is discussion in the literature of possible bias introduced by considering death as a non-informative censoring event in studies of nursing home admission (Szychowski et al., 2010) , this study will follow the standard practice of censoring deaths as noninformative (Andel et al., 2007; Geldmacher et al., 2003; Phillips & Diwan, 2003; Tun et al., 2007).

2.4.7 Left-Truncation

When using time-on-study as the timescale, the usual practice is to drop left-censored observations because time-to-event cannot be accurately measured for these observations. This represents a compromise, however, because it introduces unknown selection bias into the sample. In this study I elect to use age-as-timescale because it calculates risk as function of age, which is more appropriate to highly age-dependent outcomes than time-on-study, and allows for the inclusion of left-truncated observations (Kom et al., 1997).

2.4.8 Statistical Analysis

2.4.8.1 Kaplan-Meier Survival Estimate

I estimate the probability of nursing home admission at a given time using the Kaplan-Meier method (Kaplan & Meier, 1958):

$$S(t_j) = S(t_{j-1})(1 - \frac{d_j}{n_j})$$

where $S(t_j)$ is probability of admission, $S(t_{j-1})$ is probability of admission at the previous timepoint, d_j is number of failures (nursing home admissions) at time t_j , and n_j is number of people with no admission remaining in the sample at time t_j. This method yields a survival curve with probability of survival as the y-axis and time as the x-axis for each HUD program population.

2.4.8.2 Nelson-Aalen Cumulative Hazard Estimates

The hazard of nursing home admission is the probability that a subject has a nursing home admission in the next instant, given that the subject has survived to time t, given as

$$h(t_j) = f(t_j)/S(t_j)$$

where $f(t_j)$ is probability of nursing home admission at time t_j. Because hazard estimates are difficult to interpret, they are represented in survival analysis by cumulative hazard, which is the integral of the hazard function. The Nelson-Aalen cumulative hazard plot (Aalen, 1978) uses nonparametric estimation to represent the accumulation of hazard over time. The y-axis, in our case, is loosely interpreted as the predicted number of nursing home admissions expected if the failure event were repeatable. The main purpose of the Nelson-Aalen cumulative hazard plot is to supplement the Kaplan-Meier plot by representing the form of the hazard over time, and to visualize the hazard function on an interpretable y-axis.

2.4.8.3 Cox Proportional Hazards Model

The Cox proportional hazards model (Cox, 1972) as applied to this study population is given as

$$h(t) = h_0(t)\exp\{\beta_1 DEMOGRAPHY_i + \beta_2 HEALTH\ AND\ FUNCTION_i + \beta_3 HOUSEHOLD\ SIZE_{ij} + \beta_4 SERVICE\ COORDINATION_{ij}\}$$

where $h_0(t)$ is the nonparametrically estimated baseline hazard function. The covariate vector is estimated parametrically. Because the exponentiation is constant with respect to $h_0(t)$, any combination of beta coefficients will yield Cox hazard estimates that are in constant proportion to the baseline. This relationship gives rise to the "proportional hazards" assumption of the Cox model.

2.4.8.4 Restricted Mean Survival Time

A limitation of the Cox model is that it computes a single summary measure (the hazard ratio) of the difference between comparison group survivor functions across the full range of analysis time. If the survival curves cross, or show great variation in distance apart, the hazard ratio--estimated in the Cox model from the average difference in levels between comparison-group survivor functions, weighted by number of observations—becomes less informative as a summary measure. Restricted mean survival time (RMST) is an alternative method used to compare survival functions when the proportional hazards assumption is not met (Royston & Parmar, 2011; Uno et al., 2014) If the data are right-truncated by a censored observation, the RMST procedure estimates a last failure t for the last right-truncated value, and differences the area under the reference and comparison group survival curves. This difference in survival can be expressed as a ratio, and has the advantage of providing an informative summary of the total gain or loss over the full range of observation.

2.5 Results

2.5.1 Characteristics of The Study Population

The study sample included 14,634 waiver-eligible Pennsylvania Medicaid enrollees matched to likely residence in either HUD Public Housing (PH), a Project-based Section 8 development, or a Section 202 development. The youngest enrollee observed in the population was 21 and the oldest was 104. The weighted and unweighted and weighted populations matched closely on demographic, health, and HUD development-level characteristics. The weighted population showed a shift away from Public Housing and Section 202 into Project-based Section 8 program status, reflecting the known distribution of population among HUD developments (Table 1).

The study's comparison groups show contrasting profiles in demography, health and functional status, and HUD-development characteristics. The Public housing population skews youngest in age, Section 202 oldest. The Public Housing population is disproportionately nonwhite, while the Project-based Section 8 and Section 202 populations are disproportionately White. Medicaid HCBS use is greatest among Section 202 residents, while prevalence of

Alzheimers and Dementia-related disorders (ADRD) and a chronic condition count of 6 or above is prevalent at similar levels among all comparison groups. A majority of the study population's Section 202 residents live in developments that are reported by HUD to have a contract for a service coordinator on the premises, less than a quarter of Project-based Section 8 residents live in a development with service coordination, and no residents live in Public Housing developments with service coordination. The large majority of Public Housing residents in the sample live in developments that report >=2 people per household on average, while all Section 202 residents live in developments with <2 people per household on average (Table 2). In the unweighted sample, the median age of entry into observation was 61.0, the median age of exit (by censoring or nursing home admission) was 65.0, and there were 1164 failure (nursing home admission) events (Table 4).

2.5.2 Characteristics of HUD Developments

The study population lives among 931 HUD developments in Pennsylvania, including 347 Public Housing developments, 360 Project-based Section 8 developments, and 224 Section 202 developments. See Table 4 for HUD-reported development-level characteristics. Public Housing developments, on average, have the greatest number of units, the greatest population number and density, the greatest proportion of nonwhite residents, and the greatest proportion of disabled residents. Project-based Section 8 developments have the greatest proportion of extremely low-income residents and the greatest monthly per unit HUD expenditure. Section 202 developments have, on average, the fewest units, the fewest total residents, the lowest proportion of nonwhite residents, the highest proportion of residents >= age 62, the lowest proportion of disabled residents, and lowest percent tract-poverty (Table 3).

2.5.3 Unadjusted Measures of Time-To-Nursing Home Admission

Curves describing the probability of persisting without a nursing home admission are presented in figures 1 and 2. Visually, both the Kaplan-Meier survival estimate and Nelson-Aalen cumulative hazard plot suggest similarity in the risk trajectory between residents of Public Housing and Project-based Section 8 until the age of approximately 85, when residence in Project-based Section 8 housing begins to exceed the survival rate of Public Housing residents. Section 202 survival probability is lowest of the three housing categories across the range of observation, as expected for housing that residents select into for its associated support services. When expressed in an unadjusted Cox regression as hazard ratios, residents of Project-based Section 8 housing have 4% lower hazard of nursing home admission on average in the course of the observation period, however this result is not significant (*HR: 0.96, p=0.57)*. Residents of Section 202 housing have a 26% greater hazard of nursing home admission, an expected result which is significant in the model (*HR: 1.26, p<0.01)* (Table 5). A postestimation Cox test (carried out in place of the more standard log rank test because this population is weighted) indicates there is no evidence that the proportional hazards assumption is violated *(p=0.50)*.

Table 7 displays the results of a restricted mean survival time analysis of the data. The point estimate indicates that, on average, Medicaid enrollees in the Project-based Section 8 population persist without a nursing-home admission to age 1.37 years greater than residents in the Public Housing population (Diff: 1.37, p=0.22). Expressed as a ratio, the Project-based Section 8 population persist for 1.8% more time than the Public Housing population (Ratio: 1.018, p=0.22). Neither of these results is statistically significant. The point estimate for the second comparison indicates that Medicaid enrollees in Section 202 population persist, on average, without a nursing home admission to an age 22.0 years less than enrollees in the Public Housing population (Diff: -21.99, p=0.01)—or, to a 29% lower age (Ratio: 0.71, p=0.20). This result is significant.

2.5.4 Adjusted Measure of Time to Nursing Home Admission

Table 6 displays the results of a Cox regression that adjusts for all covariates. The adjusted results indicate that enrollees in the Project-based Section 8 population have a 19.7% reduction in hazard with respect to the Public Housing population *(HR: 0.803, p=0.07)*. Enrollees in the Section 202 population show an adjusted 20.5% reduction in hazard *(HR: 0.795, p=0.01)*. A postestimation Cox test of the proportional hazards assumption indicates that we reject the null hypothesis that the hazard functions are equal *(p<0.001)*. This indicates that the hazard ratios yielded by the model must be interpreted with caution—if the postestimation survival curves cross, the single estimate measured by the hazard ratio may be misleading over some parts of the range of observation. (See (Stensrud & Hernán, 2020), however, for discussion of the degree to which the "proportional hazards assumption" can be reasonably applied to clinical and other real-world data.)

2.6 Discussion

This study examined differences in time-to-nursing home admission associated with HUD program status in a policy-relevant subset of the HUD-resident dual-eligible Medicaid population in Pennsylvania from 2013-2019. I conducted a time-to-event analysis that compared hazard of nursing home admission among waiver-eligible Medicaid beneficiaries whose enrollment information indicated high probability of residence in housing administered through one of three

HUD program categories: Public Housing, Project-based Section 8, or Section 202. First, I constructed plots of Kaplan-Meier survival estimates and Nelson-Aelen cumulative hazard estimates to observe unadjusted differences between time-to-nursing-home-admission among HUD program populations, with Public Housing as the reference group. Second, I used a Cox test (a likelihood ratio test performed in place of the more standard log rank test when survival data are weighted) to determine that the null hypothesis of the survivor function equivalence could not be rejected, and that, therefore, the proportional hazards assumption could be applied. Third, I estimated hazard ratios of nursing home admission for Project-based Section 8 and Section 202 housing with respect to the Public Housing reference group. As an alternative summary measure of differences in hazard between comparison groups, I applied the restricted mean survival time procedure to the unadjusted survival model.

Fourth, I added covariates to a Cox proportional hazards model intended to control for observable independent risk factors for nursing home admission in an effort to isolate the association between HUD program status and time-to-nursing-home admission. This procedure yielded statistically significant hazard ratios for all covariates, however a Schoenfield residuals test indicated rejection of the null hypothesis that, postestimation, survivor functions were equivalent.

This study offers a detailed profile of a segment of high-need Pennsylvania Medicaid enrollees that live in housing administered by HUD. Of note in this study population is the high and even distribution of chronic disease burden across housing types accompanied by an uneven distribution of on-premise service coordination. The unadjusted time-to-event analysis indicates no evidence for difference in hazard between Project-based Section 8 and Public Housing, and a statistically significant 26% increase in hazard associated with Section 202 in comparison to Public

Housing. A Cox model adjusted for enrollee demographics, health and functional status, and development-level characteristics, yields significant and sizable reductions in nursing home hazard for both Project-based Section 8 and Section 202, however these results must be interpreted with caution given that the proportional hazards assumption is not met after model estimation.

2.7 Limitations

This study has limitations. First, Medicaid enrollee characteristics and HUD program status are held constant through the observation period. It is possible these could have changed in the course of the study. Second, because this study does not model death as a competing risk, it is possible that the interpretation of nursing home hazard as something to be minimized must be qualified in light of this. Third, this study selects the waiver-eligible state from one US state during a limited time period. Waiver populations in other states may be composed differently and operate under different program rules. Fourth, this study does not control for birth-cohort effects. Fifth, this study does not take into account the nursing home admission history of subjects prior to sample entry. Fifth, this was an observational study, so we cannot ascribe causality to the association between HUD program status and time to nursing home admission.

2.8 Conclusion

This study provides evidence that chronic disease burden and other risk factors for nursing home admission are distributed broadly among the HUD housing programs under examination, but HUD-provided supportive services are not. The accompanying models suggest there may be a nursing home diversion effect associated with Section 202 and PBV residence in contrast to Public Housing. This study is a first step in the description of the impact of HUD program status on nursing home admission. Further research should employ these and similar methods to observe associations with HUD program status on other policy-relevant outcomes, such hospital readmissions and ambulatory-care sensitive admissions. Further research should also examine associations between HUD program status and Medicaid-relevant outcomes among more highly specified at-risk subpopulations.

2.9 Tables and Figures

Table 1. Characteristics of The Study Population, 2013-2019

Characteristics of the study population, 2013-2019		
	N=14,634	
	Unweighted	Weighted
HUD program, %		
Public housing	75.6	59.4
Project-based Section-8	14.3	31.8
Section 202	10.1	8.8
Demographics, %		
Age		
21-49	24.7	24.5
50-61	25.7	25.3
62-74	35.2	35.0
75-84	10.6	11.6
>85	3.7	3.6
Female	65.5	65.9
Race/ethnicity		
White , non-Hispanic	44.1	47.6
Black, non-Hispanic	39.2	35.8
Hispanic	13.1	12.9
Other race or ethnicity	3.6	3.6
Health and functional status, %		
Receives Medicaid HCBS	23.2	21.9
Alzheimers or dementia-related disorder	31.4	31.8
Chronic conditions >=6	31.1	30.8
HUD development-level characteristics, %		
Contract with service coordinator	10.5	12.9
Mean household size >= 2	57.2	52.9

Table 2. Distribution of The Study Population by HUD Status

Characteristics of the study population (2013-2019), by HUD status	All		Public housing		Project-based Section 8		Section 202	
	N=14,634		n=11,069		n=2,088		n=1,477	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
Demographics, %								
Age								
21-49	24.7	24.5	28.9	28.9	17.1	21.8	4.7	4.1
50-61	25.7	25.3	28.6	27.6	22.7	25.8	8.2	8.3
62-74	35.2	35.0	31.6	31.9	41.3	35.3	54.0	54.9
75-84	10.6	11.6	8.4	8.9	14.3	13.7	22.3	22.9
>85	3.7	3.6	2.6	2.8	4.6	3.3	10.8	9.8
Female	65.5	65.9	65.6	65.7	63.7	66.3	67.2	66.2
Race/ethnicity								
White , non-Hispanic	44.1	47.6	40.2	42.4	55.0	53.6	57.7	61.1
Black, non-Hispanic	39.2	35.8	41.9	39.3	32.4	32.1	28.7	26.0
Hispanic	13.1	12.9	15.1	15.3	7.3	10.0	7.1	7.3
Other race or ethnicity	3.6	3.6	2.9	3.0	5.3	4.3	6.5	5.7
Health and functional status, %								
Receives Medicaid HCBS	23.2	21.9	22.7	21.6	22.1	20.1	28.8	30.6
Alzheimers or dementia-related disorder	31.4	31.8	31.8	31.9	32.6	31.8	26.4	30.7
Chronic conditions >=6	31.1	30.8	30.3	30.4	33.9	30.7	32.6	33.5
HUD development-level characteristics, %								
Contract with service coordinator	10.5	12.9	0.0	0.0	29.2	22.3	62.9	66.6
Mean household size >= 2	57.2	52.9	71.4	65.5	22.2	43.9	0.0	0.0

Table 3. Characteristics of HUD Developments

Characteristics of HUD developments included in study sample (sourced from the HUD inventory file)	All		Public housing		Project-based Sec 8		Section 202	
	N=931		n=347		n=360		n=224	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Units	108.5	87.8	147.2	113.7	100.4	60.4	61.6	40.2
Occupancy, %	95.5	6.4	95.4	8.3	95.0	5.2	96.2	4.1
Residents, n	174.4	201.7	278.0	278.2	143.6	103.2	63.4	43.0
Residents per household, n	1.5	0.7	1.9	0.8	1.5	0.7	1.0	0.1
HUD expenditure per unit, per month, $	633.66	287.48	592.87	345.31	701.11	228.61	587.82	253.22
Household headed by female, %	71.4	13.9	73.9	13.8	71.0	13.3	68.1	14.4
Households headed by person >=age 62, %	57.8	35.7	38.0	28.5	55.0	33.9	92.5	19.3
Nonwhite, % residents	42.2	37.4	51.6	37.9	39.8	35.4	32.0	36.4
Average household income, $	13749.6	2740.1	13582.3	3083.4	13354.0	2645.8	14618.8	2049.9
Extremely low income, % residents, avg	71.7	15.8	68.3	14.5	76.2	13.8	69.7	18.9
Disabled, % residents	27.1	23.1	31.3	22.3	29.4	21.9	17.1	23.4
Contract with service coordinator, % developments	23.0	1.4	0.0	0.0	22.8	2.2	58.9	3.3
Census tract poverty, %	24.6	14.1	27.0	13.1	25.1	14.9	19.9	13.2

Table 4. Characteristics of The Risk Set

Characteristics of the risk set (calculated from the unweighted sample)					
	Total	Mean	Min	Median	Max
Entry age	NA	58.717	20.999	60.979	101.925
Exit age	NA	62.888	21.123	65.044	104.958
Years at risk	61049.038	4.172	0.003	3.997	6.995
Failures (nursing home admissions)	1164.000	0.080			

Table 5. Cox Proportional Hazards Model for Time to Nursing Home Admission, Unadjusted

Cox proportional hazards model for time to nursing home admission, unadjusted				
HUD status	Hazard Ratio	SE	p-value	CI
Public Housing	Ref	Ref	Ref	Ref
Project-based Section 8	0.9609001	0.067255	0.569	(.84-1.10)
Section 202	1.261605	0.097637	0.003	(1.08-1.47)

Table 6. Cox Proportional Hazards Model for Time To Nursing Home Admission, Covariate Adjusted

Cox proportional hazards model for time to nursing home admission, covariate adjusted				
HUD program	Hazard Ratio	Robust SE	p-value	CI
Public housing	Ref	Ref	Ref	Ref
Project-based Section 8	0.79	0.06	0.00	(0.68-0.91)
Section 202	0.80	0.07	0.01	(0.67-0.95)
Demographics				
Age				
21-49	Ref	Ref	Ref	Ref
50-61	3.97	1.40	0.00	(1.99-7.92)
62-74	14.09	6.20	0.00	(5.95-33.37)
75-84	50.86	24.37	0.00	(19.88-130.06)
>=85	229.67	154.93	0.00	(61.22-861.64)
Female	0.82	0.08	0.03	(0.68-0.98)
Race/ethnicity				
White , non-Hispanic	Ref	Ref	Ref	Ref
Black, non-Hispanic	0.58	0.08	0.00	(0.44-0.75)
Hispanic	0.53	0.16	0.04	(0.28-0.97)
Other race or ethnicity	0.60	0.16	0.05	(0.36-1.01)
Health and functional status				
Receives Medicaid HCBS	2.30	0.44	0.00	(1.58-3.35)
Alzheimers or dementia-related disorder	1.42	0.21	0.02	(1.07-1.90)
Chronic conditions >=6	2.05	0.36	0.00	(1.46-2.89)
HUD development-level characteristics				
Contract with service coordinator	0.92	0.03	0.00	(0.87-0.97)
Mean household size >= 2	0.71	0.07	0.00	(0.59-0.85)

Table 7. Restricted Mean Survival Time, Unadjusted

Restricted Mean Survival Time , Unadjusted			
Housing program	**Estimate**	**CI**	
Public Housing	76.292	(38.79-69.80)	
Proj Sec 8	77.657	(75.89-79.42)	
Section 202	54.297	(75.02-77.57)	
Between group contrast			
	Estimate	**CI**	**p-value**
Proj Sec 8 - Public Housing	-21.994	(-37.54-6.44)	0.006
Proj Sec 8 / Public Housing	0.712	(0.53-0.94)	0.02
Section 202 - Public Housing	1.366	(-0.81-3.54)	0.219
Section 202 / Public Housing	1.018	(0.99-1.05)	0.218

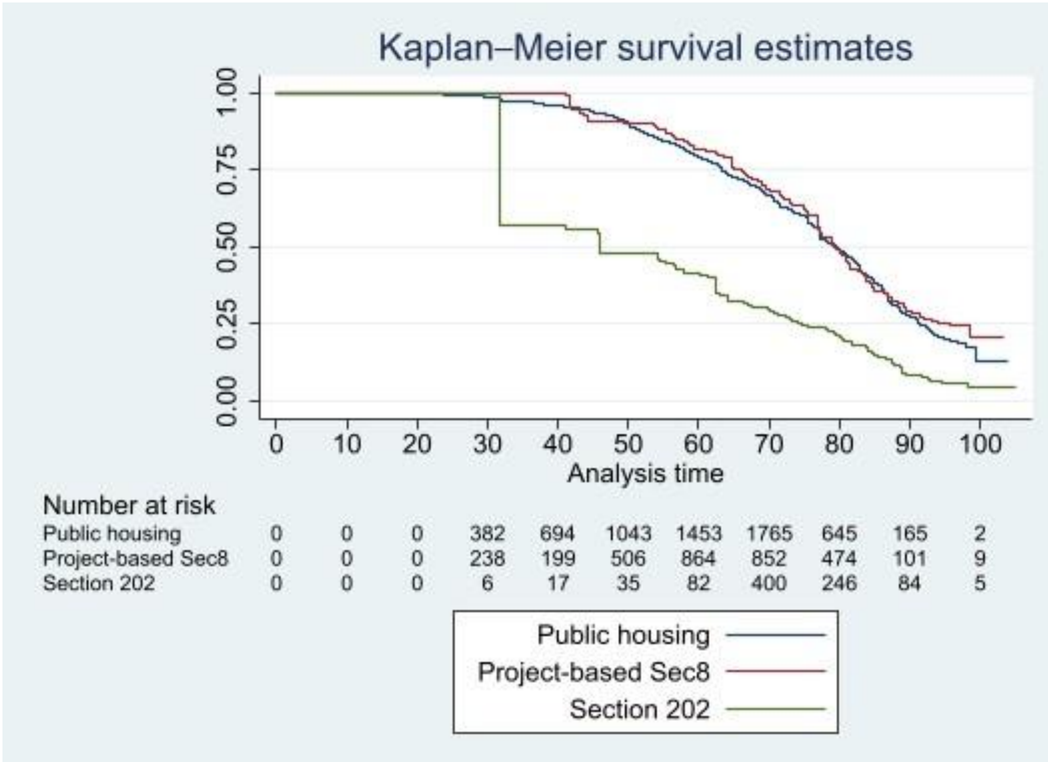


Figure 1. Kaplan Meier Survival Estimates

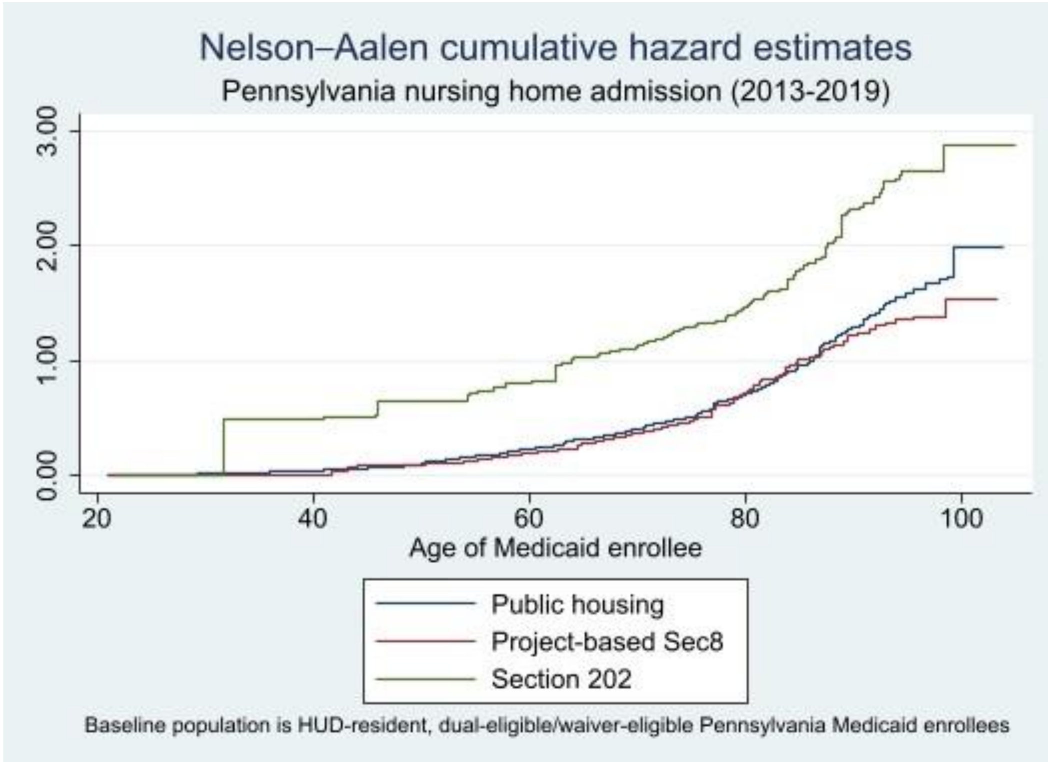


Figure 2. Nelson Aalen Cumulative Hazard Estimates

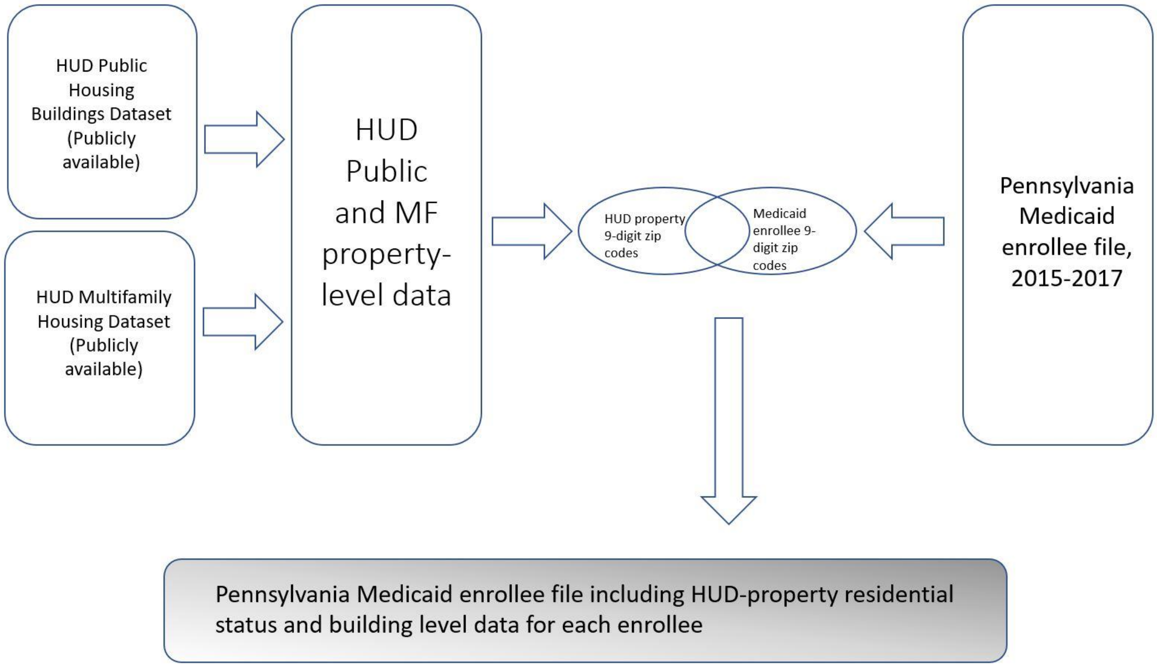


Figure 3. Data Merge Diagram

3.0 Changes In Successful Discharge to The Community for Longstay Nursing Home Residents Associated with Medicaid Managed Care Adoption in Pennsylvania, 2014-2019

3.1 Abstract

Beginning in 2018, Pennsylvania moved coverage of its Medicaid LTSS population to a mandatory managed care model. The rationale for this change was that managed care organizations would have an economic incentive to provide high quality care in the most financially efficient way through effective coordination of services. A desired outcome of this for the LTSS population was that managed care would contribute to the “rebalancing” of LTSS delivery toward more preferred community-based settings. Using difference-in-difference analysis, I exploit Pennsylvania’s staggered implementation of mandatory Medicaid managed care to investigate whether longstay (>100 day) nursing home residents in counties that received the intervention were more likely to be successfully discharged to a community setting within six months of being admitted to a nursing home with no stay in the previous months. I select longstay residents as the study population because Medicaid becomes the sole payer for services at 100 days. Models controlled for resident demographics, health and functional status, and facility characteristics. The eligible pre-intervention (2014-2017) population included 26,816 Medicaid-enrolled incident longstay nursing home residents in Pennsylvania. I observed no significant association between implementation of mandatory managed care and change in likelihood of successful community discharge for this population. Further research should explore the effectiveness of the Medicaid managed care intervention in earlier-stage nursing home populations.

3.2 Background

Medicaid Long-Term Supports and Services (MLTSS) have been traditionally divided into, on the one hand, fee-for-service nursing home care and, on the other, home and community-based services (HCBS) covered under state-specific “waiver” programs (Eiken et al., 2004; Skira et al., 2022). The LTSS population has drawn attention from policy makers who believe that the high cost of services and variable quality of care experienced by these enrollees is partly due to misaligned economic incentives among payers (Berwick et al., 2008; Grabowski, 2007). To address this concern, many state Medicaid programs have introduced a managed care model of health services delivery (Hurley & Somers, 2003; Hwang & Keohane, 2022; Rowland & Hanson, 1996). In this model, states pay Medicaid Managed Care Organizations (MCOs) a set amount, determined on a risk-adjusted basis, to manage all aspects of care for LTSS populations. States hold MCOs accountable for the quality of participant outcomes, in theory thus incentivizing MCOs to provide the highest quality care in the most financially efficient way (Butler, 2019).

In line with the national policy goal of “rebalancing,” CMS has favored policies such as managed care adoption in an effort to shift LTSS delivery away from institutional settings in favor of community settings (Kaye, 2012). In this paper I select one LTSS subpopulation—residents of nursing facilities aged 65 and above who have reached day 100 of a nursing home stay—and ask whether moving this population to Medicaid Managed Care (MCO) coverage is associated with a higher rate of successful discharge to a community setting within 6 months of becoming a long-stay resident. I limit my study population to the age 65 and over population because the mechanisms underlying transition of this population likely differ from those associated with transition of the under-65 population (D. Hoffman et al., 2017; S. E. Simon et al., 2010). I select the outcome on the theory that transitioning long-stay nursing home residents to community settings requires an intensive version of the "person-centered" care that is essential to the MCO model (Bowers et al., 2017). Providers must be familiar enough with individual residents to identify those whose level-of-care needs can met by HCBS, and whose preference is to reside in the community. Once this is achieved, service coordinators must arrange to identify appropriate housing, connect the resident to needed community services, and ensure that the resident can access the full benefits afforded by Medicaid and Medicare coverage.

By exploiting the three-stage staggered implementation of managed care in the LTSS user population in Pennsylvania from 2018-2020, I use difference-in-difference analysis to compare the rate of successful discharge to the community among nursing home residents aged 65 and above who have reached day 100 of a nursing home stay in counties where managed care was implemented, to the rate among nursing home residents in counties where it was not yet implemented.

3.3 Methods

3.3.1 Pennsylvania's Community HealthChoices Program

Community HealthChoices is Pennsylvania's mandatory Medicaid managed care program that covers two populations: people eligible for both Medicare and Medical Assistance (Pennsylvania Medicaid) and people residing in community or facility settings who are assessed by Medicaid as meeting nursing-home level-of-care requirements. In its program materials, Pennsylvania estimates that 420,618 people are covered by CHC, with sixty-four percent of participants qualifying primarily through dual-eligibility and the remainder qualify primarily by receiving Medicaid LTSS services in facility or community-based settings (*Who Is Served by CHC.Pdf*, 2018). For dual-eligible participants, MCOs must provide an initial health screening, a comprehensive needs assessment and LTSS eligibility determination (conducted by an independent assessment entity) on request of the participant, a person-centered service plan, a benefit package comparable to traditional Medicaid, and care coordination with Medicare and MCO-provided behavioral health services. For LTSS participants, MCOs must provide benefit packages for physical health, behavioral health (administered through a separate state program known as Behavioral HealthChoices), and MLTSS. Participants must be assigned a service coordinator tasked with coordinating all services, including Medicare and a separately provided Medicaid behavioral health plan. MCOs must conduct an annual comprehensive needs assessment followed by update to person-centered service plans.

Prior to CHC, the dual eligible population was enrolled in a fee-for-service Medicaid program where the Pennsylvania Department of Health and Human Services (DHS) directly paid claims for beneficiaries' care. There was no managed care infrastructure to coordinate care, such as transitions from long-term care to community or vice versa. The goal of CHC was to both enhance care coordination and optimize how Medicaid financed long-term care by providing an incentive for plans to provide long-term services and supports, where possible, in community-based settings. Pennsylvania developed the CHC program in response to the consensus that dual-eligible Medicaid populations are, by virtue of their combined socioeconomic and at-risk health profile, most in need of integrated care, and yet, due to the often-conflicting incentives of Medicaid and Medicare coverage, least likely to receive it (Grabowski, 2007; Walsh et al., 2012). CHC consolidates the adult dual-eligible and nursing-home-level-of-care enrollees into managed care plans in which MMCOs, rather than Pennsylvania Medical Assistance, assume day to day responsibility for meeting quality targets within the financial limitations set by the state. In its core documents, CHC emphasizes that its mandate is to promote "person-centered" care in which participants exercise choice and control over their care by participating with their providers in development and documentation of goals, and work with care coordinators to secure the resources needed to achieve them (*CHC Fact Sheet.Pdf*, 2018).

The CHC population faces a combination of socio-economic and health-related challenges (Cai et al., 2019; Hwang & Keohane, 2022). In recognition of this, CHC participants who qualify for the nursing-home-level of care designation receive a package of nonmedical long-term services and supports (LTSS) aimed at addressing social determinants of health, including employment counseling, financial management, home modifications, and, for those who reside in facilities, community transition services. These services serve the related major policy goal of rebalancing. This objective was mandated by the Supreme Court's *Olmstead* decision of 1999, which established the right of citizens to receive state-provided services in the most integrated setting practicable (*Olmstead v. LC*, 1999). Rebalancing is further motivated by research demonstrating that, in contrast to institutional care, community-based care is better aligned with the preferences of LTSS consumers (Kasper et al., 2019; Wolff et al., 2008).

Pennsylvania implemented CHC on a staggered basis. The program was first introduced on January 1, 2018 to the cluster of 14 counties surrounding the Pittsburgh-metropolitan area. In the following January of 2019 it introduced CHC to 5 counties surrounding the Philadelphia area. In January 2020 it introduced CHC to the remaining central 48 counties of the state. These regions are referred to in the program literature as the Phase 1 (Southwestern), Phase 2 (Southeastern), and Phase 3 (Lehigh/Capital) regions of the state. For the first 36 months of CHC implementation in each region, the Pennsylvania Department of Health and Human Services mandated that MCOs pay nursing facilities a facility-specific rate no less than the average rate paid by DHS in the four quarters preceding CHC, with an additional adjustment determined by whether the nursing facility is private or run by the county. MCOs must pay Medicare deductibles and coinsurance for dual-eligible participants, with the exception of cost-sharing or copayments for Medicare Part D prescriptions. Nursing facility residents and nursing-facility-clinically-eligible (NFCE) HCBS participants are joined under a single budget-neutral capitated rate adjusted for enrollment mix. DHS requires MCOs to contribute to a pool of reserve funds that are redistributed quarterly back to MCOs to cover the cost of care for participants who are dual-eligible and/or nursing-facility-clinically-eligible, in excess of specified threshold (*2022 CHC Agreement*, 2022).

3.3.2 Study Population

I examined changes in community discharge in the longstay nursing home population because this population's likelihood of transition to a community setting is likely to be affected by aspects of care that managed care seeks to improve, including care coordination, referral to services, and orientation in favor of home-based care(Fries & James, 2012; Simons et al., 2012; Zimmerman et al., 2012). I analyzed MDS 3.0 assessments for all Pennsylvania Medical Assistance enrollees a nursing facility aged 65 and above who reached day 100 of their stay. Enrollees entering the study population in the pre-implementation period (2014-2017 for the phase 1 region, 2014-2018 for the phase 2 region, and 2014-2019 for the phase 3 region) received services on a fee-for-service basis through Pennsylvania Medical Assistance. In the post-implementation period, enrollees received services through one of three CHC managed care plans. Access to MDS 3.0 and Medicaid enrollment records was provided by the state of Pennsylvania to the Medicaid Research Center (MRC) at the University of Pittsburgh Graduate School of Public Health under a data use agreement.

I included all eligible nursing home residents who reached day 100 of a nursing home stay in a freestanding (i.e. non-hospital based) facility with no intervening discharge or transfer to another facility during the calendar years 2014-2019. This therefore excludes nursing home residents whose episodes were interrupted by temporary discharges to acute care settings followed by nursing home readmission. I designated 100 days as the threshold for a long stay in a nursing facility for two reasons: first, to align the study population with the CMS standard definition of the longstay nursing home population for purposes of quality measurement; second, because 100 days is the point in a nursing facility stay at which Medicaid assumes all LTSS costs. (Medicaid liability does not begin until day 20 of a Medicare Skilled Nursing Facility Stay. Medicaid becomes the primary payer after the SNF benefit period ends at 100 days.)(*Medpac Payment Basics: Skilled Nursing Facility Services Payment System*, 2022) I limited the eligible cohort to "new admissions"—that is, residents with no nursing home admission for one hundred days prior to the admission date of the index stay. I limit the population in this way in order to observe residents from the start of a new episode of LTC utilization rather than starting from a readmission from an acute care facility. Each member of the study cohort was assigned to one of three CHC Phase comparison groups based on their residence as recorded in their Medicaid enrollment. CHC Phase 1 comprised 14 counties in the Southwest, CHC Phase 2 comprised 5 counties in the Southeast, and CHC phase 3 comprised the remaining 46 counties in the central part of the state.

3.3.3 Resident and Facility Covariates

I used MDS 3.0 data to determine each resident's age, sex, ethnicity, and urban status. From the MDS assessment closest to the date of 100-day incidence, I calculated the MDS ADL-long form score score (Morris et al., 1999) and Cognitive Function Score (CFS) (1-4, with 4 as highest impairment) (Thomas et al., 2017). The MDS ADL long-forms score is the sum of seven items from Section G of the MDS that measure dependency in the areas of bed mobility, transfer, locomotion on unit, dressing, eating, toilet use, and personal hygiene on a scale of 0-4, with 4 indicating total dependence. The MDS 3.0 Cognitive Function Score combines self-reported and administrator-reported MDS items to calculate a standardized four-category hierarchical scale of cognitive function. A score of one on the scale indicates that the resident is cognitively intact; a score of four on the scale indicates that the resident is severely cognitively impaired. I included indicators for the presence of Alzheimers and Dementia-related Disorders (ADRD), endstage disease, and mental illness, defined as Schizophrenia, Psychotic Disorder, or Bipolar Disorder derived from Section I (Active Diagnoses in the Last 7 Days) on the MDS item set.

I used data from the Centers for Medicare & Medicaid Services ("Centers for Medicare and Medicaid Services, Nursing Home Compare," 2022)and from LTCFocus.org (*LTCFocus.Org*, 2022) to characterize facilities. Facilities are described in terms of their total number of beds and residents, deficiency score, Medicare and Medicaid payer mix, CMS Nursing Home Compare overall star rating, star rating for quality, and star rating for staffing. Each nursing home is given an indicator for its for-profit status and whether it is part of a chain.

3.3.4 Outcome

I used MDS 3.0 to construct a measure of successful discharge to the community within 180 days of longstay incidence, assessed each year as a percent of incident longstays . I specified "successful discharge" to match the definition given by LTCFocus.org—a successful discharge is one in which the resident is discharged alive (A2100 = 1) to a community setting and has no subsequent MDS assessment for thirty days following the discharge date (*LTCFocus.Org*, 2022) Item A2100 specifies discharge to a community setting as discharge to a "private home/apt, board/care, assisted living," or "group home." The item distinguishes such discharges from discharge to other settings, such as to a hospital or other acute care setting.

3.3.5 Statistical Analysis

I used difference-in-difference analysis to measure changes in the annual rate of successful discharge to a community setting within 180 days among the incident population of Medicaid-covered longstay (>=100 day) nursing facility residents from a baseline period prior to Community HealthChoices implementation.

The staggered nature of CHC implementation made it possible to conduct the analysis using several different approaches. First, I pooled all pre-intervention observations, comparing their rate of successful discharge to the rate among pooled post-intervention observations. For resident i in CHC phase j in year k, I estimated:

$$Y_{ijk} = \beta_0 + \beta_1 CHC_{jk} + Phase_{jk} + Year_k + Resident_{ijk} + Facility_{ijk} + \varepsilon_{ijk}$$

where CHC is a dummy variable indicating whether the intervention was active during the phase-year, $Phase$ is a vector of phase fixed effects, $Year$ is a vector of year fixed effects, $Resident$ is a vector of resident-level adjusters, $Facility$ is a vector facility-level adjusters, and ε is an idiosyncratic error term. This yielded a single estimate of the program effect pooled over all phase-years of the intervention.

Second, I estimated separate program effects for each year and phase of CHC implementation using an event-study model in order to observe how the program effect evolved over time:

$$Y_{ijk} = \beta_0 + \beta_1 CHC_{jk} + Year_k + Resident_{ijk} + Facility_{ijk} + \varepsilon_{ijk}$$

I ran this model twice, first excluding the Group 2 population from the analysis, comparing Group 1 only (which received the CHC intervention in 2018) to Group 3 as control (which did not receive the intervention during the study observation period). Second, I exclude Group 1, comparing Group 2 only, which received the intervention in 2019, to Group 3 as control. Limiting the analysis to a single intervention group and a single control group in each step allowed me to compare pre-CHC trends in the outcome and population composition against a single timepoint of intervention. I used linear regression to obtain all effect estimates.

3.4 Results

3.4.1 Resident and Facility Characteristics in The Pre-CHC Population

This study included 26,816 Medicaid-enrolled nursing facility residents who reached day 100 of a stay during the pre-CHC period of 2014-2017. Of this population, 6,121 (22.8%) lived in a CHC Phase 1 (Western) county, 5,919 (22.1%) lived in a CHC Phase 2 (Eastern) county, and 14,774 (55.1%) lived in a CHC Phase 3 (Central) county. The mean age of this population was 83.8, 70% were female, and 84% came from a county classified as urban. This cohort was 90% white, 7% Black non-hispanic, 1% Hispanic, and 2% other race or ethnicity. 54% were diagnosed with Alzheimer's or related disorder(n=20,300), 58% were diagnosed with schizophrenia or bipolar disorder (n=21,700), and 3% were diagnosed with end-stage disease. The mean MDS long-form ADL score for this population was 15.99 (out of 28). The modal Cognitive Function Score (CFS) (Thomas et al., 2017) was 3 out of 4, indicating moderate impairment.

On average, the nursing facilities for this study cohort had a CMS overall star rating of 2.85 (out of 5), a CMS quality star rating of 3.68, and CMS staffing star rating of 2.52. Mean payer mix for these facilities was 67.21% Medicaid and 8.86% Medicare. 58% of facilities were for-profit, and 56% were part of a chain. A cross-sectional analysis of the 2017 resident population (figure 2) finds that, of the total population of 659 nonhospital-based nursing facilities, 643 (97.6%) served any Medicaid residents, and 585 (89%) served >=1 longstay Medicaid resident. On average, facilities that served the study's longstay Medicaid resident cohort were broadly similar in quality measures and other characteristics to the general population of facilities. However a downward gradient of CMS star ratings can be observed when comparing facilities with no Medicaid residents to facilities with Medicaid residents but no incident longstayers, then further to facilities with Medicaid-enrolled incident longstayers.

In the pre-implementation period, 1,577(5.8%) of Medicaid participants with an incident long-stay nursing home admission were successfully discharged to a community setting within 180 days of incidence. Compared to residents who were not discharged with 180 days of incidence, those who were successfully discharged were, on average, younger ($p<0.01$), less likely to be female ($p<0.01$), more likely to be Black ($p<0.01$), and less likely for their Medicaid enrollment to have originated in an urban county ($p<0.01$). On average, the discharged population had a lower ADL score (14.1), indicating less dependence ($p<0.01$); a lower likelihood of having been diagnosed in the nursing facility as having a Serious Mental Illness (schizophrenia or bipolar disorder) ($p<0.01$); a much lower prevalence of Alzheimer's and Dementia-related disorder (24% versus 54%) ($p<0.01$); and a much higher prevalence of intact cognitive function (62% versus 30%) ($p<0.01$).

Compared to the general population, successfully discharged residents lived, on average, in nursing facilities with a higher prevalence of both Medicaid and Medicare payment (likely indicating a lower proportion of private pay residents) ($p<0.01$); higher CMS deficiency score ($p<0.01$); higher likelihood of being for-profit and part of a chain ($p<0.01$); and lower CMS overall star ratings and CMS staffing star ratings ($p<0.01$).

3.4.2 Differences in Trends in The Composition of The Study Population

The goal of this analysis is to isolate changes in the rate of successful discharge to the community among Medicaid-enrolled longstay nursing home residents due to implementation of Community HealthChoices. Some potential confounders are compositional changes in the population that differ across CHC regions over time.To test whether these potential confounders were present, I compared CHC-regional trends in resident-level demography and functional status across the 2018-2019 study period. Estimates indicated parallel trends for gender, ADL, Alzheimer's and Related Dementia Disorders, and Cognitive Function; and statistically significant differential trends for Mental Illness in Phase 3 during 2019 (*Coeff=-0.06, p<0.01*) for, and Black race in Phase 2 during 2018 (*Coeff=-0.03, p<0.01*) and 2019 (*Coeff=-0.03, p=0.01).*

3.4.3 Changes in Community Discharge Rates Following Implementation of Community HealthChoices

3.4.3.1 Estimating the Pooled Effect

Leveraging the full available population of incident nursing-facility longstay residents, I assigned a dummy variable for CHC participation to all Medicaid-enrolled residents who reached day 100 of a stay in a county where mandatory managed care had been implemented. This yielded a single estimate of the CHC program effect that controlled for resident characteristics, facility characteristics, year-effects, and CHC-region effects.

I found no statistically significant effect of Community HealthChoices implementation on odds of successful discharge for Medicaid-enrolled nursing facility residents who reached day 100 of a stay. Comparing all members of the pre-intervention population to all members of the post-intervention population, I find no differential change in successful discharge rate associated with Community HealthChoices coverage *[Coeff = 0.001, (CI: -0.010-0.012), p=0.83]*.

3.4.3.2 Estimating Differential Time Trends for Phase 1 and Phase 2 of Community HealthChoices

I separately compared the Phase 1 and Phase 2 populations, which introduced Community HealthChoices in 2018 and 2019 respectively, to the Phase 3 population, which received no CHC intervention for the duration of the observation period, using an event-study approach (see figure 2). Following the standard practice, all annual estimates of difference are shown relative to the last pre-intervention period (2017 in the case of the Phase 1 event study, 2018 in the Phase 2).

In comparison to the Phase 3 control region, the Phase 1 (Western) intervention region increasingly underperforms Phase 3 in successful discharge when controlling for resident and facility-level variables in the 2014-2016 period. Phase 1 reverses this trend in 2017 and 2018 before sloping downward again in 2019. The magnitude of the adjusted annual difference between Phase 1 and Phase 3 ranges from -0.3 to 0.4 percentage points of outcome prevalence. In comparison to the Phase 3 control region, the Phase 2 (Eastern) intervention consistently underperforms the Phase 3 in successful discharge relative to the 2019 reference year, both pre- and post-implementation of mandatory managed care. The magnitude of the annual difference between Phase 2 and Phase 3 ranges from -.003 to 0.012 percentage points of outcome prevalence. None of the estimates are statistically significant.

3.5 Discussion

I used a difference-in-difference study design to evaluate the hypothesis that, controlling for resident and facility variation, Medicaid-enrolled nursing home residents who reached day 100 of a nursing home stay were more likely to be successfully discharged to a community setting within 180 days of longstay incidence if they were enrolled in Community HealthChoices managed care. I applied two approaches. First, I modeled a pooled program effect that controlled for year and region effects. Second, I modeled disaggregated program effects for each year and region where mandatory managed care was implemented. None of these analyses detected evidence in support of the hypothesis under examination. Overall, the rate of successful discharge in the population receiving the CHC intervention was 6.0%, and in the non-intervention population was 5.8%.

There are several plausible reasons that no effect was detected. First, the observation period of the outcome—successful discharge within 180 days of longstay incidence—extended to June 30, 2020. The first case of COVID-19 in a nursing home was detected on February 28, 2020 (McMichael et al., 2020), and, by May 15, 2020 cross-sectional prevalence of COVID-19 prevalence among all Pennsylvania nursing home residents was estimated at 16% (Da Costa & Degenholtz, 2021). This is likely to have had a distorting impact on the present study's 2019 findings, because residents who reached day 100 of a nursing home stay in 2019 likely faced exogenously heightened risk of death in 2020 due to COVID-19. Second, we observe only the first two intervention years of Community HealthChoices. It is possible that program effects will become stronger over time as managed care organizations gain feedback through experience in optimizing outcomes for the nursing home longstay population. Third, it is conceivable that efforts undertaken by Medicaid managed care organizations to aid residents in transitioning to community settings are most effective among subpopulations specified differently than the 100-day incident nursing facility population examined in this study. Research suggests that efforts to target nursing home populations with Nursing Home Transition resources, including those provided my MFP, can be effective when resources are tailored according to the population profile as it presents itself at different timepoints during the nursing home stay (Arling et al., 2010, 2011; Hass et al., 2017). Fourth, it is possible there is a "ceiling" effect on the number of residents who can be successfully discharged, and that the system was already running at peak efficiency with regard to successful nursing home discharge (Holland & Hemann, 2011).

3.6 Limitations

This study had several limitations. First, the outcome under evaluation was a relatively rare one (annual prevalence range between 5% and 7%) that, given a greater sample size, might have yielded a significant effect or allowed for stratified analysis to discover heterogeneous effects among important subpopulations. Second, I was not able to observe the availability of a community-dwelling spouse or relatives with a household that could accommodate the discharged person. Availability of such caregivers and household capacity is strongly associated with both nursing home admission (Freedman, 1996) and discharge (Fabius & Robison, 2019; Martikainen et al., 2009). Third, the event-study comparisons isolating the single effects of managed care implementation in Phase 1 and Phase 2 respectively, in contrast to Phase 3 as a control region, rested on the assumption that time-varying counfounders between the resident- and facility-populations were sufficiently controlled for in the models. Fourth, Pennsylvania participates in the Nursing Home Transitions, a CMS program that provides financial incentives to state Medicaid programs based on the number of nursing home residents transitioned out of nursing facilities, into community settings. Because resident-level data on exposure to this program were not available, I could not include it as a variable in this study's models. It is likely that unobserved variation in exposure to Nursing Home Transitions biased this study's estimates of the effect of mandatory managed care on successful discharge to a community settings (Eiken & Heestand, 2003; Irvin, 2017). This study should not be construed as an evaluation of Pennsylvania Nursing Home Transitions, which focuses solely on the subpopulation of residents who face a known barrier to discharge.. Fifth, this study does not measure the HCBS service environment, which research has been shown to influence nursing home admission and discharge rates (Kane et al., 2013; Robison et al., 2012b). Finally, this study did not observe whether successfully discharged residents experienced hospital admission in the period following discharge. This may be a further important indicator of the quality of MCO care coordination in the post-discharge period.

3.6.1 Conclusion

Two years into implementation of the Community HealthChoices program, I detected no effect of mandatory managed care on the rate of successful discharge to a community setting on the Medicaid-eligible incident longstay nursing home population in Pennsylvania. Community HealthChoices effect on longstay nursing home resident discharge should continue to be monitored for changing impacts over a longer follow up period.

3.7 Tables and Figures

Table 8. Characteristics of The Study Population by Region

Table 1. Characteristics of the Pre-implementation Study Population (2014-2017) by Region					
	All	Region 1	Region 2	Region 3	
Resident-level characteristic	*(N=26,816)*	*(n=6,121)*	*(n=5,919)*	*(n=14,776)*	*p-value*
Successfully discharged, %	5.8	6.1	4.7	6.1	0.00
Age (mean)	83.8	84.2	83.3	83.8	0.00
Female, %	70.0	71.7	68.3	70.1	0.00
Race/ethnicity, %					
White	90.28	92.47	75.84	95.15	
Black	6.9	5.8	20.0	2.1	
Hispanic	1.2	0.1	1.6	1.5	
Other race	1.6	1.6	2.6	0.0	0.00
Urban, %	84.1	86.4	100.0	76.8	0.00
ADL score (mean)	16.0	16.1	16.0	15.9	0.06
Alzheimers or Dementia-Related Disorder, %	54.3	53.0	54.7	54.7	0.06
Mental Illness, %	58.2	58.0	53.9	60.0	0.00
Cognitive Function Scale, %					
Intact	29.7	28.3	30.7	29.9	
Mildly impaired	26.3	26.5	26.4	26.2	
Moderately impaired	37.2	37.8	35.7	37.5	
Severely impaired	6.8	7.4	7.2	6.4	0.00
Endstage disease, %	2.6	2.8	2.4	2.5	0.29
Facility-level characteristic					
Total beds (mean)	191.1	167.2	215.7	191.1	0.00
Total residents (mean)	172.7	145.8	197.2	174.0	0.00
Deficiency score (mean)	49.9	47.5	39.5	55.0	0.00
Percent Medcaid payer, (mean)	67.2	66.6	68.2	67.1	0.00
Percent Medicare payer, (mean)	8.9	6.8	9.2	9.5	0.00
Part of a chain, %	56.0	49.0	57.9	58.2	0.00
For-profit, %	58.1	59.4	61.2	56.4	0.00
Percent occupancy (mean)	90.6	88.1	91.7	91.2	0.00
CMS overall star rating (mean)	2.8	2.8	3.2	2.7	0.00
CMS quality star rating (mean)	3.7	3.3	3.9	3.7	0.00
CMS staffing star rating (mean)	2.5	2.7	2.7	2.4	0.00

Table 9. Characteristics of The Study Population by Successful Discharge Status

Table 2. Characteristics of the Pre-implementation Study Population (2014-2017) By Successful Discharge Status				
	Successfully Discharged Within 180 Days of Longstay Incidence			
	All	No	Yes	
Resident-level characteristic	*(N=26,816)*	*(n=25,259)*	*(n=1,557)*	*p-value*
Age (mean)	83.8	84.1	78.6	0.00
Female, %	70.0	70.4	64.0	0.00
Race/ethnicity, %				
White	90.3	90.7	83.9	
Black	6.9	6.6	11.9	
Hispanic	1.2	1.2	2.1	
Other race	1.6	1.6	2.1	0.00
Urban	84.1	84.4	80.4	0.00
CHC Region				
Phase 1	22.8	22.8	23.9	
Phase 2	22.1	22.3	17.8	
Phase 3	55.1	54.9	58.3	0.00
ADL score (mean)	16.0	16.1	14.1	0.00
Alzheimers or Dementia-Related Disorder, %	54.3	56.2	24.5	0.00
Mental Illness, %	58.2	58.7	50.4	0.00
Cognitive Function Scale, %				
Intact	29.7	27.7	62.5	
Mildly impaired	26.3	26.6	22.7	
Moderately impaired	37.2	38.6	13.2	
Severely impaired	6.8	7.1	1.5	0.00
Endstage disease, %	2.6	2.7	0.3	0.00
Facility-level characteristic				
Total beds (mean)	191.1	192.3	170.9	0.00
Total residents (mean)	172.7	174.0	152.5	0.00
Deficiency score (mean)	49.9	49.7	53.6	0.00
Percent Medcaid payer, (mean)	67.2	67.1	68.5	0.00
Percent Medicare payer, (mean)	8.9	8.8	9.9	0.00
Part of a chain, %	56.0	55.5	64.3	0.00
For-profit, %	58.1	57.3	71.0	0.00
Percent occupancy (mean)	90.6	90.6	90.5	0.68
CMS overall star rating (mean)	2.8	2.9	2.6	0.00
CMS quality star rating (mean)	3.7	3.7	3.7	0.85
CMS staffing star rating (mean)	2.5	2.5	2.3	0.00

Table 10. Characteristics of Pennsylvania Skilled Nursing Facilities, 2017

Table 3. Characteristics of Pennsylvania Skilled Nursing Facilities, 2017

	All	No Medicaid Residents	>=1 Any Medicaid Residents, 0 Incident Longstay Residents	>=1 Incident Medicaid Longstay Resident
Facility characteristic	*(N = 659)*	*(n = 16)*	*(n = 58)*	*(n = 585)*
Total beds (mean)	130.6	61.4	103.9	135.2
Total residents (mean)	114.2	42.7	93.6	118.2
Deficiency score (mean)	58.5	27.0	50.0	60.2
Percent Medcaid payer, (mean)	59.9	0.0	53.1	62.2
Percent Medicare payer, (mean)	9.9	39.0	10.5	9.0
Part of a chain, %	58.6	62.5	60.3	58.3
For-profit, %	54.5	50.0	44.8	55.6
Percent occupancy (mean)	87.5	74.5	90.0	87.6
CMS overall star rating (mean)	3.1	4.4	3.5	3.0
CMS quality star rating (mean)	3.8	3.7	4.0	3.8
CMS staffing star rating (mean)	2.7	4.3	3.2	2.6

Table 11. Differential Changes from Preintervention

Table 4.

Differential Changes from the Pre-intervention Period

	Coeff.	*CI*	*p-value*
Pooled over all phase-years of intervention	0.001	(-0.010-0.012)	0.83
Disaggregated by phase and year of intervention			
Phase 1, 2018	0.005	(-0.015-0.026)	0.60
Phase 1, 2019	-0.001	(-0.022-0.021)	0.96
Phase 2, 2019	-0.004	(-0.025-0.017)	0.71

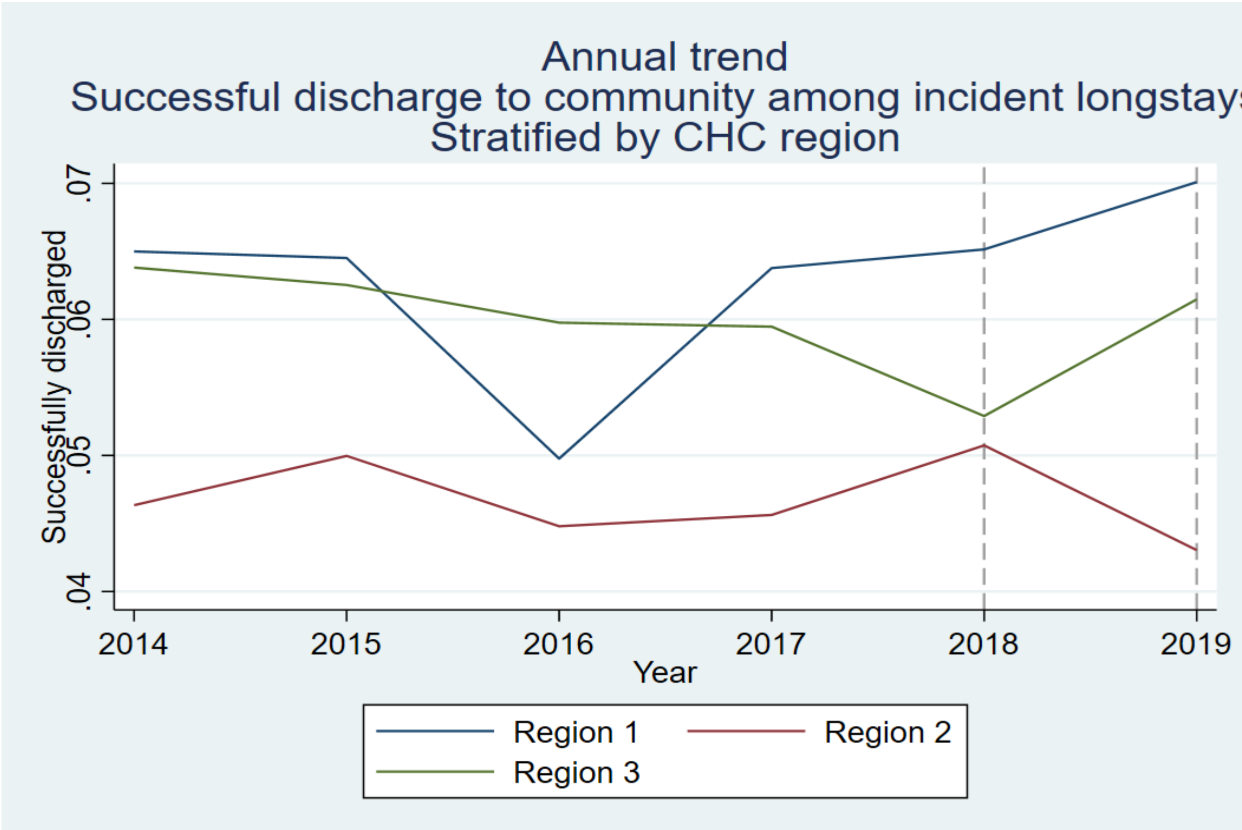
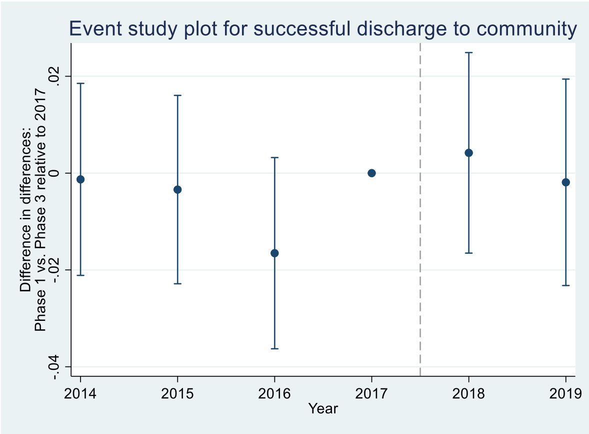


Figure 4. Unadjusted Annual Trend, Successful Discharge to The Community Within 180 Days of Longstay Incidence



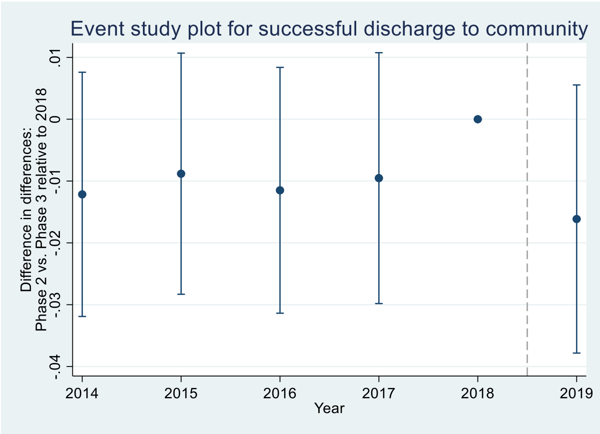


Figure 5. Adjusted Differential Trends in Successful Discharge for CHC Region 1 (Intervention) Versus Region 3 (Control); and CHC Region 2 (Intervention) Versus Region 3 (Control)

4.0 Association Between County-Level HUD Housing Density and Discharge to The Community Among Medicaid Longstay Nursing Home Residents in Pennsylvania, 2015-2017

4.1 Abstract

The CMS Money Follows the Person program provides incentives to state Medicaid agencies to transition long-term nursing home residents to community settings for care. These state programs, known as Nursing Home Transition (NHT) programs, provide nursing homes with resources to aid residents who wish to receive care in a community-based setting. In qualitative evaluations of NHT programs, staff consistently report that lack of affordable housing is the primary barrier to transferring Medicaid-enrolled nursing facility residents to community settings for care. To date, however, little work has been done to model the association between regional subsidized housing access and discharge to a community setting among longstay (>100 day) nursing facility residents. In this paper, I examined 20,044 nursing home residents enrolled in Pennsylvania Medicaid who reached day 100 of a stay during the years 2015-2017. I developed models to observe the adjusted association between county-level subsidized-housing density and resident odds of discharge to a community setting within 365 days of longstay incidence. Models estimate a 0.6% increase in resident probability of community discharge associated with each additional subsidized housing unit per 1000 of population in the resident's county of origin, although this effect is not statistically significant (OR = 1.006, p=0.20). Sensitivity analysis in which HUD density is modelled categorically by quintile indicates a 35% increase in resident odds of community discharge for residents in the fourth quintile of HUD exposure (OR = 1.35, p<.01),

suggesting a threshold effect. Further research should develop more refined measures of subsidized housing access for the longstay nursing home population and investigate the interaction between housing access and specific resident- and facility-level determinants of community discharge.

4.2 Background

In response to numerous studies indicating that people receiving long-term care prefer to do so in community, rather than institutional, settings, Money-Follow-the-Person (MFP) was launched in 2008 as a federal program to provide state Medicaid agencies with funding incentives to transition Medicaid-enrolled nursing home residents to community settings for care. Evaluators of MFP subsequently reported that program staff perceived lack of suitable housing options as the primary barrier to accomplishing program objectives(Lipson et al., 2011; Meador et al., 2011). This perception is corroborated by studies showing that interventions addressing housing need are associated with favorable outcomes for people who receive long-term care--for example, a pilot effort by the Department of Housing and Urban Development (HUD) that granted vouchers to low-income disabled people was found to be effective in increasing nursing home exit and reducing nursing home admission (D. Hoffman et al., 2017). In addition, housing cost-burden significantly predicts nursing home admission among older adults (Jenkins Morales & Robert, 2020). Other studies have failed to find a significant between regional housing affordability and nursing home diversion outcomes more generally (Anguelov & Frank, 2020).

HUD administers housing subsidy and direct housing provision for people who meet eligibility requirements based on annually determined income limits adjusted by region and household size. HUD programs include Public Housing, which is administered directly by local public housing authorities, and housing subsidy and finance programs, including Housing Choice Vouchers, Section 202 housing for the elderly, and section 811 housing for people with disabilities. HUD programs require applicants to fall below 80% or 50% of Area Median Income as measured by the American Community Survey (ACS)(*Programs of HUD*, 2020) depending on guidelines set by locally by Public Houisng Authorities. Requirements for Medicaid eligibility vary by state, however eligibility is automatically extended to people over 65 who qualify for Supplemental Security Income (SSI). To be eligible for Medicaid coverage of a nursing home stay in Pennsylvania, resident income must not exceed 300% of the the federal SSI payment (a limit most recently calculated at $2383 per month) and other resident assets must not exceed $8000 in total, with some exceptions including primary residence and one motor vehicle There is thus considerable overlap between eligibility for Medicaid nursing home coverage and HUD housing among the population of age 65-and-over longstay nursing home residents. In recognition of this, advocates have recommended greater coordination among service-providing agencies (Butler, 2022), while policymakers have moved to greater coordination among housing ahe health agencies at the local, state and federal levels. (Division, 2021).

This study is a contribution to the growing evidence base for the mutual impact of housing and health policy (Brucker et al., 2018; Cole et al., 2022; Dawkins & Miller, 2017). It tests the hypothesis that greater population-denominated density of subsidized housing in a Medicaid-enrolled, longstay nursing home resident’s county of origin will be associated with greater odds of discharge to a community setting for care.

4.3 Study Data and Methods

4.3.1 Data

Data for this study were derived from the Nursing Home Minimum Dataset (MDS 3.0) and Medicaid eligibility records provided to the University of Pittsburgh Graduate School of Public Health by the Pennsylvania Department of Human Services (DHS). MDS 3.0 is a longform assessment administered on admission and quarterly thereafter to all residents of skilled nursing facilities certified by the US Centers for Medicare and Medicaid Services (CMS). Resident county of origin and eligibility for Medicaid nursing home coverage was obtained from Medicaid enrollment and eligibility records.

4.3.2 Study Population

The study population is all Medicaid financed long-stay nursing home residents in Pennsylvania during 2014 to 2017. I examined the cross-sectional association between resident odds of discharge to a community setting within 365 days of longstay incidence and county-level density of HUD project-based housing because evaluations of NHT programs frequently report that lack of affordable housing is the primary barrier to transitioning Medicaid-enrolled nursing home residents to community settings for care (Freeman et al., 2017; Poole et al., 2006). I analyzed 2014-2017 MDS 3.0 records for residents enrolled in Medicaid by day 100 of their nursing home stay and observed them for 365 days post-incidence. I determined Medicaid eligibility by matching resident MDS records to Medicaid enrollment records obtained from the Pennsylvania DHS.

To limit the sample to "new" admissions, sample eligibility was restricted to nursing home resident with no MDS record one year prior to the index admission. I specified the pooled 2015-2017 calendar years for analysis.

4.3.3 Subsidized Housing Exposure

I used "Picture of Subsidized Households," a dataset publicly available from the US Department of Housing and Urban development (HUD), to obtain the total number of project-based subsidized housing units present in each Pennsylvania county in 2016(*Assisted Housing: National and Local | HUD USER*, 2022) . To calculate a measure of density adjusted to county population, I divide number of HUD units by 2016 county population present in resident's county of nursing home residence, obtained from the Area Health Resource file, a publicly-use file from US Health Resources and Services Administration (HRSA). I selected this measure in order to broadly capture the level of housing access locally afforded to enrollees through government subsidy. Density of HUD project-based housing should be viewed as high-level summary of housing exposure that is agnostic to the mechanism or channel of influence by which housing access impacts resident odds of community discharge (see Figure 1).

4.3.4 Resident Covariates

From MDS records, I determined resident age, sex, race and ethnicity, urbanicity, and health and functional status. Health and functional status variables included as controls were ADL score (measured on a 28 point scale, with 27 as most dependent), diagnosis of mental illness, Alzheimers or dementia-related disorder, endstage disease, and rating on a four-level Cognitive

Function Scale (from intact to severely impaired). These variables were evaluated from the MDS assessment taken closest in time to the resident's date of longstay incidence.

4.3.5 Outcome

I used MDS records to construct a binary indicator for whether a resident was discharged to a community setting within one year of longstay incidence. Skilled nursing facilities are required to administer an MDS assessment on admission, quarterly, and upon discharge as a condition of CMS accreditation.

4.3.6 Statistical Analysis

I specify two models for the association between community discharge and subsidized housing density. Model 1 is a logistic regression controlling for resident-level demography, health, functional status, and year-effects (equation 1) that accounts for within-facility correlation using robust standard errors clustered at the facility level (equation 2).

$$Model\ 1\colon Y_{ij} = \beta_{0j} + \beta_1 HUD_{ij} + \beta_2 DEMO_{ij} + \beta_3 FUNCTION_{ij} + YEAR_{ij} + e_{ij},$$

estimated with cluster-robust standard errors(1)

Model 2, developed in the supplement section of this paper, is a logistic regression that accounts for within-facility correlation by estimating random intercepts for each facility (equation 2).

$$Model\ 2: Y_{ij} = \delta_{00} + \beta_1 HUD_{ij} + \beta_2 DEMO_{ij} + \beta_3 FUNCTION_{ij} + YEAR_{ij} + [u_{0j} + e_{ij}]$$

(2)

The random part of the equation, contained in brackets, includes a resident specific error term (e_{ij}) and a facility specific error term (u_{0j}).

In these models I specify the main effect of HUD density as a continuous variable in order to obtain an estimate that can be interpreted as the association between an additional unit of HUD project-based housing per 1000 of county population on resident odds of community discharge within 365 days of longstay incidence.

4.3.6.1 Sensitivity Analysis

In addition to the continuous specification for HUD exposure posited in the main analysis, I conducted a sensitivity analysis in which HUD exposure is modeled categorically by quintile of density. This specification allows us to estimate associations that are heterogeneous along the range of HUD exposure.

4.4 Results

The pooled 2015-2017 study population included 20,044 Medicaid nursing home residents who reached day 100 of a nursing home stay during the study period. On average, residents who were discharged to the community were younger, and more likely to be male, nonwhite, and reside in a non-urban county. Community-discharged residents exhibited lower ADL-dependency, less Alzheimers or dementia-related disorder, and less end-stage disease. Community-discharged residents were also more likely to be judged cognitively intact on the Cognitive Function Scale (Table 2).

Residents lived in 596 free-standing nursing homes in Pennsylvania, and 64 of 67 Pennsylvania counties. The mean (SD) number of eligible residents per nursing home was 33.6 (26.1) and the mean (SD) number per county was 313.2 (347.7) Three counties—Cameron, Fulton, and Greene—were excluded from analysis because there were no MDS records indicating presence of Medicaid-enrolled longstay nursing home residents in those counties.

The mean (SD) number of HUD project-based units per thousand of county population among the 64 counties included in the analysis was 15.4 (7.2). Figure 1 displays unadjusted community-discharge rates by eligible Pennsylvania county. Figure 2 displays density of HUD project-based housing by Pennsylvania county.

Table 1 displays the outcome distribution by quintile of HUD project-based housing exposure. Bivariate analysis indicates that HUD density is significantly associated with greater probability of discharge to a community setting for Medicaid enrollees (Table 2).

4.4.1 Effect Estimate for HUD Subsidized Housing Exposure

I found no statistically significant association between exposure to county-level HUD project-based housing and odds of community discharge among Medicaid incident longstay nursing home residents.

Table 3 displays effect estimates for HUD density from three models that progressively account for between-facility variation in the outcome. All models estimate a 0.6% increase in resident odds of community discharge associated with 1 additional HUD unit per 1000 of county population. Model 1a, which does not adjust for facility clustering, estimates a p-value of 0.08;

Model 2a, which clusters standard errors by facility, estimates a p-value of 0.14; and Model 3a, which accounts for facility-level variation with facility random intercepts, estimates a p-value of 0.20.

4.4.1.1 Sensitivity Analysis

Table 4 displays effect estimates by quintile of HUD exposure. Effects are measured as null for all quintiles except the fourth (corresponding to 17.08-28.40 units per 1000 of county population), the effect of which is estimated in the range of a 33-35% increase in resident odds of community discharge with a high level of significance. (Model 1b: *OR*=1.33, $p<0.01$; Model 2b: *OR*=1.33, $p<0.01$; Model 3b: *OR=1.35, p<0.01).*

4.5 Discussion

This study examined the cross-sectional association between discharge to a community setting and county-level HUD project-based housing exposure among Medicaid-enrolled nursing home residents who reached day 100 of a nursing home stay in the 2015-2017 period. First, I determined the appropriate specification to account for the hierarchical nature of the data by developing an unconditional model that allowed estimation of intraclass correlation at the facility and county level. I then estimated a design effect for each level, which indicated that it was appropriate to specify a multilevel model with two levels: resident and facility. Next, I developed three models, each progressively accounting for facility-level variation in the outcome. Models 1a and 2a each yielded a point-estimated 0.6% increase in resident odds of community discharge for each additional unit of HUD housing exposure per 1000 of county population when controlling for resident characteristics and year fixed-effects. Model 3a, which controlled for resident characteristics and year fixed-effects, and included random-intercepts for facilities, estimated a 0.6% increase in odds of community discharge for each additional unit of HUD exposure, and estimated a standard error 26% greater than Model 1a, which included only resident-level covariates. While the directionality of these results are aligned with the hypothesis that HUD-exposure would be positively associated with community discharge, they do not reach the threshold of statistical significance.

This analysis demonstrates the importance of proper model specification to estimate effects where outcome variation is plausibly attributable to layered contexts (Oshchepkov & Shirokanova, 2022). In this analysis, we see significant correlation among residents who share the institutional setting of a nursing facility, but negligible correlation among residents who share the wider spatial and administrative context of a county. Similarly, accounting for facility-level variation in the association between county-level housing subsidy and resident odds of community discharge greatly dilutes the precision of the observed positive association between them.

There are several potential reasons that this analysis did not detect the hypothesized association between subsidized housing density and community discharge among longstay Medicaid residents. First, county-level HUD-density may not adequately represent the type of housing access that most determines a nursing home resident's odds of community discharge. Measures of the density of specific housing types—supportive housing for the aged and disabled, for example—may be more appropriate to this group. There are several ways this potential measurement error may introduce bias into HUD effect estimates. For example, the historical expansion of HUD agency activities outward from urban to less urban areas meant that urban and rural areas gained units of different quantities program types depending on the period when they were introduced, possibly introducing systematic bias into the distribution of program types (A. von Hoffman, 2000). If relative proportions of project-based units and voucher units are correlated with population density, the count of project-based Public Housing units may not be an unbiased proxy for HUD exposure. Second, the volume of housing present in a given area may inadequately represent the volume of housing that is available to be occupied, or to be occupied by a group with special needs. It may be more accurate, for example, to measure the density of vacant units, or the rate of turnover in occupancy. Third, it is possible that the most relevant geographic area for measuring relevant housing exposure is not the county, but a smaller area, such as the metropolitan statistical area (MSA) or municipality. Fourth, the considerable proportion of variation accounted for in these models at the resident- (ICC: 0.90) and facility-level (ICC: .09) suggest that, empirically in this model, it is resident- and facility-level characteristics that drive differences in longstay community discharge. Studies of the influence of resident and facility level correlates of community discharge support this view (Arling et al., 2011; Holup et al., 2016).

As an alternate specification, I modeled HUD-density as a categorical variable by quintile in order to observe whether the association estimated in the main set of models was heterogeneous along the range of HUD exposure. Taking the lowest quintile of HUD exposure as the reference class, the models estimated the effect of all quintiles of exposure as null, with the exception of the fourth quintile (17.08-28.40 units per 1000 of county population), which the models estimated, with strong significance, to increase resident odds of community discharge by 33%-35% [1b: OR = 1.33, $p<0.01$; 2b: OR=1.33, $p<0.01$; 3b: OR=1.35, $p<0.01$)]. This suggests that the point estimates for the continuous linear specification of HUD exposure are driven by fourth quintile HUD exposure. This strong discontinuity does not also apply to the highest quintile of exposure, however. This finding may be due to geographically specific confounding factors not observed in this study, including variation in the HCBS supply environment or other region- or population-specific factors.

4.6 Limitations

This study had several limitations. First, there may have been unobserved differences among counties in the home-and-community-based services (HCBS) environment that led to differential results in the outcomes. In addition to housing itself, NHT programs must also seek out services that provide home care, transportation, and other supportive services that allow residents to maintain a household in the community(Robison et al., 2012a). Second, the measure of county-level density of HUD units was not adjusted for the household size or capacity of the units—it is conceivable that the same number of units in two counties could serve different numbers of people. Third, the main effect measured by this study—density of HUD project-based housing—excludes other types of HUD housing plausibly relevant to the Medicaid longstay population, including non-project based units subsidized through HUD Housing Choice Voucher program. Fourth, because this is an observational study, it cannot ascribe a causal relationship between housing density and discharge to the community—there may be unobserved differences among longstay nursing home residents across facilities and counties that limit our ability to isolate the relationship between housing density and odds of community discharge from confounders (Fabius & Robison, 2019). Fifth, this study does not address specific channels of causality between subsidized housing access and longstay discharge. There are many ways a nursing home resident could benefit from an increased supply of subsidized housing relative the population—availability of affordable vacant units, direct receipt of a housing voucher through a targeted program, or increased space or financial capacity in the households of family caregivers, to name few (Freeman et al., 2017).

Sixth, because the final year of outcome follow-up (2018) saw the staggered phase-in of managed care for this population by region, unobserved geographic variation in population composition and coverage dynamics may have biased results for the 2017 incident study population. Finally, I was unable to observe whether residents owned a home in the community, a factor that would influence the relevance of HUD public housing density to their discharge outcome.

4.7 Conclusion

In conclusion, I found no strong evidence of an independent association between HUD project-based housing density and discharge to community setting among incident Medicaid longstay nursing home residents in Pennsylvania during the study period. Future research should test hypotheses based on highly specified causal models of how subsidized housing access influences community discharge outcomes for Medicaid longstay nursing home residents.

4.8 Tables and Figures

Table 12. Population Characteristics by Quintle of County Level HUD Density

Population characteristics by quintle of county-level HUD project-based housing exposure						
	All	**First**	**Second**	**Third**	**Fourth**	**Fifth**
HUD units per thousand of county population		(2.28-8.82)	(8.83-12.50)	(12.51-17.07)	(17.08-28.40)	(28.41-31.38)
	N=20,044	n=4,742	n=3,310	n=4,101	n=5,349	n=2,542
Discharged to community	7.52	6.71	7.07	6.66	9.03	7.83
Age (mean)	83.74	83.64	83.71	83.73	83.93	83.55
Female	69.77	69.25	70.63	68.91	70.18	70.10
Urban	84.14	96.71	76.44	84.27	73.08	93.82
Race/ethnic						
White, nonhispanic	90.42	90.26	90.60	95.12	92.73	78.05
Black, nonhispanic	6.96	6.43	6.68	1.76	5.98	18.80
Hispanic	1.24	1.33	1.66	1.49	0.37	1.93
Other race	1.39	1.98	1.09	1.63	0.93	1.22
ADL score (mean)	15.96	16.11	16.24	15.63	15.70	16.40
Alzheimers or dementia-related disorder	54.06	56.39	54.89	55.01	52.91	49.49
Mental illness	57.54	60.08	58.64	58.64	57.81	49.06
Endstage disease	2.65	2.59	3.47	2.56	2.82	1.49
Cognitive Function Scale						
Intact	30.04	30.03	29.21	29.85	29.93	31.71
Mildly impaired	26.37	25.62	25.53	26.58	26.32	28.64
Moderately impaired	36.78	37.45	38.55	35.50	37.76	33.24
Severely impaired	6.80	6.90	6.71	8.07	5.98	6.41

Table 13. Population Characteristics by Community Discharge Status

Population characteristics by community discharge status Fee-for-service Medicaid Incident longstay nursing home residents in Pennsylvania skilled nursing facilities 2015-2017				
	All N=20,044	**No discharge to community n=18,537**	**Discharged to community n=1,507**	**p-value**
HUD units per 1k county population	17.11	17.05	17.76	0.00
Age (mean)	83.74	84.16	78.47	0.00
Female	69.77	70.32	62.91	0.00
Urban	84.14	84.38	81.29	0.00
Race/ethnic				
White, nonhispanic	90.42	90.96	83.74	
Black, nonhispanic	6.96	6.55	12.01	
Hispanic	1.24	1.13	2.52	
Other race	1.39	1.36	1.73	0.00
ADL score (mean)	15.96	16.12	14.03	0.00
Alzheimers or dementia-related disord	54.06	56.18	27.94	0.00
Mental illness	57.54	58.04	51.43	0.00
Endstage disease	2.65	2.83	0.53	0.00
Cognitive function scale				
Intact	30.04	27.55	60.72	
Mildly impaired	26.37	26.68	22.63	
Moderately impaired	36.78	38.61	14.33	
Severely impaired	6.80	7.16	2.32	0.00

Table 14. Odds of Community Discharge Within 365 Days of Longstay Incidence, Medicaid Enrolled SNF Residents, 2015-2017

Table 3. Odds of community discharge within 365 days of longstay incidence, Medicaid-enrolled SNF residents, 2015-2017, continuous HUD variable

Parameter	Model 1a: Logistic			Model 2a: Logistic with robust SE clustered by facility			Model 3a: Logistic with Facility random-intercepts		
Regression coefficients (fixed effects)	OR	SE	*p-value*	OR	SE	*p-value*	OR	SE	*p-value*
HUD-density (1 unit per 1K county pop)	1.006	0.0034	0.08	1.006	0.0041	0.14	1.006	0.0043	0.20
Age (centered)	0.941	0.0033	0.00	0.941	0.0034	0.00	0.941	0.0034	0.00
Female	1.035	0.0627	0.57	1.035	0.0638	0.58	1.047	0.0034	0.46
Urban	0.731	0.0536	0.00	0.731	0.0704	0.00	0.756	0.0703	0.00
Race/ethnic									
White, nonhispanic (ref)	ref			ref			ref		
Black, nonhispanic	1.707	0.1598	0.00	1.707	0.1681	0.00	1.720	0.1767	0.00
Hispanic	2.198	0.4239	0.00	2.198	0.4281	0.00	2.223	0.4475	0.00
Other	1.203	0.2625	0.40	1.203	0.2553	0.39	1.225	0.2743	0.36
ADL	0.969	0.0046	0.00	0.969	0.0049	0.00	0.965	0.0048	0.00
Cognitive Function Scale									
Intact	ref			ref			ref		
Mild	0.526	0.0370	0.00	0.526	0.0383	0.00	0.514	0.0370	0.00
Moderate	0.302	0.0264	0.00	0.302	0.0276	0.00	0.296	0.0264	0.00
Severe	0.283	0.0521	0.00	0.283	0.0504	0.00	0.285	0.0530	0.00
ADRD	0.561	0.0384	0.00	0.561	0.0374	0.00	0.564	0.0394	0.00
Mental Illness	0.783	0.0453	0.00	0.783	0.0474	0.00	0.778	0.0461	0.00
Endstage prognosis	0.253	0.2533	0.00	0.253	0.0913	0.00	0.242	0.0882	0.00
Incidence year 2015	ref			ref			ref		
Incidence year 2016	0.880	0.8798	0.06	0.880	0.0580	0.05	0.873	0.0605	0.05
Incidence year 2017	0.904	0.9044	0.14	0.904	0.0621	0.14	0.895	0.0625	0.11
Intercept	0.328	0.0427	0.00	0.328	0.0479	0.00	0.326	0.0486	0.00
							Variance (SE)		95% CI
Variance components (random effects)									
Intercept (τ_jk)							0.2156778	0.041183	(0.148-0.314)

Table 15. Odds of Community Discharge Within 365 Days of Longstay Incidence, Medicaid Enrolled SNF Residents, 2015-2017, with Categorical HUD Variable

Table 4. Odds of community discharge within 365 days of longstay incidence, Medicaid-enrolled SNF residents, 2015-2017, categorical HUD variable									
Parameter	Model 1b: Logistic			Model 2b: Logistic with robust SE clustered by facility			Model 3b: Logistic with Facility random-intercepts		
Regression coefficients (fixed effects)	OR	SE	*p-value*	OR	SE	*p-value*	OR	SE	*p-value*
HUD-density quintile (Units per 1K county pop)									
Lowest (2.28-8.82)	ref			ref			ref		
Second (8.83-12.50)	1.021	0.0967	0.83	1.021	0.1400	0.88	1.093	0.1309	0.46
Third (12.51-17.07)	0.977	0.0877	0.80	0.977	0.1141	0.85	1.058	0.1198	0.62
Fourth (17.08-28.40)	1.330	0.1080	0.00	1.330	0.1258	0.00	1.351	0.1389	0.00
Highest (28.41-31.38)	0.983	0.0981	0.87	0.983	0.1110	0.88	0.988	0.1226	0.92
Age (centered)	0.941	0.0033	0.00	0.941	0.0034	0.00	0.941	0.0034	0.00
Female	1.034	0.0627	0.58	1.034	0.0642	0.59	1.045	0.0647	0.48
Urban	0.785	0.0599	0.00	0.785	0.0773	0.01	0.813	0.0775	0.03
Race/ethnic									
White, nonhispanic (ref)	ref			ref			ref		
Black, nonhispanic	1.744	0.1651	0.00	1.744	0.1749	0.00	1.758	0.1811	0.00
Hispanic	2.297	0.4442	0.00	2.297	0.4513	0.00	2.281	0.4597	0.00
Other	1.228	0.2682	0.35	1.228	0.9700	0.33	1.247	0.2790	0.32
ADL	0.970	0.0046	0.00	0.970	0.0049	0.00	0.965	0.0048	0.00
Cognitive Function Scale									
Intact	ref			ref			ref		
Mild	0.525	0.0370	0.00	0.525	0.0380	0.00	0.514	0.0370	0.00
Moderate	0.299	0.0262	0.00	0.299	0.0272	0.00	0.295	0.0263	0.00
Severe	0.284	0.0523	0.00	0.284	0.0504	0.00	0.285	0.0530	0.00
ADRD	0.562	0.0385	0.00	0.562	0.0374	0.00	0.565	0.0395	0.00
Mental illness	0.777	0.0450	0.00	0.777	0.0471	0.00	0.774	0.0459	0.00
Endstage prognosis	0.251	0.0908	0.00	0.251	0.0906	0.00	0.240	0.0877	0.00
Incidence year 2015	ref			ref			ref		
Incidence year 2016	0.877	0.0596	0.05	0.877	0.0577	0.05	0.872	0.0604	0.05
Incidence year 2017	0.907	0.0621	0.16	0.907	0.0622	0.16	0.897	0.0627	0.12
Intercept	0.315	0.0425	0.00	0.315	0.0460	0.00	0.302	0.0466	0.00
							Variance	SE	95% CI
Variance components (random effects)									
Intercept (τ_jk)							0.202521	0.040264	(0.137-0.300)

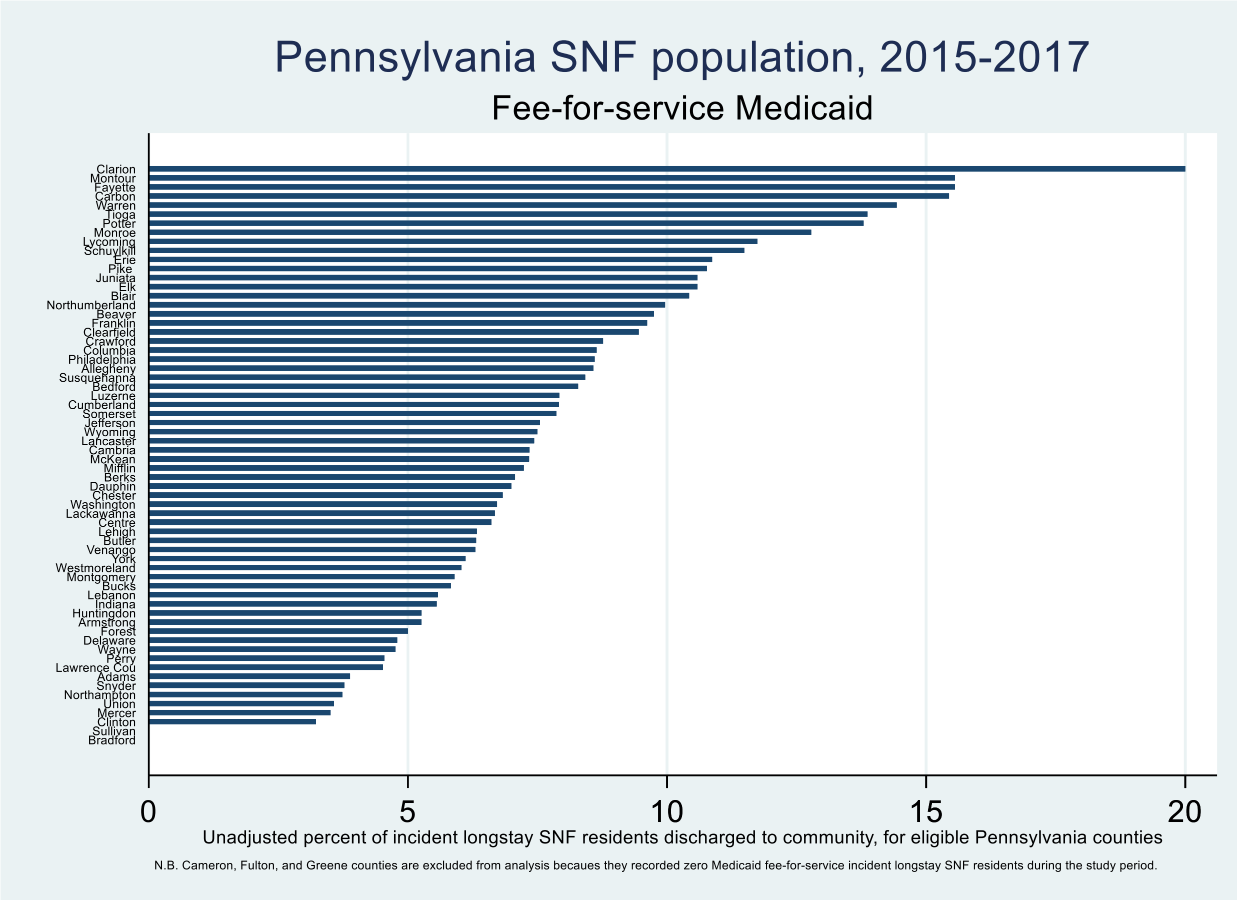


Figure 6. Unadjusted Percent of Incident Longstay SNF Residents Discharge to Community, by Eligible Pennsylvania County

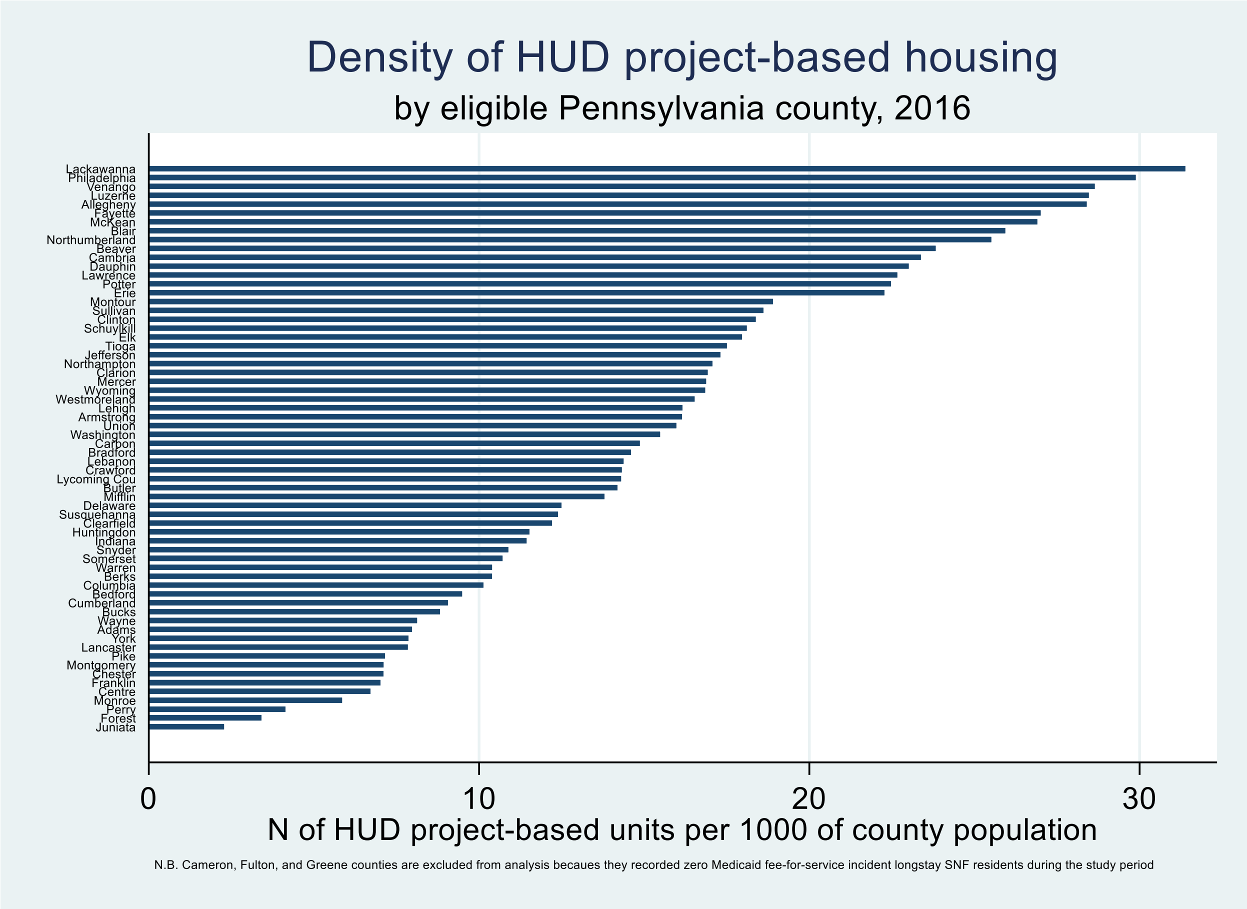


Figure 7. Density of HUD Project Based Housing, by Eligible Pennsylvania County, 2016

5.0 A Synthesis of Findings from Studies of The Association between Medicaid Nursing Home Utilization and Three Program Environments—Section 202 Supportive Housing for the Elderly, Medicaid Managed Care, and Regional Subsidized Housing Supply

5.1 Overview

This essay attempts to situate the topics of this dissertation in the wider context of programs designed to enable the greatest possible proportion of Medicaid enrollees to receive care in the most integrated setting possible. The first part offers background on the existing motivations toward greater integration of services, particularly with respect to health and housing. The second part frames this dissertation's findings in terms of implications for policy.

5.2 HUD and The Medicaid LTSS Population

The Olmstead decision created a legal obligation for the US government to provide services in the least restrictive setting possible (*Olmstead v. LC*, 1999). In response, the 2005 Deficit Reduction Act set out a coordinated national agenda for shifting the balance of Medicaid long-term services and supports from institutional settings to community-based settings (Gregg, 2006). While Medicaid, as LTSS provider to the low-income elderly and disabled, was the program most directly affected by the mandate, the executive branch also issued guidance to the Department of Housing and Urban Development (HUD) directing the agency to implement program activities in support of Olmstead compliance. These activities included demonstration of housing vouchers earmarked for institution-dwelling disabled people who preferred community residence, renewed attention to existing HUD supportive housing programs for the elderly and disabled, and active collaboration between HUD and HHS to identify opportunities for increased coordination and effectiveness (Crowley, 2006). The stream of health services research that resulted from this movement has focused mainly on “rebalancing” as measured by the relative proportions of Medicaid resources directed toward HCBS versus nursing home care (Kane et al., 2013, p.; Kaye, 2012; Robison et al., 2012b).

Research in support of these efforts uncovered new evidence about the state of HUD supportive housing and the population it serves. HUD administrative records indicate that 41% of HUD households include at least one person with a disability, compared to 24% in the general population. Based on a recent linkage of individual-level NHIS with HUD data, 44% of adults served by HUD were estimated to have a disability as defined by the standard ACS measure. Disabled HUD residents report significantly higher prevalence of fair or poor self-rated health in comparison to the non-disabled HUD population, and exhibit higher rates of ED utilization (Dawkins & Miller, 2017). At the same time, public housing residents are more likely to be insured than the general low-income population, suggesting that the cost of treating this population is likely borne by Medicaid or other government funding sources (A. E. Simon et al., 2017).

Researchers have begun to explore whether factors beyond the scope of Medicaid policy and program implementation can be shown to impact Medicaid long term care utilization and expenditure (Kaye & Harrington, 2015). Survey evidence collected by evaluators of a multi-year Medicaid demonstration program that provided states with incentives to facilitate resident transitions from nursing homes back community settings indicated that the most common barrier to community transition was lack of affordable housing units or vouchers (Denny-Brown &

Lipson, 2009). In response, researchers have investigated the efficacy of specific programs designed to provide additional housing resources to residents who with transition to community-based settings (D. Hoffman et al., 2017).

Direct subsidy by Medicaid of housing costs is generally considered to be prohibited—however, the original basis for Medicaid rent exclusion is a matter of some dispute. The commonly cited guidance on this is a CMS brief from 2015 (*Coverage of Housing-Related Activities and Services for Individuals with Disabilities*, 2015), which itself provides no citation to federal law or regulation. Older ASPE guidance from 2005 (Mollica & Johnson-Lamarche, 2005) cites §441.360(b) in the Code of Federal Regulations (*42 CFR § 441.360 - Limits on Federal Financial Participation (FFP).*, n.d.) , which bars expenditures for "room and board," but this regulation specifically references HCBS waiver services—i.e. it doesn't appear to establish an exclusion in principle. This suggests that rent exclusion derives not from the scope of Medicaid's original mandate, but from the context of HCBS reform—which was motivated, in part, by the desire to reduce Medicaid nursing-home room and board expenditures to the extent possible. As Joseph Bamberger writes in a JAMA Internal Medicine, "CMS has asserted that paying for housing costs is outside of its congressionally allowed functions. However, I have been unable to find any regulations or laws to support this claim"(Bamberger, 2016).

The reasoning behind a rent prohibition, in practice if not in statute, is put forth in an ASPE HCBS primer from 2000 (*Understanding Medicaid Home and Community Services*, 2000).The authors write, "the expectation is that individuals will use their own income and resources (e.g. SSI benefits and earnings from employment) to meet room and board expenses," and that "Medicaid is deemed a payer of last resort … for example if two public programs such as Medicare and Medicaid cover the same service … Medicare only can pay for the first services. Medicaid can only pay once Medicare benefits are exhausted." One argument likely to drive future policy (aside from reducing cost to the state and program effectiveness) is what legal researcher Mary Crossley calls the argument from justice (Crossley, 2018) : Medicaid pays for room and board for those with physical and cognitive impairments, so, according to this argument, discriminates against people with mental and behavioral health problems by not paying directly for their condition-induced housing needs as well.

5.3 Dissertation Findings: Implications for Policy and Future Research

Each of the first two studies presented in this dissertation pose the empirical question of whether there is evidence that programs that claim reduced nursing home utilization as one of their stated objectives work as intended. The third study poses a different type of question: can we find evidence, through a proxy measure, to support the commonly reported observation about barriers to nursing home transition. The results, as described, below, are mixed, and motivate further study more narrowly targeted to specific populations.

5.3.1 Study 1: HUD Program Status and Hazard of Nursing Home Admission in The Pennsylvania Medicaid Population, 2013-2019

The main descriptive findings of this paper concern the distribution of the study population's health and functional status across HUD housing types in Pennsylvania. Specifically, the burden of >=6 chronic conditions is even across the three programs observed in the study (Public Housing: 30.4%; Project-based Section 8: 30.7%; Section 202: 33.5%). In addition, prevalence of Alzheimer's or Dementia-related disorder is present at similar levels across programs as well (Public Housing: 31.9%; Project-based Section 8: 31.8%; Section 202: 30.7%). In spite of what appear to be high levels of these demonstrated risk factors for nursing home utilization, it is only Section 202 that is programmatically required to provide supportive services to tenants. Of Section 202 residents represented in the study sample only 66.6% reside in developments reported by HUD to have contracts for service coordination. Of project-based Section 8 residents in the study sample, only 22.3% live in a development with a service coordination contract. Public Housing, which includes no programmatic element for elderly support services, is reported to have no service coordination contracts. This significant unmet need for supportive services for dual- and waiver-eligible residents of Public and Project-based Section 8 housing implies that Medicaid may gain significant improvements in effectiveness by working with HUD to expand supportive services to these populations.

The main analytic finding of this paper is that residence in housing programs with some service coordination and support services element (Section 202 and Project-based Section 8) is independently associated with reduced risk of nursing home admission. This would suggest that increased collaboration between Medicaid and HUD to deliver needed support services and coordination, especially to Public Housing residents, may result in less nursing home utilization, which would amount to a positive benefit to state Medicaid programs.

Future research on this topic should isolate populations more specifically at risk for nursing home admission as well as for other Medicaid utilization outcomes thought to be mitigated by supportive services, such as ED admission for ambulatory sensitive conditions.

5.3.2 Study 2: Changes in Successful Discharge to The Community for Longstay Nursing Home Residents Associated with Medicaid Managed Care Adoption in Pennsylvania, 2014-2019

The main finding of this study was that the introduction of managed care, with its attendant economic incentives for effective care coordination, exerted no detectable effect on successful discharge to the community among the population of Medicaid nursing home longstay residents. This lack of an immediate detectable effect is qualified, however, by the relative newness of the program—it is possible that program effects will grow over time as Community HealthChoices becomes established. It is also qualified by the special difficulties posed by the longstay population in regard to community transition: it is a population that is, on average, severe in terms of physical health, behavioral health, and cognitive function. Even with the active intervention of a Nursing Home Transition program facilitated by the Money Follows the Person program, Pennsylvania recorded a total of 355 transitions during 2019 (Peebles & Dolle, 2020). The challenges associated with person-centered care among the nursing home longstay population can be thought of as the most distilled form of the challenges associated with managing the care of dual-eligible generally. Evidence suggests that multiple configurations of care coordination and payer-alignment can achieve positive results. MACPAC has promoted a multipronged strategy to advance integration of Medicare and Medicaid that does not rely on managed care as a necessity for improved care coordination (Hwang & Keohane, 2022), including programs such as Medicaid Health Homes, in Washington (Archibald et al., 2019). Tennessee takes yet another approach by automatically assigning its dually-eligible Mandatory Medicaid Managed Care population to a Medicare Advantage Dual-Eligible Special Needs Plan (D-SNP) run by the same insurer. Research estimates that members of aligned D-SNPs use nursing home services at a far lower rate than traditional Medicare beneficiaries when adjusting for age and sex (Keohane et al., 2022).

5.3.3 Study 3: Association between County-level HUD Housing Density and Discharge to The Community among Medicaid Longstay Nursing Home Residents in Pennsylvania, 2015-2017

This study point-estimates a positive association between a longstay nursing home resident’s exposure to county-level density of HUD Public Housing and odds of community discharge within one year of incidence, however this effect is not statistically significant, and it becomes less so in models that adjust for facility-level variation. On its face this finding may call into question the validity of the frequent identification of lack of affordable housing as a primary barrier to successful transition to the community. However this would be an overinterpretation of the evidence, since the established presence of housing subsidy in a county may interact with other factors influencing odds of discharge, including urbanicity and racial and ethnic status. For example, the secondary analysis of the association between HUD-density and community discharge suggests a non-linear relationship that might be masked when treating HUD-density as a continuous variable. Future research should examine whether HUD-subsidized housing plays a different role in urban vs. non-urban (i.e. suburban or rural) communities. Finally, since exogenous shocks to housing supply are rarely observed, further observational research in this area should refine model specification based on solid theoretical foundations.

5.4 Conclusion

This dissertation found mixed evidence of the effects of broad-based, goal-targeted programs such as Section 202 Housing for the Elderly and Disabled and Community HealthChoices on Medicaid nursing home utilization. Similarly inconclusive evidence was evinced for the influence of regional housing affordability on odds of discharge to the community for longstay nursing facility residents. Future research should develop strong conceptual foundations for the specification of models and selection of study populations when seeking to isolate exogenous change due to LTSS policies implemented in dispersed community settings.

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