THE UNIVERSITY OF CHICAGO

UNINTENDED CONSEQUENCES OF MEDICAID POLICY FOR HIGH-NEED BENEFICIARIES

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE IRVING B. HARRIS
GRADUATE SCHOOL OF PUBLIC POLICY STUDIES
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

BY
REBECCA JEAN GORGES

CHICAGO, ILLINOIS
JUNE 2020

This dissertation is dedicated to my family: Walter, Wilhelmina, and especially Boone. Boone, thank you for your unwavering support over the many years that have led up to this dissertation.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I would like to thank my dissertation committee: R. Tamara Konetzka, David Meltzer, and Dan Black, for their insightful comments and advice over the course of my doctoral studies. I would especially like to thank Tamara Konetzka for her excellent mentorship. She has provided me with encouragement and guidance from my admissions interviews through my dissertation defense and I look forward to our future collaborations. My dissertation research was also supported by the the Agency for Healthcare Research and Quality under grant award T32 HS000084 (PI: Kathleen Cagney, PhD). I'd also like to thank my colleagues at the Harris School of Public Policy and in the Department of Public Health Sciences.

Chapter 1, *A National Examination of Long-Term Care Setting, Outcomes and Disparities among Elderly Dual-Eligibles* is co-authored with Prachi Sanghavi and R. Tamara Konetzka. We are grateful for funding for the National Institute on Aging grant award RF1AG054071 (PI: R. Tamara Konetzka, PhD). Anup Patel provided excellent programming assistance.

Chapter 2, *Impacts of long-term care setting on health outcomes for older adults with cognitive limitations* is co-authored with R. Tamara Konetzka. We are grateful for funding for the National Institute on Aging grant award RF1AG054071 (PI: R. Tamara Konetzka, PhD).

Chapter 3, *The effects of Medicaid managed care on outcomes for the Medicare-Medicaid dually enrolled* has been greatly improved by discussions at presentations at the Harris PhD student workshop, UCANU Health Services Research Trainee workshop, Health Economics Student group, and Mathematica Policy Research. I would also like to thank participants in the University of Chicago Center for Health Studies Medicaid Working Group programming meetings.

ABSTRACT

This dissertation critically examines two areas of Medicaid policy affecting especially costly and vulnerable populations: long-term care and managed care.

The first chapter provides the first national examination of long-term care setting, hospitalization and spending among the elderly, Medicare-Medicaid dually enrolled. The benefits of expanding funding for Medicaid home- and community-based long-term care services (HCBS) relative to institutional care are often taken as self-evident. However, little is known about the outcomes of HCBS, especially for racial and ethnic minorities who tend to use HCBS more, and for people with dementia who may need high intensity care. Using national Medicaid claims data on elderly dual-eligibles, we found that overall hospitalization rates were similar for HCBS and nursing facility users, despite nursing facility users generally being sicker as reflected in their claims history. Among HCBS users, blacks were more likely to be hospitalized than whites, and the gap widened among blacks and whites with dementia. Also, conditional on receiving HCBS, Medicaid HCBS spending was higher for whites than non-whites; higher Medicare and Medicaid spending on hospitalizations for blacks and Hispanics did not offset this difference. Our findings suggest that HCBS need to be carefully targeted to avoid adverse outcomes and that the racial disparities in access to high-quality institutional long-term care are also present in HCBS.

The second chapter builds on these descriptive findings by estimating causal impacts of care setting on a variety of health outcomes using the Health and Retirement Study (HRS). I use instrumental variables methods to estimate a plausibly causal effect of care setting on outcomes for a specific group of "marginal" individuals: those induced to choose home care versus nursing home care because the state they reside in adopts Medicaid policies that emphasize HCBS. The use of the HRS complements other studies examining questions about LTC setting using administrative data (including Chapter 1) in two important ways. First, the HRS contains measures of a broad range of outcomes better reflecting overall well-being and factors influencing the choice of care setting than available in claims data which

is generated for administrative (billing) purposes. Second, the HRS allows me to examine a larger population: a nationally representative sample of long-term care users aged 50+, that uses a mix of Medicaid paid LTC and private pay/other insurance covered LTC that is not Medicaid. I find that hospitalization rates are higher but functional decline is slower among home care users than nursing home care users with mild or severe cognitive impairment. While I find differences in observable characteristics among home care versus nursing home care users by race and ethnicity group, the state level instrument lacks sufficient power in the relatively small black and Hispanic samples to explore differences in causal effects of care setting on outcomes by race and ethnicity.

Finally, the third chapter examines the effect of another Medicaid policy change, the inclusion of the Medicare-Medicaid dually enrolled in Medicaid managed care programs. Beneficiaries that are Medicare-Medicaid dually enrolled (duals) account for a disproportionately large share of Medicaid and Medicare spending due to their poor health and propensity to use expensive long-term care services. In order to control program costs, many state Medicaid agencies have recently expanded their Medicaid managed care (MMC) programs to include duals. Enrollment in MMC could result in better health outcomes if health plans improve care coordination and emphasize high-value routine care to avoid costly care in the future. However, quality of care could decline if plans restrict access to needed services due to financial incentives to increase profits. In this study, I provide the first national estimates of the effects of MMC expansion from 2005 to 2012 for duals using claims data. Because the majority of duals have fee-for-service Medicare coverage, I am able to examine hospital use using FFS Medicare claims. I use difference-in-differences (DID) and instrumental variables (IV) methods to estimate plausibly causal impacts of three different types of MMC: comprehensive managed care (CMC), managed long-term service and supports (MLTSS), and primary care case management (PCCM). I find different effects of MMC on hospital use for the three different plan types. First, MLTSS plans are associated with increases in the rates of hospitalization and potentially avoidable hospitalization. For example, mandatory

MLTSS programs are associated with increases in hospitalization of 1.7-4.2% of the baseline rate of hospitalization of 11.7%. Increases are concentrated among beneficiaries with many (as opposed to few) chronic conditions. I find mixed effects of CMC program expansions that exclude long-term care services: in mandatory enrollment settings, I find modest increases in hospitalization while in voluntary enrollment settings, I find decreases in hospitalization. Finally, PCCM plans are not associated with changes in hospital use. This study provides the first national estimates of how a major financing change, the inclusion of duals in MMC, impacts hospital use, providing policymakers with much needed evidence as they face the challenge of financing public health insurance programs as health care costs rise and the population ages.

CHAPTER 1

A NATIONAL EXAMINATION OF LONG-TERM CARE SETTING, OUTCOMES AND DISPARITIES AMONG ELDERLY DUAL-ELIGIBLES

1.1 Introduction

Expanding the use of home- and community-based services (HCBS) as an alternative to institutional long-term care has become a priority for many state Medicaid programs. In 1996, only 19 percent of Medicaid long-term care expenditures were for HCBS with the remaining 81 percent for nursing facilities, but, by 2016, 57 percent of expenditures were for HCBS (Eiken et al., 2018). Policy makers have motivated this shift in funding on the grounds that HCBS is better aligned with people's preferences to age in place and the belief that HCBS are less costly than nursing facility services. The benefits of this policy shift have been taken as self-evident in much of the policy discussion, with very little focus on the outcomes of HCBS for care recipients.

States have expanded Medicaid funding for HCBS largely through Section 1915(c) waivers (Eiken et al., 2018). Under such waivers, Medicaid beneficiaries obtain access to the services only if their needs meet a nursing-facility level of care. In other words, funds for the services are explicitly directed toward providing an alternative to more expensive nursing facility care. Policy makers take pains to avoid a "woodwork" effect - in which where people who otherwise wouldn't receive services are encouraged by the availability of HCBS to use formal (paid) long-term care. Some expansion of HCBS to healthier people has nonetheless occurred, but the increased intensity of funding for sicker people - consistent with the goal of keeping people out of nursing facilities - remains the more pronounced trend(Gonçalves, Weaver, and Konetzka, 2018).

Many waivers are meant to provide HCBS options for frail, elderly beneficiaries with long-term care needs. In this study, we focused on the subset of the elderly, known as "dual-eligibles" or "duals" (people who are enrolled in both Medicare and Medicaid), who are often physically and cognitively impaired, are disproportionately from racial/ethnic minority groups, and have high use of health care services and high costs. In 2013, duals accounted for 15 percent of Medicaid enrollment but for 32 percent of Medicaid expenditures, and for 20 percent of Medicare enrollment but for 34 percent of Medicare expenditures (MedPAC and MACPAC, 2018). Thus, Medicaid programs may see HCBS options as a way to reduce spending on dual-eligibles. At the same time, these beneficiaries often face challenges navigating care across the Medicaid and Medicare programs, which makes them vulnerable to poor outcomes.

The benefits of HCBS to care recipients and their families, especially in terms of preferences for aging in place and increased quality of life, may be substantial and have not been well quantified. However, it is not clear that health outcomes should be better with HCBS than in nursing facilities. HCBS generally entails lower intensity care relative to the round-the-clock care available in a nursing facility. Furthermore, HCBS shifts some of the care burden from trained, paid staff members to largely untrained family members or friends who must fill the critical gaps in care intensity. Home environments may not be safe or appropriately designed to accommodate needs, home care workers may face challenges implementing high-intensity treatments in the home environment, and informal caregivers may not be well trained to handle clinical issues. Thus, HCBS could lead to worse health outcomes relative to nursing facility care.

The challenges of HCBS may have particularly large implications for members of racial/ethnic minority groups, who are disproportionally represented among Medicaid long-term care users (Thach and Wiener, 2018). Historically, non-Hispanic blacks and Hispanics have demonstrated different patterns of use than those of non-Hispanic whites, with members of minority groups using fewer institutional services and more home care and informal care(Miller and Weissert, 2000) (Wallace et al., 1998) (Konetzka and Werner, 2009) (Kaye, Harrington, and LaPlante, 2010). Additionally, when members of minority groups use long-term care services, they tend to receive lower quality care (Mor et al., 2004) (Brega et al., 2005) (Smith et al., 2007). Given these differences in use and quality, policies emphasizing HCBS may exacerbate differences in outcomes by race/ethnicity group, especially if the intensity of care in HCBS is lower than what is needed.

In addition to implications for racial/ethnic disparities, any negative outcomes of HCBS use are likely to be exacerbated for sicker care recipients, especially those with Alzheimer's Disease and other dementias (hereafter referred to as dementia). Caring for people with dementia can be more stressful than caring for people with other conditions. Costs to caregivers of people with dementia, such as lost work productivity and caregiving-related health problems, are substantial (Sansoni et al., 2013). Caregiver stress exists even with nursing facility placement(Schulz and Martire, 2004) but is especially burdensome in the home. As informal caregivers are a critical part of the care team under HCBS, the presence of dementia may exacerbate caregiver burden so that outcomes for the care recipient suffer.

Despite the dramatic shift in Medicaid funding, there is surprisingly little evidence about outcomes of HCBS relative to alternatives. There have been evaluations of specific types of HCBS programs or demonstrations that found that HCBS use is beneficial to care recipients(Carlson et al., 2007) (Wieland Darryl et al., 2015) (Coughlin et al., 2017), but these results are not likely to be broadly generalizable to elderly, dual-eligible HCBS users. A recent report examined high-cost HCBS users defined by Medicaid spending only, thereby focusing largely on under-65 non-dual Medicaid beneficiaries younger than age sixty-five (Peebles et al., 2017). Several studies have documented high rates of potentially avoidable hospitalizations among HCBS users (Konetzka, Karon, and Potter, 2012) (Walsh et al., 2012) but did not provide comparisons. In two key studies that compared rates of potentially preventable hospitalizations between elderly, dual eligible HCBS users and to nursing facility residents, results suggested that HCBS users were more likely to be hospitalized than similar nursing facility residents were (Wysocki Andrea et al., 2014) (Wysocki et al., 2014). However, these studies were limited to people in seven states in 2003–2005 and did not examine differences by race/ethnicity or dementia status.

Our study built on prior literature to inform policy in several ways. First, we provide sorely needed evidence on HCBS use and key associated outcomes among dual-eligibles. Second, we used national claims data. Our study constitutes an important first step to help policy makers evaluate the effects of current policy in shifting resources from nursing facilities to HCBS, especially the effects of this shift on the most vulnerable groups among Medicaid long-term care users: non-whites, and people with dementia.

1.2 Study Data And Methods

We used the 2012 national Medicaid Analytic eXtract (MAX) linked with Medicare claims to describe Medicaid long-term care utilization. The MAX is a claims-based data set created by the Centers for Medicare and Medicaid Services from data submitted quarterly by the states. The most recent year in the MAX that includes all states is 2012 (Medicare and Medicaid Services, 2019). We identified Medicaid long-term care program enrollment, service use, and expenditures from the MAX person summary and claims files. We then linked the data to Medicare records at the individual level. The Master Beneficiary Summary File was used to identify demographic characteristics (age, sex, race, and ethnicity), managed care enrollment, and chronic conditions. The Medicare Provider Analysis and Review file was used to identify hospitalizations.

To identify the study target population, we first identified long-term care users who were dually enrolled in Medicare and Medicaid and elderly (ages sixty-five and older). Following prior literature (Konetzka, Karon, and Potter, 2012) (Eiken, 2016), we identified long-term care users through Medicaid waiver enrollment and fee-for-service claims. HCBS were identified from 1915(c) HCBS waivers, state plan services, and enrollment in the Program of All-Inclusive Care for the Elderly. For a full list of services and associated codes used to identify long-term care users, see online appendix table A1. We then used the Master Beneficiary Summary File to identify long-term care users who were duals and elderly - a group that accounted for approximately 31 percent of all fee-for-service Medicaid beneficiaries who used long-term care.

We made several exclusions to the main analysis sample. First, we excluded three states from the sample (Arizona, Hawaii, and New Mexico) because more than 50 percent of long-term care users in those states were enrolled in managed long-term services and supports plans. We also limited the sample to the 98 percent of long-term care users for whom we had complete demographic information and whose race/ethnicity was coded as non-Hispanic white, black, Hispanic, or Asian/Pacific Islander. For our analysis of expenditures and hospitalizations, we made two further restrictions. First, we excluded the approximately 20 percent of long-term care users who were enrolled in Medicare managed care because we relied on fee-for-service claims to identify hospitalizations. We also excluded people who died during the year so that all observations in the sample had the same exposure time. For a tabulation of the sample restrictions, see appendix table A2.

Key variables for stratification in the analyses were race and ethnicity and dementia diagnosis. Beneficiary race and ethnicity were identified using the Research Triangle Institute race code in the Master Beneficiary Summary File(Eicheldinger and Bonito, 2008). A person was identified as having dementia if he or she met the claims criteria for the Alzheimer's Disease and related disorders or senile dementia chronic conditions flag in either the MAX or Medicare chronic conditions supplement files*Condition Categories - Chronic Conditions Data Warehouse*. Hospitalizations were identified using the Medicare Provider Analysis and Review file and were classified as potentially avoidable using the Prevention Quality Indicator algorithms from the Agency for Healthcare Research and Quality*AHRQ - Quality Indicators*. Finally, Medicaid expenditures for long-term care were calculated from the MAX claims, while hospital expenditures were the sum of the Medicaid and Medicare payment amounts.

1.2.1 Analysis

We describe characteristics of Medicaid long-term care users overall and by care setting (institutional only, HCBS only, or both). Because distributions of age and sex were different across racial/ethnic groups, we adjusted our main results for both age and sex.

To examine our subpopulations of interest, we calculated rates of use of each setting by race/ethnicity and dementia status. To examine outcomes by care setting, we compared hospitalization rates - rates for all hospitalizations and for those that were potentially avoidable - across care settings and by race/ethnicity and dementia status. Finally, focusing on HCBS users, we examined annual long-term care and inpatient hospital expenditures by race/ethnicity and dementia status. We performed several sensitivity analyses, which are described briefly in the "Study Results" section and in more detail in the appendix.

1.2.2 Limitations

Although our study had distinct advantages over prior evidence, our results are subject to several limitations. First, our analysis was descriptive, and the results should be interpreted as associations rather than causal relationships. Second, our measure of dementia status was binary and did not allow for analysis by stage of dementia.

Third, we did not provide a full accounting of Medicare and Medicaid program costs for long-term care users. Instead, we focused on the subset of program expenditures that were most relevant to our purposes: fee-for-service spending on hospitalizations across Medicare and Medicaid and on Medicaid long-term care.

Finally, we examined only fee-for-service Medicaid long-term care services because we could not reliably identify services delivered under managed care arrangements.28,29 These results may not be generalizable to beneficiaries who are nonelderly, not dually eligible, or in a managed care plan. In 2012, approximately 389,000 people, or 6.8 percent of long-term care users, received long-term care through managed care plansSaucier et al., 2012.

1.3 Study Results

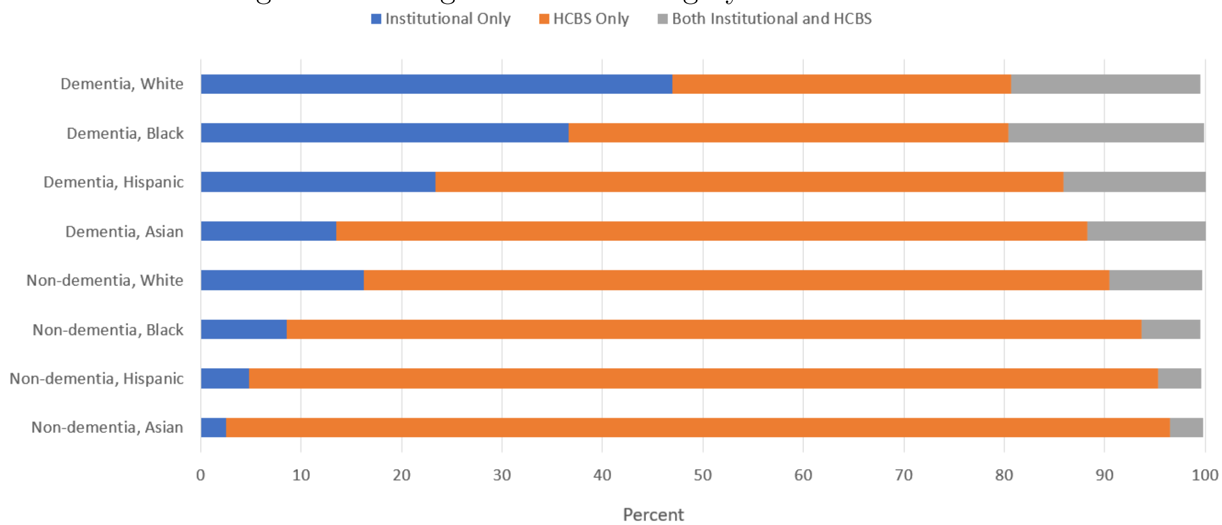
We identified 5.36 million individuals as Medicaid long-term care users in 2012, of whom approximately 1.69 million were elderly, dually eligible, long-term care users. Just over half (51.7 percent) of the sample had been diagnosed with dementia (Table 1.1). The mortality rate was high (14.4 percent), and 67.0 percent of the sample had four or more chronic conditions, which illustrates the relatively poor health of this group.

1.3.1 Use

We present characteristics of users by long-term care setting in three groups: institutional settings only, HCBS only, and both institutional and HCBS during the year. Of the long-term care users, 26.7 percent used institutional services only, with nearly all of those services being nursing facility services; 60.6 percent used HCBS only; and 12.7 percent received services in both settings during the year. Compared to HCBS-only users, users of institutional services only were older, more likely to be non-Hispanic white, and less likely to be enrolled in managed care; and had higher rates of mortality and dementia and more chronic conditions. The group that received long-term care in both settings appeared to be in even poorer health than institutional-only users: Users of care in both settings had the highest mortality rates. While they also had the highest rates of having four or more chronic conditions, they had lower rates of dementia than users of institutional services only did.

Overall, non-Hispanic whites had the highest rate of institutional services use, with the highest shares of institutional only and both institutional and HCBS use (data not shown). In contrast, nonwhites had higher shares using HCBS only. Within each racial/ethnic group, dementia was associated with higher reliance on institutions, but stratifying by dementia status did not change the overall pattern that whites relied more on institutions and nonwhites relied more on HCBS (Table 1.1). Even among care recipients with dementia, almost 44 percent of blacks, two-thirds of Hispanics, and three-quarters of Asians/Pacific Islanders used

Figure 1.1: Long-term care setting by race and dementia



Source: 2012 MAX linked with MBSF. Notes: Adjusted for age and sex.

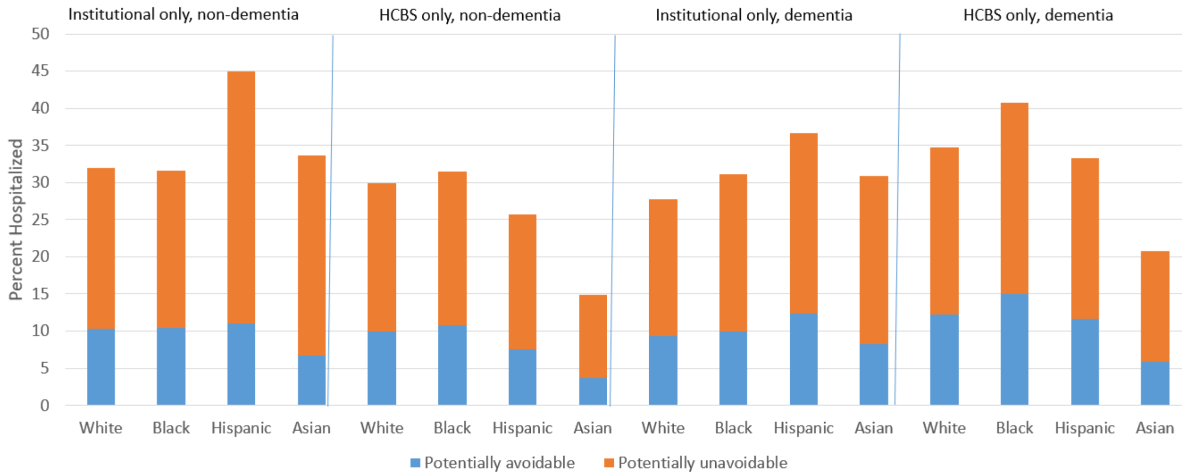
HCBS only, whereas only one-third of non-Hispanic whites did. Thus, examining outcomes of care and the associated potential disparities among HCBS users is critical.

1.3.2 Hospital Admissions

Restricting the sample to those long-term care users who were enrolled in fee-for-service Medicare and were alive for the full year, we explored differences in hospital admissions by race and dementia. Because our focus was on the comparison between HCBS and institutional care, we limited the main analysis of hospitalizations to the groups who used only institutional services or only HCBS, setting aside the unique issues of people who used care in both settings. Beneficiaries who used either institutional services or HCBS alone had similar rates of overall hospitalization and potentially avoidable hospitalization, even though institutional service users tended to be older, have more chronic conditions, and have higher mortality rates (Table 1.1).

Among people without dementia, HCBS users had lower hospitalization rates than institutional services users (27.4 percent versus 32.5 percent; data not shown), consistent with our sample characteristics showing that users of institutional services only were in poorer

Figure 1.2: Hospitalization rates among long-term care users



Source: 2012 MAX linked with MedPAR. Limited to FFS Medicare, alive full year sub-sample. Notes: Adjusted for age and sex. Differences by race statistically significant, $p < 0.001$.

health than users of HCBS only. However, among people with dementia, the pattern was reversed: Hospitalization rates were higher among HCBS users than institutional users (34.3 percent versus 28.7 percent). This finding was consistent for non-Hispanic whites and blacks (Figure 1.2). For the Hispanic and Asian/Pacific Islander groups, while hospitalization rates were higher for institutional users regardless of dementia status, the difference in hospitalization rates between the two settings was smaller for the dementia group. Thus, among sicker people - those with dementia - HCBS were associated with worse outcomes than nursing facility care was.

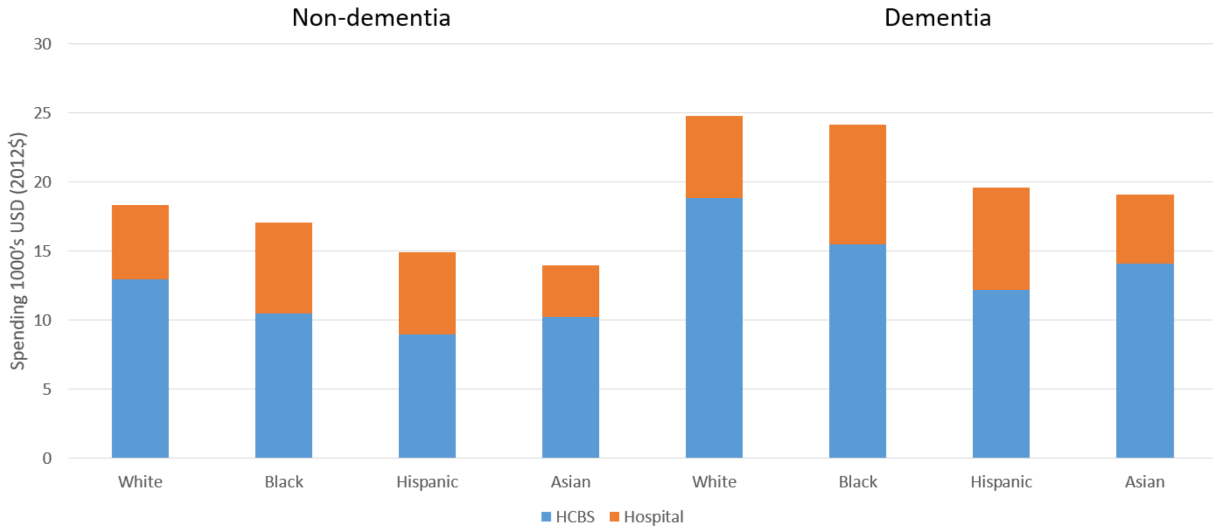
When we examined HCBS users more closely, we found that blacks had the highest rates of hospitalization, including potentially avoidable hospitalization, followed by non-Hispanic whites and Hispanics, and finally Asians/Pacific Islanders. These patterns held across both beneficiaries with and those without dementia. For each racial/ethnic group, not surprisingly, there were higher rates of any hospitalization and of any potentially avoidable hospitalization among care recipients with dementia, but the presence of dementia exacerbated the differences in hospitalization rates by race/ethnicity. In other words, among those without dementia blacks had higher rates of hospitalization than members of other racial/ethnic groups, but among those with dementia, the difference between blacks and others became more pronounced.

1.3.3 Spending

Finally, we examined Medicaid long-term care and hospital (Medicare and Medicaid) spending by race/ethnicity and dementia status, focusing on HCBS users. Not surprisingly, total HCBS plus hospital spending was higher for care recipients with dementia than for those without (Figure 1.3). Within the groupings by dementia status, total HCBS plus hospital spending was highest for non-Hispanic whites, followed by blacks, Hispanics, and then Asians/Pacific Islanders, and HCBS spending alone was higher for non-Hispanic whites than for others. However, consistent with the hospitalization rates shown in Figure 1.2, hospital spending was higher for blacks than for other racial/ethnic groups (Figure 1.3). Thus, overall, HCBS expenditures were highest for non-Hispanic whites and hospital expenditures were highest for blacks and Hispanics, but total expenditures were still higher for non-Hispanic whites. The higher HCBS expenditures for non-Hispanic whites more than outweighed the difference in hospitalization expenditures.

In addition to differences between non-Hispanic whites and others, interesting differences emerged among the nonwhite groups. While each nonwhite group relied more on HCBS than whites did, Asians/Pacific Islanders were most likely to rely only on HCBS, followed by Hispanics and then blacks (Table 1.1). Among users of HCBS only, Asians/Pacific Islanders and Hispanics had rates of hospitalization that were lower than that of non-Hispanic whites, while blacks had higher hospitalization rates than non-Hispanic whites did (Figure 1.2). On average, the three nonwhite subgroups had lower spending on HCBS than their non-Hispanic white counterparts did (Figure 1.3). While Hispanics had lower hospitalization rates than non-Hispanic whites, they had higher average spending due to hospitalization. These differences among the nonwhite groups illustrate the importance of examining patterns of long-term care separately, as each racial/ethnic group may experience the effects of HCBS

Figure 1.3: Spending Among HCBS Users



Source: 2012 MAX linked with MedPAR. Limited to FFS Medicare, alive full year sub-sample. Notes: Adjusted for age and sex. Differences by race statistically significant, $p < 0.001$.

expansions differently.

We conducted several sensitivity analyses to explore the consequences of health-related controls, the age of our data, and our exclusion of beneficiaries who died, the results of which were generally reassuring. Details of these tests and their results are in the appendix.

1.4 Discussion

We found that among elderly, dually eligible, long-term care users, beneficiaries who used either institutional services or HCBS had similar rates of hospitalization and potentially avoidable hospitalization overall, even though institutional service users tended to be older and to have more chronic conditions and higher mortality rates. Among people with dementia, HCBS users actually had higher rates of hospitalization than nursing facility users.

We also saw distinct patterns of use and outcomes by race/ethnicity. Non-Hispanic whites relied more on nursing facilities, while nonwhites relied more on HCBS, and this pattern persisted among care recipients with dementia. Importantly, we found that among HCBS users, non-Hispanic whites spent more on HCBS but had lower hospitalization rates and hospital spending than blacks and Hispanics did. Thus, disparities by race/ethnicity that have been well documented in nursing facilities also appear to extend to the HCBS setting.

There are several possible explanations for the patterns we found. First, differences in health status may explain some of the patterns we saw but could not consistently explain our key findings. For example, if we posit that lower HCBS spending on blacks was due to better health, then hospitalization rates should not be higher among blacks. Our sensitivity analysis that added health-related controls reinforced the inadequacy of this explanation to the extent that we could control for health using claims data. Second, cultural preferences have sometimes been used to explain racial/ethnic differences in the use of home-based versus institutional care and might play a role in patterns of use, but people do not generally prefer to have high hospitalization rates. Third, differences by race/ethnicity in the availability of informal care could lead to differential use of HCBS and rates of hospitalization, but if greater availability of informal care leads to HCBS use, it does not necessarily follow that such greater availability is associated with higher hospitalization rates.

Although combinations of the above explanations might play a role in our results, several other explanations seem more plausible. First, social determinants of health and the availability of medical services, such as physician home visits (Yao et al., 2016) (Yao et al., 2018), might vary by geography in a way that is correlated with race. If black HCBS users had less access to medical services than non-Hispanic whites did, higher hospitalization rates could result even if there were equal spending on HCBS. Second, high hospitalization rates might mean that HCBS are inadequate in quality or quantity, especially for beneficiaries with dementia and for nonwhites. The inadequacy might be due to having too few or not the right services, insufficient frequency of care, low-quality providers, or inadequate attention to coordinating services - which might be harder with HCBS than in a nursing facility setting, where staff members are available to help.

The inadequacy of HCBS could also be related to geography, since HCBS are heterogeneous across and within states, and non-Hispanic whites may live in areas with more HCBS funding or looser eligibility standards. To explore whether geography plays a role, we tested our findings including county-level fixed effects, effectively looking at whether our results held within counties. (See appendix page 16 for predicted rates of hospitalization and spending, adjusted for county fixed effects). This controlled for differences across counties in supply and quality of HCBS and other medical services. Our key findings remained, which suggests that local (county) supply and quality of medical services and HCBS might not explain our results. A caveat is that counties might be too large to represent markets, and differences in access by race/ethnicity within counties might still exist.

Although our main focus was on national results, as an exploration of potential heterogeneity we examined a subset of states with high and those with low HCBS spending (see appendix pages 12–15 for details). While there was more HCBS use among states with high HCBS spending, the patterns we observed by care setting, race/ethnicity, and dementia status were generally consistent across the two groups of states.

These results have several policy implications. First, the high rates of hospitalization among HCBS-only users suggest that outcomes of HCBS need additional scrutiny, especially for members of racial/ethnic minority groups and people with serious health issues such as dementia. If hospitalization rates are high due to limited access to medical services, policy makers might wish to focus HCBS provision on areas where medical services and HCBS can work in tandem or to encourage the supply of medical services in underserved areas. If hospitalization rates are high due to inadequacy of HCBS, it might be necessary to enhance HCBS packages so that they become a true alternative to nursing facility care without resulting in adverse outcomes. This might include spending more on caregiver support, which is a neglected area of importance to HCBS. Development of validated measures of HCBS quality would help states determine how to improve their HCBS offerings.

Second, because hospitalization costs among HCBS users are not insignificant, calculations of the cost-effectiveness of HCBS programs should consider Medicare hospital spending, rather than just Medicaid spending. Furthermore, accounting for full social costs of these programs must also include costs to caregivers and care recipients for adverse outcomes. Almost by definition, HCBS places a greater responsibility on families to support the formal care being received, and this mostly unpaid support is likely to be one reason why Medicaid finds it cheaper to fund HCBS than institutional care. Yet it is well established that informal care is not free, since caregivers incur substantial costs in the form of reduced labor market participation and poorer health - costs that have been estimated to be substantial in long-term care (Coe and Van Houtven, 2009) (Skira, 2015). At the same time, calculations of the cost-effectiveness of HCBS need to include the full benefits of the services, including quality of life outcomes, an area in which measurement is still in need of substantial development.

Finally, the high rates of institutional service use among elderly, dually eligible beneficiaries with dementia suggest that institutional care may be required or even preferred by some beneficiaries and their families due to high needs for intensive long-term care that may not be met in the home setting. Even as HCBS options are expanded, the need for access to high-quality nursing facilities should remain on the agenda as policy makers consider ways to improve the long-term care options available to Medicaid beneficiaries.

1.5 Conclusion

Our study provides compelling evidence that Medicaid's push to shift long-term care from institutions to the community, although intuitively appealing, is in need of a closer look and more careful targeting. If HCBS are promoted as a preferred setting of care to Medicaid beneficiaries who need high-intensity care or who lack appropriate support at home, access to high-quality HCBS, or access to essential medical services, unintended consequences can result unless these gaps are addressed. Our findings also show that racial/ethnic disparities exist in HCBS just as they do in nursing facilities. It will be important for further research to examine the causes and mechanisms related to our findings, especially for differences by race/ethnicity, to develop more specific policy strategies.

Table 1.1: Characteristics of elderly dual-eligible users of Medicaid long-term care, by long-term care setting

	Overall	Inst. Only	HCBS Only	Both
White, non-Hispanic	57.3	73.9	48.2	65.9
Black, non-Hispanic	19.0	16.4	20.0	19.2
Hispanic	14.8	7.3	19.0	10.2
Asian	9.0	2.3	12.8	4.6
Dementia	51.7	81.6	34.1	73.1
Died	14.4	22.7	8.9	23.8
Age 65-69	14.8	8.8	17.9	12.9
Age 70-74	16.6	11.1	19.4	14.6
Age 75-79	17.5	13.8	19.3	16.4
Age 80-84	18.2	18.1	18.3	18.3
Age 85-89	16.7	21.1	14.3	18.7
Age 90+	16.2	27.1	10.8	19.0
Female	72.1	73.9	71.7	70.5
Eligibility group - Aged	87.9	96.0	83.7	90.6
Disabled	11.7	3.1	16.0	9.2
Other (child, adult, unknown)	0.4	0.8	0.3	0.2
4+ chronic conditions	67.0	70.2	62.3	82.5
Medicaid managed care enrolled+	9.4	4.1	13.1	3.2
Medicare Advantage enrolled	19.3	14.3	22.7	13.7
Any hospitalization*	33.5	29.3	29.9	61.4
Potentially avoidable hospitalization*	11.3	9.6	10.0	21.7
Long-term care spending*	25,486.8	49,038.5	13,129.4	38,683.5
Hospital spending*	7,341.2	5,731.0	5,996.7	17,671.2
N	1,659,645	442,998	1,006,565	210,082

Source: 2012 MAX linked with MBSF.

Percentages reported for binary variables, means for continuous variables.

+ = Enrolled in a Medicaid comprehensive managed care plan.

* = Hospitalization and spending limited to FFS Medicare, Alive full year sample.

1.6 Appendix

1.6.1 Methods

Identification of long-term care users

We identify long-term care users using enrollment status from the personal summary file and FFS claims to identify specific service use. Institutional services are identified using the MAX type of service (TOS) codes. HCBS is identified across both 1915(c) HCBS waivers and state plan services. Beneficiaries are identified as using 1915(c) services if they are enrolled in a 1915(c) waiver for at least one month in the calendar year and/or if they utilize waiver services as identified by the community-based long-term care (CLTC) codes. State plan services are also identified by community long-term care (CLTC) codes specific to non-waiver HCBS. Appendix Table 1.2 contains specific service codes and variable fields for each of the LTSS services identified.

Sample restrictions

The main text outlines how the analysis sample was developed. Appendix Table 1.3 tabulates the stepwise restrictions made.

Age and sex adjustment

Differences by race in care setting, hospitalization rates, and spending illustrated in Figures 1.1-1.3 are all statistically significant, with $p<0.001$. Statistical significance of differences by race was determined using a test of joint significance for the coefficients for race (indicator variables for black, Hispanic, and Asian subgroups with white as the base category) using regression and run separately for the non-dementia and dementia groups. Binary outcomes were modeled using logistic regression and Wald statistics were used for joint significance testing. Continuous (spending) outcomes were modeled using linear regression, with F-statistics for significance testing, but conclusions are the same if generalized linear models with link-logit and gamma distribution, which may fit the skewed distribution of spending better, are used. We also tabulated the main results in the raw, unadjusted data and results were consistent with the main findings.

1.7 Sensitivity to use of 2012 data

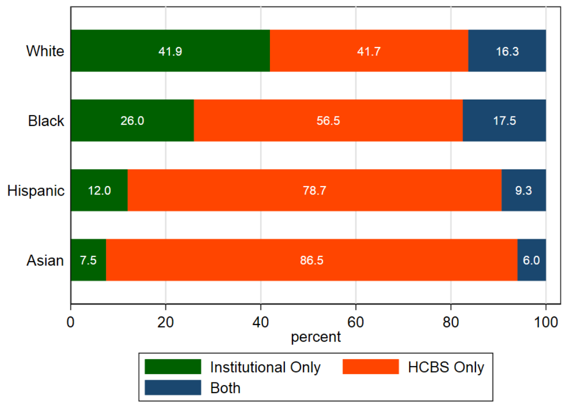
We focus in the main analyses on LTC users in 2012 because this is the most recent year for which all states have MAX data, as noted above. To begin to explore whether there are large changes over time in LTC use, and the extent to which relying on data from 2012 limits our conclusions, we identified LTC use in the 2005, 2012, 2013, and 2014 MAX data for the 17 states that had MAX data over the four years[1]. We illustrate long-term care setting by year in Appendix Figure 1.4. We limit to elderly, dual eligible long-term care users with full demographic information in the MAX PS file and adjust for age and sex. From 2005 to 2014, there are decreases in the share of LTC users that use institutional services as shown by the declines in both the Institutional Only and Both Institutional and HCBS users and increases in the share using HCBS Only. This reflects the trends of states expanding HCBS services. However, in this subgroup of states, we only observe small changes in care setting between 2012 and 2014, and changes over time are consistent across race groups, giving us confidence that the differences we observe in the main analysis are relevant to today's policies.

Due to data limitations (we do not have chronic conditions files in 2013, 2014 because they are not available for the MAX data those years), we also replicated the full set of main exhibits for 2005 to compare the characteristics of LTC users and hospitalization and spending patterns with the main results.

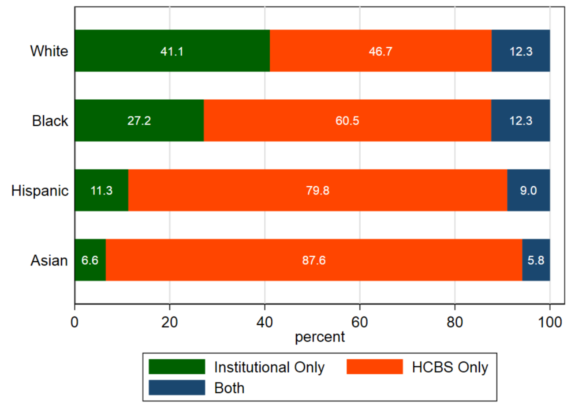
Table 1.4 shows that the composition of elderly duals using each long-term care setting has changed over time, likely reflecting states' expansion of HCBS over the time period.

1. Limited to the following states with 2014 MAX data: CA, GA, ID, IA, LA, MI, MN, MS, MO, NJ, PA, SD, TN, UT, VT, WV, WY (17 states)

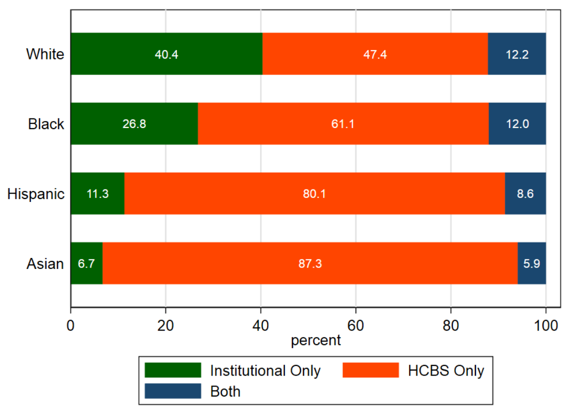
Figure 1.4: Long-term care setting by race, 2005, 2012-2014



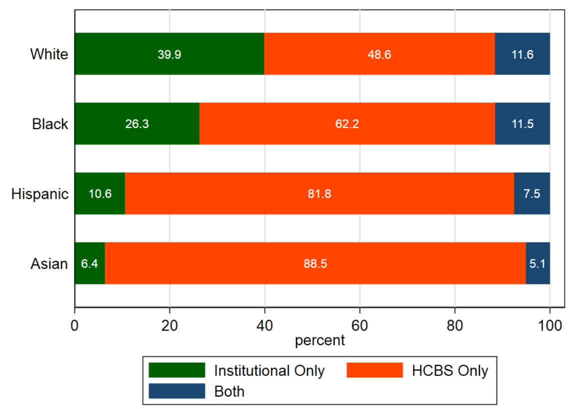
(a) 2005



(b) 2012



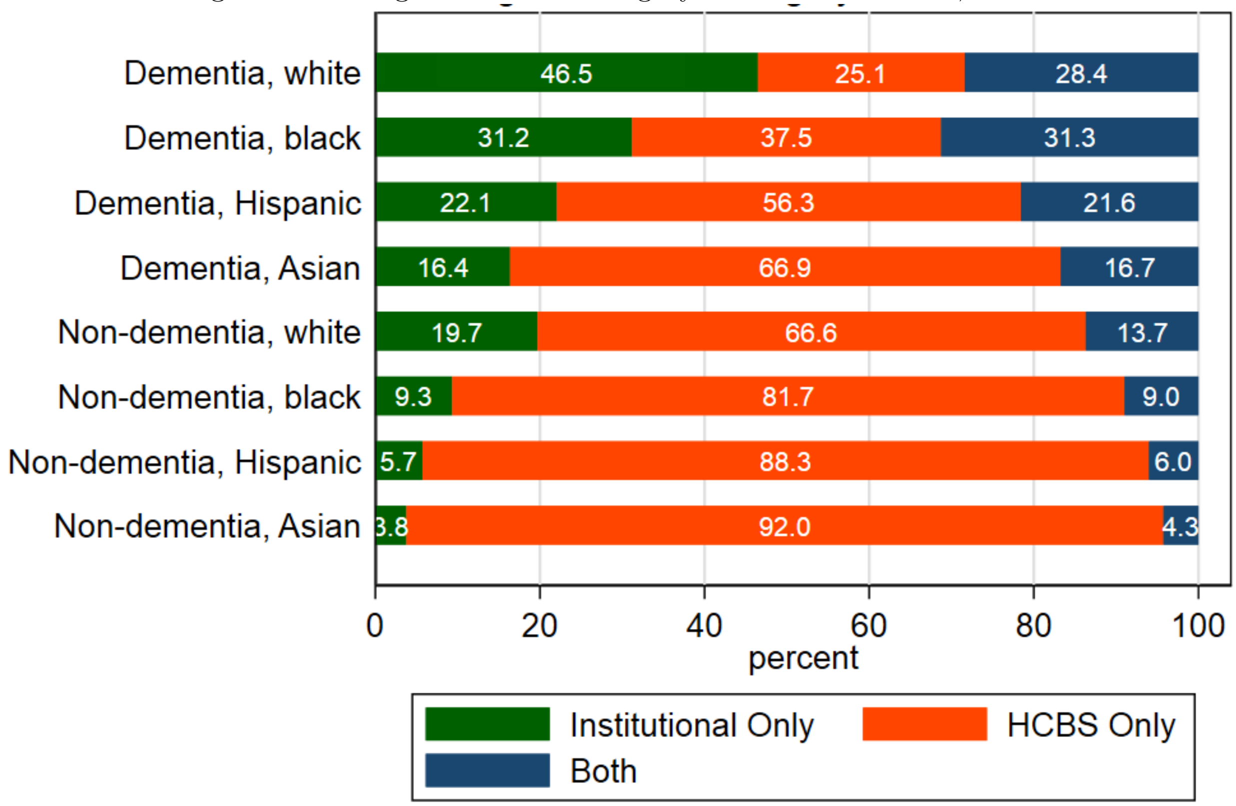
(c) 2013



(d) 2014

Source: 2005,2012-2014 MAX, elderly, duals. Limited to 17 states available in 2014. Adjusted for age and sex.

Figure 1.5: Long-term care setting by race and dementia, 2005

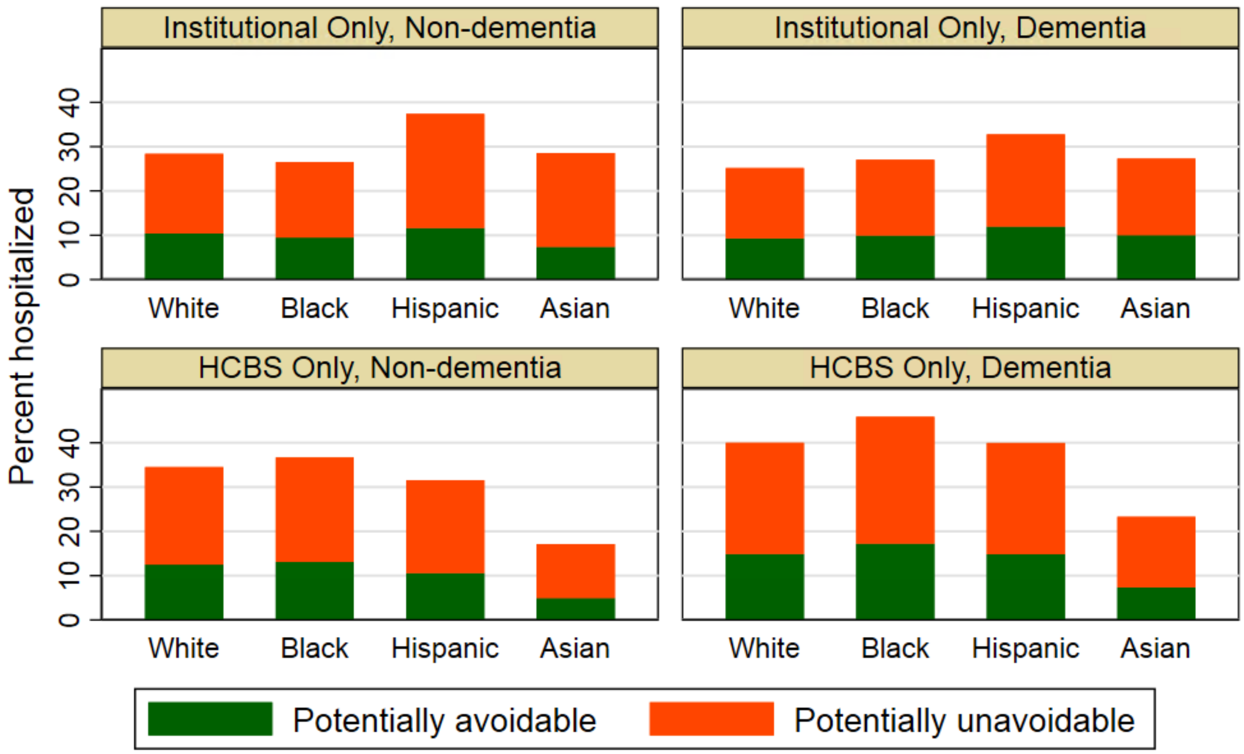


Source: 2005 MAX linked with MBSF. Notes: Adjusted for age and sex.

Overall patterns comparing institutional vs HCBS-only users are similar; institutional users in 2005 were older, more white, and had higher mortality. The rates of 4+ chronic conditions and hospitalization are different though. In 2005, institutional users had lower rates of 4+ chronic conditions and hospitalization than HCBS users but in 2012, institutional users had higher rates of multiple chronic conditions and similar hospitalization rates as HCBS users.

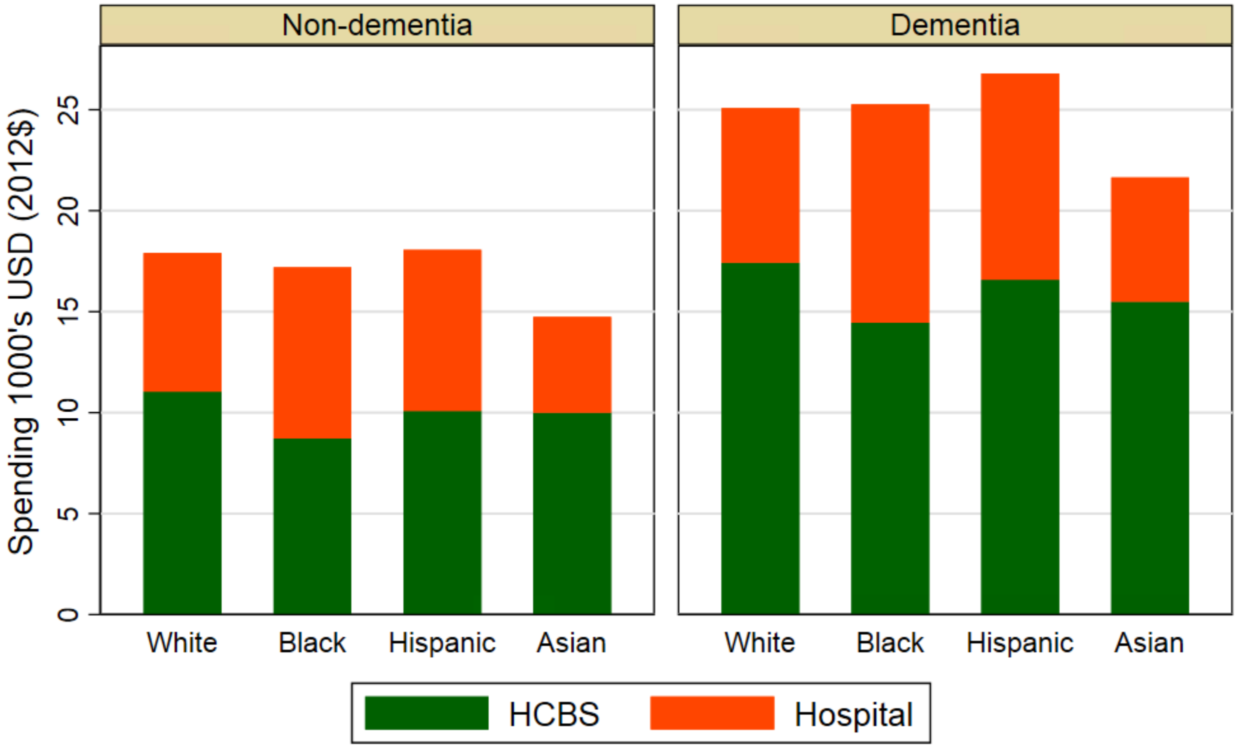
Overall patterns of long-term care setting by race and dementia group found in the 2012 data are consistent in 2005: Whites use the most institutional care, followed by blacks, Hispanics and Asians, and for each race group, those with dementia rely more on institutional care than those without dementia (Figure 1.5). From 2005 to 2012, all race groups reduced the share using both institutional care and HCBS and increased the share using HCBS only. However, blacks and Hispanics increased their use of institutional LTC from 2005 to 2012 while Whites and Asians reduced use of institutional care.

Figure 1.6: Hospitalization rates among long-term care users, 2005



Source: 2005 MAX linked with MedPAR. Limited to FFS Medicare, alive full year sub-sample. Notes: Adjusted for age and sex. Differences by race statistically significant, $p < 0.001$.

Figure 1.7: Spending among HCBS only users, 2005

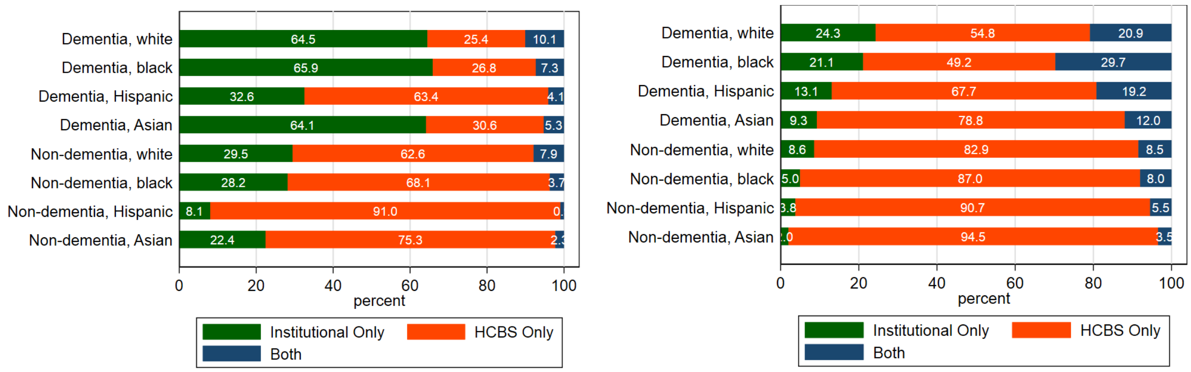


Source: 2005 MAX linked with MedPAR. Limited to FFS Medicare, alive full year sub-sample. Notes: Adjusted for age and sex. Differences by race statistically significant, $p < 0.001$.

While in 2012, for non-dementia individuals we found higher hospitalization rates for institutional LTC users than for HCBS users, we find the opposite pattern in 2005, with rates for institutional and HCBS of 28.5% vs 32.5% respectively. Even with that overall difference, the pattern by race within the non-dementia group is similar to what we found in 2012, with white and black HCBS users having higher hospitalization rates than institutional users and Hispanic and Asian HCBS users have hospitalization rates that are lower than their institutional care counterparts (Figure 1.6). In the dementia group, we observe similar patterns by race and care setting in 2005 as in 2012.

In 2005, among the non-dementia group, pattern of spending by race are similar to 2012, with the exception of Hispanics who spent more on HCBS and hospital services in 2005 (Figure 1.7). In the dementia group, again Hispanics had different patterns in 2005 than 2012, with higher spending both for HCBS and hospital care in 2005 than in 2012. In both

Figure 1.8: Long-term care setting by race and dementia



(a) Low HCBS states (b) High HCBS states

Source: 2012 MAX linked with MBSF. Notes: Adjusted for age and sex. Low HCBS states: FL, AL, KY, WI, ME, NJ. High HCBS states: TN, AK, OR, NY, WA, CA.

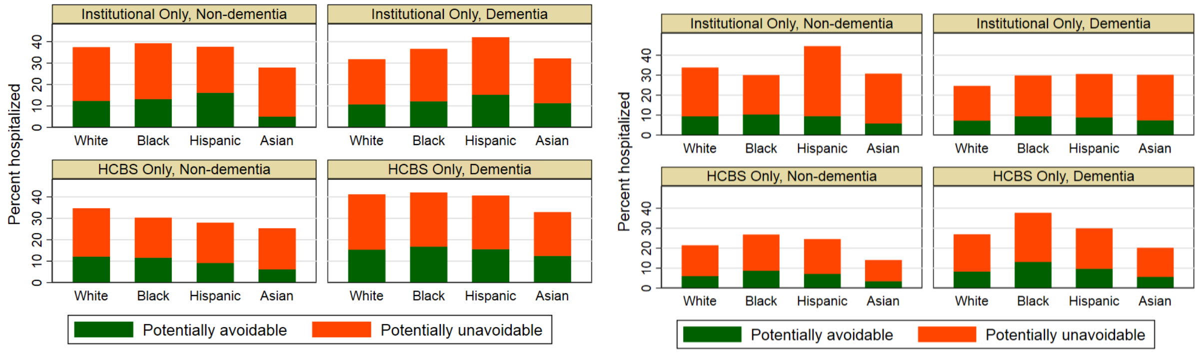
years, we observe that whites spend more on HCBS than blacks but blacks spend more on hospital care than whites. While the total spending is just slightly higher for blacks in 2005, total spending was lower among blacks in 2012.

1.7.1 Exploring state level variation

States have varied in their adoption of expanded coverage for HCBS and a common measure in the literature to measure HCBS emphasis is the share of LTSS spending devoted to HCBS. To explore how the extent to which states shift spending between care settings impacts use and hospitalization rates, we split the sample into states that had a high share of LTSS spending for HCBS vs low share of spending for HCBS. We identified six the highest share spending states, with 50% spending devoted to HCBS and compare them to the six lowest share spending states, with HCBS spending at 15% or less of total LTSS spending, using spending observed in our main sample of elderly duals with LTC use. We then replicated the main exhibits illustrating hospitalization rates and spending, separately for each group of states.

As expected, institutional use is higher and HCBS use is lower in low HCBS spending states as compared with high HCBS spending states (Figure 1.8). The shares of the white,

Figure 1.9: Hospitalization rates among long-term care users



(a) Low HCBS states (b) High HCBS states

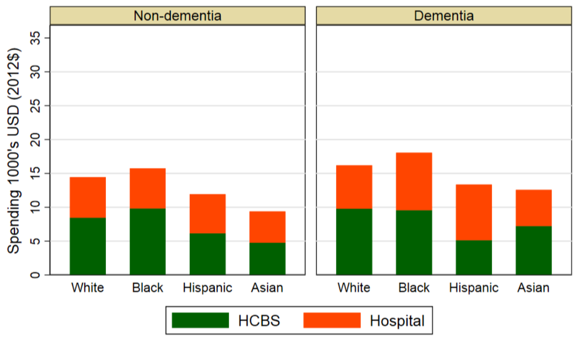
Source: 2012 MAX linked with MedPAR. Limited to FFS Medicare, alive full year. Notes: Adjusted for age and sex. Low HCBS states: FL, AL, KY, WI, ME, NJ. High HCBS states: TN, AK, OR, NY, WA, CA. Differences by race statistically significant, $p < 0.001$.

black and Hispanic groups using institutional only services is much more similar in the low HCBS spending states than in the high HCBS spending states (as well as in the national data shown in Figure 1.1). It should be noted that patterns in the high HCBS spending states are more similar to the overall results mechanically, due to the larger share of all HCBS users represented in the high-HCBS states relative to the low-HCBS states.

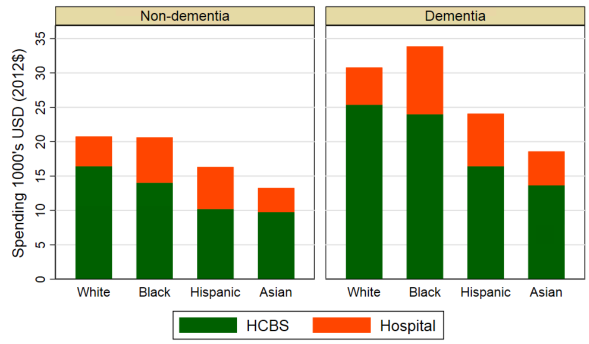
With the exception of the institutional, non-dementia and Hispanic subgroup, hospitalization rates are higher in the low HCBS spending states than in the high HCBS spending rates (Figure 1.9). In both groups of states, we find similar patterns by race and dementia status as in the main results for the national data. That is, in the non-dementia group, institutional only users have higher rates of hospitalization than HCBS users but in the dementia group, the pattern is reversed for whites and blacks but not for Hispanics and Asians.

In low HCBS spending states, we find much lower spending for HCBS users, both for HCBS and total HCBS and hospital spending, as compared to high HCBS spending states (Figure 1.10). Low spending states have more similar levels of HCBS spending when comparing non-dementia to dementia groups while in high HCBS states, spending among individuals with dementia is higher than those without dementia. Strikingly, in the low HCBS states, Hispanics without dementia spend more on HCBS than Hispanics with dementia. Consis-

Figure 1.10: Spending among HCBS users



(a) Low HCBS states



(b) High HCBS states

Source: 2012 MAX linked with MedPAR. Limited to FFS Medicare, alive full year. Notes: Adjusted for age and sex. Low HCBS states: FL, AL, KY, WI, ME, NJ. High HCBS states: TN, AK, OR, NY, WA, CA. Differences by race statistically significant, $p < 0.001$.

tent with the higher hospitalization rates in low HCBS spending states, there is also higher hospital spending for most of the subgroups as compared to the high HCBS spending states.

For individuals with dementia, in both the high and low HCBS spending states, we find that lower HCBS spending among blacks, compared to whites, is offset by hospital spending, and blacks with dementia have higher total HCBS and hospital spending than whites.

1.7.2 *Further adjustments: Individual characteristics and geography*

In the main exhibits, we adjust hospitalization rates and program spending for beneficiary age and sex. Taken together, the main exhibits illustrate that there are different patterns of care setting, hospitalization rates, and spending by race and dementia status. Our results do not speak to the mechanisms for these findings. For example, the differences we describe could be due to differences in underlying health among groups, differences in access due to state program characteristics (e.g. eligibility, covered services), or differences due to access within states, or a combination of these and other factors. In exploratory analyses to examine mechanisms, we tested the extent to which our results change when controlling for additional individual-level characteristics we observe in the claims data and county fixed effects. Appendix Tables 1.5-1.8 show the marginal effects of race, adjusting for age and sex (base model, as illustrated in main Figures 1.2 and 1.3), adding controls for individual-level characteristics (chronic conditions, eligibility type (aged vs disabled), and urban county of residence), and then adding county fixed effects. As in the main exhibits, we stratify by dementia and exclude those individuals using both institutional care and HCBS during the year.

In general, adding individual-level characteristics results in smaller magnitude differences by race as compared to the baseline models controlling for age and sex. Adding county fixed effects further reduces these differences by race, but to a smaller degree. Thus, although the magnitudes change, the key underlying findings and relationships by race remain, suggesting that health conditions and state policy do not fully explain the patterns that we see in our main exhibits.

Table 1.2: Identification of long-term care in MAX data

Service	File	Variables
Institutional services		
Mental hospital services for the aged	LT	MAX TOS 02
Inpatient psychiatric facility for individuals under the age of 21	LT	MAX TOS 04
Intermediate care facility for individuals with intellectual disabilities	LT	MAX TOS 05
Nursing facility services - all other	LT	MAX TOS 07
HCBS		
1915(c) Waivers	PS,OT	Enrollment or expenditures (CLTC codes 30–40)
Breakdown of waiver services		
Personal care	OT	CLTC 31
Private duty nursing	OT	CLTC 32
Adult day care	OT	CLTC 33
Home health	OT	CLTC 34
Residential care	OT	CLTC 35
Rehabilitation	OT	CLTC 36
Targeted case management	OT	CLTC 37
Transportation	OT	CLTC 38
Hospice care	OT	CLTC 39
Durable medical equipment	OT	CLTC 40
Other waiver services	OT	CLTC 30
State Plan Services		
Personal care	OT	CLTC 11
Private duty nursing	OT	CLTC 12 (Note 1)
Adult day care	OT	CLTC 13
Home health	OT	CLTC 14 (Note 2)
Residential care	OT	CLTC 15
Rehabilitation	OT	CLTC 16
Targeted case management	OT	CLTC 17
Transportation	OT	CLTC 18
Hospice care	OT	CLTC 19 (Note 1)
Durable medical equipment	OT	CLTC 20
Other long-term care		
Program for All-Inclusive care for the elderly (PACE)	PS	Enrollment for 1 or more months

Notes: 1. Limited to place of service code=12 (patient's home). 2. Limited to having services for 3 or more consecutive months to avoid capturing post-acute care home health use.

Table 1.3: Sample Restrictions

	N	%
All FFS LTSS Users, from MAX claims/enrollment 2012	5,364,444	
Not duplicate by beneid or if dup, no conflicts - note 1	5,354,949	99.82
With link to MBSF file	3,416,303	63.80
Medicare-Medicaid dual eligible - note 2	2,655,797	77.74
Age 65+ per MBSF	1,702,503	64.11
Dropping excluded states - note 3	1,696,572	99.65
Full demographic information in MBSF - note 4	1,689,648	99.59
Race=white, black, Hispanic, Asian, exclude other categories	1,659,645	98.22
FFS Medicare - note 5	1,338,567	80.65
Alive full year - note 6	1,138,382	85.04

1. If multiple entries for same beneid, require date of birth, race and sex to consistent across entries
2. Dual for 12m or if died, all months alive, per mbsf
3. States dropped=AZ, HI, NM large MLTSS programs.
4. Dropped if missing age, sex or race from MBSF
5. For hospitalization outcomes only, dropped if Medicare Advantage, PACE.
6. For hospitalization outcomes only, dropped if died during the year.

Table 1.4: Characteristics of Institution Only and HCBS Only Medicaid long-term care users by year, 2005 and 2012

	Institutional Only		HCBS Only	
	2005	2012	2005	2012
White, non-Hispanic	80.0	73.9	51.7	48.2
Black, non-Hispanic	13.6	16.4	21.9	20.0
Hispanic	4.9	7.3	16.7	19.0
Asian	1.6	2.3	9.7	12.8
Dementia	77.8	81.6	27.8	34.1
Died	35.7	22.7	11.2	8.9
Age 65-69	5.5	8.8	17.5	17.9
Age 70-74	8.6	11.1	20.0	19.4
Age 75-79	13.7	13.8	21.0	19.3
Age 80-84	20.2	18.1	18.9	18.3
Age 85-89	22.4	21.1	12.7	14.3
Age 90+	29.6	27.1	9.8	10.8
Female	75.7	73.9	73.7	71.7
Eligibility group - Aged	96.7	96.0	81.6	83.7
Disabled	3.2	3.1	18.4	16.0
Other (child, adult, unknown)	0.1	0.8	0.0	0.3
4+ chronic conditions	60.0	70.2	66.2	62.3
Medicaid CMC plan enrolled	2.8	4.1	7.0	13.1
Medicare Advantage enrolled	8.8	14.3	7.5	22.7
Any hospitalization*	26.5	29.3	34.5	29.9
Potentially avoidable hospitalization*	9.7	9.6	12.3	10.0
Long-term care spending*	50,790	49,038	11,909	13,129
Hospital spending*	4,766	5,731	7,563	5,996
N	498,931	442,998	930,367	1,006,565

Source: 2005 and 2012 MAX linked with MBSF. Percentages reported for binary variables, means for continuous variables.CMC=Comprehensive managed care.

* = Hospitalization and spending limited to FFS Medicare, Alive full year sample.

Table 1.5: Further adjustment models - Outcome=Any Hospitalization

Pred. probability	Non-dementia			Dementia		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
White, Institution-Only	0.319	0.250	0.227	0.278	0.268	0.252
	(0.002)**	(0.002)**	(0.002)**	(0.001)**	(0.001)**	(0.001)**
White, HCBS-Only	0.299	0.292	0.278	0.347	0.358	0.361
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**
Black, Institution-Only	0.316	0.225	0.210	0.311	0.275	0.254
	(0.005)**	(0.005)**	(0.005)**	(0.002)**	(0.002)**	(0.002)**
Black, HCBS-Only	0.315	0.295	0.283	0.407	0.401	0.394
	(0.002)**	(0.001)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**
Hispanic, Institution-Only	0.450	0.374	0.413	0.367	0.327	0.331
	(0.008)**	(0.007)**	(0.007)**	(0.003)**	(0.003)**	(0.003)**
Hispanic, HCBS-Only	0.257	0.274	0.317	0.333	0.341	0.377
	(0.002)**	(0.001)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**
Asian, Institution-Only	0.337	0.303	0.326	0.309	0.315	0.328
	(0.012)**	(0.010)**	(0.010)**	(0.006)**	(0.005)**	(0.006)**
Asian, HCBS-Only	0.149	0.233	0.263	0.208	0.296	0.323
	(0.002)**	(0.002)**	(0.002)**	(0.003)**	(0.002)**	(0.003)**
R2	0.02	0.24	0.23	0.02	0.23	0.22
N	502,871	502,871	493,769	497,724	497,724	482,495
Age,sex	X	X	X	X	X	X
Individual characteristics		X	X		X	X
County FE			X			X

Notes: Individuals that use both institutional and HCBS LTSS are omiitted.

Controls for individual characteristics include chronic conditions (indicator for each of the following conditions: anemia, rheumatoid arthritis, cancer, chronic kidney disease, chronic obstructive pulmonary disorder, depression, diabetes, chronic heart failure, hypertension, ischemic heart disease, stroke), indicator for count of 4 or more chronic conditions, rural county of residence, and eligibility group (aged vs. all others).

Table 1.6: Further adjustment models - Outcome=Potentially Avoidable Hospitalization

Pred. probability	Non-dementia			Dementia		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
White, Institution-Only	0.103	0.074	0.067	0.093	0.088	0.081
	(0.001)**	(0.001)**	(0.002)**	(0.001)**	(0.001)**	(0.001)**
White, HCBS-Only	0.100	0.093	0.090	0.122	0.123	0.125
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**
Black, Institution-Only	0.104	0.076	0.066	0.099	0.091	0.081
	(0.003)**	(0.003)**	(0.003)**	(0.001)**	(0.001)**	(0.002)**
Black, HCBS-Only	0.108	0.100	0.093	0.150	0.146	0.141
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**
Hispanic, Institution-Only	0.110	0.089	0.101	0.123	0.109	0.108
	(0.005)**	(0.005)**	(0.005)**	(0.002)**	(0.002)**	(0.002)**
Hispanic, HCBS-Only	0.076	0.088	0.102	0.116	0.120	0.134
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.002)**
Asian, Institution-Only	0.067	0.065	0.072	0.083	0.093	0.100
	(0.007)**	(0.007)**	(0.007)**	(0.004)**	(0.004)**	(0.004)**
Asian, HCBS-Only	0.037	0.079	0.089	0.059	0.100	0.115
	(0.001)**	(0.001)**	(0.001)**	(0.002)**	(0.002)**	(0.002)**
R2	0.01	0.14	0.13	0.01	0.12	0.12
N	502,871	502,871	493,769	497,724	497,724	482,495
Age,sex	X	X	X	X	X	X
Individual characteristics		X	X		X	X
County FE			X			X

Notes: Individuals that use both institutional and HCBS LTSS are omiitted.

Controls for individual characteristics include chronic conditions (indicator for each of the following conditions: anemia, rheumatoid arthritis, cancer, chronic kidney disease, chronic obstructive pulmonary disorder, depression, diabetes, chronic heart failure, hypertension, ischemic heart disease, stroke), indicator for count of 4 or more chronic conditions, rural county of residence, and eligibility group (aged vs. all others).

Table 1.7: Further adjustment models - Outcome=LTC Spending

Avg. marginal effects	Non-dementia			Dementia		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
White, Institution-Only	51,424	51,986	49,233	47,751	48,367	48,959
	(137)**	(138)**	(117)**	(61)**	(62)**	(55)**
White, HCBS-Only	12,931	13,310	12,390	18,854	18,890	16,550
	(55)**	(55)**	(46)**	(72)**	(72)**	(62)**
Black, Institution-Only	50,986	51,302	48,416	50,846	50,853	51,265
	(312)**	(310)**	(254)**	(123)**	(123)**	(107)**
Black, HCBS-Only	10,479	10,849	10,729	15,501	15,353	15,818
	(89)**	(89)**	(79)**	(116)**	(117)**	(103)**
Hispanic, Institution-Only	41,456	41,336	38,829	49,173	49,004	50,079
	(451)**	(446)**	(365)**	(185)**	(184)**	(167)**
Hispanic, HCBS-Only	8,972	8,554	9,195	12,194	11,549	12,728
	(95)**	(95)**	(88)**	(116)**	(116)**	(116)**
Asian, Institution-Only	42,908	41,867	40,654	56,997	55,612	54,908
	(679)**	(672)**	(533)**	(340)**	(336)**	(276)**
Asian, HCBS-Only	10,223	8,572	8,621	14,072	12,011	10,911
	(103)**	(105)**	(92)**	(144)**	(145)**	(131)**
R2	0.17	0.19	0.22	0.30	0.31	0.37
N	502,871	502,871	493,769	497,724	497,724	482,495
R2	0.01	0.14	0.13	0.01	0.12	0.12
N	502,871	502,871	493,769	497,724	497,724	482,495
Age,sex	X	X	X	X	X	X
Individual characteristics		X	X		X	X
County FE			X			X

Notes: Individuals that use both institutional and HCBS LTSS are omiitted.

Controls for individual characteristics include chronic conditions (indicator for each of the following conditions: anemia, rheumatoid arthritis, cancer, chronic kidney disease, chronic obstructive pulmonary disorder, depression, diabetes, chronic heart failure, hypertension, ischemic heart disease, stroke), indicator for count of 4 or more chronic conditions, rural county of residence, and eligibility group (aged vs. all others).

Table 1.8: Further adjustment models - Outcome=IP Hospital Spending

Avg. marginal effects	Non-dementia			Dementia		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
White, Institution-Only	6,862	4,972	5,004	4,655	4,646	4,854
	(84)**	(79)**	(85)**	(39)**	(38)**	(41)**
White, HCBS-Only	5,426	5,404	5,272	5,971	6,244	6,145
	(34)**	(32)**	(34)**	(47)**	(44)**	(46)**
Black, Institution-Only	9,202	6,311	6,374	6,924	5,805	5,693
	(192)**	(178)**	(185)**	(79)**	(74)**	(80)**
Black, HCBS-Only	6,608	5,946	5,847	8,669	8,179	8,051
	(55)**	(51)**	(58)**	(75)**	(71)**	(77)**
Hispanic, Institution-Only	16,011	13,471	14,375	9,428	8,139	8,107
	(278)**	(256)**	(266)**	(120)**	(112)**	(124)**
Hispanic, HCBS-Only	5,918	6,190	6,818	7,489	7,421	7,338
	(59)**	(55)**	(64)**	(75)**	(71)**	(87)**
Asian, Institution-Only	12,914	11,550	11,419	9,657	9,531	8,659
	(418)**	(385)**	(389)**	(220)**	(204)**	(206)**
Asian, HCBS-Only	3,738	5,914	5,800	5,041	7,196	5,973
	(64)**	(60)**	(67)**	(93)**	(88)**	(98)**
R2	0.01	0.16	0.16	0.02	0.17	0.16
N	502,871	502,871	493,769	497,724	497,724	482,495
Age,sex	X	X	X	X	X	X
Individual characteristics		X	X		X	X
County FE			X			X

Notes: Individuals that use both institutional and HCBS LTSS are omiitted.
Controls for individual characteristics include chronic conditions (indicator for each of the following conditions: anemia, rheumatoid arthritis, cancer, chronic kidney disease, chronic obstructive pulmonary disorder, depression, diabetes, chronic heart failure, hypertension, ischemic heart disease, stroke), indicator for count of 4 or more chronic conditions, rural county of residence, and eligibility group (aged vs. all others).

After adjusting only for age and sex, we found non-dementia, institutional-only users had higher rates of hospitalization than non-dementia HCBS users for all race groups (Table 1.5). After adding adjustments for additional individual-level characteristics, this pattern reversed for white and black groups and moderated for Hispanic and Asians. These patterns remained after adding county fixed effects. In the dementia group, for all race groups but Asian, HCBS users had higher hospitalization rates than institutional users and this pattern persisted and grew larger when including for individual-level characteristics and county fixed effects. Blacks and Hispanics had higher hospitalization rates than whites and Asians for both care settings and by dementia status. Adding these additional controls resulted in similar changes in patterns of potentially avoidable hospitalization as for hospitalization overall (Table 1.6).

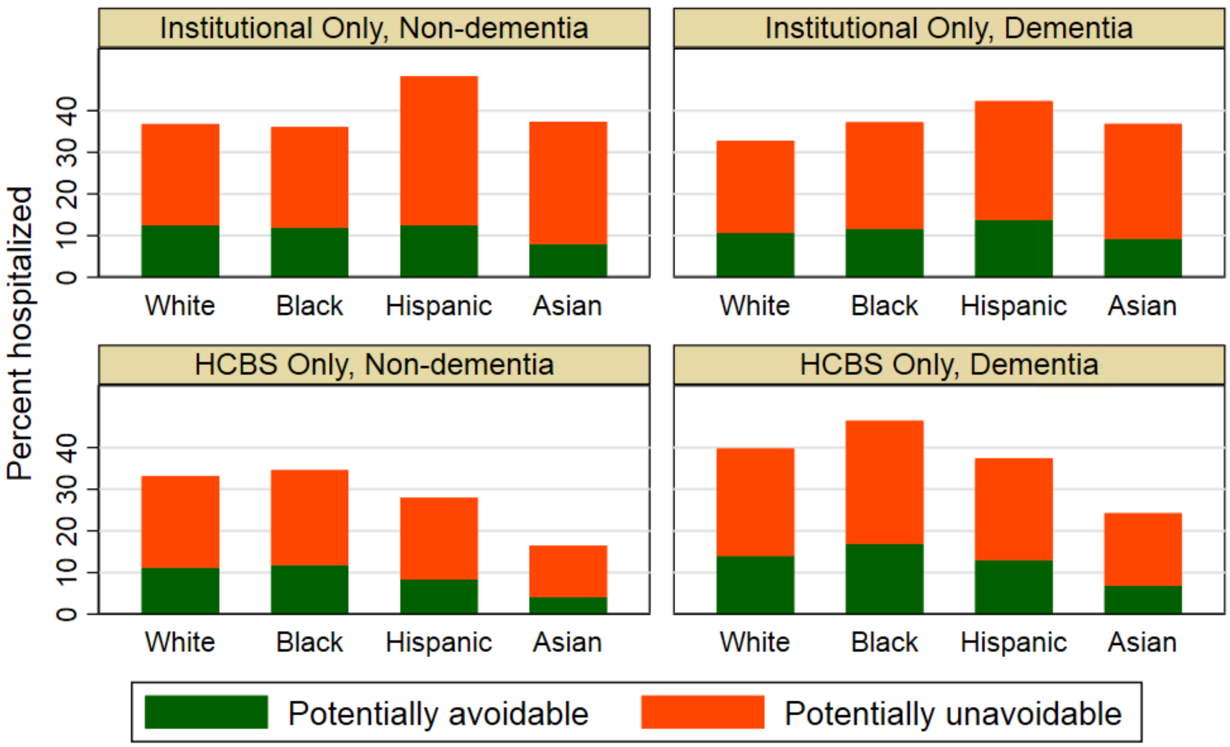
Adjusting for age and sex only, we found that conditional on using HCBS, whites spend more on HCBS than non-whites (Table 1.7). Adding adjustments for additional individual characteristics and county fixed effects moderated the differences in spending somewhat, but even after adjustment whites continued to have higher HCBS spending. In the dementia group, we found that total hospital and HCBS spending was lower for blacks than for whites. After including controls for additional individual characteristics and county fixed effects, while whites continued to spend more on HCBS than blacks, higher hospital spending among blacks resulted in higher total spending for blacks than whites (Table 1.8).

1.7.3 Sensitivity to exclusion of individuals that died

Finally, we examined the sensitivity of our results to the decision to exclude individuals that died in two ways. First, we replicated Exhibits 3 and 4, including all LTC users, that is, including those who were alive the whole year and those who died. Next, we repeated the same figures, but among just those who died.

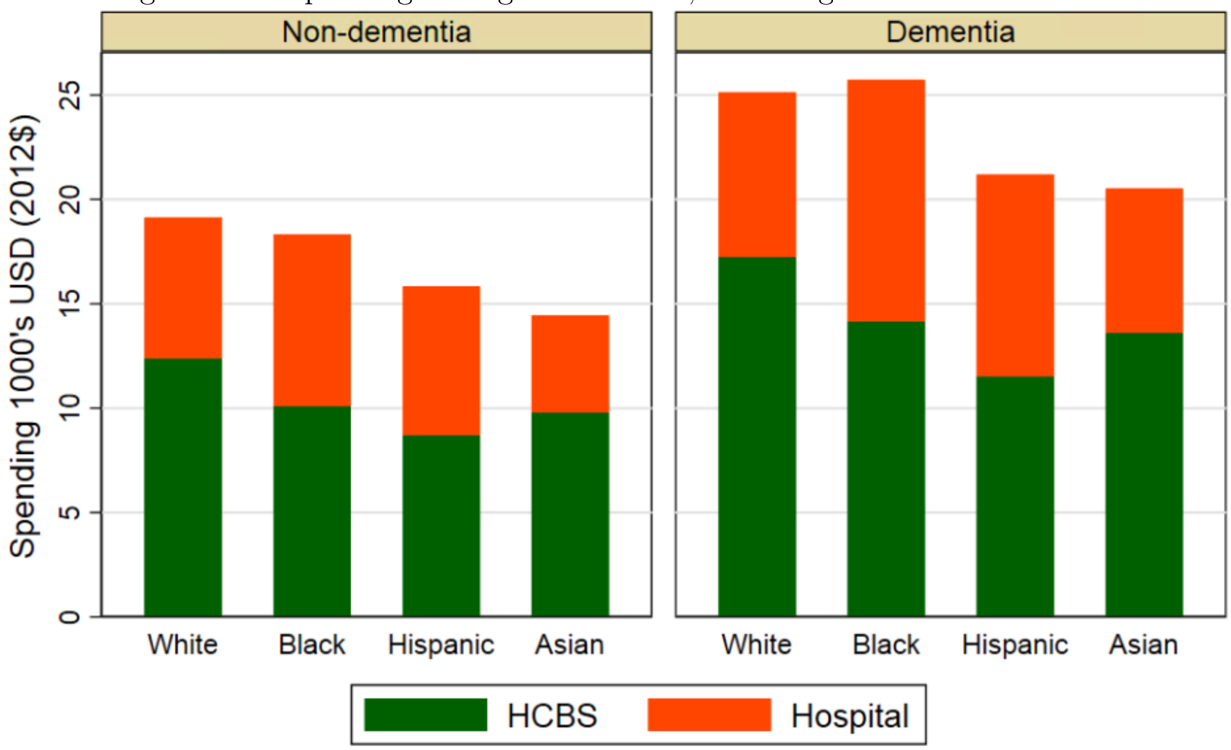
As compared to excluding individuals that died during the year, including them resulted in higher hospitalization rates for all groups (Figure 1.11). However, similar patters were

Figure 1.11: Hospitalization among LTC users, Including individuals that died



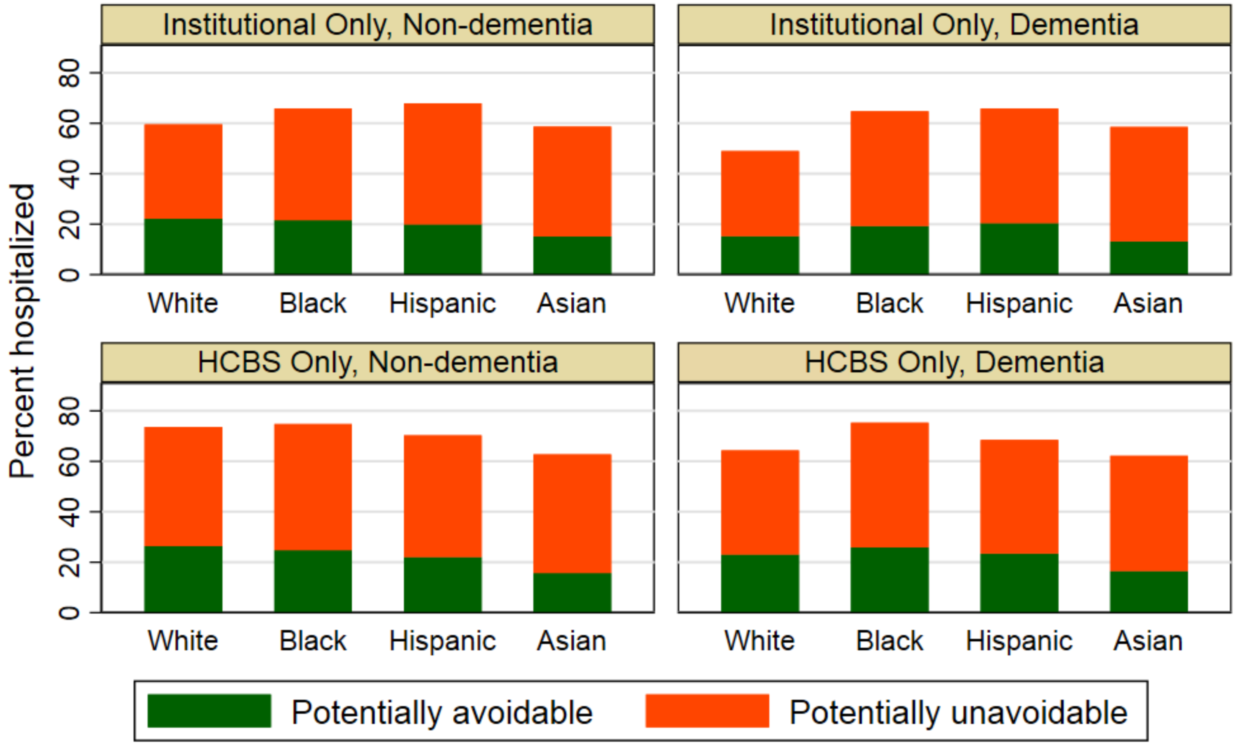
Source:2012 MAX linked with MedPAR. Limited to FFS Medicare. Notes: Adjusted for age and sex. Differences by race statistically significant, $p < 0.001$.

Figure 1.12: Spending among HCBS users, Including individuals that died



Source:2012 MAX linked with MedPAR. Limited to FFS Medicare. Notes: Adjusted for age and sex. Differences by race statistically significant, $p < 0.001$.

Figure 1.13: Hospitalization among LTC users, Limited to individuals that died

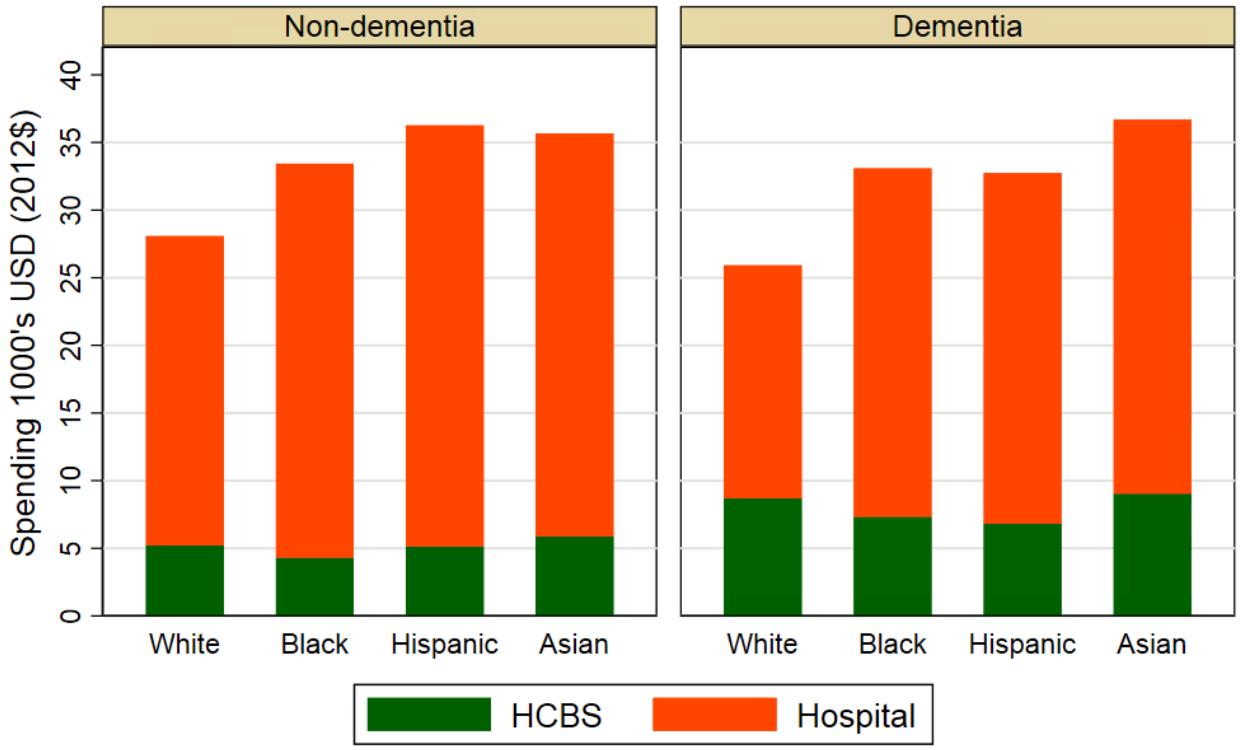


Source:2012 MAX linked with MedPAR. Limited to FFS Medicare and individuals that died. Notes: Adjusted for age and sex. Differences by race statistically significant, $p < 0.001$.

found by care setting, dementia status and race. HCBS spending was slightly lower, and hospital spending was higher when with the inclusion of decedents (Figure 1.12), but again patterns by subgroup remained similar to what we report in the main exhibits.

Limiting to just observations on people who died resulted in much higher hospitalization rates and spending. Among decedents, hospitalization rates are higher among HCBS users than institutional users for both the non-dementia and dementia groups (Figure 1.13). Spending was much more skewed towards hospital spending among the group that died (Figure 1.14). Hospitalization costs continued to be higher for the non-white groups as compared to whites in this subset of individuals. While Asians had the lowest total spending among the HCBS groups in the sample that was alive the full year, they had the highest total spending among decedents driven by their high hospital spending.

Figure 1.14: Spending among HCBS users, Limited to individuals that died



Source:2012 MAX linked with MedPAR. Limited to FFS Medicare and individuals that died. Notes: Adjusted for age and sex. Differences by race statistically significant, $p < 0.001$.

CHAPTER 2

IMPACTS OF LONG-TERM CARE SETTING ON HEALTH OUTCOMES FOR OLDER ADULTS WITH COGNITIVE LIMITATIONS

2.1 Introduction

In 2013, \$338 billion was spent on long-term care (LTC) in the United States (Colello and Talaga, 2015). Over 70% of LTC was financed by public payers, with the largest shares paid for by Medicaid and Medicare. LTC expenditures are projected to rise as the population ages; the Congressional Budget Office projects that LTC spending for older adults will increase from 1.3 percent of GDP in 2010 to 3 percent by 2050 (Office, 2013). Financing these rising costs is a growing policy concern as the population ages and states face uncertainty in federal health care funding due to the current political climate.

At the same time, over the last 30 years, there has been a dramatic policy shift in where LTC is provided. State Medicaid programs have expanded the use of home- and community-based services (HCBS) as a substitute for nursing home care. Proponents of this shift claim that expanding HCBS saves states money because HCBS is less expensive than nursing home care and that HCBS better matches preferences of individuals to remain in the community. However, there has been little evidence as to the consequences of this policy shift. HCBS is by definition a lower intensity care setting than the institutional setting. Care in a lower intensity setting may not always be appropriate. There is also strong evidence of racial disparities in access and quality of LTC. Policymakers need to understand the consequences of this policy shift in terms of quality of life and health outcomes for LTC users and how they may disproportionately affect minorities in order to make equitable policies going forward.

These concerns about lower intensity of formal care and racial disparities in LTC access and quality are exacerbated for individuals with cognitive impairment including Alzheimer's disease and dementia (hereafter referred to as dementia). Dementia is a chronic condition characterized by a long decline and need for high-intensity LTC over a long period of time. In a study examining social costs of care in the last five years of life, individuals with dementia had higher total spending, Medicare and Medicaid costs, informal care costs, and out-of-pocket spending than people with other conditions, and the uninsured costs were particularly burdensome for those of black race and with lower education levels (Kelley et al., 2015). Higher costs were driven by the need for LTC over a longer duration, high reliance on nursing home care, and higher intensity of informal caregiving among individuals with dementia as compared to other diseases. As policy emphasizing expansion of HCBS encourages individuals with dementia, which disproportionately affects those of non-white race/ethnicity, to avoid or delay nursing home entry, the effects of these policies on this vulnerable population must be better understood.

In this paper, I analyze the longitudinal Health and Retirement Study (HRS) to describe home care versus nursing home care use among a nationally representative sample of older adults with cognitive impairment. I estimate the impact of care setting on outcomes characterizing both health and quality of life. I account for the endogeneity of the choice to use home care versus nursing home care using instrumental variables techniques. Specifically, I instrument the number of Medicaid 1915(c) HCBS waivers and the share of Medicaid long-term services and supports spending devoted to HCBS at the state level for receipt of home care. I estimate the impact of home care in both the overall sample and stratified by race and ethnicity to seek to better understand whether the shift to more HCBS has impacted minorities differentially as compared to whites.

I find that, in models adjusting for observable characteristics only, home care is associated with lower mortality and lower rates of incident dementia and severe functional impairment. However, there are similar hospitalization rates and poor self reported health between nursing home users and home care users using these methods. When using instrumental variables to address any remaining selection on unobservable characteristics, I find that hospitalization rates are higher among home care users while the rate of incident severe functional impairment is lower. Stratifying by race reveals that the positive effects on functional status are driven by those of white race and are not present for those of black race or Hispanic ethnicity.

The rest of this paper proceeds as follows. First, I describe some background on long-term care policy and the previous literature on how care setting impacts outcomes. Next, in

Section 2.3, I describe a utility maximization framework that informs the empirical approach. I then describe the Health and Retirement Study data and methods used in Sections 2.4 and 2.5. Finally, in Sections 2.6 and 2.7, I conclude with a discussion of the results and their policy implications.

2.2 Background and Previous Literature

Long-term care is assistance with activities of daily living (ADLs) and/or instrumental activities of daily living (IADLs) due to functional or cognitive impairment. Because of the nature of these activities, help does not necessarily need to be provided by a helper with medical training. In fact, LTC is provided by both formal and informal caregivers. The focus of this paper is formal caregiving but an important area to further explore is how the provision of HCBS and institutional care affects informal care.

Formal LTC for older adults is provided in two settings: institutions, primarily nursing homes, and in community-based settings including the home. Quality is generally measured across or within nursing homes or across and within home health agencies but not across the two setting types. Proponents of the policy emphasis on HCBS presume that HCBS is a lower cost, more-preferred substitute for nursing home care. However, there is only sparse research comparing outcomes for those getting care in nursing homes with outcomes of recipients of HCBS. One comparable quality metric that has been used, because of the availability in claims data to do the comparison, is rate of hospitalization. It has been found that users of HCBS have higher rates of hospitalization and potentially preventable hospitalization than the general Medicaid population (Konetzka, Karon, and Potter, 2012). Using propensity score matching to account for selection on observable characteristics in the choice to use HCBS versus nursing home care, Wysocki et al., 2014 show that HCBS users in fact have higher rates of hospitalization and potentially avoidable hospitalization than nursing home users. This suggests the potential for the shift away from nursing homes to result in poorer health outcomes.

Receipt of LTC via HCBS could also have implications for informal caregivers. There is a large literature documenting costs to informal caregivers of providing care including physical and mental health effects and reduction in labor market participation (Coe and Van Houtven, 2009) (Skira, 2015). In a study most similar to this one, (Dong, Pollack, and Konetzka, 2018) use instrumental variables (nursing home supply to predict LTC setting choice) and find that HCBS results in poorer physical health but better mental health outcomes for spouses, suggesting that there are also effects on family members that should be accounted for when policymakers shift LTC users from institutions to the community.

While it is important to better understand the impacts of care setting on the LTC population overall, the emphasis on HCBS over nursing home care also has the potential to impact racial disparities in LTC. There is strong evidence of racial disparities in LTC. In their literature review, Konetzka and Werner, 2009 document that in the 1980s and 1990s, as states began implementing policies expanding HCBS, minorities used significantly less nursing home care than whites. As expensive, mainly private pay, alternatives to nursing homes, such as assisted living and continuing care retirement communities, became more available in the 2000s, there was a decline in nursing home use among whites and an increase among minorities suggesting that the earlier lower use among minorities reflected a lack of access and not necessarily stronger preferences for home care (Feng et al., 2011). There is also strong evidence that nursing homes serving primarily minority and Medicaid residents have lower quality (Mor et al., 2004). There is much less evidence on disparities in HCBS but one study showed higher rates of poor functional status outcomes among blacks than whites among home health users (Brega et al., 2005). Walsh et al., 2012 show that blacks had higher rates of potentially avoidable hospitalization than other race/ethnicity groups in both the Medicaid nursing facility and HCBS settings. Kitchener, Carrillo, and Harrington, 2003 examine state level factors influencing HCBS expansions in the late 1990s. They find that states with a greater number of Medicaid HCBS participants per capita also had a higher proportion of white residents, suggesting that the early HCBS expansions did not provide equitable access to these services by race and ethnicity. Because the goal of Medicaid policy is to reduce the share of low-need nursing home residents, who often use HCBS as a substitute for nursing home care, it is important to understand how changes in use and quality in one group of services affect changes in the others. The findings in the descriptive study in Chapter 1 of this dissertation suggest that there are different patterns of LTC use by race and dementia status and provides evidence of associations of higher hospitalization rates among non-whites, especially blacks and those with dementia, that use HCBS. This paper further explores this finding using causal analysis techniques to fill the gap in the literature linking the associations described in the mainly cross-sectional literature to date to evidence of causal relationships between care setting and outcomes.

This brief summary suggests that researchers and policymakers need to better understand how the policy shift in LTC impacts outcomes for care recipients broadly and how it impacts disparities specifically. Often researchers are limited in what outcomes they can study because they are using administrative data which does not adequately capture outcomes reflecting quality of life. In this study, I use longitudinal survey data which measures mortality, self-reported utilization (hospitalization), functional and cognitive status, depression, and self-reported health in order to get a fuller picture of the impact of home care on quality of life. I use an instrumental variables study design to estimate a local average treatment effect for the subset of individuals that are induced to use home care, as opposed to nursing home care, due to state policy that expands covered home- and community based long-term care services. I explore differences by race using stratified analyses to investigate whether the HCBS expansions have impacted racial groups differently. It is important to note that while the instruments used are measures of the degree of HCBS expansion in state Medicaid programs, I estimate effects of HCBS versus nursing home care for a broader population represented by the HRS survey respondents. This is a distinct advantage of this study because Medicaid HCBS expansions could also increase access to HCBS for individuals that are not Medicaid insured if norms of where LTC is received are changed or the supply of home care providers is increased more broadly.

2.3 Theory

I use a utility maximization framework based on the Grossman model to inform the empirical study. As in the standard economic model, individuals maximize utility, subject to a budget constraint. Utility, U, is derived from consumption of goods X, health H, and preference to remain living at home μ which can be of either positive or negative sign. Individuals allocate their income between spending on long-term care l and other consumption goods X.

$$U = f(X, H, \mu)$$
$$I \geq p_x X + p_l l$$

Individuals choose quantities of non-health care goods, X and LTC l. LTC can be provided in home- and community-based settings or in a nursing home.

$$l = [HCBS, NH]$$
$$\text{Spending on LTC} = p_{HCBS} HCBS + p_{NH} NH$$

Health evolves over multiple time periods. Individuals have a level of endowed health H_{t-1} in the first period and then decisions in the first period about long-term care setting impact health in the second period.

$$H_t = H_{t-1} + h(l_{t-1})$$

HCBS and nursing home care are (mutually exclusive) substitutes and could have different impacts on health depending on level of need and intensity of care in each setting. Furthermore, intensity could depend on availability of informal caregivers to supplement formal, paid care, especially in the HCBS setting.

The utility maximization problem faced in period $t-1$ is therefore:

$$\max_{X_{t-1}, HCBS_{t-1}, NH_{t-1}} U_{t-1}(X_{t-1}, H_{t-1}, \mu) + U_t(X_t, H_t+, \mu)$$
$$\text{s.t. Income}_t = p_X X_t + p_{HCBS} HCBS_t + p_{NH} NH_t \text{ for each } t$$
$$H_t = H_{t-1} + h(HCBS_{t-1}, NH_{t-1})$$

The individual chooses either HCBS or NH care in period $(t-1)$ to maximize the sum of utility today and tomorrow (periods $(t-1)$ and t). The question we are interested in answering is how does the choice of care setting impact health outcomes and, more generally, quality of life. That is, how does utility change as people shift from nursing home care to home care? Quality of life and health outcomes could improve if the preference to remain at home is large and/or if care intensity and/or quality better meet the needs of the care recipient. But quality of life and health outcomes could worsen if care intensity and/or quality of care declines when care is provided in the home or community relative to the nursing home.

We use the expansion of HCBS in Medicaid programs to provide variation to estimate the following reduced form relationship:

$$U_{i,t} = f(l[\text{HCBS,NH}]_{i(t-1)}, X_{i(t-1)})$$

The expansion of HCBS coverage in Medicaid programs results in a decrease in the price individuals pay for HCBS relative to nursing home care. This, in turn, results in some individuals choosing HCBS over nursing home care because of the decrease in price.

There is, of course, another margin whereby the HCBS expansion induces individuals to switch from choosing no formal (paid) LTC to using HCBS when it becomes covered by Medicaid. This margin is often referred to by policymakers as a "woodwork effect." While an interesting and important alternative consequence of expanding Medicaid HCBS coverage, this margin is beyond the scope of the current study.

2.4 Data

I use the 1998-2016 waves of Health and Retirement Study (HRS)(*Health and Retirement Study 1998-2016 Core, Exit, and Helper Files public use dataset.*). The HRS is a longitudinal survey of older adults that is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. The HRS sample is selected to be nationally representative of the United States population aged 50 and older. Baseline interviews are conducted in-person with each survey respondent and attempts are made to also enroll the respondent's spouse. After the baseline interview, follow up interviews are conducted every two years. Interviews are conducted with a proxy in the event that the respondent cannot complete an interview. The HRS began in 1990; however in this study, I use the 1998-2016 waves to allow for comparisons across years with consistent questions about nursing home and home care utilization, among other survey measures.

To construct the analysis dataset, I began with the RAND HRS data(*RAND HRS Longitudinal File 2016* 2019).[1] I limit to observations with core interviews in 2000-2014 as the main analysis sample, and then use information from the 1998 and 2016 interviews/files as period $t-1$ and $t+1$ interviews respectively to measure pre-LTC use controls and post-LTC use outcomes. Because not all variables of interest are included in the RAND file, I supplement it with data fields from the RAND family file, the HRS Core and Exit files, and the Cross-Wave Imputation of Cognitive Functioning Measures file. I use variation in state level policy to predict home care; state of residence is obtained using the restricted HRS geography data.

State policy information is collected from multiple sources. While nursing home ser-

1. The RAND HRS Longitudinal File is an easy-to-use dataset based on the HRS core data. This file was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

vices are a mandatory state plan benefit, and therefore provided as an entitlement to all qualified Medicaid beneficiaries, HCBS is provided through three different Medicaid programs: mandatory state plans (home health benefit), optional state plans, and 1915(c) HCBS Waivers. If a state provides a service through a waiver, it allows for more flexibility in how the benefit is provided; the state can limit the number of recipients, geographic area, and/or target population covered or provide additional services as long as the waiver provided services are cost neutral relative to providing nursing home care. States report spending and use of LTC to CMS in several ways, including CMS Forms 64 and 273, state surveys conducted by various organizations, and state Medicaid Statistical Information Systems (MSIS) reporting. After exploring many of these data sources, the state level policy information used here is collected from multiple sources. The percentage of Medicaid LTC spending devoted to HCBS was collected from CMS-64 forms, state estimates of 1115 waiver spending, and Money Follows the Person budget data and tabulated in Wenzlow, Eiken, and Sredl, 2016. Count of 1915(c) HCBS waivers was generously provided by UCSF[2] and supplemented with researcher collected data on waiver target populations and 2012 and 2014 waiver characteristics from the Medicaid website.[3].

2.4.1 Treatment

Treatment is defined as those individuals that report using home care services over the two-year look-back period. The control group is those individuals that report using nursing home care. Individuals that report both home care and nursing home care in one interview are excluded from the main analyses. As a robustness check, in the appendix I include individuals using both care settings in the control group.

The HRS identifies home care using two survey questions: the first question asks "Has

2. UCSF collected data is described in Kitchener, Carrillo, and Harrington, 2003 for 1999. UCSF continued this data collection effort through 2012 using similar sources and methodology.

3. UCSF data was supplemented with state waiver information available at Medicaid.gov link: `https://www.medicaid.gov/medicaid/section-1115-demo/demonstration-and-waiver-list/index.html`

any medically-trained person come to your home to help you?" This captures home health care services. The second question seeks to capture other services used: "Did you use any special facility or service which we haven't talked about, such as: an adult care center, a social worker, an outpatient rehabilitation program, or transportation or meals for the elderly or disabled?" For the purposes of this analysis, I combine the responses to both questions to create a single indicator of home care.

Nursing home use is also self-reported. Respondents asked if they are currently living in a nursing home and, if yes, for how long. If not currently living in a nursing home, they are asked if they had an overnight stay in a nursing home since the last interview and again asked for duration. Respondents are included in the control group if they report any nursing home care use in any of these questions.

Trends in home care vs. nursing home use over time for all HRS respondents by type of impairment are illustrated in Figure 2.1. Surprisingly, 46% of individuals that report using either nursing home or home care services report no difficulties with ADLs/IADLs and have normal cognitive functioning at the time of the interview. This likely reflects a limitation of using the HRS to ascertain long-term care use. It is likely that many of these individuals used nursing home or home care after an acute event for rehabilitation, and that this care is not long-term in nature. This group with no limitations receives a consistently high share of nursing home and home care in the home setting over the study time period: annual means range from 93.0% in 2000 to 95.3% in 2014. Of those with cognitive or functional impairment, 20.6% have functional impairment only; 36.9% have cognitive impairment only, and 42.4% have both functional and cognitive limitations. In this study, I limit to respondents in the bottom two panels of Figure 2.1. Among individuals with cognitive impairment only, the rate of home care (versus nursing home care) rises from 87.5% to 94.1%; among respondents with both cognitive and functional impairment, the rate of home care increases even more during the study period, from 56.6% in 2000 to 74.5% in 2014.

2.4.2 Outcomes

Outcomes are selected to broadly reflect physical and mental health. I will describe each outcome measure, along with its specific data source, in detail below.

Mortality Mortality is ascertained at 2 years from the month of the core interview using the HRS tracker file data. The HRS collects date of death from exit interviews, which are conducted with a knowledgeable proxy after the respondent dies, or from spouse core interviews. The two year window is measured in months: the public data only contains month and year of interviews and deaths, and not the exact date.

Hospitalization Hospitalization is measured in the two year period after the core interview in which LTC use was reported (i.e. the $t + 1$ interview). This is approximately the same time window in which 2 year mortality is determined. Hospital use is collected from both core and exit interviews. In core interviews, the respondent is asked if they had been hospitalized since the previous interview. In exit interviews, proxy respondents are asked to report on hospital use of decedents since the prior core interview, including the final hospitalization of the place of death was the hospital. A binary indicator for any hospital use is then created combining information from the core and exit interviews in period $t + 1$ to get responses for all period t respondents.

Self-reported health Respondents are asked to rate their overall health, on a scale of 1=poor to 5=excellent, each interview. I create a binary indicator that is coded as 1 if fair or poor health is reported and 0 otherwise. It is measured at the time of the interview and reflects self-reported health at the end of the lookback period where LTC is reported.

Depression Depression is assessed in the HRS core interview using the Center for Epidemiologic Studies Depression Scale (CES-D), on a scale from 0-8. A score of 4 or higher is classified as clinical depression. The cutoff was used to create a binary indicator of depression. Observations in which interviews are conducted with a proxy respondent are not included in analyses of this outcome as the CES-D module is not part of the proxy interview.

Severe functional impairment Functional impairment is derived from the core interview questions relating to difficulty with ADLs and IADLs. Individuals are asked to report if they have difficulty with the following 10 tasks: walking across a room,dressing, bathing, eating, getting in and out of bed, using the phone, taking medications, managing money, shopping for groceries, and preparing meals. If they answer that they have difficulty, or that they cannot do the task, they are coded as having difficulty with that task. A binary indicator is then created to identify individuals that have difficulty with 4 or more of the 10 tasks to identify those with severe functional impairment. This outcome is concurrent to treatment status; it is measured at the time of the period t interview and reflects functional impairment relative to the end of the 2-year lookback period in which LTC was reported.

Dementia The HRS assesses cognitive functioning using the modified Telephone Interview for Cognitive Status (TICS); TICS scores range from 0-34 with a score of 8 or lower indicating severe cognitive impairment (Herzog and Wallace, 1997). For proxy interviews, the 16 item Jorm IQCODE is administered; a score of greater than 3.38 indicates severe cognitive impairment (Jorm, 1994). These measures, along with proxy interview status and past interview information, are used to impute dementia status (and cognitive impairment without dementia) in a researcher provided supplemental file(Langa et al., 2018). The binary indicator for dementia is then derived from the cognitive function status in the period t interview.

BMI not in normal range During the core interview, height and weight are recorded and then BMI is calculated from the self reported values. BMI not in normal range is a binary outcome, coded as 1 if BMI is greater than 25 (overweight, obese) or below 18 (underweight). The BMI outcome is from the period t interview.

Health limits work Finally, in the core interview, respondents are asked whether they have any impairment or health problem that limits the type or amount of paid work they can do. This outcome is coded as a binary indicator of a response of yes to this question in the period t interview.

2.4.3 Predictors of Treatment (home care)

To predict home care (versus nursing home care) I include a wide range of fixed and time varying characteristics. Fixed person level characteristics are sex; race and ethnicity (non-Hispanic white, non-Hispanic black, Hispanic); and education (less than high school degree versus high school degree or higher). Time varying covariates predicting treatment at time t are derived from the previous wave interview responses $t-1$ to avoid overcontrolling. Time varying predictors of home care can be conceptualized as enabling factors or need factors. Enabling factors included are quintile of household assets (from the RAND Imputations), currently married, any children, receiving informal care, and insurance coverage (Medicaid, Veterans Affairs health insurance, private health insurance, and long-term care insurance). Several need factors are also observed in the HRS data. Two measures of the are degree of cognitive impairment are included: impairment that is not dementia (CIND) and dementia (imputed from interviews (Langa et al., 2018)) as well as the need for a proxy respondent to the HRS core interview. Level of physical functional impairment is measured using report of difficulty with ADLs and IADLs (no tasks with difficulty, 1-3, and 4+ tasks with difficulty). Because the interaction of receipt of home care and level of functional impairment was more predictive of LTC setting than either on its own, I control for the following interaction of the two categorical variables functional impairment and receipt of informal care. Self-report of specific medical conditions (high blood pressure, diabetes, cancer, lung disease, heart disease, stroke, psychological problem, arthritis) and an indicator of 3 or more medical conditions as a proxy for severity of health problems are also included. Finally, poor or fair self-reported health, depression, and previous period hospitalization are included as controls.

2.4.4 Instruments - State Medicaid HCBS Policy

Two measures intended to capture generosity of Medicaid HCBS coverage and emphasis of HCBS over nursing home care at the state level are (1) the number of Section 1915(c) HCBS Waivers and (2) share of LTC spending for HCBS among the ID/DD population. Trends in these measures from 2000-2014 are plotted in Figure 2.3. Much of the growth in the number of beneficiaries using Medicaid funded HCBS has been through the use of 1915(c) waivers. For example, using data compiled from Kaiser Family Foundation reports derived from state surveys and state reporting to CMS, the number of 1915(c) waiver participants increased from approximately 700,000 to 1.6 million between 2000 and 2014 (Kitchener et al., 2005) (Watts and Musumeci, 2018). In 2000, 43 states had at least one 1915(c) waiver in operation, with the median number of waivers being 4 and maximum 10. By 2014, the use of waivers had increased: among 42 states with 1915(c) waivers, the median number was 6 and a maximum of 11. From 2000-2008, there was a steady rise in the number of 1915(c) waivers in operation while the flattening during 2010-2014 was due to consolidation of these waivers in some states to reduce administrative burden as well as the replacement of 1915(c) waivers, which allow for fee-for-service HCBS financing, with 1115 waivers which provide HCBS through managed care financing models.

An alternative measure of HCBS expansion is the share of Medicaid LTSS spending used for HCBS relative to institutional services. This spending data is tabulated using various data sources in annual reports, both overall and by specific target population (Wenzlow, Eiken, and Sredl, 2016). A conceptually valid instrument predicts home care use among HRS respondents but cannot be directly related to the outcomes examined (see the Methods section for further discussion). In order to avoid using a spending measure that is derived from care received by the older adults that make up the HRS sample, I use the share of HCBS/LTSS spending among a different population: those with intellectual and developmental disabilities (ID/DD). While the focus of deinstitutionalization of this population occurred earlier than the current push to care for older adults in the home and community, there was still considerable growth in HCBS/LTSS spending in this group: the mean share HCBS/LTSS spending at the state level increased from 51% to 77% from 2000 to 2014.

2.4.5 Sample restrictions

Table 2.1 summarizes the sample restrictions. There are n=149,184 interviews for n=30,849 unique respondents aged 50+ in the 2000-2014 HRS that report residing in one of the 42 states included in the analysis. Of those interviews, 18.2% report using home care or nursing home care (period t interview). In order to control for respondent characteristics, I only include observations with an interview conducted in the prior wave (period $t-1$). Individuals with missing data or with race other than white, black or Hispanic are excluded. Finally, to restrict to the subgroup for whom HCBS expansions in the 2000s are especially relevant, we limit to those with cognitive impairment (with or without dementia), resulting in a final sample size of 7,976 interviews of 5,009 individuals.

2.5 Methods

First, I compare unadjusted outcomes in a two-way comparison for the group that used home care and the group that used nursing home care. However, these groups are different in ways that are correlated with both treatment (the choice to use home care) and the outcomes examined.

Second, in an initial approach to account for observable characteristics, multivariate regression is used to control for the rich set of observable characteristics available in the HRS data. I estimate the parameters in the following linear equation using ordinary least squares regression (OLS):

$$Y_{is(t+1)} = \beta_0 + \beta_1 HCBS_{ist} + \alpha_2 X_{is(t-1)} + State_s + \lambda_t + \epsilon_{ist} \tag{2.1}$$

The subscripts i,s, and t represent individual i in state s at time t. In the absence of omitted variables bias and simultaneity bias, the coefficient on $HCBS_{ist}$, β_1, is the effect of care setting on the outcomes occurring after receipt of LTC. $X_{is(t-1)}$ are the predictors of treatment described previously and are lagged one period (2 years) to avoid controlling for characteristics that could be impacted by the choice of long-term care setting. I also include state fixed effects $State_s$ and time fixed effects λ_t to account for time-invariant differences between states and time trends.

Third, I create two matched samples, constructed both to balance on observed characteristics of home care and nursing home care users and to increase the strength of the instruments. I generate a propensity score of the following form:

$$(Pr(HCBS_{ist} = 1)) = \alpha_0 + \alpha_1 X_{is(t-1)} \tag{2.2}$$

$X_{is(t-1)}$ consists of all of the control variables described previously and several interaction of these variables that improved balance of the matched samples. After exploring several matching and weighting methods, two caliper matching methods were identified, each achieving sufficient balance across observable characteristics and maximizing first stage strength of each instrument. To maximize strength of instrument count of 1915(c) HCBS waivers, 1:2 nearest neighbor matching with replacement was best. To maximize strength of the HCBS/LTSS spending among the ID/DD population, 1:1 nearest neighbor matching without replacement is used.

Using the matched samples, I then re-estimate equation 2.1. However, matching only accounts for observable differences between the treatment and control groups. These estimates using the matched sample could be biased due if there are characteristics which are related to home care and the outcomes which I do not observe, and therefore do not control for using matching/regression (i.e. omitted variables bias). For example, if individuals that use nursing home care are in poorer health (conditional on observed characteristics) than those that use home care, and poorer health results in increased risk of hospitalization, then the estimated results of the impact of care setting on hospitalization would overstate the effect of nursing home care in predicting hospitalization. Additionally, there is the possibility of reverse causation: it is possible that quality-of-life factors could drive the decision to use HCBS versus nursing home care; estimation without accounting for this could result in simultaneity bias.

To account for these potential biases, i.e. the endogeneity in the choice of home care versus nursing home care, I use an instrumental variables study design. I use two measures of Medicaid HCBS generosity at the state level to predict home care use versus nursing home use: (1) the number of Section 1915(c) HCBS Waivers and (2) the share of Medicaid LTSS spending devoted to HCBS for the intellectually disabled/developmentally disabled (ID/DD) population. Conceptually, as the state expands HCBS services through HCBS waivers or by increasing the share of LTSS spending on HCBS, individuals are induced to use HCBS as a substitute for nursing home care. The extent to which a state's Medicaid program has emphasized HCBS over nursing home care may nudge a subset of the population into selecting HCBS over nursing home care when they make their individual level decision. Therefore, the variation in state policy over time allows me to estimate a local average treatment effect (LATE). It is the LATE for individuals that are induced to choose home care versus nursing home care because the state has a more generous HCBS Medicaid policy.

I implement the IV analyses using two-stage least squares (2SLS) methods. The estimating equations are as follows:

$$\begin{aligned} \text{1st stage: } & HCBS_{ist} = \alpha_0 + \alpha_1 Z_{st} + \alpha_2 X_{is(t-1)} + State_s + \lambda_t + \upsilon_{ist} \\ \text{2nd stage: } & Y_{is(t+1)} = \beta_0 + \beta_1 HC\hat{B}S_{ist} + \delta_2 X_{is(t-1)} + State_s + \lambda_t + \varepsilon_{ist} \end{aligned} \tag{2.3}$$

β_1 is the coefficient of interest; it is the LATE for those individuals induced to choose home care rather than nursing home care due to state Medicaid policy. Z_{st} is the instrument; it is the number of HCBS waivers active in the state s in year t or an indicator of whether the state ratio of HCBS spending to total LTSS spending for the ID/DD population is greater than the median ratio during the study time period. $X_{is(t-1)}$ are the predictors of treatment described previously and are lagged one period (2 years) to avoid controlling for characteristics that could be impacted by the choice of long-term care setting. I also include state fixed effects $State_s$ and time fixed effects λ_t to account for time-invariant differences between states and time trends.

IV estimates a local average treatment effect (LATE) for compliers. Compliers in this case are the subset of individuals that are induced to choose home care by the state policy. In the absence of the policy, they would elect nursing home care but when states have generous HCBS policies, they elect HCBS. This marginal group is policy relevant because it is the group that can be moved to choose HCBS by policy. I argue that, in fact, this is precisely the group we want to learn about. For the seriously ill, with severe functional limitations that cannot be supported in the community and would choose nursing home care regardless (never-takers), the treatment effect is not relevant. Similarly, for those with low-needs or perhaps a strong preference for home care (or aversion to nursing home care), again, policy will not sway their decision (always takers) and their treatment effect is not relevant because they will never use nursing home care.

The key identifying assumption is that the policy variation impacts outcomes only through the choice of treatment, and not through some other channel. This can be described more specifically using the three IV assumptions: (1) strength, (2) exogeneity and (3) the exclusion restriction. Instrument strength requires that the instrument impacts the choice of treatment. In this application, living in a state with more growth in number of HCBS waivers or the share of HCBS/LTSS spending for the ID/DD population must predict more home care use. This assumption is tested in the first stage regression: the estimated coefficient on the instrument, α_1, must be positive and sufficiently statistically significant.

Second, the exogeneity assumption requires that the instrument must be conditionally independent of the confounding factors in the original equation. That is, HCBS policy at the state level must not be related to the unobserved underlying factors that impact both the decision to use home care and the outcomes of home care users. While this cannot be directly tested, a regression of the control variables from the main regression, $X_{is(t-1)}$ on the outcome of the instrument, can provide some assurance that the instrument is not correlated with observable confounding factors, conditional on each of the other control variables.

The third assumption, the exclusion restriction, requires that the instrument does not directly affect the outcomes. That is, HCBS generosity at the state level cannot directly impact the health and other quality of life outcomes examined. If states that expanded HCBS during the time period also improved other aspects of care such as hospital quality or pay for long-term care providers differentially than states that did not expand HCBS, this would violate this assumption.

I outline two specific threats to these assumptions that cannot be tested. First, one potential threat to the assumption is that individuals choose where to live based both state policy and underlying health. Only 2.2% of the LTC sample moved between states in the wave prior to reporting LTC use (between t-1 and t-2) which alleviates this concern. In the appendix, analyses are repeated excluding these respondents from the sample to check if the main results are driven by this small share of movers. Another concern is that states that have sicker populations invest in HCBS policies, so that the instrument is correlated with outcomes.Miller and Kirk, 2016 show that state level factors such as initial (year 2000) low share HCBS spending, political environment (i.e. Democratic governor), and greater housing affordability were associated with greater increases in HCBS share from 2000 to 2011. In their documentation of spending on LTSS over time Wenzlow, Eiken, and Sredl, 2016 describe legislation at the national level that has encouraged states to expand HCBS relative to nursing care beginning with the Omnibus Budget Reconciliation Act of 1981 which first established Section 1915(c) waivers.

In the appendix, I re-estimate the multivariate regressions and matched IV models using non-linear methods as a sensitivity test to ensure that the results are not driven by the linear functional form imposed. Two stage least squares (2SLS) provides a consistent estimate of

LATE when linear regression is used in both stages but ignores the fact that treatment and outcomes are binary (Terza, Basu, and Rathouz, 2008) (Basu, Coe, and Chapman, 2018). Two stage residual inclusion (2SRI) is an alternate method which is equivalent in the linear setting but not in the discrete setting (Deb, Norton, and Manning, 2017). Therefore, as an alternative to the 2SLS models in the main results, in the appendix I use 2SRI to perform the estimations accounting for endogeneity of the home care choice.

To investigate differences in the effects of home care on outcomes by race and ethnicity, I re-estimate the 2SLS equations in samples stratified by race using three race groups: non-Hispanic white, non-Hispanic black, Hispanic.

2.5.1 Limitations

It should be noted that, as in other studies relying on survey data, all outcomes, treatment and control variables are based on self-reported data. This self-reported data could be biased due to inaccurate survey responses. The benefit of the richness of the survey questions and corresponding ability to examine outcomes and control for survey respondent characteristics that are not available in administrative data sources make this study valuable in light of this limitation.

The sample is restricted to home care or nursing home users with cognitive impairment. This restriction limits the generalizability of these results. Medicaid HCBS expansions in many states have also impacted the choice of care setting for other long-term care users that do not have cognitive impairment, such as older adults with physical disabilities or younger children and adults with intellectual or developmental disabilities. While it is important to examine outcomes among these other populations, that is beyond the scope of the current study.

2.6 Results

2.6.1 Analysis sample description

Table 2.2 provides descriptive statistics for the sample of LTC users with cognitive impairment, overall and by LTC setting: nursing home only, home care only, and both nursing home and home care. Overall, 65.3% are female, and there is a large share that are female and not married reflecting the demographic make up of paid long-term care users. 28.9% have Medicaid coverage, and only 7.2% have private long-term care insurance coverage. 401% of the sample has dementia while the remaining 59.9% have cognitive impairment that is not dementia. While approximately 1/3 of the sample report no functional limitations, another 1/3 have severe functional limitations, with difficulty with four or more ADL/IADLs. The sample is also in relatively poor health: nearly 60% report fair or poor overall health, 60% report three or more chronic conditions, and 50% report being hospitalized in their previous interview.

While the sample overall is in poor health, it appears that those using nursing homes or both nursing home and home care are in worse health than those using HCBS. This is consistent with our descriptive findings in Chapter 1 examining all elderly, dual eligible Medicaid LTSS users. Nursing home users are older, more likely to have dementia, and more likely to be severely functionally limited. However, both groups are equally likely to report fair or poor self-rated health and the group using HCBS are more likely to report 3+ chronic conditions than those using nursing homes. In addition to these differences in health, there are differences in enabling factors: nursing home users have fewer household assets, are less likely to be married, less likely to have a child, and less likely to have received informal care in the prior interview suggesting that health and availability of potential informal caregivers both impact the decision to use home care versus nursing home care. There are also racial differences between the groups: whites are more likely to use nursing homes while blacks and Hispanics are more likely to use home care, again consistent with our findings examining the

Medicare-Medicaid dually enrolled.

These differences in sample characteristics highlight the benefits of using the rich HRS data to complement previous studies relying on administrative data alone. If we measured health status only based on previous hospitalization and chronic condition diagnoses, it would appear that home care and nursing home users are quite similar. However, information on functional limitations and level of cognitive impairment makes it clear that home care users are less impaired than nursing home users. Also, family structure and the availability of informal caregivers are different between the two groups. While these factors cannot be measured in most administrative data sources (for example, fee-for-service claims), they are important differences that should be controlled for in any comparison of the effect of care setting on health and other outcomes.

Table 2.3 examines outcomes of care recipients, again overall and by nursing home versus home care use. Consistent with the poorer health of nursing home users, they also experience worse outcomes across the majority of measures examined. Mortality rates are more than twice as high among nursing home users than home care users. In contrast to that large difference, hospitalization rates, fair/poor self rated health, and depression, while higher for nursing home than home care users, are much more similar across the two groups. Consistent with baseline ($t-1$) levels, rates of dementia and severe functional limitations remain higher among nursing home users. BMI not in normal range is the only negative outcome that is higher among home care users than nursing home users.

Next, these sample characteristics and outcomes are reported separately by race and ethnicity group and LTC setting in Tables 2.4 and 2.5. The pattern that nursing home users are older, have fewer potential informal caregivers, lower assets, and a higher degree of cognitive and functional impairment is consistent in each of the race groups. But this tabulation does reveal some interesting differences between groups. For instance, approximately half white and Hispanic home care users are married (51.7% and 47.8%) while only 35.6% of black home care users are. When we look by gender and marital status, the differences are driven by women and not men. While whites have nearly the same rates of informal care use in the interview prior to when formal long-term care is provided across the two care settings, black home care users report higher use of informal care than their nursing home counterparts while Hispanic home care users report lower use of informal care than those in nursing homes. Whites using nursing homes have household assets four times greater than non-whites and nearly five times greater among home care users. Reflecting these differences in wealth, whites also have lower rates of Medicaid coverage and higher rates of private insurance than do non-whites. Rates of dementia and severe functional impairment are higher among non-white home care users than white home care users. In the period prior to home care use, the difference in hospitalization rates between home care and nursing home care users are smallest for whites (hospitalization rates for home care users are 93% that of nursing home users), then blacks at 90%, and largest for Hispanics at 74%.

In terms of outcomes, consistent with the overall results, mortality rates are higher among nursing home users than home care users within each race group, although the differences are larger among the non-white groups than among the white groups, perhaps partly reflecting the fact that white nursing home users are older than those of other groups. Hospitalization rates among nursing home users are higher among blacks and Hispanics than whites. Interestingly, in comparing care setting within groups, hospital use in the period after nursing home care is reported among whites is higher than for white home care users while for blacks and Hispanics, hospitalization is lower among home care users than nursing home users. For the other outcomes, patterns by race are similar as in the overall sample: nursing home users have higher rates of reporting fair or poor health, higher rates of depression, and higher rates of severe functional and cognitive impairment than home care users.

2.6.2 Multivariate regression results

Next, results from the naïve regression estimates of Equation 2.1 are reported in Table 2.6 for each of the outcomes. The coefficients for home care (versus nursing home care) are reported along with the standard errors of the estimates. Sample sizes vary reflecting the fact that a small number of observations are missing some of the outcome measures. The CES-D depression screening is not administered during proxy interviews, explaining the large reduction in sample size for that outcome in particular. These adjusted effects are largely consistent with the unadjusted tabulations: home care is associated with lower rates of these negative outcomes. Consistent with the large differences in mortality rates across care settings, home care is associated with 12.2% lower 2 year mortality in the regression model. Home care is also associated with lower reporting of fair/poor health, severe functional impairment, dementia, and health limiting paid work. Controlling for observable characteristics, home care, relative to nursing home care, is not associated with a statistically significant difference in hospital use or depression.

This same model is estimated separately for each race/ethnicity group using stratification and results are tabulated in Table 2.7. The effects of home care on the outcomes for white LTC users largely mirror the overall effects. However, the sign of the coefficient for home care for the outcome of hospitalization is positive, consistent with the unadjusted rates of hospitalization for whites using home care relative to those using nursing homes. Among black LTC users, the association between home care and better self-rated health and lower rates of depression are smaller than for the white and Hispanic subgroups. Finally, for the Hispanic subgroup, the coefficient on hospital use is statistically significant: users of home care have adjusted rates of hospitalization rates 19% lower than nursing home users.

2.6.3 Matching

Distribution of the propensity score, estimated with Equation 2.2, is shown in Figure 2.4. For the sample used with the instrument number of Section 1915(c) HCBS waivers, 1:2 nearest neighbor matching is used. n=196 observations with the highest propensity scores (probability of home care greater than 97.8%) are excluded because they are outside of the range of common support (i.e. there are no nursing home users with probability of home care that high). For the sample used with the instrument HCBS/LTSS spending ID/DD greater than median, 1:1 nearest neighbor matching without replacement is used, resulting in a smaller sample. n=3,318 home care users are excluded from the sample and n=1,097 home care users are matched with n=1,097 nursing home users.

Matching is intended to make the characteristics of the nursing home users more comparable to the home care users with the goal of being able to then get an unbiased estimate of the effect of home care on outcomes. One way to check this "balance" on treatment status is to compare standardized differences of the observable characteristics of the treated and control groups. Standardized difference less than 10% is generally considered "balanced" (Garrido et al., 2014). Standardized differences before and after matching are reported in Tables 2.8 and 2.9 for the sample used with the instrument of HCBS waiver count and Tables 2.10 and 2.11 for the instrument of HCBS/LTSS spending. The matched samples generally are much more balanced, with smaller standardized differences, than the matched samples. The larger 1:2 matched sample achieves better balance, with all observable characteristics having a matched standardized difference less than 10%. The smaller 1:1 matched sample, in contrast, remains unbalanced in age, marital statusXsex interaction, Hispanic ethnicity, and two measures of cognitive status: dementia and proxy interview. Regression in the matched samples include controls for all of these characteristics to account for their differences in the matched samples. Differences in the instruments increase with matching, as intended, as well.

2.6.4 Instrument conditional exogeneity

Before turning to the IV results, I provide an examination of the conditional exogeneity assumption. Linear regression is used to estimate the effect of each of the independent variables on the instrument. If the instrument is unrelated to individual level characteristics of LTC users, than this provides some assurance that the instrument is valid. Tables 2.12 and 2.13 show the coefficients from this regression and the p-value from the test of significance of each characteristic individually, conditional on the other controls for the two instruments. For most of these tests, the values of the coefficients are small and p-values high suggesting that the null hypothesis that the individual level characteristic is not related to the instrument cannot be rejected. In the regression with the number of HCBS waivers is the outcome, none of the independent variables is statistically significant ($p < 0.05$). Using HCBS/LTSS spending for the ID/DD population greater than the median as the outcome, only Hispanic ethnicity, education, and heart disease have statistically significant effects. Higher Medicaid HCBS spending among the ID/DD population is associated with Hispanic ethnicity, lower education levels and lower prevalence of heart disease. However, given the large number of tests (due to the large number of coefficients), this relatively few number of significant coefficients, along with the conceptual appeal of these state-level instruments, give us confidence that our instruments are valid.

2.6.5 First stage results

In Tables 2.14 and 2.15, first stage estimation results are shown in the two matched samples. From Table 2.14, an additional Medicaid 1915(c) HCBS waiver at the state level results in an increase in home care of 3.7%. The chi-squared test statistic of 21.5 of the strength of the IV shows that, in the matched sample, the instrument has sufficient power. Similarly, being in a state that moves from providing HCBS/LTSS spending below the median to above the median during the study period increases the likelihood of using home care 14.4%. Both instruments significantly increase the likelihood of home care use among this population of older, cognitively impaired LTC users.

2.6.6 IV results: Overall Sample

Table 2.16 reports both the OLS regression and IV estimates using 2SLS of the effect of home care versus nursing home care in the matched sample using count of HCBS waivers as the instrument. Matching with OLS regression results in estimates similar to the results in the unmatched sample reported in Table 2.6. Without using IV, home care is associated with better outcomes for all outcomes examined except for BMI not in the normal range. However, using IV methods to account for any remaining selection after matching shows that only the outcomes of severe functional impairment and dementia appear to be improved by home care. For those individuals induced to use home care vs nursing home care because of growth in the number of HCBS waivers in their state, home care is associated with a 51% lower rate of severe functional impairment and 51% lower rate of dementia.

When HCBS/LTSS spending share in the ID/DD population is used as the instrument, only the effect on hospital use is (marginally) statistically significant. Consistent with our descriptive results in Chapter 1, accounting for selection on unobserved characteristics and narrowing in on the population likely to be influenced by state policy shows that home care is associated with increased hospital use for the compliers.

It should be noted that the precision of the estimates are much lower using 2SLS than OLS regression for both instruments. However, examining the signs of the estimates helps us interpret the results using both instruments/samples. With both instruments, the OLS coefficients of home care on hospital use are negative or zero, but the sign switches to positive when using IV methods. This suggests that, for marginal individuals that can be induced to use home care by state policies, they are trading off the risk of hospitalization for the benefits of remaining at home. Similarly for self-rated health, the apparent better self-rated health among home care users using matching alone is not present when IV methods are used. The instruments are less strong when examining the outcome of depression because of the reduction in sample size: depression scores are only assigned to people that complete the interview themselves, resulting a large decrease in sample size and instrument strength due to the large number of proxy interviews among this sample of cognitively impaired respondents. The results for severe functional impairment are not consistent across the two instruments/samples. This could be due to the fact that different instruments may capture effects for different groups of compliers.

2.6.7 IV Results - Stratified by Race

Finally, I repeat the OLS and IV estimation in the matched samples stratified by race to determine if the effects of home care on outcomes are similar for the three race groups. However, the instrument number of HCBS waivers does not have sufficient strength in the first stage when stratifying by race as indicated by the relatively low F-statistics reported in Tables 2.18 and 2.19). Interestingly, the instrument has more predictive power among Hispanics than the other race groups. But because all of the F-statistics are less than 10, these results are subject to bias due to the weak instrument and therefore, I do not interpret them here.

Results using the instrument of HCBS/LTSS spending in the stratified samples are shown in Tables 2.20 and 2.21. Like the count of waivers, this instrument is also weak for the black and Hispanic subgroups. For the white group, results are quite similar to that in the overall sample, with a positive coefficient on home care for the outcome of hospital use and coefficients of the same sign, but no statistical significance, for the other outcomes.

2.6.8 Sensitivity analyses

Several sensitivity analyses were conducted, the results of which are tabulated in the Appendix and summarized here. First, I included the group of respondents that reported using both nursing home care and home care in the control group, rather than excluding them as in the main analyses. These results are quite similar to those in the main analyses, although the instrument of HCBS/LTSS spending for the ID/DD population has less strength when the users of both nursing home and home care are included.

Second, respondents that moved, as determined by having different a state of residence between the $t-2$ and $t-1$ interviews are excluded from the analyses to assess whether the small number people that may have moved due to the HCBS policy environment in their state, drive the main results. Results are essentially the same with this small group of respondents omitted from the sample as when they are included giving me confidence that these individuals are not driving the results.

Finally, I repeated the estimates on the overall samples, using each instrument, using non-linear methods (logit regression and two-stage residual inclusion) to ensure that the choice to use linear models to estimate the effects on binary outcomes did not drive the main findings. The increased hospital use among home care users when IV methods are used was consistent regardless of whether 2SRI or 2SLS was used for estimation. However, the association of home care and better functional outcomes was less strong when non-linear methods were used, and more consistent across the two instruments, suggesting that that effect may better be estimated using these non-linear methods.

2.7 Discussion and conclusions

This paper uses the rich HRS survey data to estimate the impact of LTC setting, home care versus nursing home care, on a variety of outcomes meant to broadly reflect quality of life. I limit the analysis sample to HRS respondents that use either home care or nursing home care and that have cognitive impairment, in order to restrict to a subgroup for whom the recent Medicaid HCBS expansions are most relevant. I use a combination of matching and instrumental variables techniques to estimate plausibly causal effects. In models accounting for selection on observable characteristics only (multivariate regression, multivariate regression on matched samples), I find that home care is associated with lower mortality, better self-reported health, and lower rates of severe functional and cognitive impairment, and lower likelihood of reporting that health limits paid work.

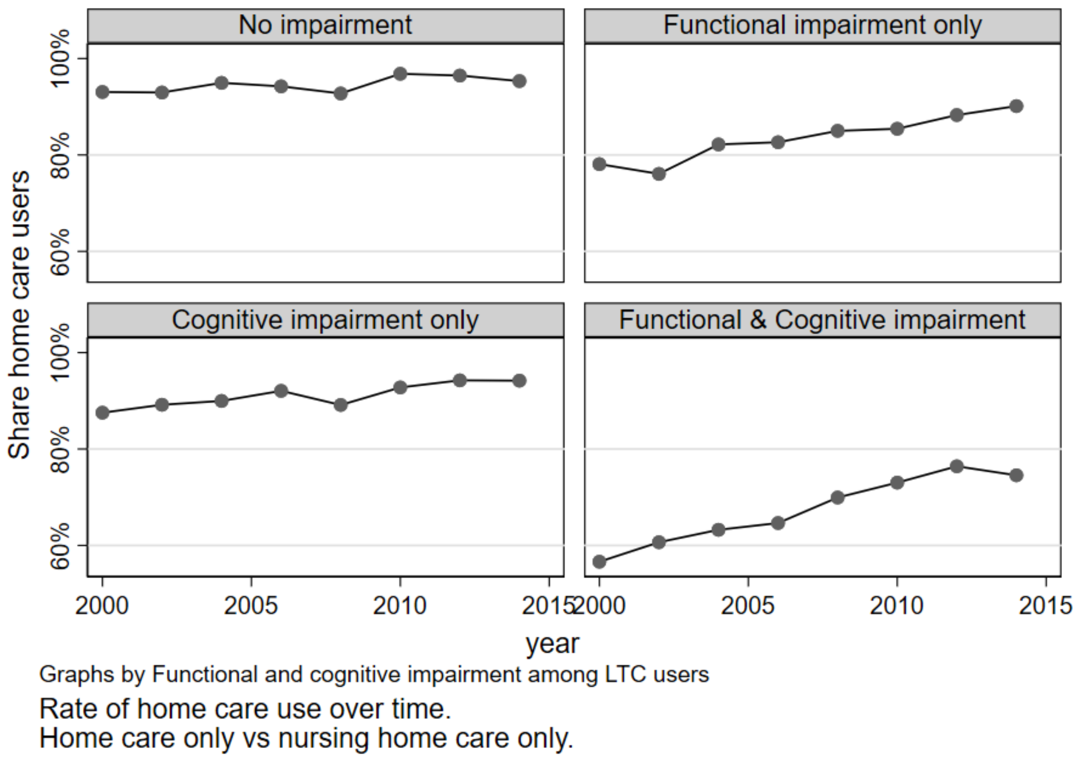
However, using IV methods and instruments that measure HCBS policy emphasis at the state level, I account for selection that may be unobserved. I find that home care is associated with lower rates of severe functional impairment but higher rates of hospital use. In analyses to be further refined, I also find that home care is associated with increased mortality among Hispanic LTC users and that the reduction in severe functional impairment found in the overall sample is present among whites and not Hispanics.

While the sample size is a limitation, the descriptive differences between home care users and nursing home users available in the HRS highlight the need to control for characteristics that are typically unobserved in administrative data. Home care users have different family structures and availability of informal caregivers than nursing home users. Additionally, the HRS measures of household assets reveal that black and Hispanic home care users have much lower financial resources than their white counterparts. If care recipients requiring a high intensity of long-term care are transitioned to home care settings, and they have fewer financial resources to support that care (and informal caregivers), there is the potential to overburden already vulnerable populations.

States have made shifting the setting of LTC from nursing homes to home- and community-based settings a priority over the last several decades. But little attention has been paid to the outcomes of this shift on care recipients and their families. In this paper, we show that there are differences across race groups in who receives paid long term care and in care setting for that care. While home care is associated with reduced incident severe functional impairment, it may be associated with increased risk of hospitalization. For policymakers to make LTC more effective and equitable, effects both for care recipients and their families should be considered. This paper provides a first examination of how care setting affects quality of life for LTC users with cognitive impairment, a group particularly reliant on LTC services.

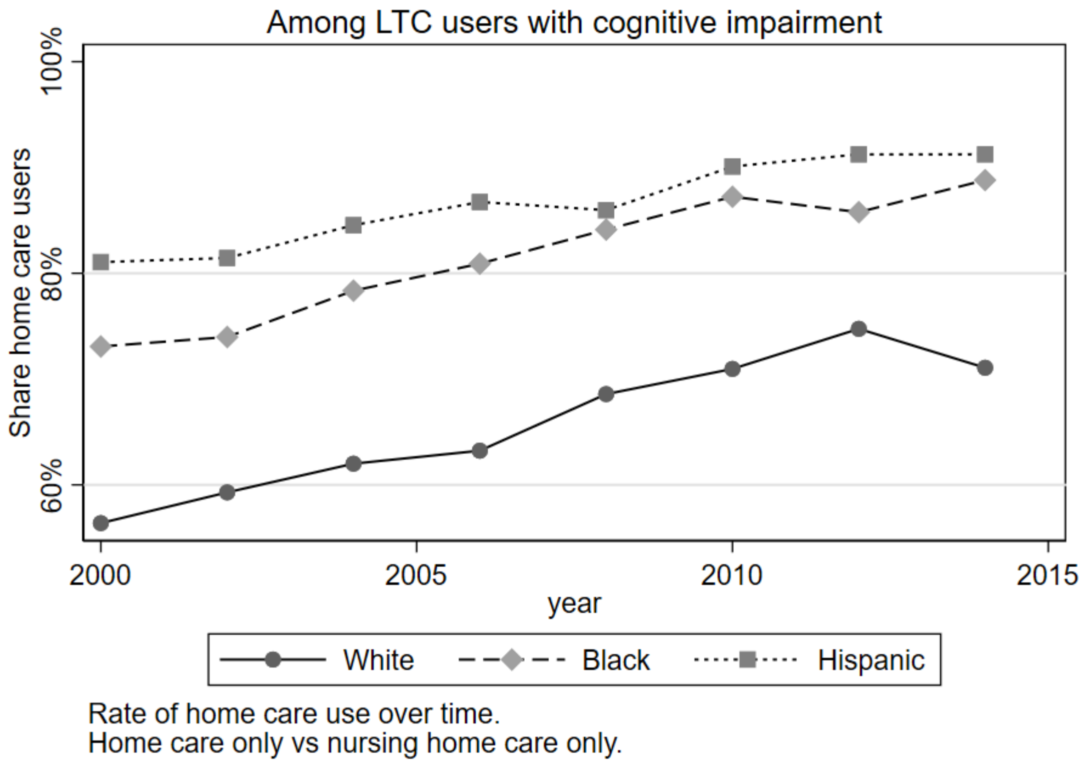
2.8 Figures

Figure 2.1: Home care use over time by type of impairment



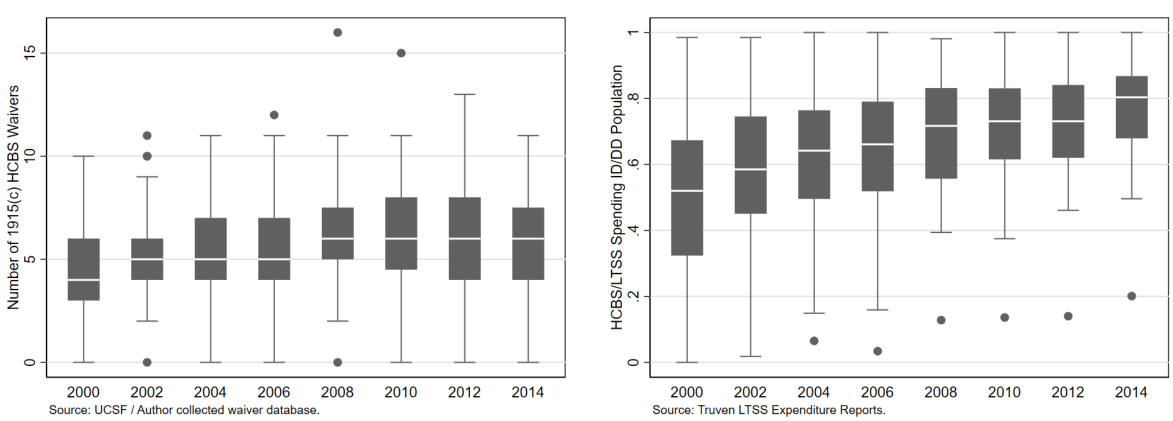
Source: HRS 2000-2014. Limited to respondents aged 50+ reporting either home care only or nursing home care only. Cognitive status from Langa-Weir imputed measures.

Figure 2.2: Home care use over time by race among respondents with cognitive impairment



Source: HRS 2000-2014. Limited to respondents aged 50+ reporting either home care only or nursing home care only. Cognitive status from Langa-Weir imputed measures.

Figure 2.3: State-level HCBS Expansion over Time

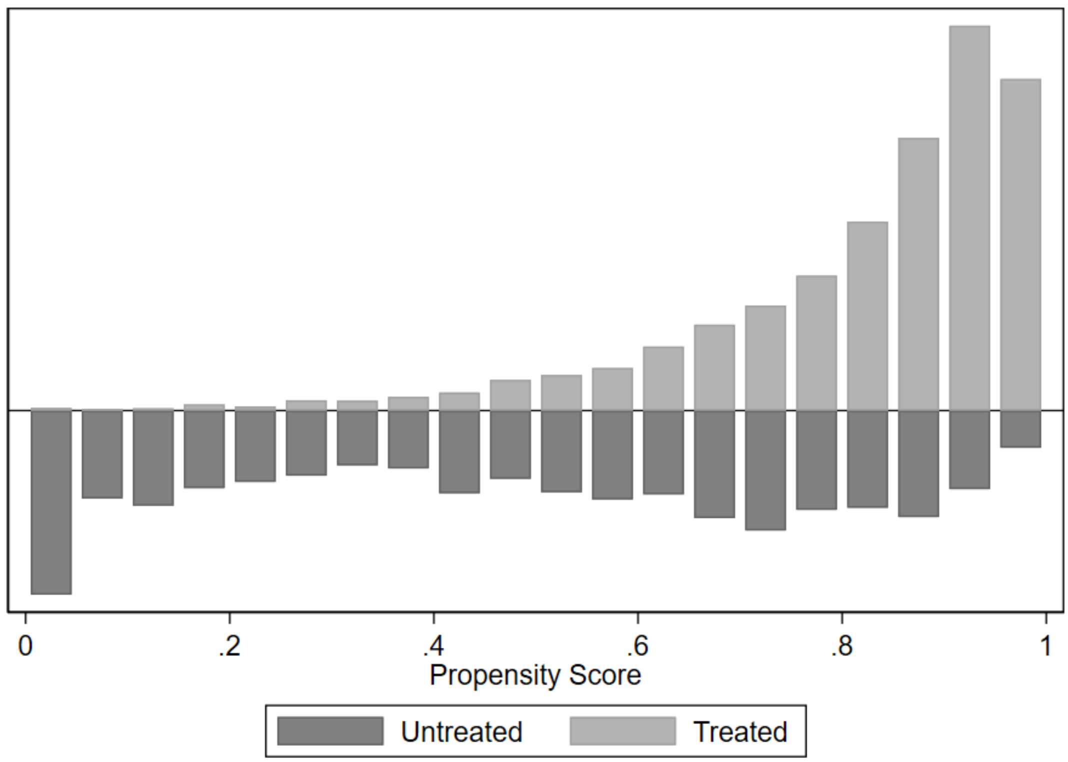


(a) 19195(c) HCBS Waivers

(b) Share of LTSS spending devoted to HCBS ID/DD Population

Limited to states represented in the HRS analysis dataset. Boxes represent 25th and 75th percentiles with median shown as line. HCBS=Home- and community-based services. LTSS=Long term services and supports. ID/DD= Intellectual disabilities/developmental disabilities.

Figure 2.4: Distribution of propensity score



Treatment: variable hctreat4 =1 if home care use only; =0 if nursing home use only. Omits individuals reporting both home care and nursing home care use.

2.9 Tables

Table 2.1: Sample restrictions

	Interviews	Individuals
2000-2014 Core Interview	149,184	30,849
Long-term care use	27,186	14,519
Interview prior to LTC interview	25,907	13,904
Complete data, Race/ethnicity=White,Black or Hispanic	23,519	13,028
Cognitive impairment	7,976	5,009
White	4,966	3,227
Black	1,981	1,165
Hispanic	1,029	617

Mean number of interviews per respondent is 4.84.

Core interview criteria: Complete interview, Age 50+, state of residence reported and reside in included state.

Excluded states: AK, HI, ID, MT, RI, SD, UT, VT($n \leq 20$)

Cognitive impairment=Cognitive impairment not dementia or dementia. Assessed in interview prior to LTC interview.

Table 2.2: Sample characteristics

	Overall	Nursing home	HCBS	Both
Age, years	79.3	83.7	76.5	82.4
Married,Female	18.2	13.8	20.0	17.6
Married,Male	22.0	13.2	26.3	19.2
Not Married,Female	47.1	57.6	41.6	51.5
Not Married,Male	12.7	15.3	12.1	11.7
White non-Hispanic	62.3	75.5	53.2	73.4
Black non-Hispanic	24.8	17.6	29.7	19.0
Hispanic	12.9	6.9	17.1	7.6
HS degree (inc. GED)	30.4	32.5	28.6	33.2
Household assets[1] (mean)	191,402	167,793	186,694	227,223
At least 1 living child[1]	90.6	85.6	92.4	90.7
Received informal care[1]	43.1	39.5	42.5	48.2
No functional limitations[1]	32.7	20.7	39.5	26.6
1-3 ADL/IADL limitations[1]	29.4	21.6	32.8	28.0
4+ ADL/IADL limitations[1]	37.9	57.8	27.7	45.5
CIND [1]	59.9	37.4	70.7	53.4
Dementia[1]	40.1	62.6	29.3	46.6
Proxy interview[1]	26.9	50.2	17.1	30.1
Medicaid[1]	28.9	32.4	29.4	24.1
VA Health Insurance[1]	4.3	3.6	4.3	4.8
Private Health Insurance[1]	40.2	42.1	38.6	42.4
LTC Insurance[1]	7.2	7.5	6.8	8.1
Any hospitalization[1]	50.0	52.5	46.9	55.8
SR health fair or poor[1]	59.7	59.3	60.2	58.7
Depression [1]	23.4	15.1	27.3	21.3
High blood pressure[1]	70.1	64.3	71.8	71.1
Diabetes[1]	29.6	23.2	31.8	30.1
Cancer[1]	15.1	13.2	15.3	16.4
Lung disease[1]	14.3	9.5	16.5	12.9
Heart disease[1]	38.9	34.4	39.6	41.6
Stroke[1]	21.9	27.2	18.8	25.1
Psychiatric condition[1]	29.8	32.2	28.7	30.5
Arthritis[1]	74.1	69.6	75.4	74.9
1 or 2 chronic conditions[1]	35.7	40.3	35.0	33.2
3+ chronic conditions[1]	59.9	54.6	60.8	62.8
Resides in metropolitan county	77.0	74.1	77.1	79.5
N	7,976	1,693	4,567	1,716

Source: 2000-2014 HRS analysis sample.

Percentages reported for binary variables, means for continuous variables.

1=At interview prior to LTC (i.e. $t-1$); CIND=Cognitive impairment not dementia.

Table 2.3: Care recipient outcomes

	Overall	Nursing home	HCBS	Both
Died 2 years	29.8	43.8	20.1	41.7
Any hospitalization 2 years	59.5	59.1	57.2	66.2
Fair or poor self reported health	65.2	65.2	64.2	68.0
CESD score >3	33.9	34.6	33.8	34.0
4+ ADL/IADL limitations	53.8	76.4	38.2	73.2
Dementia	50.8	75.1	36.2	65.4
BMI not in normal range	59.3	52.1	64.7	51.9
Health limits work	76.6	84.1	69.9	89.0
N	7,976	1,693	4,567	1,716

Source: 2000-2014 HRS. Percentages reported for binary variables, means for continuous variables. HCBS use from the 2 HRS questions N189 Home health used and N202 other services.

Table 2.4: Sample characteristics by care setting and race/ethnicity

	Nursing Home			Home care		
	White	Black	Hispanic	White	Black	Hispanic
Age, years	85.05	79.73	79.05	78.41	74.15	74.90
Married,Female	13.69	14.09	14.53	21.25	15.84	23.27
Married,Male	12.05	15.77	19.66	30.52	19.82	24.55
Not Married,Female	60.09	49.33	52.14	36.29	51.44	40.79
Not Married,Male	14.16	20.81	13.68	11.94	12.90	11.38
HS degree (inc. GED)	36.85	23.15	9.40	35.01	25.28	14.45
Household assets[1] (mean)	206,442	51,049	42,971	298,614	58,438	61,760
At least 1 living child[1]	87.01	78.19	89.74	92.50	90.42	95.65
Received informal care[1]	38.81	38.93	48.72	38.59	47.09	46.80
No functional limitations[1]	20.34	23.83	16.24	43.00	35.45	35.81
1-3 ADL/IADL limitations[1]	22.30	20.47	16.24	33.48	33.46	29.67
4+ ADL/IADL limitations[1]	57.36	55.70	67.52	23.52	31.10	34.53
CIND [1]	38.65	33.56	34.19	74.30	66.62	66.88
Dementia[1]	61.35	66.44	65.81	25.70	33.38	33.12
Proxy interview[1]	51.02	44.30	56.41	17.71	15.40	18.03
Medicaid[1]	26.68	45.64	60.68	13.67	39.65	60.23
VA Health Insurance[1]	3.52	4.70	1.71	5.19	4.05	1.92
Private Health Insurance[1]	50.08	20.13	11.11	55.07	23.95	13.04
LTC Insurance[1]	8.92	3.69	1.71	8.98	4.86	3.20
Any hospitalization[1]	52.40	51.01	57.26	48.74	46.19	42.64
SR health fair or poor[1]	55.79	67.79	76.07	52.43	67.28	72.12
Depression [1]	13.62	19.80	18.80	21.83	31.32	37.34
High blood pressure[1]	60.80	77.85	68.38	67.09	82.54	68.03
Diabetes[1]	18.54	36.91	38.46	24.79	37.51	43.86
Cancer[1]	14.63	8.05	10.26	17.67	14.08	10.10
Lung disease[1]	10.56	6.71	5.13	19.89	13.49	11.38
Heart disease[1]	35.68	31.54	28.21	42.46	39.94	29.92
Stroke[1]	28.09	24.50	23.93	19.23	21.22	13.30
Psychiatric condition[1]	32.86	27.85	35.90	28.42	26.01	34.14
Arthritis[1]	68.39	76.51	64.96	74.38	77.97	74.17
1 or 2 chronic conditions[1]	41.31	37.25	37.61	36.66	31.61	35.68
3+ chronic conditions[1]	53.13	60.40	55.56	59.31	64.78	58.57
Resides in metropolitan county	72.46	76.85	85.47	73.15	78.78	86.32
N	1,278	298	117	2,428	1,357	782

HRS 2000-2014 waves, excludes respondents reporting both nursing home and home care.

[1]= response from previous interview

Chronic conditions for count are high blood pressure, diabetes, cancer, lung disease, Heart disease, stroke, psychiatric condition, and arthritis.

Table 2.5: Outcomes by care setting and race/ethnicity

	Nursing Home			Home care		
	White	Black	Hispanic	White	Black	Hispanic
Died 2 years	45.38	38.93	38.46	23.35	17.46	14.83
Any hospitalization 2 years	56.49	66.08	70.64	58.93	58.81	49.00
Fair or poor self reported health	62.60	72.15	76.07	58.46	69.28	73.02
CESD score >3	32.37	38.26	48.57	28.55	36.48	45.45
4+ ADL/IADL limitations	76.24	74.07	83.62	35.46	40.09	43.22
Dementia	75.90	71.81	75.21	33.36	40.16	38.36
BMI not in normal range	50.85	60.07	45.87	59.12	72.23	68.96
Health limits work	83.90	82.28	91.67	68.55	71.95	70.07
N	1,278	298	117	2,428	1,357	782

HRS 2000-2014 waves, excludes respondents reporting both nursing home and home care.

Table 2.6: Multivariate regression approach

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal range	(8) Health limits work
Home care	-0.122	-0.013	-0.040	-0.021	-0.186	-0.169	0.040	-0.065
	(0.021)**	(0.022)	(0.012)**	(0.015)	(0.016)**	(0.017)**	(0.019)*	(0.017)**
R^2	0.15	0.08	0.22	0.26	0.41	0.36	0.10	0.17
N	6,241	6,044	6,226	4,077	6,236	6,241	6,096	4,850

Coefficients and standard errors from linear probability model reported. Home care only vs nursing home care only.
Regression includes individual level controls and state and year fixed effects.
Standard errors clustered by state.

Table 2.7: Multivariate regression approach - Stratified by Race

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal range	(8) Health limits work
Race=White								
Home care	-0.124	0.023	-0.037	-0.024	-0.182	-0.197	0.011	-0.068
	(0.024)**	(0.028)	(0.017)*	(0.015)	(0.018)**	(0.022)**	(0.023)	(0.020)**
R^2	0.16	0.08	0.22	0.26	0.45	0.40	0.10	0.20
N	3,692	3,581	3,680	2,269	3,689	3,692	3,627	2,813
Race=Black								
Home care	-0.109	-0.061	-0.035	-0.007	-0.185	-0.118	0.061	-0.044
	(0.033)**	(0.038)	(0.027)	(0.036)	(0.025)**	(0.034)**	(0.025)*	(0.041)
R^2	0.16	0.13	0.22	0.31	0.38	0.32	0.12	0.18
N	1,651	1,602	1,648	1,191	1,650	1,651	1,604	1,356
Race=Hispanic								
Home care	-0.132	-0.190	-0.055	-0.040	-0.202	-0.123	0.149	-0.122
	(0.049)*	(0.027)**	(0.030)	(0.069)	(0.055)**	(0.063)	(0.050)**	(0.043)**
R^2	0.20	0.15	0.23	0.28	0.42	0.40	0.21	0.28
N	898	861	898	617	897	898	865	681

Coefficients and standard errors from linear probability model reported. Home care only vs nursing home care only.
Regression includes individual level controls and state and year fixed effects.
Standard errors clustered by state.

Table 2.8: Sample characteristics before and after matching: Count of 1915(c) Waivers, Part 1

	Unmatched Sample			Matched Sample		
	Home Care	Nursing Home	Std. Diff.	Home Care	Nursing Home	Std. Diff.
Z=Waiver count	6.91	6.53		6.88	6.56	
Home Care	1.00	0.00		1.00	0.00	
Age 60-69	0.19	0.07	0.3574	0.19	0.19	0.0073
Age 70-79	0.31	0.19	0.2716	0.31	0.30	0.0322
Age 80-89	0.31	0.45	-0.2774	0.33	0.34	-0.0259
Age 90+	0.11	0.28	-0.4246	0.12	0.12	-0.0033
Married,Female	0.20	0.14	0.1633	0.20	0.17	0.0923
Married,Male	0.26	0.13	0.3346	0.26	0.28	-0.0382
Not Married,Female	0.42	0.58	-0.3251	0.41	0.41	0.0046
Black	0.30	0.18	0.2866	0.30	0.30	0.0062
Hispanic	0.17	0.07	0.3180	0.16	0.15	0.0458
Lt high school	0.52	0.45	0.1328	0.52	0.54	-0.0453
HH Assets Q1(low)	0.41	0.47	-0.1234	0.41	0.41	0.0026
HH Assets Q2	0.22	0.20	0.0685	0.22	0.22	-0.0040
HH Assets Q3	0.16	0.15	0.0147	0.15	0.15	0.0059
HH Assets Q4	0.12	0.10	0.0900	0.12	0.11	0.0199
Child alive	0.92	0.86	0.2177	0.92	0.93	-0.0224
1-3 func diff, no informal care	0.16	0.13	0.0857	0.16	0.15	0.0137
4+ func diff, no informal care	0.02	0.27	-0.7550	0.02	0.02	0.0199
1-3 func diff, informal care	0.17	0.09	0.2497	0.17	0.19	-0.0676
4+ func diff, informal care	0.26	0.31	-0.1164	0.26	0.27	-0.0172

Matched sample: caliper 1:2 nearest neighbor matching with replacement

Std. Diff. = Standardized difference.

HH=Houshold; ADL/IADL = Activities of daily living, Instrumental activities of daily living; max=10;

SRH=Self reported health; CESD>3=Depression per 8 item CES=D assessment

Table 2.9: Sample characteristics before and after matching: Count of 1915(c) Waivers, Part 2

	Unmatched Sample			Matched Sample		
	Home Care	Nursing Home	Std. Diff.	Home Care	Nursing Home	Std. Diff.
Medicaid	0.29	0.32	-0.0654	0.29	0.26	0.0743
VA Insurance	0.04	0.04	0.0365	0.04	0.04	0.0113
Private insurance	0.39	0.42	-0.0699	0.38	0.39	-0.0212
LTC Insurance	0.07	0.08	-0.0295	0.07	0.07	0.0161
Prev Hospitaliz.	0.47	0.52	-0.1112	0.47	0.49	-0.0417
Dementia	0.29	0.63	-0.7124	0.30	0.31	-0.0049
Proxy interview	0.17	0.50	-0.7504	0.18	0.17	0.0222
SRH fair/poor	0.60	0.59	0.0185	0.60	0.62	-0.0342
CESD¿3	0.27	0.15	0.3017	0.27	0.25	0.0462
High blood pressure	0.72	0.64	0.1625	0.72	0.72	-0.0056
Diabetes	0.32	0.23	0.1963	0.32	0.36	-0.0767
Cancer	0.15	0.13	0.0618	0.15	0.15	-0.0066
Lung disease	0.16	0.10	0.2079	0.15	0.14	0.0456
Heart disease	0.40	0.34	0.1058	0.40	0.40	-0.0126
Stroke	0.19	0.27	-0.2029	0.19	0.19	-0.0057
Psychiatric problems	0.29	0.32	-0.0783	0.28	0.28	-0.0063
Arthritis	0.75	0.70	0.1318	0.75	0.75	0.0077
1-2 Chronic conds	0.35	0.40	-0.1114	0.35	0.35	0.0022
3+ Chronic conds	0.61	0.55	0.1264	0.61	0.61	-0.0078
Metro county	0.77	0.74	0.0710	0.77	0.78	-0.0283

Matched sample: caliper 1:2 nearest neighbor matching with replacement

Std. Diff. = Standardized difference.

HH=Houshold; ADL/IADL = Activities of daily living, Instrumental activities of daily living; max=10;

SRH=Self reported health; CESD>3=Depression per 8 item CES=D assessment

Table 2.10: Sample characteristics before and after matching: Medicaid HCBS/LTSS Spending ID/DD population, Part 1

	Unmatched Sample			Matched Sample		
	Home Care	Nursing Home	Std. Diff.	Home Care	Nursing Home	Std. Diff.
Z=HCBS/LTSS Spend	0.44	0.43	0.0311	0.48	0.41	0.1516
Home Care	1.00	0.00		1.00	0.00	
Age 60-69	0.19	0.07	0.3574	0.06	0.09	-0.1429
Age 70-79	0.31	0.19	0.2716	0.18	0.22	-0.0867
Age 80-89	0.31	0.45	-0.2774	0.50	0.44	0.1171
Age 90+	0.11	0.28	-0.4246	0.25	0.23	0.0640
Married,Female	0.20	0.14	0.1633	0.12	0.16	-0.1095
Married,Male	0.26	0.13	0.3346	0.14	0.17	-0.0831
Not Married,Female	0.42	0.58	-0.3251	0.55	0.52	0.0713
Black	0.30	0.18	0.2866	0.18	0.21	-0.0666
Hispanic	0.17	0.07	0.3180	0.06	0.08	-0.1000
Lt high school	0.52	0.45	0.1328	0.46	0.46	-0.0055
HH Assets Q1(low)	0.41	0.47	-0.1234	0.43	0.42	0.0221
HH Assets Q2	0.22	0.20	0.0685	0.21	0.21	0.0067
HH Assets Q3	0.16	0.15	0.0147	0.17	0.17	0.0097
HH Assets Q4	0.12	0.10	0.0900	0.09	0.11	-0.0453
Child alive	0.92	0.86	0.2177	0.86	0.87	-0.0374
1-3 func diff, no informal care	0.16	0.13	0.0857	0.17	0.17	-0.0024
4+ func diff, no informal care	0.02	0.27	-0.7550	0.08	0.06	0.0676
1-3 func diff, informal care	0.17	0.09	0.2497	0.11	0.12	-0.0198
4+ func diff, informal care	0.26	0.31	-0.1164	0.40	0.36	0.0940

Matched sample: caliper 1:1 nearest neighbor matching without replacement

Std. Diff. = Standardized difference.

HH=Houshold; ADL/IADL = Activities of daily living, Instrumental activities of daily living; max=10;

SRH=Self reported health; CESD>3=Depression per 8 item CES=D assessment

Table 2.11: Sample characteristics before and after matching: Medicaid HCBS/LTSS Spending ID/DD population, Part 2

	Unmatched Sample			Matched Sample		
	Home Care	Nursing Home	Std. Diff.	Home Care	Nursing Home	Std. Diff.
Medicaid	0.29	0.32	-0.0654	0.25	0.26	-0.0167
VA Insurance	0.04	0.04	0.0365	0.03	0.04	-0.0404
Private insurance	0.39	0.42	-0.0699	0.44	0.43	0.0239
LTC Insurance	0.07	0.08	-0.0295	0.09	0.09	0.0256
Prev Hospitaliz.	0.47	0.52	-0.1112	0.54	0.50	0.0822
Dementia	0.29	0.63	-0.7124	0.55	0.48	0.1445
Proxy interview	0.17	0.50	-0.7504	0.39	0.33	0.1371
SRH fair/poor	0.60	0.59	0.0185	0.58	0.58	0.0148
CESD¿3	0.27	0.15	0.3017	0.18	0.20	-0.0745
High blood pressure	0.72	0.64	0.1625	0.66	0.68	-0.0387
Diabetes	0.32	0.23	0.1963	0.25	0.26	-0.0335
Cancer	0.15	0.13	0.0618	0.14	0.14	0.0000
Lung disease	0.16	0.10	0.2079	0.09	0.10	-0.0526
Heart disease	0.40	0.34	0.1058	0.35	0.36	-0.0171
Stroke	0.19	0.27	-0.2029	0.26	0.23	0.0740
Psychiatric problems	0.29	0.32	-0.0783	0.28	0.29	-0.0263
Arthritis	0.75	0.70	0.1318	0.70	0.72	-0.0381
1-2 Chronic conds	0.35	0.40	-0.1114	0.40	0.38	0.0448
3+ Chronic conds	0.61	0.55	0.1264	0.55	0.57	-0.0477
Metro county	0.77	0.74	0.0710	0.73	0.74	-0.0208

Matched sample: caliper 1:1 nearest neighbor matching without replacement

Std. Diff. = Standardized difference.

HH=Houshold; ADL/IADL = Activities of daily living, Instrumental activities of daily living; max=10;

SRH=Self reported health; CESD>3=Depression per 8 item CES=D assessment

Table 2.12: Conditional exogeneity of instrument: Count of 1915(c) Waivers

Indep. variable	Coefficient	P-value
Age 60-69	-0.198	0.054
Age 70-79	-0.162	
Age 80-89	-0.084	
Age 90+	0.015	
Female,Not Married	0.006	0.869
Male,Married	-0.013	
Female,Married	-0.034	
Black	0.027	0.950
Hispanic	-0.009	
Less than HS deg	0.052	0.350
HH Assets Quartile 2	0.041	0.640
HH Assets Quartile 3	0.096	
HH Assets Quartile 4	0.118	
HH Assets Quartile 5(High)	0.151	
Child alive	0.058	0.502
Moderate funct limit, no informal care	-0.046	0.412
Severe funct limit, no informal care	-0.147	
Moderate funct limit, informal care	-0.070	
Severe funct limit, informal care	-0.009	
Medicaid	0.066	0.123
VA Insurance	-0.064	0.517
Private health insurance	-0.013	0.789
LTC insurance	0.161	0.181
Prev hospitaliz.	0.126	0.097
Dementia	-0.025	0.616
Proxy interview	0.105	0.107
Self-rated health fair/poor	0.015	0.746
Depression	-0.001	0.990
High blood pressure	0.037	0.481
Diabetes	0.043	0.484
Cancer	0.113	0.184
Lung disease	-0.102	0.220
Heart disease	0.014	0.836
Stroke	0.085	0.211
Psych. problem	-0.026	0.585
Arthritis	-0.002	0.980
1-2 Chronic conditions	-0.034	0.825
3+ Chronic conditions	-0.147	
Metro county	0.013	0.886

Regression also includes year and state fixed effects.

Table 2.13: Conditional exogeneity of instrument: HCBS/LTSS Spending ID/DD greater than median

Indep. variable	Coefficient	P-value
Age 60-69	0.012	0.103
Age 70-79	-0.010	
Age 80-89	0.031	
Age 90+	0.042	
Female,Not Married	0.014	0.845
Male,Married	0.006	
Female,Married	0.000	
Black	0.003	0.003
Hispanic	0.067	
Less than HS deg	0.028	0.029
HH Assets Quartile 2	-0.009	0.579
HH Assets Quartile 3	-0.026	
HH Assets Quartile 4	0.011	
HH Assets Quartile 5(High)	0.008	
Child alive	-0.013	0.360
Moderate funct limit, no informal care	-0.022	0.408
Severe funct limit, no informal care	-0.007	
Moderate funct limit, informal care	-0.028	
Severe funct limit, informal care	-0.023	
Medicaid	-0.001	0.939
VA Insurance	-0.017	0.676
Private health insurance	-0.021	0.107
LTC insurance	0.001	0.972
Prev hospitaliz.	0.024	0.134
Dementia	-0.004	0.781
Proxy interview	0.012	0.427
Self-rated health fair/poor	-0.011	0.363
Depression	-0.010	0.515
High blood pressure	0.007	0.637
Diabetes	-0.019	0.232
Cancer	0.008	0.683
Lung disease	0.025	0.352
Heart disease	-0.036	0.045
Stroke	-0.002	0.845
Psych. problem	0.009	0.507
Arthritis	-0.021	0.122
1-2 Chronic conditions	0.009	0.779
3+ Chronic conditions	0.032	
Metro county	0.006	0.735

Regression also includes year and state fixed effects.

Table 2.14: First stage results, IV=Count of 1915(c) Waivers

Home care	Coef.	Std. Error	p
Count of waivers	0.037	0.008**	0.00
Age 60-69	0.064	0.063	0.32
Age 70-79	0.069	0.070	0.33
Age 80-89	0.057	0.050	0.26
Age 90+	0.044	0.051	0.40
Married,Female	0.109	0.050*	0.04
Married,Male	0.044	0.036	0.23
Not Married,Female	0.049	0.036	0.18
Black non-Hispanic	-0.001	0.030	0.96
Hispanic	0.051	0.047	0.29
Less than high school	-0.015	0.029	0.60
Assets 1st quintile (low)[1]	0.012	0.046	0.80
2nd quintile[1]	0.028	0.033	0.41
3rd quintile[1]	0.021	0.053	0.69
4th quintile[1]	0.030	0.040	0.46
At least 1 living child[1]	-0.051	0.050	0.32
1-3 limits, no help n1	-0.016	0.046	0.73
4+ limits, no help n1	-0.022	0.057	0.70
1-3 limits, help n1	-0.052	0.036	0.16
4+ limits, help n1	-0.048	0.036	0.19
Medicaid[1]	0.041	0.041	0.33
VA Health Insurance[1]	-0.010	0.062	0.87
Private Health Insurance[1]	0.022	0.030	0.46

Table 2.14: Continued from previous page

Home care	Coef.	Std. Error	p
LTC Insurance[1]	0.021	0.049	0.68
Any hospitalization[1]	-0.018	0.023	0.43
Dementia[1]	-0.010	0.031	0.74
Proxy interview[1]	0.056	0.032	0.09
SR health fair or poor[1]	-0.005	0.027	0.85
Depression [1]	0.053	0.026	0.05
High blood pressure[1]	-0.022	0.047	0.65
Diabetes[1]	-0.066	0.027*	0.02
Cancer[1]	-0.024	0.040	0.55
Lung disease[1]	0.039	0.036	0.28
Heart disease[1]	0.000	0.038	1.00
Stroke[1]	0.010	0.036	0.78
Psychiatric condition[1]	-0.019	0.038	0.61
Arthritis[1]	0.009	0.029	0.76
1 or 2 chronic conditions[1]	-0.017	0.067	0.80
3+ chronic conditions[1]	-0.001	0.102	0.99
Resides in metropolitan county	0.002	0.029	0.95
F-test IV	21.28		

* $p < 0.05$; ** $p < 0.01$

State and year fixed effects omitted from table, standard errors clustered by state

Matched sample: 1:2 nearest neighbor matching with replacement.

Table 2.15: First stage results, IV=HCBS/LTSS Spending ID/DD greater than median

Home care	Coef.	Std. Error	p
HCBS/LTSS Spend ID/DD > median	0.144	0.031**	0.00
Age 60-69	0.115	0.075	0.13
Age 70-79	0.189	0.078*	0.02
Age 80-89	0.293	0.079**	0.00
Age 90+	0.275	0.082**	0.00
Married,Female	-0.127	0.044**	0.01
Married,Male	-0.117	0.038**	0.00
Not Married,Female	-0.076	0.028*	0.01
Black non-Hispanic	-0.100	0.038*	0.01
Hispanic	-0.133	0.045**	0.00
Less than high school	-0.018	0.031	0.56
Assets 1st quintile (low)[1]	0.052	0.036	0.16
2nd quintile[1]	0.036	0.042	0.40
3rd quintile[1]	0.031	0.043	0.48
4th quintile[1]	-0.012	0.044	0.78
At least 1 living child[1]	-0.032	0.052	0.54
1-3 limits, no help[1]	0.025	0.037	0.51
4+ limits, no help[1]	0.158	0.067*	0.02
1-3 limits, help[1]	0.010	0.034	0.77
4+ limits, help[1]	0.044	0.043	0.32
Medicaid[1]	-0.014	0.031	0.66
VA Health Insurance[1]	-0.094	0.052	0.08
Private Health Insurance[1]	0.003	0.023	0.91

Table 2.15: Continued from previous page

Home care	Coef.	Std. Error	p
LTC Insurance[1]	0.064	0.048	0.19
Any hospitalization[1]	0.038	0.020	0.06
Dementia[1]	0.043	0.033	0.19
Proxy interview[1]	0.061	0.033	0.07
SR health fair or poor[1]	0.030	0.022	0.17
Depression [1]	-0.012	0.036	0.74
High blood pressure[1]	-0.011	0.030	0.71
Diabetes[1]	0.021	0.040	0.60
Cancer[1]	-0.019	0.041	0.65
Lung disease[1]	-0.069	0.040	0.10
Heart disease[1]	-0.024	0.036	0.50
Stroke[1]	0.050	0.025	0.05
Psychiatric condition[1]	0.005	0.031	0.87
Arthritis[1]	-0.028	0.040	0.49
1 or 2 chronic conditions[1]	-0.003	0.062	0.96
3+ chronic conditions[1]	-0.043	0.097	0.66
Resides in metropolitan county	0.016	0.029	0.58
F-test IV	20.96		

* $p < 0.05$; ** $p < 0.01$

State and year fixed effects omitted from table, standard errors clustered by state

Matched sample: 1:1 nearest neighbor matching without replacement.

Table 2.16: IV Results - Overall Sample - Instrument: Count of 1915(c) Waivers

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care, OLS	-0.121	-0.058	-0.036	-0.043	-0.212	-0.203	0.075	-0.112
SE	(0.028)**	(0.029)	(0.013)**	(0.019)*	(0.027)**	(0.027)**	(0.026)**	(0.024)**
N	5,304	5,304	5,293	3,682	5,301	5,304	5,194	4,147
Home care, IV	-0.073	0.087	0.136	0.883	-0.510	-0.509	-0.064	-0.375
SE	(0.224)	(0.222)	(0.204)	(0.427)*	(0.197)**	(0.128)**	(0.237)	(0.210)
N	5,304	5,304	5,293	3,682	5,301	5,304	5,194	4,147
F-test IV	21.28	21.28	22.39	4.83	21.61	21.28	23.48	20.66

Coefficients and standard errors OLS and IV (2SLS) models reported. Home care only vs nursing home care only.

Regression includes individual level controls and state and year fixed effects.

Standard errors clustered by state.

Table 2.17: IV Results - Overall Sample - Instrument: HCBS/LTSS Spending ID/DD greater than median

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care, OLS	-0.130	0.007	-0.035	0.001	-0.177	-0.163	0.032	-0.074
SE	(0.025)**	(0.028)	(0.015)*	(0.019)	(0.018)**	(0.021)**	(0.025)	(0.019)**
N	2,194	2,194	2,188	1,117	2,191	2,194	2,143	1,634
Home care, IV	-0.061	0.477	0.054	0.540	-0.096	-0.356	0.073	0.109
SE	(0.234)	(0.207)*	(0.210)	(0.358)	(0.147)	(0.204)	(0.283)	(0.195)
N	2,172	2,172	2,166	1,103	2,169	2,172	2,121	1,621
F-test IV	20.96	20.96	21.08	11.41	21.11	20.96	19.77	23.20

Coefficients and standard errors OLS and IV (2SLS) models reported. Home care only vs nursing home care only.
Regression includes individual level controls and state and year fixed effects.
Standard errors clustered by state.

Table 2.18: Stratified IV (2SLS) Results - IV = waiver count

Race Group = White

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care, OLS	-0.132	-0.005	-0.048	-0.043	-0.187	-0.261	0.033	-0.121
SE	(0.034)**	(0.042)	(0.020)*	(0.024)	(0.029)**	(0.031)**	(0.030)	(0.029)**
N	3,033	3,033	3,025	2,052	3,031	3,033	2,992	2,337
Home care, IV	-0.002	-0.246	0.441	1.601	-0.288	-0.405	-0.651	-0.357
SE	(0.361)	(0.524)	(0.247)	(1.342)	(0.257)	(0.301)	(0.514)	(0.396)
N	3,033	3,033	3,025	2,052	3,031	3,033	2,992	2,337
F-test IV	4.13	4.13	4.12	0.94	4.18	4.13	4.49	5.34

Race Group = Black

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care, OLS	-0.111	-0.057	0.003	-0.047	-0.189	-0.116	0.079	-0.055
SE	(0.039)**	(0.042)	(0.034)	(0.036)	(0.045)**	(0.040)**	(0.028)**	(0.037)
N	1,489	1,489	1,486	1,091	1,489	1,489	1,447	1,218
Home care, IV	-0.768	0.819	-0.301	0.817	-1.245	-0.939	0.704	-1.017
SE	(0.595)	(1.032)	(0.390)	(4.615)	(0.895)	(0.787)	(0.800)	(0.963)
N	1,489	1,489	1,486	1,091	1,489	1,489	1,447	1,218
F-test IV	1.46	1.46	1.47	0.06	1.46	1.46	2.16	1.05

Table 2.19: Stratified IV (2SLS) Results - IV = waiver count

Race Group = Hispanic

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care, OLS	-0.060	-0.251	-0.034	0.016	-0.250	-0.176	0.177	-0.189
SE	(0.039)	(0.029)**	(0.031)	(0.039)	(0.069)**	(0.064)*	(0.042)**	(0.051)**
N	782	782	782	539	781	782	755	592
Home care, IV	0.603	0.168	-0.178	0.487	0.089	-0.246	0.343	0.140
SE	(0.290)*	(0.130)	(0.169)	(0.281)	(0.136)	(0.144)	(0.260)	(0.271)
N	782	782	782	539	781	782	755	592
F-test IV	8.01	8.01	8.01	3.63	9.96	8.01	7.78	8.67

Matched sample: 1:2 nearest neighbor matching with replacement

Sample limited to respondents with cognitive and/or functional impairment

Table 2.20: Stratified IV (2SLS) Results - IV = HCBS/LTSS spending ID/DD greater than median

Race Group = White

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care, OLS	-0.129	0.038	-0.024	-0.006	-0.182	-0.178	0.012	-0.093
SE	(0.026)**	(0.032)	(0.022)	(0.021)	(0.022)**	(0.029)**	(0.029)	(0.024)**
N	1,609	1,609	1,603	874	1,607	1,609	1,581	1,176
Home care, IV	0.036	0.783	0.476	1.079	0.096	-0.550	0.171	0.209
SE	(0.337)	(0.391)*	(0.367)	(0.570)	(0.168)	(0.292)	(0.387)	(0.271)
N	1,593	1,593	1,587	864	1,591	1,593	1,565	1,167
F-test IV	9.71	9.71	9.89	4.22	9.91	9.71	9.74	12.99

Matched sample: 1:1 nearest neighbor matching without replacement

Race Group = Black

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care, OLS	-0.133	-0.040	-0.069	0.136	-0.191	-0.147	0.070	-0.036
SE	(0.051)*	(0.049)	(0.038)	(0.154)	(0.057)**	(0.050)**	(0.048)	(0.059)
N	431	431	431	188	431	431	415	337
Home care, IV	-0.161	-0.468	-0.576	-3.966	-0.508	-0.046	-0.832	-0.435
SE	(0.366)	(0.469)	(0.388)	(13.846)	(0.421)	(0.320)	(0.579)	(0.368)
N	428	428	428	186	428	428	412	335
F-test IV	3.06	3.06	3.06	0.06	3.06	3.06	2.71	2.02

Matched sample: 1:1 nearest neighbor matching without replacement

Table 2.21: Stratified IV (2SLS) Results - IV = HCBS/LTSS spending ID/DD greater than median

Race Group = Hispanic

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care, OLS	-0.234	-0.183	-0.008	0.558	-0.163	-0.198	0.182	-0.031
SE	(0.121)	(0.088)	(0.051)	(0.723)	(0.028)**	(0.061)**	(0.056)**	(0.094)
N	154	154	154	55	153	154	147	121
Home care, IV	0.930	-4.309	1.504	0.202	-4.011	-2.047	-0.380	-0.135
SE	(2.153)	(4.744)	(2.765)	(0.687)	(3.353)	(2.218)	(0.939)	(0.666)
N	151	151	151	53	150	151	144	119
F-test IV	0.46	0.46	0.46	0.58	0.50	0.46	0.74	0.71

Matched sample: 1:1 nearest neighbor matching without replacement

2.10 Appendix

2.10.1 Inclusion of respondents using both nursing home and home care

In the main analyses, individuals reporting both home care and nursing home care use in the two year lookback period are excluded. In this section, I repeat the main analysis with those individuals included in the control group, essentially doubling the size of the control group relative to examining those that use nursing home care only. They are classified in the control group for two reasons, both of which relate to results in Chapter 1. First, in describing Medicaid LTC users, we show that the group using both HCBS and institutional services is much more similar in terms of observable characteristics to the group that uses nursing homes only; they are older and in poorer health, as compared to HCBS only users. This finding is confirmed in the HRS data in Table 2.2. Second, in an exploration of changes in LTC setting from 2005 to 2014, we showed that over time, as states implement HCBS expansions, the share of individuals using both HCBS and institutional care declines and the share using HCBS only increases. Theoretically, then, this classification of treatment and control groups matches what happens in practice as states expand their HCBS programs.

Prior to matching or using IV methods, I repeated the estimation of Equation 2.1 using the alternative treatment variable. Coefficients on the indicator for home care only (versus nursing home care or both) are reported in Table 2.22 below.

Table 2.22: Include both in control group - Multivariate regression approach

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care	-0.131	-0.062	-0.050	-0.022	-0.219	-0.176	0.065	-0.115
	(0.014)**	(0.013)**	(0.011)**	(0.017)	(0.011)**	(0.014)**	(0.013)**	(0.011)**
R^2	0.15	0.07	0.20	0.25	0.39	0.35	0.10	0.16
N	7,950	7,687	7,932	4,841	7,943	7,950	7,761	6,070

Coefficients and standard errors from linear probability model reported. Home care only vs nursing home care only or both home care and nursing home care.

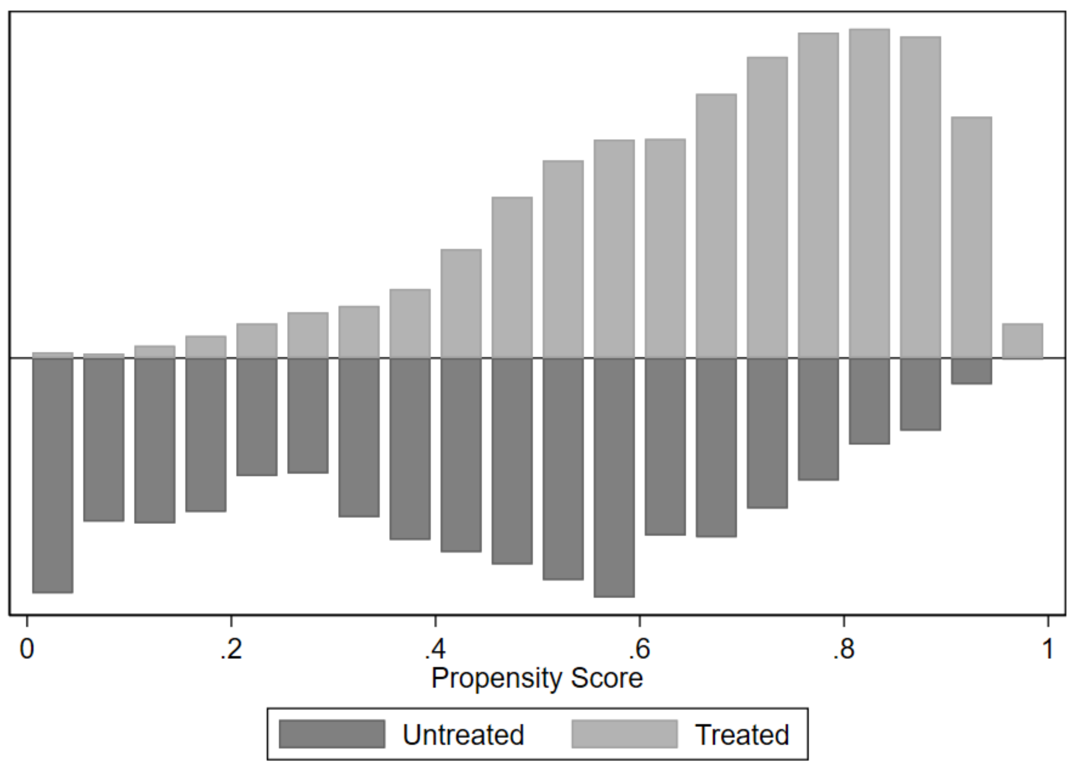
Regression includes individual level controls and state and year fixed effects.

Standard errors clustered by state.

When users of both nursing home and home care are included in the control group, the signs and significance of the coefficients on home care are generally the same as in the main analyses. The magnitudes of the coefficients are slightly larger, reflecting the fact that in this version of the sample a group of even sicker individuals are added to the control group. Intuitively, it makes sense that the benefits of home care are even larger when we compare home care to nursing home care or both if the group using both services are in especially poor health.

Next, in order to replicate the IV analyses from the main results, I generated the propensity score in this alternative sample. The distribution of propensity score is plotted in Figure 2.5 below.

Figure 2.5: Distribution of propensity score



Treatment: variable hctreat2 =1 if home care use only; =0 if nursing home use only or both home care and nursing home care.

Comparing this to the distribution using the main sample, there are many more control observations and they are distributed both in the region of common support and also in the region of very low values of propensity score. This highlights the idea that this group using both nursing home and home care is heterogeneous and does seem to contain some marginal individuals that would use home care only in a generous HCBS state but use both nursing home and home care in the counter-factual less generous HCBS state.

Using the matched samples, the OLS and 2SLS models were re-estimated and results are tabulated in Table 2.23 for the two instruments. Caliper, 1:1 nearest neighbor matching without replacement resulted in the best balance and instrument strength for both instruments in this sample. This means the same sample was used for both instruments. The three sections (rows) of Table 2.23 are therefore (1) from the OLS regression in the matched sample, (2) for the instrument of HCBS waivers, and (2) the instrument of HCBS/LTSS spending for the ID/DD population.

Table 2.23: Include both home care and nursing home care - IV Results

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care, OLS	-0.138	-0.042	-0.057	-0.005	-0.219	-0.182	0.065	-0.118
SE	(0.017)**	(0.015)**	(0.014)**	(0.018)	(0.012)**	(0.015)**	(0.018)**	(0.017)**
N	4,376	4,376	4,368	2,532	4,372	4,376	4,286	3,247
Z=HCBS Waivers								
Home care, IV	-0.289	-0.027	-0.082	0.249	-0.485	-0.108	-0.306	-0.232
SE	(0.239)	(0.233)	(0.303)	(0.516)	(0.177)**	(0.224)	(0.331)	(0.222)
N	4,376	4,376	4,368	2,532	4,372	4,376	4,286	3,247
F-test IV	13.98	13.98	14.64	4.53	14.19	13.98	16.05	10.45
Z=HCBS/LTSS ID/DD Population greater than median								
Home care, IV	0.051	0.580	-0.016	0.619	-0.023	-0.144	-0.442	0.008
SE	(0.461)	(0.403)	(0.237)	(0.717)	(0.347)	(0.380)	(0.313)	(0.164)
N	4,340	4,340	4,332	2,511	4,336	4,340	4,250	3,224
F-test IV	7.26	7.26	8.21	2.43	7.29	7.26	9.46	8.78

Coefficients and standard errors OLS and IV (2SLS) models reported. Home care only vs nursing home care only or both home care and nursing home.

Regression includes individual level controls and state and year fixed effects.

Standard errors clustered by state.

First, the OLS estimates in the matched sample are quite similar to those in the unmatched sample (Table 2.22). The instrument HCBS waivers has sufficient strength (F-statistics greater than 10) for all outcomes other than depression but the instrument HCBS/LTSS spending is weaker with this revised definition of treatment. Therefore, I focus on comparison of the estimates using the two treatment definitions and the instrument of HCBS waivers, Tables 2.23 and 2.16. First, the coefficients on home care when users of both home care and nursing home care are included in the control group have much larger magnitudes for the effects on mortality than when the both group is omitted, but they remain statistically insignificant. For the outcome of hospital use, the coefficient remains negative when IV is used in this sample. Finally, while both the effects on severe functional impairment and dementia were statistically significant and large in the main results, in this version only the effect on severe functional impairment is significant.

Overall, these findings are consistent with the main results and are consistent with the intuition that people using both nursing home care and home care in a two year period are in especially poor health.

2.10.2 Sensitivity to excluding movers

As discussed in the main text, one potential violation of the IV assumptions would be if people choose where to live based on the state HCBS policy generosity measures used as instruments. The main analyses are repeated here in the overall sample, removing individuals that move between states in either the $t-1$ or $t-2$ interviews. This excludes n=176 observations from the sample of long-term care users (nursing home only or home care only) with cognitive impairment.

I replicate the naïve regression estimates (main Table 2.6) but excluding movers in Table 2.24 below. Then, I repeat the OLS and 2SLS regressions with the two instruments for the overall sample in Tables 2.25 and 2.26

Table 2.24: Excluding Movers - Multivariate regression approach

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care	-0.125	-0.014	-0.040	-0.024	-0.189	-0.170	0.042	-0.065
	(0.021)**	(0.023)	(0.012)**	(0.016)	(0.016)**	(0.018)**	(0.020)*	(0.018)**
R^2	0.16	0.08	0.22	0.26	0.41	0.36	0.10	0.17
N	6,120	5,931	6,106	4,006	6,115	6,120	5,977	4,760

Coefficients and standard errors from linear probability model reported. Home care only vs nursing home care only or both home care.

Excludes observations that moved between states prior to reporting LTC use.

Regression includes individual level controls and state and year fixed effects.

Standard errors clustered by state.

Table 2.25: Excluding Movers - Instrument: Count of 1915(c) Waivers

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Home care, OLS	-0.118	-0.072	-0.016	-0.033	-0.212	-0.186	0.074	-0.092
SE	(0.026)**	(0.027)*	(0.017)	(0.024)	(0.026)**	(0.028)**	(0.021)**	(0.028)**
N	5,211	5,211	5,202	3,630	5,208	5,211	5,104	4,083
Home care, IV	-0.122	0.318	0.074	0.704	-0.433	-0.285	-0.271	-0.169
SE	(0.186)	(0.203)	(0.178)	(0.288)*	(0.152)**	(0.135)*	(0.145)	(0.233)
N	5,211	5,211	5,202	3,630	5,208	5,211	5,104	4,083
F-test IV	38.36	38.36	40.79	11.35	38.22	38.36	40.93	26.67

Coefficients and standard errors OLS and IV (2SLS) models reported. Home care only vs nursing home care only.

Excludes observations that moved between states prior to reporting LTC use.

Regression includes individual level controls and state and year fixed effects.

Standard errors clustered by state.

Table 2.26: Excluding Movers - Instrument: HCBS/LTSS Spending ID/DD greater than median

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal range	(8) Health limits work
Home care, OLS	-0.121	-0.018	-0.046	-0.001	-0.180	-0.162	0.030	-0.079
SE	(0.023)**	(0.027)	(0.017)**	(0.026)	(0.018)**	(0.022)**	(0.025)	(0.021)**
N	2,150	2,150	2,146	1,087	2,148	2,150	2,099	1,606
Home care, IV	-0.013	0.502	-0.059	0.548	0.018	-0.364	0.158	0.203
SE	(0.280)	(0.245)*	(0.237)	(0.430)	(0.175)	(0.235)	(0.279)	(0.262)
N	2,130	2,130	2,126	1,075	2,128	2,130	2,079	1,594
F-test IV	15.33	15.33	15.58	8.63	15.24	15.33	15.16	15.33

Coefficients and standard errors OLS and IV (2SLS) models reported. Home care only vs nursing home care only.

Excludes observations that moved between states prior to reporting LTC use.

Regression includes individual level controls and state and year fixed effects.

Standard errors clustered by state.

Results of the multivariate regression approach are essentially the same when movers are included (main Table 2.6) and when they are omitted (Table 2.24. The instrument HCBS waivers is stronger when the observations that move are omitted but the IV estimates of the effects of home care on the outcomes are similar: the only statistically significant effects of home care are on the outcomes of severe functional impairment and dementia (Table 2.25). Similarly, using the instrument of HCBS/LTSS spending, the home care remains associated with higher hospitalization rates in the two years after reporting LTC use when these observations are omitted (Table 2.26). This provides evidence that individuals that move did not drive the main findings.

2.10.3 Non-linear models to account for binary treatment and outcomes

Linear models (OLS regression, two-stage least squares) are estimated for the main results. However, both the treatment and outcomes are binary and can only take on a value of zero or one. Two stage least squares (2SLS) provides a consistent estimate of LATE when linear regression is used in both stages but ignores the fact that treatment and outcomes are binary (Terza, Basu, and Rathouz, 2008) (Basu, Coe, and Chapman, 2018). Two stage residual inclusion (2SRI) is an alternate method which is equivalent in the linear setting but not in the discrete setting (Deb, Norton, and Manning, 2017). Therefore, in the following sensitivity analyses, I repeat the main analyses, using non-linear models: logit regression and 2SRI.

The first stage is identical to the standard 2SLS implementation except that a logit regression is used rather than a linear regression:

$$\text{Logit}(Pr(HCBS_{ist} = 1)) = \alpha_0 + \alpha_1 Z_{st} + \alpha_2 X_{is(t-1)} + State_s + \lambda_t$$

The residuals from this first stage equation, $\hat{\upsilon_{ist}}$ are then estimated, and included in the second stage regression:

$$\text{Logit}(Pr(Y_{ist} = 1)) = \beta_0 + \beta_1 HCBS_{ist} + \delta_2 X_{is(t-1)} + State_s + \lambda_t + \hat{v_{ist}}$$

Standard errors are bootstrapped 500 iterations. The second stage coefficient on home care β_1 can be interpreted as the LATE of the effect of home care on the outcomes.

First, I report the first stage coefficients when a logit regression is used in Tables 2.27 and 2.28 below. While the logit regression coefficients are not easily interpreted, the marginal effects are reported in the last rows of the tables.

Table 2.27: First stage results, IV=Count of 1915(c) Waivers

Home care	Coef.	Std. Error	p
Count of waivers	0.160	0.035**	0.00
N	5,292		
Chi2-test IV	21.51		
Marginal effect IV	0.037		
SE	(0.008)		

Individual (lagged) characteristics, state and year fixed effects omitted from table.
Standard errors clustered by state
Matched sample: 1:2 nearest neighbor matching with replacement.
Limited to observations with cognitive impairment or dementia.

The coefficient point estimates for the first stage effects of the instruments are the same using the linear model and the marginal effects in the non-linear model. The tests of significance of the effects are also quite similar. Next, I estimate the effects in the two matches samples using the naïve multivariate regression and 2SRI methods.

Table 2.28: First stage results, IV=HCBS/LTSS Spending ID/DD greater than median

Home care	Coef.	Std. Error	p
HCBS/LTSS Spend ID/DD > median	0.637	0.141**	0.00
N	2,162		
Chi2-test IV	20.33		
Marginal effect IV	0.144		
SE	(0.031)		

Individual (lagged) characteristics, state and year fixed effects omitted from table.
Standard errors clustered by state
Matched sample: 1:1 nearest neighbor matching without replacement.
Limited to observations with cognitive impairment or dementia.

Table 2.29: 2SRI Results - Overall Sample - Instrument: Count of 1915(c) Waivers

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Logit								
Home care	-0.111	-0.057	-0.050	-0.026	0.026	-0.189	0.092	-0.106
SE	(0.019)**	(0.024)*	(0.018)**	(0.025)	(0.012)*	(0.028)**	(0.021)**	(0.025)**
N	5,299	5,299	5,292	3,666	5,291	5,290	5,184	4,129
2SRI								
Home care	-0.113	0.308	0.161	0.304	0.052	-0.455	-0.146	0.037
SE	(0.201)	(0.178)	(0.208)	(0.222)	(0.203)	(0.182)*	(0.227)	(0.190)
N	5,303	5,303	5,292	3,672	5,302	5,303	5,187	4,143
Chi2 IV	20.19	20.19	21.62	5.86	20.12	20.19	20.73	30.69
Mean outcome	0.244	0.578	0.640	0.333	0.144	0.437	0.618	0.721

Bootstrapped standard errors 500 iterations.

Marginal effects and standard errors of marginal effects reported.

Propensity score matched sample.

Table 2.30: 2SRI Results - Overall Sample - Instrument: HCBS/LTSS Spending ID/DD greater than median

	(1) Died 2 years	(2) Hospital Use 2 years	(3) Fair/Poor Health	(4) CES-D Depression	(5) Severe funct. Impairment	(6) Dementia	(7) BMI not normal	(8) Health limits work
Logit								
Home care	-0.129	0.006	-0.032	0.001	-0.175	-0.165	0.032	-0.067
SE	(0.024)**	(0.027)	(0.015)*	(0.019)	(0.018)**	(0.022)**	(0.024)	(0.020)**
N	2,186	2,186	2,187	1,108	2,188	2,180	2,138	1,617
2SRI								
Home care	0.086	0.450	0.037	0.215	-0.013	-0.357	-0.142	0.194
SE	(0.228)	(0.148)**	(0.235)	(0.220)	(0.240)	(0.200)	(0.228)	(0.206)
N	2,194	2,194	2,188	1,117	2,191	2,194	2,143	1,634
Chi2 IV	20.33	20.33	20.42	11.33	20.50	20.33	19.66	22.96
Mean outcome	0.345	0.605	0.627	0.344	0.615	0.607	0.531	0.779

Bootstrapped standard errors 500 iterations.

Marginal effects and standard errors of marginal effects reported.

Propensity score matched sample. Instrument=HCBS/LTSS Spending Greater than Median, ID/DD Population

Comparing the non-linear estimates using the HCBS waiver instrument in Table 2.29 and the linear version in Table 2.16, most of the estimated effects are similar using the different methods. Notable differences are that the coefficient on home care using the non-linear model is much larger than the linear model, although both are positively signed and not statistically significant. Also, the large, statistically significant effect of home care on severe functional limitations in the linear model is not statistically significant and of positive sign in the non-linear model.

When HCBS/LTSS spending is used as the instrument, results are generally consistent as well. Using the non-linear model, home care users have a 45% greater hospital use than nursing home users (Table 2.30) as compared with the point estimate of 47% in the linear model (Table 2.17). In the non-linear models, the estimates are more similar using the two instruments on the outcome of severe functional impairment, with a null finding for both instruments, perhaps suggesting that the non-linear model using HCBS waiver count is preferred.

Overall, though, the results from the non-linear and linear models are quite similar, suggesting that the results in the main analyses using the linear models are not driven by the choice of functional form.

CHAPTER 3

EFFECTS OF MEDICAID MANAGED CARE ON OUTCOMES FOR THE MEDICARE-MEDICAID DUALLY ENROLLED

3.1 Introduction

Medicare and Medicaid, the two largest public health insurance programs in the United States, began in 1965 with fee-for-service (FFS) reimbursement structures. In this traditional payment model, the government directly pays providers for services used by program enrollees. Over time, both programs have transitioned from FFS payment to privatized, managed care payment models to varying degrees. To illustrate this dramatic shift towards managed care, in 2018 approximately one-third (34%) of Medicare beneficiaries (Jacobson, Damico, and Neuman, 2018) were enrolled in a Medicare Advantage Plan and two-thirds (69%) of Medicaid enrollees were enrolled in a comprehensive risk-based managed care plan (Hinton et al., 2019). Although there is widespread adoption of managed care there is an ongoing policy debate about whether the traditional FFS payment system for public health insurance or the alternative managed care payment model better serves beneficiaries. Since the ultimate goal of these programs is improving the health of the covered population while shielding them from high healthcare costs, one measure by which we can judge the effectiveness of these health insurance programs is how they ultimately impact the health of enrollees.

In this paper, I study this question in the context of the Medicaid program. Medicaid is the public health insurance program for the poor that covers approximately 70 million beneficiaries annually. Medicaid managed care (MMC) introduces third party payers, health plans or managed care organizations (MCOs). The health plan enrolls Medicaid beneficiaries and receives a per-member per-month premium payment from the state Medicaid agency. The health plan is then responsible to pay providers for services their enrollees use. Health plans generate positive profits when spending on services is less than the premium payments received from the state. There is a financial incentive for plans to "manage care" by encouraging members to substitute high-value services for low-value services, the classic example of which is substituting a lower-cost physician office visit for hospital emergency department care. Health plans may encourage more efficient service use through care coordination and utilization management: requiring beneficiaries use only network providers and acting as a gate-keeper to avoid unnecessary care. These financial incentives could result in lower-cost but equally effective care relative to FFS if plans are able to reduce unnecessary service use or encourage substitutions that do not result in worse health outcomes. However, there is also the potential for skimping on high-quality or necessary care to increase profits at the expense of the beneficiary's health. Because the effect of MMC (versus FFS) on health outcomes, including hospital use, is ambiguous, it is important to study the effects of MMC expansions empirically.

The evidence to date on the relative efficiency of Medicaid managed care is mixed (Gruber, 2017). There are three key barriers to studying the effects of Medicaid managed care: (1) data limitations (2) variation in program details across states and (3) selection. First, once a beneficiary enrolls in a health plan, the fee-for-service claims which are use to measure service utilization are no longer generated. In Medicaid, there is the additional challenge of reconciling data across state programs. Second, states vary in the the details of their managed care programs, including whether programs have mandatory or voluntary enrollment, which populations are included, and which services are covered, limiting the ability of researchers to draw broad conclusions about the general effectiveness of managed care. Finally, states and individuals must choose to opt in to Medicaid managed care. If individuals that select managed care are different from those that remain in FFS, this selection must be accounted for in order to obtain unbiased estimates of the effects of managed care on outcomes.

In this study, I use national claims data combined with policy details and causal estimation techniques to overcome these barriers. I study the effects of MMC on a particular group of individuals, the Medicaid-Medicare dually enrolled (duals), for whom I can observe FFS Medicare claims for inpatient hospital care both before and after Medicaid managed care adoption. I supplement the claims data with program details and analyze different plan types separately to assess how different combinations of covered services may have different effects. These program details also drive my analysis strategy. For counties with mandatory enrollment, I use a difference-in-differences (DID) framework to exploit variation in county-level program adoption over time to estimate plausibly causal impacts of MMC versus FFS coverage. For individuals living in counties with voluntary enrollment, I address individual-level selection into managed care using instrumental variables techniques. I provide the first national estimates of the effects of three different MMC program types for duals: comprehensive managed care (CMC), managed long-term services and supports (MLTSS), and primary care case management (PCCM).

I find different effects of managed care for the three types of programs analyzed. MLTSS programs, which cover the highest cost Medicaid paid services for duals, are associated with increases in hospital use overall, and increases in the rate of potentially avoidable hospitalization in some specifications/subgroups. For example, mandatory MLTSS programs are associated with increases of 4.3% and 1.7% in non-metro and metro counties respectively using the DID specification. The increases are driven by increases in hospital use among those beneficiaries with four or more chronic conditions. While less precise, the IV estimates for voluntary program enrollment show the same pattern with individuals with many chronic conditions faring worse under MLTSS than those with few chronic conditions.

I find mixed results analyzing the effect of CMC programs that exclude long-term care services. The DID analyses of mandatory programs estimate increases in hospitalization rates similar in magnitude to those found for MLTSS programs. However, the IV analyses of voluntary programs show decreases in hospitalization associated with these CMC programs. These different effects are likely due to two related differences in the treatment effect estimated. The DID results estimate an average treatment effect for counties in which individual selection should be minimized because of mandatory enrollment policies. In contrast, the IV estimates a local average treatment effect for a specific subgroup of individuals: those that are induced to sign up for the voluntary CMC program because of the high penetration rates of CMC programs in their county among non-duals.

Finally, because only four counties in a single state had mandatory PCCM programs for duals during the time period studied, I estimate the effect of PCCM programs using IV only. I find that PCCM plans have no effect on the rates of hospitalization or potentially avoidable hospitalization for either metropolitan or non-metropolitan counties.

These findings taken together show that different types of managed care programs have different effects on hospital use, consistent with the financial incentives inherent in each program type. MLTSS plans include the largest share of Medicaid-paid costs in the plan covered services. However, the incentive to reduce hospitalization may be reduced due to the fact that long-term care services are such a large share of plan covered services than the Medicare cost-sharing portion of hospital costs plans are responsible to pay for duals. However, CMC plans, for which the largest expense is typically Medicare cost-sharing, may have a clearer financial incentive to reduce hospital use but little leverage with which to do so. PCCM plans, which assign enrollees to a primary care provider to provide enhanced case management services, have little leverage to change the hospital utilization patterns of duals for whom Medicare is the primary payer for physician services.

Findings in this paper complement evaluations of early MLTSS programs in Arizona (McCall and Korb, 1997) and Minnesota (Kane et al., 2007) as well as more recent studies of MLTSS expansions in Tennessee and New York (Libersky et al., 2018). Those single state studies found mixed results, with increases in hospital use in some states but decreases in others. In the national data, my findings with respect to MLTSS programs provide an important data point for policymakers considering whether or not these policies are successful. Proponents of managed care claim the introduction of third party health plans will reduce costs by reducing hospital use. At the same time, opponents of managed care, especially for long-term care, worry that plans will restrict access to high-quality care and hospital use will increase. While I am able to examine plans that cover Medicaid services only in this study, newer combined Medicare-Medicaid financial alignment demonstrations created by the Patient Protection and Affordable Care Act began enrolling duals beginning in 2013. It will be important for policymakers to understand how these newer models impact costs as well as utilization and health outcomes. This paper is a first step in that direction, providing the first national estimates of CMC, MLTSS, and PCCM effects on hospitalization. This study better informs policymakers as to how MMC effects hospitalization for duals and will to allow states to make more informed decisions about the effects of transitioning duals into their MMC programs. It also draws attention to how MMC expansions could impact utilization of Medicare-paid services.

3.2 Institutional Background

In this study, I focus on a particularly important group of Medicaid beneficiaries, those that are Medicare-Medicaid dually enrolled (duals). Duals account for a disproportionately large share of program spending and are the target of many recent policy reforms. Duals eligible for full-Medicaid benefits account for 10% of Medicaid beneficiaries but 31% of program spending due to their high utilization of services, especially long-term care (*Data Book: Beneficaries dually eligible for Medicare and Medicaid* 2018).

Duals qualify for Medicare benefits due to age or long-term disability and Medicaid due to low income and assets[1]. Duals are a diverse group with varied and complex health care needs. In 2013, 46% of duals originally qualified for Medicare due to age and 54% due to disability (*Data Book: Beneficaries dually eligible for Medicare and Medicaid* 2018). The pathways for enrollment in both programs vary by age. The majority of duals that first qualify for Medicare only due to age (elderly pathway) experience high out-of-pocket spending for non-Medicare covered services such as long-term care, "spending-down" their assets and eventually qualifying for Medicaid (Feng et al., 2019). This group has high rates of Alzheimer's disease and other dementias and severe mental illness and high reliance on

1. States vary in their income and asset eligibility criteria with a minimum eligibility level of income at the federal poverty level and $2,000 (individual) or $3000 (couple) in assets. In some states, individuals can also qualify for Medicaid due to high medical need, when qualifying medical expenses meet a minimum threshold.

institutional care. In contrast, duals that first qualify for Medicaid only due to low-income or disability, most of whom are less than 65 years of age when they qualify, then age into the Medicare program when they turn 65.

Duals may be eligible for partial Medicaid support, receiving coverage for Medicare premiums and cost sharing only, or full Medicaid benefits. Full benefits include long-term care, such as nursing facility care and home- and community-based alternatives to nursing facilities, behavioral health services, and dental and vision coverage if the state covers these optional state plan services. Because the focus of this paper is the effects of changes in payment policy, this paper limits to full benefit duals, which in 2013, made up 72% of all duals (*Data Book: Beneficaries dually eligible for Medicare and Medicaid* 2018).

Because of the concern that managed care may be harmful to high-cost groups due to the incentive for plans to skimp on high-quality care, duals were largely excluded from early MMC programs. However, recently states have begun to enroll duals in MMC programs with the hope that MMC can curb program spending and increase access to necessary services relative to the traditional FFS payment system. However, there has been little evidence to date on how this change in financing has affected health outcomes and utilization among this population.

By definition, duals are covered by two health insurance programs: Medicare and Medicaid. Medicare is the primary payer for medical services including hospital care (Part A), post-acute care, physician visits and other outpatient services (Part B), and prescription drugs (Part D). Medicaid is the primary payer for long-term care services and other services that Medicare does not cover. While there are a set of mandatory services that states must provide (ex. nursing facility care, home health), there are also optional benefits that states may choose include in their programs (ex. personal care, case-management, vision, dental). Medicare benefits are structured such that there are premium payments to enroll and deductibles and coinsurance once services are used. For duals, Medicaid pays these cost-sharing payments.

In addition to the variation in services covered by state Medicaid programs, states also vary in their implementation of MMC. Medicaid traditionally was a FFS system and, over time, MMC has been adopted to varying degrees by the states. To enact a MMC program, states must get approval from CMS. However, states have flexibility in many aspects of how they implement their MMC program. This results in significant variation across states in MMC program features: eligibility groups included, whether the enrollment is mandatory or voluntary, whether MMC is available statewide or in specific counties, and what services are covered by the program versus what services are "carved-out" and remain FFS.

When Medicaid managed care plans were first adopted by states in the 1990s, most states specifically excluded duals from the eligibility groups that could enroll, instead enrolling primarily low-income families and children. These early MMC programs specifically excluded long-term care services from their managed care contracts, and long-term care continued to be paid on a FFS basis. States excluded duals and long-term care services from these early programs because of two major challenges to their inclusion. First, setting managed care premiums in such a way that encourages plan participation without increasing Medicaid total costs for this relatively high-cost population is difficult. Second, health plans had little experience contracting with the types of providers that duals used (namely long-term care providers), making network adequacy requirements difficult to meet. However, as states gained experience in operating their MMC programs, in the late 1990s and 2000s, states began enrolling elderly and disabled Medicaid beneficiaries, including duals, in managed care plans. This corresponded with the creation of managed long-term care programs. To illustrate, in the 2000s, the number of states offering these long-term care plans rose dramatically, from 8 in 2004 to 16 in 2012 (Saucier et al., 2012).

Because duals are enrolled in both Medicare and Medicaid, there are four possible combinations of Medicare and Medicaid coverage: (1) FFS for both; (2) Medicaid managed care and Medicare FFS (3) Medicaid FFS and Medicare managed care and (4) Managed care for both Medicare and Medicaid. Both health insurer participation and policies with respect to dual-eligible enrollment in health plans vary considerable from state to state and markets within a state (Walsh and Clark, 2002). During the study time period, from 2005 to 2012, the majority of duals had FFS Medicare and Medicaid. While there was an increase in the share of duals enrolling in Medicare managed care, there was also a rise in the share of duals that remained enrolled in FFS Medicare and enrolled in Medicaid managed care; this trend provides the basis of my study design. I will compare individuals with FFS Medicare and FFS Medicaid (control group) to those individuals that transitioned to Medicaid managed care but maintained FFS Medicare coverage.

3.3 Literature Review

3.3.1 Effects of managed care in general

There is a large literature on the effects of managed care, with several literature reviews. One often cited example is Glied (2000)'s Handbook chapter which synthesizes results from studies examining managed care from 1980 through the late 1990s. During this time, there was marked growth in managed care in commercial health insurance and the Medicare program and the review focuses on effects in these two markets. Glied highlights that both commercial Health Maintenance Organizations (HMOs) and private Medicare plans have considerable selection, with healthier individuals choosing managed care, making cross-sectional comparisons of outcomes under managed care and FFS subject to selection bias. However, even when this selection is accounted for, most of the studies highlighted in the review find that managed care reduces health care costs by reducing the use of inpatient hospital care without resulting in adverse health consequences in the commercial and Medicare markets.

The RAND Health Insurance Experiment provides a rare randomized control trial of HMO performance compared with FFS insurance with various degrees of cost-sharing. Compared with the FFS insurance study arms, the HMO provided cost savings through reduced hospital utilization and there was not evidence of adverse health outcomes for the overall sample (Manning et al., 1987). However, for those individuals in poor health and with low income, there was evidence of poorer outcomes under HMO coverage, with increased hospital use and serious symptoms. This finding suggests that as states expand MMC to duals, who are generally in poor health and have low incomes, the potential for adverse effects of these expansions on the health of this group should be considered.

3.3.2 Effects of managed care in Medicaid and Medicare

Two newer review papers focus specifically on managed care in Medicare and Medicaid: Sparer (2012) and Gruber (2017). Sparer (2012) synthesizes the literature on how Medicaid managed care affects costs, access, and quality. This review found mixed results with respect to all three outcomes. Most of the studies reviewed were based on populations from specific states, health plans or providers. There were two national studies reviewed: Duggan and Hayford (2013) and Herring and Adams (2011). Duggan and Hayford (2013) ask how the expansion of Medicaid managed care from 1991 to 2009 affects Medicaid expenditures. Their use of national data allows them to find that MMC generates cost savings only in states with high FFS Medicaid reimbursement rates. MMC is either cost neutral, or associated with higher program spending, in states with low FFS reimbursement rates. This suggests that MMC plans are able to generate cost savings primarily through negotiation of lower prices with providers. While an important first step in understanding effects of MMC expansions nationally, these results may not be generalizable to expansions of MMC to duals and the authors do not consider impacts of MMC on health outcomes. The second national study, Herring and Adams (2011), examines the effects of MMC expansions from 1999-2002 on utilization and access measures among non-elderly and non-dual Medicaid enrollees in metropolitan counties using survey data. Using a difference-in-differences framework similar to what I use in this study (treatment is MMC penetration at the MSA level), they find generally null and mixed results, with both Medicaid MCO and commercial MCO penetration rates not affecting overall expenditures or having a non-emergency department usual source of care. While the sample restrictions to non-duals allow the authors to focus on the populations and geographic areas that expanded MMC during the study time period, again, their results may not be generalizable to duals.

There are a limited number of other national studies that were not included in these reviews, none of which focus on the duals. Currie and Fahr (2005) used state level variation in MMC penetration rates in the early 1990s to examine the effects of MMC on low-income children. They find a change in the composition of Medicaid covered children due to MMC expansions with black children and young children losing coverage and associated decreases in annual doctor visits for these groups and, among the Medicaid covered, differential effects in annual doctor visits by age, chronic conditions and race. Zuckerman, Brennan, and Yemane (2002) used cross-sectional survey data and county-level policy information to distinguish between effects of risk-based MMC (HMO) and PCCM programs and examined effects on both children and Medicaid-only adults. They found that HMOs and PCCM provide increased access (non-emergency room source of usual care) for children but less beneficial effects for adults. Building on these earlier studies,Garrett, Davidoff, and Yemane (2003) examined effects of expansions from 1991-1995 on children and AFDC women using county level treatment assignment and distinguished between HMO and PCCM programs but used longitudinal data. They found no effect of PCCM on access measures for women or children; decreases in utilization and increased reports of unmet need for women living in counties with mandatory HMO programs; and reduced emergency room use and improved access to specialists among children in HMO counties. Both of these studies also estimated effects of living a county with the choice between PCCM and HMO enrollment: however, because of a lack of individual level data on which plan type individuals selected, they could not speak to the effects of either plan type separately in these counties.

In a more recent study, Toseef, Jensen, and Tarraf (2019) examined the effects of MMC on the non-elderly, non-institutionalized Medicaid enrolled, a subset of which are duals eligible for Medicare due to disability using the Medical Expenditures Panel Survey (MEPS).

They estimate separate effects for duals and non-duals on the rate of potentially avoidable hospitalization. Using propensity score matching to account for differences in characteristics of individuals that enroll in MMC versus those that remain FFS, they find that duals have increases in potentially avoidable hospitalization associated with MMC while there is no effect for non-duals. The use of the MEPS results in several limitations. First, treatment must be assigned at the individual level based on survey responses because geographic identifiers finer than Census region were not available. While the propensity score method is used to account for observed differences across individuals that opt in to managed care, it cannot account for unobserved differences. Also, because the survey does not distinguish between types of managed care, this study includes all MMC plan types as a single treatment. Finally the MEPS excludes two important groups of duals: older adults and those residing in institutions.

Two studies were cited in Gruber (2017) that directly studied the effects of MMC expansions on patient outcomes, again with mixed findings. Both studies examine the effects of mandatory comprehensive managed care (CMC) in California in the 1990s on birth outcomes. Duggan (2004) finds that while CMC did not result in worse health outcomes for infants, it did increase the costs of care. In contrast, Aizer, Currie, and Moretti (2007) find a decrease in prenatal care in the first trimester and poorer health outcomes as a result of CMC adoption. In contrast to these single state studies,Kaestner, Dubay, and Kenney (2005) examined the effects of MMC expansions in from 1990-1996 on infant health nationally, separately for PCCM and HMO programs. Using a pre-post study design, where variation comes from changes in MMC program availability at the county level over time, and comparisons by demographic groups (marital status, education level), they find that while there were small decreases in prenatal care and increases in the incidence of low birth weight associated with HMO programs, those decreases occurred among all groups analyzed, even those groups that were unlikely to be Medicaid enrolled (married women, more than 12 years of education) suggesting that the decreases were not caused by MMC. While these studies investigate an outcome that is not relevant to duals, their mixed results highlight the need for further study of the effects of MMC on health outcomes.

Perhaps more relevant to duals, in 2014 CMS commissioned an evaluation of 1115 Demonstration Waivers, with one evaluation specifically focused on MLTSS programs[2]. Due to data limitations, the interim evaluation of utilization-based outcomes was limited to MLTSS programs in two states, New York and Tennessee (Libersky et al., 2017). Using propensity score matching to create comparison groups, the authors find that MLTSS expansions were associated with increased hospitalization in Tennessee and decreased hospitalization in New York (Libersky et al., 2018). The authors acknowledge there is incomplete data on hospitalization for duals enrolled in Medicare managed care due to lack of encounter records so results reported should be interpreted with caution as they do not control for changes in composition of the sample due to changes in Medicare managed care during the study period. The final evaluation, expanding in scope to include additional states and a longer period of time (2010-2017) is underway, but evaluations of the effect of MLTSS on hospital utilization are limited to Medicaid only beneficiaries, again due to lack of encounter data for Medicare managed care (Wysocki et al., 2019). The current study, therefore, complements this evaluation work by (1) examining MLTSS and other MMC plan types nationally and (2) focusing on duals with FFS Medicare.

3.3.3 Effects of managed care for duals

Duals may be especially vulnerable to Medicaid plans providing inadequate care for several reasons. First, two payers, Medicare and Medicaid, are jointly responsible for financing their care. Medicare is the primary payer for medical services for duals, but Medicaid plans are only responsible for Medicaid-paid services such as long-term care. Because Medicaid plans do not cover all costs of care, the financial incentives to reduce hospital use may be less strong than under a single payer. Related to this fragmentation, Medicaid care coordination under

2. *1115 Demonstration Federal Evaluation & Meta-Analysis.*

MMC is limited to Medicaid-paid services and therefore may not be effective. Policymakers have introduced Medicare special needs plans and combined Medicare-Medicaid plans to address these issues of competing incentives of two payers. However, only a small share of duals have been enrolled in these plans to date (Grabowski, 2009)(Grabowski et al., 2017). Additionally, states often seek to include quality standards in their agreements with health plans to limit plans' ability to lower quality. The bulk of Medicaid spending for duals is for long-term care but there are few agreed-upon standards for measuring long-term care quality(Harrington, Wiener, and Musumeci, 2017) (Lipson, 2018). Regulating quality is therefore especially challenging in this setting. Finally, and perhaps most importantly, duals are in poorer health and have fewer social supports than the average Medicaid beneficiary (*Data Book: Beneficaries dually eligible for Medicare and Medicaid* 2018). Attempting to minimize costs in a very sick population that requires a high intensity of services may be riskier than in a healthier population. These theoretical reasons suggest that expansion of MMC may have different effects for duals than for the average Medicaid-only beneficiary that has been the subject of most of the literature to date.

Supporting these concerns, there is suggestive evidence that managed care may result in adverse outcomes for groups that are both low-income and in poor health. For example, the RAND Health Insurance Experiment compared spending and outcomes among individuals enrolled in a Health Maintenance Organization (HMO) to FFS insurance in a randomized controlled trial. For the general population, the HMO reduced hospital use without resulting in negative outcomes. However, for the subset of low-income participants in poor health, the HMO resulted in increased hospitalization and higher incidence of serious symptoms (Manning et al., 1987).

Several studies have examined the effects of Medicare managed care for duals. One analysis of Medicare managed care plan switching rates found that high-cost Medicare beneficiaries have higher rates of switching back to FFS than low-cost beneficiaries (Rahman et al., 2015), suggesting that high-need individuals are not happy with their Medicare plans. There is also evidence that Medicare Advantage plans concentrate their enrollees in lower quality nursing homes (Meyers, Mor, and Rahman, 2018) and home health agencies (Schwartz, 2018). Studying outcomes under Medicare Advantage have been limited because the lack of Medicare encounter records.

There are a few older studies examining the effects of Medicare managed care for Medicare home health users. Medicare home health users are an example of a high-cost group of Medicare beneficiaries as because home health care use indicates a serious adverse health event requiring post-acute care. Results of these studies generally are consistent with other evidence that high-cost beneficiaries may experience worse outcomes under managed care. Shaughnessy, Schlenker, and Hittle (1994) found that HMO enrollees used lower intensity home health services (fewer number of visits per week and fewer overall visits) than FFS home health users and this lower intensity home health care was associated with poorer outcomes related to functional status. Another study of hospitalized Medicare home health users in California found that Medicare managed care enrollees and duals had higher rates of readmission and preventable readmission than did their FFS counterparts (Experton et al., 1999).

Compared to the evidence on Medicare managed care, the evidence on MMC for duals is much more sparse. Grabowski (2006) summarizes evaluations of six different early managed care programs that included long-term care in the managed care contracts. Programs were mixed in their level of integration with Medicare and included PACE, the Arizona MLTSS program, and county-based programs in WI, MN, TX, NM. Findings from these six programs generally showed that there was no increase (or decrease) in hospitalization associated with MLTSS. Effects on costs were mixed, with some programs experiencing with lower long-term care costs and others had cost increases. Importantly, it was noted that all of these evaluations suffer from a lack of rigorous evaluation methodology: evaluations either compared unadjusted rates of hospital use and spending or adjusted only for observable characteristics of enrollees. This is a key limitation for evaluating programs with voluntary enrollment.

Perhaps most similar to the current study, Kim et al. (2017) analyzed all-payer claims data from Oregon in 2011-2014 to compare utilization patterns among duals enrolled in the four possible Medicare and Medicaid managed care combinations. The current study compares two of these combinations: (1) FFS Medicare and Medicaid managed care and (2) FFS Medicare and Medicaid. The authors of the study in Oregon found that service use, including hospitalization, was similar across MMC and FFS Medicaid enrollees with FFS Medicare. However, this single state study does not describe changes nationally or aim to determine the effect of MMC on outcomes, instead focusing on describing differences across enrollment groups. As the authors point out, during their study time period, Oregon had relatively high enrollment rates in managed care in both the Medicare and Medicaid programs, and so their findings in their single state study may not be representative of the experiences of other states. The current study, using national data, will complement this earlier work limited to a single state.

In summary, there is a vast literature on the effects of managed care on the general population, but much less is known about the effects of Medicaid managed care for duals. The evidence on the effects of managed care for high-cost, low income groups suggests that these populations could suffer poorer health outcomes as a result of the change in payment structure. Evidence in Medicaid managed care is mixed and based mainly on single state studies of non-duals. While single states studies are currently being conducted to examine recent MLTSS expansions, data limitations restrict evaluation of the effects on hospitalization to non-duals. This paper seeks to fill this gap in evidence by providing the first national estimates of the effect of three Medicaid managed care play types (CMC, MLTSS, and PCCM) on hospitalization use for full-benefit duals.

3.4 Conceptual Framework

Medicaid was initially implemented with a FFS payment system, where providers are payed directly by the state for services used by Medicaid beneficiaries. The FFS system may be inefficient for many reasons: prices are determined by the state, beneficiaries do not pay directly for services, and beneficiaries do not have perfect information about the costs and benefits of medical services. Under-use of services could arise if states set reimbursement rates below the cost of providing care resulting in a lack of provider participation. Conditional on sufficient supply, over-use could occur due to both supply and demand side incentives. On the demand side, Medicaid beneficiaries face little or no out-of-pocket cost when using services implying they have no incentive to seek out the lowest cost option when substitutes are available. On the supply side, there is little incentive for care coordination across settings. Additionally, demand inducement is also a concern: physicians both diagnose conditions and recommend treatments so they may have the financial incentive to recommend services beyond the point where the costs equal the benefits to the patient under the FFS system.

To combat these inefficiencies of the FFS system (and to provide budget stability), managed care has been adopted by many state Medicaid programs. Rather than paying providers directly for services, the state Medicaid agency provides premium payments to health plans and health plans are responsible for paying providers for services used by their enrollees. To prevent under-use of necessary services, plans are required to meet minimum network adequacy requirements to participate in the program. States adopt different standards, but generally, health plans must show that there are enough participating providers in their networks and in the geographic area they serve to meet the demand of their enrollees. Inefficiencies of FFS resulting in over-use are reduced by the financial incentives inherent in transferring risk of high health care costs from the state to the health plan. Health plans act as profit maximizing firms. As such, health plans have the financial incentive to reduce costs of care for their enrollees in order to increase profits. The simplified profit function of the health plan for time period t is:

$$\text{Profit}_t = \text{Premiums}_t - \text{Cost of services}_t$$

$$\text{where Cost of services}_t = \text{Price}_t \times \text{Quantity}_t$$

Health plans can increase profits by reducing prices and/or quantities of services their enrollees use. First, health plans could reduce prices if they are able to negotiate with providers for prices lower than the FFS rates. However, this is unlikely in the setting of Medicaid. In fact, in their study examining the effects of MMC on program spending, (Duggan, 2004) find that in relatively high FFS price states, there were spending reductions associated with the introduction of MMC but in low-FFS price states, spending was unaffected or increased due to the introduction of MMC. Alternatively, health plans could reduce prices and quantities through care coordination and utilization management. They could (1) limit access to low-value care, (2) shift the mix of utilization away from high cost types of care (for example, substituting primary care office visits for more expensive emergency room care), and/or (3) better manage care (e.g. manage blood-sugar for diabetes patient to avoid costly complications). The third mechanism, better managing care, is especially relevant when plans enroll the same beneficiaries over multiple time periods. To illustrate this point, if a health plan enrolls an individual in periods t and $t+1$, and if health care in period t can result in better health in period $t+1$, then the plan may have the financial incentive to provide health care in period t to avoid more costly care in the future. It should be noted that, in addition to directly shifting prices and/or quantities, plans may also increase profits by selecting enrollees for whom the premium payments are higher than their expected expenditures on services when there is imperfect risk adjustment.

It is unclear if these reductions in costs will be associated with changes in quality. If plans are able to encourage reductions in unnecessary care and/or appropriate substitutions between care settings/services, health outcomes could be improved. However, if plans reduce costs by reducing quality of care, "skimping" on quality or necessary services, MMC could result on adverse health outcomes. State Medicaid agencies do regulate plan quality to prevent this through public reporting of plan ratings, network adequacy requirements, and minimum quality standards. However, for services and populations for which there is little consensus on what constitutes high quality care, such as long-term care or care for complex patients, it is difficult for states to effectively monitor the quality of care provided by health plans. Furthermore, high-cost duals with low incomes may be especially vulnerable to skimping because of lack of advocacy and social supports. Incentives for skimping may be stronger for these high-need individuals who have largely been excluded from studies of effects of MMC on quality of care.

Another concern specific to duals is that they are insured by two public payers which often face conflicting incentives. Medicare is the primary payer for medical services, such as inpatient hospital, post-acute, and outpatient care, as well as prescription drugs while Medicaid is the primary payer for long-term care (LTC) and other services excluded from Medicare. Medicaid also pays the beneficiary cost-sharing payments: co-payments and coinsurance for Medicare covered services and Medicare premiums. Grabowski (2007) outlines how the incentives inherent faced by each program may result in inefficient service use, specifically with the case of LTC. Especially relevant to considering how MMC affects hospitalization rates is the incentive for cost-shifting between the two programs. Medicare reimbursement rates are generally higher than Medicaid rates for services such as nursing facility care. Medicare only pays for nursing facility care that is classified as post-acute care, occurring directly after a hospital stay. This provides a financial incentive for nursing homes to hospitalize patients with Medicaid coverage in order to be able to have Medicare pay for care after the hospitalization. This fragmentation can also limit the financial incentive of a Medicaid health plan to reduce hospitalizations. The Medicaid plan is responsible for Medicaid-paid services only.

The two payer system, then, results in a modified profit function for the Medicaid health plan. A fully comprehensive Medicaid health plan would be responsible for only Medicaid-covered services and payments. That is, the profit function becomes:

$$\text{Profit}_t = \text{Premiums}_t - \text{Costs}\ (\text{Medicare cost-sharing} + \text{LTC} + \text{other Medicaid services})_t$$

In the example of LTC and hospitalization, the MMC plan faces a trade-off. The health plan could provide high quality LTC to reduce hospital use. This would result in high LTC spending but low Medicare cost-sharing spending. Alternatively, the plan could provide lower quality LTC and risk paying higher Medicare cost-sharing hospital payments. The relative amounts of cost-savings due to low-quality LTC or reduced hospital Medicare-cost sharing determine which scenario maximizes the health plan's profit. If plans were responsible for the full cost of hospital care, the relative weight put on reducing hospitalizations would be increased. As a result, the lack of accountability for the full scope of services due to fragmentation could result in plans providing lower quality Medicaid services relative to if they were responsible for the full scope of services. The main financial incentive for MMC to reduce hospital spending relative to FFS, that plans provide coordinated, high-value care to avoid high-cost care in the future, is blunted when the high-cost care in the future is paid for by other payers.

In reality, though, most MMC programs exclude some Medicaid costs from the health plan's covered services. These exclusions are often referred to as "carve-outs". Carving-out services from Medicaid health plans further mediates the financial incentives for MMC to reduce hospitalization. The three main program types adopted by states that include duals, comprehensive managed care (CMC), managed long-term services and supports (MLTSS), and primary care case management (PCCM), have different carve-outs, and therefore different incentives for reducing hospitalization. This motivates the empirical analyses in which I estimate the effect of MMC on hospital use separately by program type. Table 3.1 summarizes the costs that the health plan is responsible for for each of the three program types. Following the table, I describe each model in more detail.

Despite having "comprehensive" in the name, for duals, CMC plans are generally only required to pay Medicare premiums and cost-sharing. They vary by state as to whether they include dental and behavioral health services, but as I classify them for this study, they do not include LTC. For Medicaid-only beneficiaries, these plans are comprehensive with respect to acute care and physician services. However, because those services are Medicare-

Table 3.1: Comparison of Medicaid managed care program types and the traditional FFS payment model

Service	MLTSS	CMC	PCCM	FFS
Medicare cost-sharing	Y*	Y	FFS	FFS
Long-term care	Y	FFS	FFS	FFS
Other Medicaid Services	Y*	Y	FFS	FFS
Case management	Y	Y	Y	N

Y = Service is included in health plan covered services; FFS=service is carved out, payed FFS; N=Service is not covered.

*=Services included in comprehensive MLTSS plans only, not in LTSS-Only plans.

paid for duals, they only provide the Medicare cost-sharing portion of those costs for duals. Importantly, LTC continues to be paid directly by the state on a FFS basis. The profit function for CMC plans is therefore:

$$\text{Profit}_{CMC,t} = \text{Premiums}_t - \text{Costs (Medicare cost-sharing + other Medicaid services)}_t$$

Plans may have the incentive to reduce unnecessary hospitalizations because they primarily pay for Medicare cost-sharing. However, because the scope of Medicaid services is limited, they may have little means to reduce hospital use.

In contrast, MLTSS plans do include LTC within the scope of plan provided services. MLTSS plans are implemented in two ways: comprehensive MLTSS and LTSS-only. Comprehensive MLTSS plans cover LTC and Medicare cost sharing for medical services while LTSS-only plans only cover LTC services (i.e. nursing facility care and home-and community-based long-term care). Other Medicaid covered services are either paid FFS or included in a separate health plan. By 2017, approximately 72% of MLTSS enrollees were enrolled in the comprehensive MLTSS plan type while 28% were in LTSS-only plans (Research, 2019). For the purposes of this analysis, I categorize any plan that covers long-term care as an MLTSS plan, not distinguishing between the comprehensive MLTSS and LTSS-only plan types. The profit function for MLTSS plans (assuming they are comprehensive MLTSS plans) is then:

$$\text{Profit}_{MLTSS,t} = \text{Premiums}_t - \text{Costs (Medicare cost-sharing + LTC + other Medicaid services)}_t$$

In comparison to CMC plans that exclude long-term care, MLTSS plans may have more leverage to reduce hospitalizations because they provide more services. However, they may also have less of a financial incentive to do so, because the relative share of costs for Medicare cost-sharing and covered Medicaid services is lower.

Relative to the CMC and MLTSS models, PCCM is essentially a FFS model. It consists of paying a capitation payment to a primary care physician (PCP) to provide additional care coordination services to her panel of patients. The primary care services, and all other services, continue to be paid on a FFS basis. In this model, then, the PCCM health plan is only responsible for these care coordination services.

$$\text{Profit}_{PCCM,t} = \text{Premiums}_t - \text{Costs (PCP Care coordination services)}_t$$

It is important to note that the capitated payment is usually quite small, on the scale of \$3 per member per month and services provided are therefore quite limited(Foundation, 2012). Of the models described, due to the lack of responsibility for either Medicare cost-sharing or Medicaid-paid services, PCCM plans have the lowest financial incentive for reducing hospitalization rates.

To put these different models in perspective, it is helpful to consider the amount of spending due to the different categories of services. Table 3.2 summarizes Medicaid and Medicare spending by service category for full-benefit duals from 2012.

On average, Medicare pays approximately 94% of inpatient hospital services and 75% of outpatient services while Medicaid pays the remaining 6% and 25% respectively. For this population, spending on LTC is more than six times the amount spent on Medicare cost sharing. This highlights the differences in financial incentives by plan type, with MLTSS

Table 3.2: Medicare and Medicaid spending by service type for full-benefit duals, 2012.

Service	Average Spending ($)	Percent of program spending (%)
Medicaid		
Inpatient hospital incl. Medicare cost-sharing	275	2
Outpatient incl. Medicare cost-sharing	1978	11
LTC	14,379	81
Managed care premiums[1]	918	5
Medicare		
Inpatient hospital	5,210	37
Outpatient	5,797	41
Skilled nursing facility	1,784	13
Home health	811	6

Source: 2017 Beneficiaries Dually Eligible for Medicare and Medicaid Data Book. MACPAC and MedPAC. Average spending and percent program spending are for FFS, full-benefit Medicare and Medicaid duals. Percents do not sum to 100 because not all categories of spending are included.
Note 1: Premiums for limited benefit Medicaid managed care plans.

plans being responsible for the highest share of total Medicaid spending, followed by CMC plans, and PCCM plans responsible for the smallest share. Differences in covered services by MMC plan type and the magnitude of spending by service types motivate the following observations.

Observation 1: CMC programs have the greatest relative financial incentive to reduce hospitalizations. They are responsible for the Medicaid-paid portion of inpatient and outpatient spending but not long-term care. However, because the health plan is not the primary payer for these services, their ability to impact hospitalization rates may be small. Therefore, I expect to find that hospitalization rates to remain the same or decrease slightly under expansions of CMC plans to duals.

Observation 2: MLTSS plans are the only plans that have a strong ability to affect hospitalization rates because they cover such a large share of Medicaid covered services. This is the main argument proponents use when touting the benefits of MLTSS expansion. However, there may be limited incentive for plans to provide high-quality long-term care under MLTSS because hospitalization costs are only a small share of total expected costs, approximately 1% given average spending amounts in Table 3.2. The effect of MLTSS on hospitalization rates is therefore ambiguous and must be tested empirically.

Observation 3: PCCM will not impact hospitalization rates or only have modest effects. PCCM provides care coordination service only, with only a very small premium payment to coordinate Medicaid covered services. For duals, with their high reliance on Medicare paid services and complex care needs, this small change will not be enough to impact hospitalization rates in a meaningful way.

3.5 Data

I use linked Medicaid and Medicare administrative data from 2005 and 2011-2012. I use the Medicaid Analytic eXtract (MAX), which is generated by CMS from data submitted by the states through the Medicaid Statistical Information System. Years between 2005 and 2011 are omitted due to data availability (these years of data were not available for data reuse through existing University of Chicago data use agreements). While it would be desirable to use more recent data for this study, MAX data is not currently available for all states after 2012 due to the transition to a new data collection system. The MAX personal summary (PS) file is a beneficiary-level file containing limited demographic information (age,sex,race/ethnicity), county of residence, and Medicaid enrollment details including managed care plan enrollment.

I also use the Medicare beneficiary summary file (MBSF), the MBSF-chronic conditions supplement, and the MedPAR file. The MBSF and MBSF-chronic conditions supplement contain beneficiary level data similar to that in the MAX PS: demographic information, county of residence, and Medicare enrollment details. The chronic conditions supplement contains indicators for 27 chronic conditions using the CCW algorithm based on diagnosis codes across Medicare FFS claims [3]. MedPAR is the Medicare Provider Analysis and Review

3. Chronic conditions data warehouse Condition Categories website: `https://www.ccwdata.org/web/`

file that aggregates individual inpatient and skilled nursing facility claims to the stay level, providing information about individual hospital stays including admission and discharge dates, diagnosis and procedure codes, and Medicare payments.

A major barrier to analyzing the effects of managed care on utilization is the lack of reliable data documenting utilization once a beneficiary is enrolled in a managed care plan. When the state no longer pays providers directly for services, FFS claims are no longer generated. Health plans are instead required to submit encounter records to reflect utilization of their enrollees. However, because payment is not directly tied these records, there is little incentive for plans to comply. As a result, encounter record quality varies widely from state to state and by service within state (Byrd and Dodd, 2015). I overcome this limitation, without having to rely on encounter data of questionable quality, by studying duals, for whom Medicare remains the primary payer for hospital care even after the switch from Medicaid FFS to MMC. The vast majority of duals, including those enrolled in MMC, had FFS Medicare coverage during this time period. This allows me to use FFS Medicare claims to measure hospital use. While this sample restriction comes with a loss of generality because I omit individuals enrolled in Medicare managed care from the analysis, it is an important first step in assessing the effects of MMC for duals.

The main analysis dataset is constructed by identifying individuals enrolled in Medicaid and Medicare using the MAX PS and the MBSF. Because the dual code fields used to determine level of Medicaid benefits (full versus partial dual) are available only quarterly in 2005 (rather than monthly in later years), data for all periods is aggregated to the quarter level. Because the outcome of interest is hospital utilization as identified by fee-for-service inpatient hospital claims, I then exclude individuals enrolled in Medicare managed care for any month during the quarter. Individuals without a valid county code in the MAX data are also excluded. Individuals with county of residence in Maine and Vermont are excluded from the analyses due to anomalies in the MAX managed care enrollment data for those states.

---

guest/condition-categories

Finally, because I control for long-term care use in the prior quarter in the analyses, I exclude beneficiary-quarter observations from Q1 2005 and Q1 2011, because I do not observe prior period utilization.

3.5.1 Key variables

Outcomes

The outcome of interest is inpatient hospital utilization obtained from FFS claims in the MedPAR file. I operationalize this outcome using a binary indicator of any hospital stay in the quarter. Reducing hospital use is often cited as the way managed care reduces costs, and hospitalization among duals is an important and often targeted outcome of many programs. Additionally, hospitalization may be particularly disruptive for duals given their poor health status and lack of social supports. For instance, frail older adults may be more prone to psychological distress or iatrogenic events due to a hospital stay (Creditor, 1993).

To evaluate the effectiveness of care outside of the hospital, of which Medicaid LTC is an example, researchers have developed the concept of potentially avoidable hospitalization. Diagnosis codes from the hospitalization can be used to identify these hospitalizations that potentially could have been avoided with high-quality care in other settings. While originally developed to assess health care at the population level, there are several variations of potentially avoidable hospitalization that have been used in the context of care for older adults and long-term care users in the literature to date (Maslow and Ouslander, 2012). In this paper, I use the AHRQ Prevention Quality Indicators (PQIs) (*AHRQ - Quality Indicators*).

Treatment

Treatment is defined at the county level for the DID analyses and individual level for the IV analyses. First, using the plan type codes in the MAX PS enrollment file, I classified individuals as enrolled in (1) CMC or MLTSS (plan type 1 or 5), (2) PCCM (plan type 7) or (3) FFS (not enrolled in 1, 5, or 7). This enrollment file includes monthly indicators for up to four plans which I convert to quarterly enrollment indicators, requiring enrollment in a plan for all months in the quarter for which the beneficiary is alive to count as MMC enrolled.

The plan type variables in the MAX PS has separate codes for CMC plans (code 1) and MLTSS plans (code 5). However, states vary in how they code the plan type so that plan type codes alone cannot distinguish between CMC plans that include LTC and those that exclude LTC. For this reason, I supplemented the information from the PS file with state program information from several sources to determine whether LTC was included in the plan offerings in that county-quarter or not.[4] With this information about what programs are offered at the county level, I then classify individuals as either enrolled in a CMC plan (that excludes LTC) or a MLTSS plan (with or without other services).

For the DID analyses, I aggregate the individual-level enrollment data to the county-quarter level and calculate the rate of enrollment in each plan type (CMC/MLTSS, CMC, MLTSS, and PCCM) among full-benefit duals with FFS Medicare at the county level. I then construct a binary variable from these enrollment rates to classify counties as having each type of program if the rate of enrollment is greater than one percentage point. This is the Treatment$\times$Post interaction term that is used in the DID analysis.

For the IV analyses, I use the individual level enrollment in each plan type. I make one further refinement: for each plan type, the indicator for treatment takes on the values of 1 if enrolled in that plan type and 0 if not enrolled in any of the MMC plan types examined. This excludes individuals that are enrolled in other plan types from the control group. This restriction allows me to estimate treatment effects of each managed care plan type with

4. Sources for MLTSS program information include a series of CMS MLTSS expansion reports: (Saucier, Burwell, and Gerst, 2005), (Saucier et al., 2012), (Lewis et al., 2017); 2011-2017 Medicaid managed care enrollment reports `https://www.medicaid.gov/medicaid/managed-care/enrollment/index.html`; the NASUAD State Medicaid Integration Tracker `http://www.nasuad.org/initiatives/tracking-state-activity/state-medicaid-integration-tracker`, the Medicaid 1115 Interim Evaluation report for MLTSS Libersky et al., 2018, and the CMS report *2005 National Summary of State Medicaid Managed Care Programs* 2006.

respect to the traditional, FFS reimbursement as the alternative.

Instrument

I calculate the share of non-elderly, non-disabled Medicaid-only beneficiaries at the county level that are enrolled in MMC plans (quarterly) using just the MAX PS. I restrict to non-elderly, non-disabled individuals that are not duals to construct the instrument to get a measure at the county level of managed care penetration, but among a group of Medicaid beneficiaries that is quite different from the elderly or disabled duals that comprise the target population of the study. As described for the treatment variables above, the instrument is also calculated at the county-quarter level separately for CMC and/or MLTSS, CMC, MLTSS, and PCCM plans.

Mandatory versus Voluntary Enrollment

The "treated" groups are identified for the DID and IV analysis based on whether or not there is mandatory or voluntary enrollment in the MMC plan type for duals at the county level. I determine if plan enrollment is mandatory versus voluntary by using Medicaid managed care enrollment reports[5] and the CMS State Managed Care Profiles [6].

Controls and stratification variables

Beneficiary age, sex and race/ethnicity are obtained from the Medicare enrollment file. I use the RTI race code variable which was developed using name and zip code information to correct the under reporting of Hispanic and Asian ethnicity/race in the raw race code populated from Social Security records. Mortality is obtained from the Medicare date of death field. The MBSF-chronic conditions supplement is used to identify each of the 27

5. I relied especially on the 2016 Managed Care Program Features by State available at: `https://www.medicaid.gov/medicaid/managed-care/enrollment/index.html`

6. Profiles & Data Collections, Individual state profiles: `https://www.medicaid.gov/medicaid/managed-care/state-profiles/index.html`

chronic conditions. Then variables are constructed to identify number of chronic conditions, categorized into 0-1, 2-3, 4-5 and 6 or more, to identify multi-morbidity. Original reason for Medicare entitlement, aged or disabled, is from the MBSF as well. Finally, I identify Medicaid paid LTC use using a combination of 1915(c) waiver enrollment from the MAX PS and TOS and CLTC codes in the MAX LT and OT files. I flag an individual as using LTC if they are enrolled in a 1915(c) waiver for at least one month or have at least one institutional LTC service (TOS codes 2,4,5,7) or HCBS (CLTC codes 10-20,30-40) claim during the quarter following methods described in Peebles et al., 2017. LTC use is assessed in the prior quarter to avoid concerns that treatment (MMC enrollment) could influence receipt of LTC. However, it should be noted, that for the subgroup enrolled in MLTSS programs, it is possible that LTC is under-reported if encounter data is incomplete. This would result in misclassification in the stratification by LTC use for the MLTSS treatment analyses. That is, if encounter records are incomplete, some individuals that used LTC would be in the non-LTC user group for that stratification.

County of residence

County is assigned from the county of residence field in the MAX PS. I use the MAX PS and not the MBSF in order to consistently assign county codes to both the main sample population of duals and the Medicaid-only beneficiaries in order to construct the instrument. Individuals are excluded from the analyses (and county level enrollment rates) if they did not have a valid residence code. This includes individuals that had residence county outside the state for which they were enrolled in Medicaid since those counties are not reported in the MAX PS. Using these county codes, I link in two sources of county level data: Rural-urban continuum codes[7] and the Area Health Resource File[8]. I collapse the Rural-Urban

7. United States Department of Agriculture, Economic Research Service, 2013 version. https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/

8. Health Resources & Services Administration. Data from 2005 requested via email communication. https://data.hrsa.gov/topics/health-workforce/ahrf

Continuum codes to metropolitan counties (codes 1-3) and non-metropolitan counties (codes 4-9). I control for county-level supply of hospital beds and nursing facility beds per 1000 population from the Area Health Resource File.

3.6 Methods

I seek to estimate the causal impact of MMC expansion on hospitalization rates among duals. One can conceptualize this treatment effect by considering the following randomized controlled trial (RCT): the researcher randomly assigns treatment status among a representative sample of the population of full-benefit duals. Treated individuals are enrolled in a MMC plan and control individuals have FFS Medicaid coverage. Any differences in hospitalization rates between the two groups could be attributed to managed care due to randomization. In the absence of this RCT, I rely on quasi-experimental methods for this study. In order to estimate causal effects, we must account for selection in this non-randomized setting: i.e. the fact that who is treated depends on choices made by beneficiaries. In general, individuals that enroll in managed care tend to be healthier than their FFS counterparts. Multivariate regression, even controlling for observable characteristics, may be subject to omitted variables bias if there are unobserved factors that are related to both treatment status and health outcomes. To account for this selection, I propose two different strategies: difference-in-differences and instrumental variables.

The use of two different analysis strategies is driven by an important variation in program characteristics: whether enrollment is mandatory or voluntary. The two methods estimate treatment effects for different populations: DID estimates an average treatment effect for the entire population while IV estimates a local average treatment effect for individuals induced to take up treatment because of the instrument. DID is intuitively appealing when enrollment is mandatory and treatment is assigned at the county level. IV, in contrast, uses variation in an instrument, in this case county-level MMC enrollment among non-disabled, non-elderly Medicaid-only beneficiaries (hereafter referred to as non-duals), to predict individual MMC enrollment among duals. This addresses selection at the beneficiary level, estimating a local average treatment effect for beneficiaries who enroll in MMC due to county-level MMC rates among a different population. Results from each analysis therefore complement each other and provide a more complete picture of the effects of MMC on hospitalization for duals than either would on its own.

In the remainder of this section, I describe how I implemented each analysis in detail, along with the assumptions required for the estimated treatment effects to be interpreted as causal effects.

3.6.1 Difference-in-differences

To analyze the effects of MMC on hospitalization when MMC enrollment is mandatory, I estimate a difference-in-differences (DID) model (or more generally a fixed effects model). Treatment is assigned at the county level for each time period and counties experience changes in treatment status at different times to reflect the fact that counties implement mandatory MMC programs throughout the study period. $Treat_{MC,ct} = 1$ when county c had a mandatory MMC plan in period t and $Treat_{MC,ct} = 0$ if it had no plan in that period. The DID estimating equation is therefore:

$$Y_{ict} = \alpha + \beta_{MC} Treat_{MC,ct} + \beta_1 * X_{1,it} + \beta_2 * X_{2,ct} + \gamma_c * C_c + \gamma_t * T_t + \epsilon ict \qquad (3.1)$$

where subscripts i, c and t represent individual, county and time respectively. γ_c and λ_t are county and time (quarterly) fixed effects. $Treat_{ct}$ is equivalent to the Treatment$\times$Post interaction term in the standard DID framework. β_{MC} is the DID estimate. Three separate regressions were estimated, one for each type of managed care (CMC or MLTSS, CMC, and MLTSS[9]). $X_{1,it}$ are individual level characteristics and $X_{2,ct}$ are time varying county level

9. PCCM effects will not be estimated using DID because PCCM is nearly always implemented with voluntary enrollment. Only four counties in Utah had mandatory PCCM programs for duals during the study time period. For the same reason, CMC will not be estimated using DID for non-metropolitan

characteristics.

The DID method requires the parallel trends assumption in order for results to be interpreted as the causal impact of MMC on hospitalization rates. The intuition of the parallel trends assumption is that in the absence of treatment, treated and control counties would have exhibited the same changes in the outcome over time. For this application this assumption can be stated as follows: in the absence of MMC expansion, the rate of hospitalization would have changed the same amount in the counties that did adopt MMC as in the counties that did not adopt MMC. This assumption cannot be directly tested, because the counterfactual, what would have occurred in the treated counties had they not been treated, cannot be observed.

The parallel trends assumption would be violated if there was a shock other than managed care adoption that influenced treated and control counties hospitalization rates differentially during the study time period. There are two threats to the parallel trends assumption that I directly address: changes of other MMC plan types in the control counties and changes in the composition of the study sample due to Medicare managed care expansions. I describe each of these problems, and approaches I use to address them, in the next two sub-sections.

Control group

Since treatment is defined as having mandatory enrollment for a particular type of MMC plan in the county, counties with no changes in that type of managed care make up the control group using the specification in Equation 3.1. However, it is possible for a county to have no changes in one plan type while having changes in another plan type. This would violate the parallel trends assumption because the control counties would experience a policy change correlated with treatment status. To address this problem, I only include counties in the control group if they have no change in any MMC plan type during the study period. For example, during the study period, North Carolina implemented a PCCM program statewide

counties because very few non-metropolitan counties had mandatory enrollment for this plan type.

but had no CMC or MLTSS program. NC counties are therefore excluded from the control group for analyses of CMC and MLTSS effects. This is operationalized as follows: to be included in the control group, a county must have changes in enrollment rates among duals of less than 1 percentage point per quarter during the study time period. I identify 1,257 counties that did not have changes in enrollment rates of any type of MMC (CMC, MLTSS or PCCM) during the study period.

Sample composition changes

An additional source of bias arises if there are changes in the sample composition over time that are correlated with both treatment status (adoption of MMC program) and outcomes (hospitalization). One such change is the expansion of Medicare managed care during the study period. Consistent with national trends among all Medicare beneficiaries (Patel and Guterman, 2017), I find that Medicare managed care enrollment among full-benefit duals has increased considerably during the study time period, from approximately 5.8% in Q4 2005 to 19.3% in Q4 2012 (calculation from MBSF-MAX PS, not shown).

Because, in general, Medicare managed care plans enroll healthier beneficiaries, if Medicare managed care expansion is correlated with MMC expansion, this causes a threat to identifying the causal impact of MMC on hospital use using DID. I find that the expansions are indeed correlated. During the study period, counties with the largest decline in the share of duals that have FFS Medicare coverage are also counties with the largest increases in enrollment in CMC/MLTSS plans among FFS Medicare enrolled duals. I show this correlation by visual inspection of the changes in FFS Medicare shares and change in CMC/MLTSS enrollment changes in Figure 3.2. I also tabulate change in each plan type enrollment for each quintile of change in FFS Medicare in Table 3.3. Both exhibits illustrate that counties with large declines in the share of duals enrolled in FFS Medicare also have the largest increases in MMC enrollment. The first column in the table also shows that counties with large declines in FFS Medicare are the most likely to switch between offering CMC plans that exclude LTC at the start of the study period to offering MLTSS plans by the end of the study period.

Finally, to describe how Medicare managed care expansion appears to drive compositional changes in the sample of beneficiaries that remain in FFS Medicare, I tabulate sample characteristics separately by year and Medicare managed care status in Table 3.4. The mean age and share eligible for Medicare due to age decreased for the overall population of full-benefit duals from 2005 to 2012. However, the mean age and share aged decreased more among those with Medicare managed care as compared to FFS Medicare. That is, Medicare managed care health plans began enrolling younger beneficiaries with disabilities during the study period. Additionally, the racial compositions of the two groups also changed differentially from 2005 to 2012. The share of Medicare managed care enrollees that are white declined more while the share that are black, Hispanic and Asian rose more than among the Medicare FFS group. These large demographic changes among Medicare managed care enrollees were also associated with a sharper decline in mortality over the study period than was observed in the FFS Medicare group. This suggest that over time, the full-benefit duals that remain in the analysis sample because they have FFS Medicare coverage become sicker relative to the excluded group that has Medicare managed care coverage.

In the main results, I use inverse propensity score weighting to account for changes in sample composition over time (Rosenbaum and Rubin, 1983) (Heckman, Urzua, and Vytlacil, 2006). I do this sequentially by restricting the sample to observations in the last time period, Q4-2012 and one other period, t, and generating a propensity score for each observation of the probability of being in the Q4-2012 time period. I repeat this procedure in each time period that is not the final time period. The following specification is used to generate the propensity score sequentially for each time period:

$$Pr(t = Q42012) = probit(\beta_1 * X_{1,it} + \beta_2 * X_{2,ct}$$

Then, I use the generated propensity scores to calculate inverse propensity score weights, using nearest neighbor matching without replacement and a caliper of 0.1. This results in weights of 1 for observations in the final time period and weights between 0-1 for observations in all other time periods. Observations that are not in the common support of the propensity scores are assigned weight 0. I verify the propensity scores result in a balanced sample by, for each time period, checking that the standardized differences between the final time period characteristics and period t characteristics using weights are less than 10%. Standardized differences are plotted in Figure 3.3. To illustrate balance more intuitively, I also tabulate sample characteristics in Q4 2005 and Q4 2012 with both the raw and weighted data in Table 3.7. This shows that the changes in the sample composition are smaller using weighting than in the raw data. As expected, the policy change of MMC expansions is still present in the weighted data and there are differences in outcomes (hospitalization, mortality) that remain after matching. This approach allows me to analyze all counties but may come at the expense of internal validity because the propensity score method only accounts for observable differences in the sample composition over time and not for unobservable differences.

Evidence supporting the parallel trends assumption

I explore the validity of the parallel trends assumptions in two ways. First, I plot hospitalization rates over time for treated and control counties and use visual inspection to see that they are similar in the period before MMC adoption. This is less straightforward than in the standard case when treatment occurs at the same time for all counties. I separately plot by treatment date: generating ten plots of mean hospitalization rate over time by the first period where I observe the MMC program is present in the enrollment data (i.e. the share of duals in the MMC plan type is greater than 1%). For counties that adopt MMC in quarter 2 of 2005, whether or not there are parallel trends cannot be assessed because we do not observe enough pre-periods. However, in later periods, I can observe trends in the outcome in two or more periods to assess whether it appears that the control counties are a reasonable comparison group to the treated counties.

For the subset of counties where MMC is adopted Q2 2012 and earlier, I can also use regression to assess the validity of the parallel trends assumption. I do this by including one and two period future treatment (i.e. lead Treat) in addition to the main fixed effects by estimating the following equation:

$$\begin{aligned} Y_{ict} = &f(\alpha + \beta_{MC} Treat_{MC,ct} + \zeta_1 Treat_{MC,c(t+1)} + \zeta_2 Treat_{MC,c(t+2)} + \\ &\beta_1 * X_{1,it} + \beta_2 * X_{2,ct} + \gamma_c * C_c + \gamma_t * T_t, \epsilon) \end{aligned} \tag{3.2}$$

If treatment and control counties have the same trends in the absence of MMC expansion, then future MMC enrollment should not predict hospital use in the current period. A test of joint significance of these lead terms is equal to zero provides more evidence that the trends in the outcome in the pre-periods are the same for the treatment and control counties (Angrist and Pischke, 2009).

Initial examination of these checks led me to exclude the most rural of counties from the analyses. Counties with rural-urban continuum codes of 8 and 9 were excluded as a result. These counties are mostly in the control group, especially for the DID analyses, because they are less likely to adopt MMC for duals during the study time period.

3.6.2 Instrumental variables

The second analysis strategy I employ is instrumental variables, which I use to estimate the effects of MMC programs with voluntary enrollment policies. Rather than estimating the average treatment effect (as in DID), IV estimates a LATE, the local average treatment effect for compliers. The IV method is implemented using two stage least squares (2SLS).

The two stages are:

$$\text{1st stage: } MMC_{ict} = \alpha_0 + \alpha_1 Z_{ct} + \alpha_2 X_{ic(t-1)} + County_c + \lambda_t + \upsilon_{ict}$$

$$\begin{aligned}\text{2nd stage: } Y_{ict} = \beta_0 + \beta_1 M\hat{M}C_{ict} + \delta_2 X_{ic(t-1)} + \\ County_c + \lambda_t + \varepsilon_{ict}\end{aligned}$$

Z_{ct} is the instrument: county level Medicaid managed care penetration among non-disabled, non-elderly Medicaid-only beneficiaries (non-duals). $M\hat{M}C_{ict}$ is the predicted probability of enrolling in MMC for individual i in county c at time t due to the instrument and other individual and county characteristics. The coefficient of interest, the LATE, is β_1 from the second stage. The LATE I estimate, then, is for the group of individuals (duals) that are induced to join MMC plans because of the MMC penetration rate of non-duals, and not related to unobservable characteristics of the individuals themselves. Because the LATE is identified from individual level enrollment decisions, it is best suited for analysis of programs that are implemented with voluntary (not mandatory) enrollment policies. The instrument does not have sufficient predictive power in the first stage when enrollment is mandatory. Therefore, while the DID is limited to counties with mandatory enrollment, the IV is limited to counties with voluntary enrollment.

To interpret the IV estimates as a LATE, three assumptions must be made: (1) strength, (2) conditional independence and (3) the exclusion restriction. I describe the specific instrument and related assumptions in turn in this section.

The instrument I use is the share of non-disabled, non-elderly Medicaid-only beneficiaries enrolled in MMC at the county level. This instrument is conceptually appealing because it captures variation in the rate of non-duals, a separate population of Medicaid beneficiaries, to predict individual enrollment of duals in MMC plans. If there are characteristics about a health care market that encourage Medicaid managed care, such as state Medicaid program features, population density, and provider characteristics and market power, they likely predict MMC penetration for both non-duals and duals (strength). This first assumptions is directly tested by running the first stage regression and verifying that there is sufficient predictive power.

The conditional independence and exclusion restriction assumptions cannot, however, be directly tested. The conditional independence assumption is that the instrument is not correlated with the original confounding factors. In this case, the share of MMC enrollment among Medicaid-only beneficiaries is not correlated with underlying health of individual full-benefit duals. Conceptually, this is plausible. Because the instrument is derived from a different population than the treatment, it is reasonable to assert that the underlying health of individual dual-eligible beneficiaries is not associated with adoption of MMC among non-elderly, non-disabled Medicaid-only enrollees at the county level.

Finally, the exclusion restriction is that the instrument does not directly impact the outcome, only through the channel of the endogenous variable. In this case, this means that the share of MMC enrollment among non-duals cannot directly impact hospitalization of duals. Conceptually, this also seems plausible. Duals are by definition either elderly or disabled while the instrument is calculated for Medicaid-only beneficiaries that are explicitly not elderly or disabled. These two populations generally have distinct health care needs (ex. elderly and disabled seek care from providers with expertise in diseases of aging and disability care while Medicaid only focus is maternity, pediatric and preventative services). Because they see different providers for these different services, it is likely that spillovers of convergence such as documented in the studies of Medicare Advantage (Baicker, Chernew, and Robbins, 2013) may not be as likely in these two groups with different health care needs.

While these two assumptions cannot be directly tested, I provide evidence to support making them in two ways. First, following Baiocchi Michael, Cheng Jing, and Small Dylan S. (2014), I tabulate sample characteristics for the individuals living in counties with values of the instrument that are less than the median versus greater than the median and calculate standardized differences between those two groups (reported in the Appendix). However, because I will control for observable characteristics of individuals and counties in the IV analyses, the strong assumption of unconditional independence which is demonstrated with this approach is not necessary. As a second approach, then, I check for conditional independence using regression with the instrument as the outcome. I estimate the following equation:

$$Z_{ct} = \eta_0 + \eta_1 X_{ict} + \eta_2 X_{ic(t-1)} + County_c + \lambda_t + \upsilon_{ict}$$

I report coefficients for each of the individual and county characteristics in X_{ict} and $X_{ic(t-1)}$ and the t-test for significance of each characteristic, conditional on the other covariates. If coefficients are near zero and not significant, conditional on other observable covariates, then this provides some evidence that conditional on observable characteristics, the instrument is exogenous to the underlying characteristics of the sample.

3.6.3 Stratification

For both the DID and IV analyses, I stratify by metropolitan and non-metropolitan (metro and non-metro) county of residence. Areas with higher population density tend to have CMC and/or MLTSS programs while more rural areas tend to have PCCM programs. This is in large part due to the differences in the health care markets: rural areas often cannot attract insurers to enter more comprehensive managed care arrangements. While I do account for fixed county-specific differences in levels in hospitalization rates using county fixed effects for both the DID and IV estimation, it is possible that differences in counties that are urban vs rural could confound my results. To avoid this, I stratify all the analyses by metro versus non-metro status.

Additionally stratification is used to study if there are heterogeneous effects of MMC expansions on hospitalization. Because I am using individual level data, I am able to stratify by the following characteristics of beneficiaries: original reason for Medicare enrollment (elderly vs disabled); 0-3 vs 4 or more chronic conditions; and whether the individual used

Medicaid long-term care services in the prior quarter. Because of the suggestive evidence that managed care may result in worse outcomes for sicker populations, this will help see if those with many many chronic conditions or that use long-term care services, indicative of significant functional or cognitive impairment, do indeed fair worse under MMC than healthier individuals. I also stratify by the ten most common chronic conditions in the population of duals: Hypertension, high cholesterol, diabetes, rheumatoid arthritis, ischemic heart disease, anemia, depression, congestive heart failure, Alzheimer's disease and other dementias, and chronic obstructive pulmonary disease (COPD).

3.6.4 Limitations

I exclude Maine and Vermont because of data quality concerns as well as the most non-metropolitan counties. The DID analysis also excludes counties that had changes in more than one plan type at the same time to avoid violation of the DID identifying assumption of parallel-trends. Results in the analysis sample, therefore, may not be generalizable to these excluded counties.

Each analysis relies on fundamentally untestable assumptions. While I've provided evidence to support them, it is possible they are violated.

This study analyzes a specific combination of Medicare and Medicaid managed care. Individuals enrolled in Medicare managed care are excluded because the outcome, hospitalization, cannot be measured. As a result, performance of PACE plans or Medicaid managed care for individuals also enrolled in Medicare managed care cannot be assessed. Integrated models, where Medicare and Medicaid services are covered in a single plan or in separate plans owned by the same insurer, are excluded. These newer, more integrated models are becoming more common over time through the new Medicaid-Medicare combined plans and dual special needs plans (D-SNPs); however, many counties and states are adopting Medicaid only managed care as a first step toward integrated managed care for duals. Their experiences in this first stage should be studied and used to guide development of more integrated models as markets are developed to support them. It is also possible that some counties may never be able to realize fully integrated plans due to the nature of their health care markets; if this is true, then experiences analyzed in this paper of Medicaid only managed care programs for duals can help guide policymakers in determining how these programs affect outcomes for duals.

3.7 Results

3.7.1 Sample characteristics

I identify 46.1 million beneficiary-quarter observations that meet the main sample inclusion criteria: (1) full-benefit duals with FFS Medicare, (2) a valid county of residence code, (3) do not reside in Maine or Vermont or a county with the most rural of the rural-urban continuum codes[10], and (4) are observed for at least two sequential quarters in 2005 and 2011-2012 with no missing data. Table 3.5 describes these sample restrictions at the individual level.

From this population of duals, for the DID estimation, I restrict the sample to include only counties in the control group that have no changes in any of the MMC plan types. The treated counties are limited to those counties with mandatory enrollment. These additional sample restrictions for the DID analyses, which are specific to each plan type analysis, are shown in Table 3.6 at the county level.

I plot the county-level Medicaid managed care penetration rates over the study period by the four plan types I evaluate in Figure 3.1. This illustrates the extent of the policy change that I am evaluating. The mean penetration rate of CMC or MLTSS plans grow from 3.7% in 2005 to 13.0% in 2012 and most of this growth is due to the expansion of MLTSS plans. This is a combination of two different types of expansions in MLTSS; first is that counties with no Medicaid managed care for duals began new MLTSS programs, and second, some

10. The rural-urban continuum codes excluded are 8 and 9. Code 8=Nonmetro - Completely rural or less than 2,500 urban population, adjacent to a metro area. Code 9=Nonmetro - Completely rural or less than 2,500 urban population, not adjacent to a metro area

counties transitioned their CMC plans that excluded LTC to including LTC.

3.7.2 DID results

Weighting to address sample composition changes

First, I must address the fact that the composition of duals with FFS Medicare, the study population, changes over time in ways that may be correlated with both MMC expansions and hospitalization rates. The sample composition changes are illustrated in the first two columns of Table 3.7, tabulating sample characteristics in the fourth quarters of 2005 and 2012. Over time, FFS Medicare duals mean age decreases as the share of duals that are eligible for Medicare due to age (versus disability) decreases. The racial composition also changes: the share of FFS Medicare duals that are white decreases while the share that are Hispanic, Asian or other race increases. At the same time, the share of FFS Medicare duals has an increase in prevalence of multiple chronic conditions and long-term care use. The quarterly mortality rates, though, decline among the FFS Medicare dual population over the study period, due in part to the lower average age over time.

Last two columns of the Table 3.7 show the same sample characteristics using inverse propensity score weighting to "balance" the sample composition over time on observable characteristics. As described in the methods section, the propensity score is the propensity to be in the final period, Q4-2012. Weighting decreases the magnitude of the changes over the study period as intended for all of the characteristics used to generate the propensity score. The weights balance the share that qualify for Medicare due to age versus disability, which was one of the largest differences in the raw data. As intended, weighting with propensity scores only improves balance on the characteristics that were included in the propensity score model (demographics, aged vs. disabled, long-term care use, chronic conditions, county level metropolitan status and supply of hospital and nursing facility beds); the observed expansion in MMC enrollment and the decline in hospitalization rates observed in the raw data persists in the weighted data.

Parallel trends assumption

The DID method allows for these baseline differences between treated and control counties. However, DID requires that the trends in outcomes in both groups of counties would have been the same had the treated counties not adopted MMC programs. Next, I turn to an exploration of this assumption. First, plots of the mean rate of hospitalization over time, separately by treatment and control groups and by date of first observed MMC enrollment are shown in Figures 3.4 - 3.6. It should be noted that most new enrollment begins in the second quarter of each year and there are a large share of counties that have adopted MMC during the first period of the data so for those counties, we cannot assess whether there are common pre-trends. There is considerable noise in the data for other quarters with only a small number of counties that first adopt MMC. Therefore, I focus on plots in the second columns showing mean county level hospitalization rates for counties that first have enrollment in their MMC plans in Q2 2011 and Q2 2012. For each plan type, it does appear that the control and treated counties have similar trends prior to MMC adoption.

Second, regression estimates including leads of the treatment indicator are shown in Tables 3.8-3.10 for the three plan types. Separate regressions were run for metro and non-metro counties and for the two outcomes, any hospitalization and potentially avoidable hospitalization (PQI). For each outcome and metro/non-metro county sub-sample, the first column reports the coefficient of interest for the DID regression, only including observations Q2-2012 and earlier for which the lead treatment terms are observed. The second column lists the coefficients from estimating Equation 3.2, including the additional lead terms. If the parallel trends assumption holds, we expect to see that future treatment does not affect the current period outcomes. That is, the coefficient on the treatment indicator for the current period should remain the same when the lead terms are added to the model and the coefficients on the lead terms should be zero.

I find that this is the case for most of the treatments, outcomes and subgroups analyzed. Table 3.8 analyzing CMC/MLTSS programs, shows that none of the lead terms are statistically significant at the $p < .01$ level. The overall test of joint significance of both lead terms cannot reject the null hypothesis of zero coefficients in any of the regressions.

Next I report the coefficients examining CMC and MLTSS programs separately. The pre-trends check was only conducted for metropolitan counties for CMC plans that exclude LTSS (Table 3.9). Again, the coefficients on the lead terms are small in magnitude and not statistically significant, either individually or jointly. For the outcome of any hospitalization, the coefficient (with standard error in parentheses) on the main effect decreases from 0.005(0.001) to 0.002(0.001) with the inclusion of the lead terms. This suggests that some of the increase in hospital use associated with mandatory CMC programs could be attributable to differences in hospitalization rate trends prior to program adoption. This limitation should be kept in mind when interpreting the main results using DID to study the effects of CMC programs on hospital use.

Finally, results from these checks of pre-trends for the evaluation of MLTSS programs are reported in Table 3.10. Again, the coefficient on MLTSS program in the current period is consistent across the models without and with the lead terms included. However, for both outcomes, the coefficients are positive on the $t + 1$ lead term and negative on the $t + 2$ term. Individually, the $t+2$ coefficient in metro counties for the outcome of hospitalization is statistically significant. However, tests for joint significance cannot reject the null hypothesis at the $p < 0.01$ level and the differing signs of the two periods mean no clear difference in pre-trends is detected between counties that adopt mandatory MLTSS programs at those that do not.

Taken together, these results provide some evidence that the DID parallel pre-trends assumption holds.

3.7.3 Overall DID Results

The results of the DID estimation for the full sample are shown in Tables 3.11-3.13. In each table, columns labeled (1) are results from estimation of the DID regression with only county and time fixed effects while columns (2) include controls for individual-level characteristics and county-level time varying characteristics. Separate regressions were run for individuals residing in metropolitan counties and for non-metropolitan counties.

Without the additional controls, CMC/MLTSS programs are associated with higher overall hospitalization rates in both non-metropolitan and metropolitan counties (Table 3.11). The PQI rate is also higher in the non-metropolitan counties with CMC/MLTSS programs as compared to those with no CMC/MLTSS programs. In the preferred specification, controlling for individual and county characteristics in addition to the fixed effects, the coefficient on CMC/MLTSS is 0.005 for non-metropolitan counties. This can be interpreted as, counties with CMC/MLTSS programs experience an increase in hospitalization rates of 0.5 percentage points relative to those with no program. From the baseline rate of 11.7%, this is an increase of 4.3%. While the coefficient on CMC/MLTSS in metropolitan counties is also positive, it is no longer statistically significant when additional controls are included. For both groups of counties, the effect on the outcome of PQI is a precisely estimated zero using the preferred specification.

Results examining CMC and MLTSS programs separately are quite similar to these results looking at them as a combined treatment. The CMC program type DID analyses were only conducted in metropolitan counties because there were very few non-metro counties with mandatory enrollment CMC programs. In these metropolitan counties, the point estimates of the effect of CMC programs on both hospitalization and PQI are the same with and without the additional controls but adding the controls increases precision of the estimates. Using the preferred specifications in columns (2), CMC programs are associated with increases in overall hospitalization of 0.4 percentage point but no statistically significant increase in the rate of PQI (Table 3.12).

MLTSS programs are also associated with increases in the rate of any hospitalization, with statistically significant effects only in the non-metro counties (Table 3.13). Again, there is no change in PQI rates associated with mandatory MLTSS programs.

3.7.4 DID Results - Stratification

For each plan type and the two outcomes, I further stratified the sample by individual characteristics (in addition to metro/non-metro county). For each set of results tables, the first two tables show results split by the beneficiary characteristics of original reason for Medicare entitlement (aged versus disabled); number of chronic conditions (0-3 versus 4 or more) and long-term care use in the prior period. The next two tables shows results stratified by the (non-mutually exclusive) ten most prevalent chronic conditions.

I summarize the findings from this series of tables in the following sections.

CMC / MLTSS

Tables 3.14-3.17 show results for changes in CMC/MLTSS program enrollment for the two outcomes. The finding that CMC/MLTSS enrollment is associated with modest increases in the overall rate of hospital use but no change in PQI rate is consistent across the most of the subgroups examined. Also as in the overall results, larger effects are found for non-metropolitan counties. Table 3.14 shows that effects are larger among beneficiaries with many (versus few) chronic conditions as interpreted from the magnitudes of the coefficient point estimates in those two subgroups. While there are fewer statistically significant estimates in metro counties, patterns of magnitudes of the point estimates are similar in these counties (Table 3.15).

When I stratified by chronic condition, Tables 3.16 and 3.17 show that CMC/MLTSS does appear to cause increases in hospitalization concentrated among individuals with some conditions and not others. The largest effects are for the groups with rheumatoid arthritis, ischemic heart disease and COPD; these effects are statistically significant in the non-metro counties. Patterns of magnitudes are similar in the metropolitan counties, but as in the other results, there are fewer statistically significant effects in these counties. As in the main results, there is no association of CMC/MLTSS programs and changes in rates of PQI in any of these subgroups analyzed.

CMC excluding LTC

Results for estimation of the effects of CMC programs that exclude LTSS are reported in Tables 3.18 and 3.19. The finding in the overall DID results, that CMC programs are associated with small increases in hospitalization and no change in PQI, does appear to be driven by effects in specific subgroups. The magnitudes of the coefficients and their statistical significance in Table 3.18 suggest that the increase in hospitalization due to CMC is concentrated among individuals eligible for Medicare due to disability, not age, and those with four or more chronic conditions.

Turning to subgroups by chronic condition (Table 3.19), beneficiaries with ischemic heart disease, anemia and depression experienced the largest increases in overall hospitalization rates associated with mandatory CMC programs. Consistent with the overall results, all groups had positively signed coefficients for both outcomes.

MLTSS

Stratified DID analyses assessing heterogeneous effects of MLTSS expansions are reported in Tables 3.20-3.23. For non-metro counties, MLTSS programs are associated with statistically significant increases in the rate of any hospitalization for the subgroups split by reason for Medicare entitlement and count of chronic conditions. While the point estimates are the same for the aged and disabled sub-groups, they are different when stratifying by many versus few chronic conditions. The larger magnitude coefficient of 0.010 for those with 4+ chronic conditions, compared to 0.003 for those with 0-3 conditions, suggests that MLTSS plans may have more of a negative effect for sicker beneficiaries. Consistent with the overall results, in non-metropolitan counties, MLTSS plans were not associated with changes in the rate of PQI, with the exception of a small decrease in the rate of PQI for those beneficiaries that did not use LTC.

As in the overall results, there are fewer statistically significant effects in the metropolitan counties, with only the group with 0-3 chronic conditions having statistically significant increases in the rate of any hospitalization associated with MLTSS programs (Table 3.21). However, the magnitudes of the point estimates follow a similar pattern as in the non-metro counties. The negative and statistically significant coefficient of -0.003 among those individuals using LTC on the outcome of PQI shows the only statistically significant reduction in PQI associated with MLTSS programs.

Stratifying by chronic conditions shows findings consistent with the overall results. For non-metropolitan counties, MLTSS is associated with increases in the rate of any hospitalization among all subgroups. Those with the largest effects are hypertension, rheumatoid arthritis, ischemic heart disease, CHF, and COPD (Table 3.22). None of the condition subgroups had associations between MLTSS programs and the rate of PQI. And again, as in the overall results, the increases in hospitalization that were found in the non-metropolitan counties are of smaller magnitude in the metropolitan counties: none of the subgroups examined had statistically significant increases in the rate of overall hospitalization or PQI associated with MLTSS programs in metropolitan counties.

3.7.5 IV results

Selection and IV validity

Beneficiary characteristics split by beneficiary MMC enrollment status for the IV analysis are reported in Table 3.24. Differences across columns illustrates the selection at the individual level into MMC. In general, healthier individuals appear to enroll in CMC and PCCM plans while sicker people enroll in MLTSS plans and remain in FFS Medicaid. MLTSS enrollees are similar in age to FFS enrollees, while CMC and PCCM enrollees are younger. Whites are more likely to remain FFS and PCCM, and to a lesser extent CMC, than enroll in MLTSS plans. There are also differences across non-white groups, with blacks also more likely to enroll in PCCM and FFS than CMC or MLTSS while Hispanic and Asians are less likely to be in PCCM and FFS and more likely to be in CMC and MLTSS. These differences are likely due in large part to the geographic differences in racial composition of Medicaid enrollees in counties that offer the different types of MMC plans. While about half of enrollees in CMC and MLTSS plans are aged vs. disabled, only one third of PCCM enrollees are aged and two thirds are disabled suggesting that the composition of beneficiaries in PCCM programs is quite different from that in CMC and MLTSS programs. In terms of health status, those that remain FFS or enroll in MLTSS are more likely to use LTC and have six or more chronic conditions than those that enroll in CMC or PCCM. The rates of hospitalization and potentially avoidable hospitalization are also higher among FFS and MLTSS than CMC and PCCM enrollees. Turning to county characteristics, CMC/MLTSS programs are adopted in more metropolitan counties while PCCM is used in non-metropolitan counties. Consistent with non-metropolitan counties having poorer performing economies, the unemployment rate and poverty rates are highest and income lowest among PCCM enrollees. Beneficiaries with FFS or MLTSS enrollment tend to live in places with higher than average supply of physicians, hospital beds and nursing facility beds per capita.

This differential selection of beneficiaries into MMC motivates the use of instrumental variables methods to estimate the causal impact of MMC on hospital use. Results from the checks of conditional exogeneity using regressions for each plan type are shown in Table 3.25. The four columns represent results from separate regressions. Because of the large sample size, some tests for significance have p-values indicating statistical significance. However, in general, coefficients of the regression on the share of MMC enrollment among Medicaid-only beneficiaries are small in magnitude giving me confidence in the validity of the instrument.

Overall IV Results

Tables 3.30-3.33 show the overall IV estimation results. The first column of each table shows results from the first stage regression of the county-level share of non-disabled, non-elderly Medicaid-only beneficiaries (non-duals) on individual level enrollment of duals that type of MMC program. The Wald F-statistic from the test of significance for the instrument in the first stage is also reported. The columns labeled No IV are for the OLS regression of the indicator of MMC enrollment on hospitalization and potentially avoidable hospitalization. These coefficients are biased if there is selection into MMC. The columns labeled IV are the coefficients on predicted MMC enrollment from the second stage of the IV estimation and are the preferred estimates of the effect of MMC on hospital use.

As in the DID analyses, the IV analyses are stratified by county metropolitan status. In non-metro counties, voluntary enrollment CMC/MLTSS programs are associated with declines in the rate of any hospitalization and PQI (Table 3.30). The coefficient of -0.012 can be interpreted as follows: enrolling in a CMC/MLTSS plan is associated with a decrease in the rate of any hospitalization of -1.2 percentage points, or approximately 12% of the baseline rate of hospitalization of 9.98%. Similarly, CMC/MLTSS enrollment is associated with a decline of 0.8 percentage points, or 30% of the baseline rate of 2.69%. While the coefficients are also negative in the IV results for metropolitan counties, they are not statistically significant, due in part to the lower strength of the instrument in the analyses of metropolitan counties.

Comparing the OLS coefficients to the coefficients using IV can tell us something about the nature of the selection into CMC/MLTSS programs when there is voluntary enrollment and for a specific subgroup: the compliers specific to this instrument. Using the estimates of the outcome of any hospitalization, the OLS coefficient of -0.002(0.001) is interpreted as there is no statistically significant effect of CMC/MLTSS enrollment on hospital use. However, if there is selection into CMC/MLTSS programs (relative to who remains in FFS), then this result is biased. The coefficient in the IV estimation yields the LATE for the group of beneficiaries induced to opt in to a CMC/MLTSS plan because of the high CMC/MLTSS enrollment rate in their county among non-duals. That is, for those compliers, the local average treatment effect of CMC/MLTSS enrollment is a decrease in hospitalization rates of 1.2 pp, or 12%. Controlling for selection, among this specific subgroup of beneficiaries, results in a relatively large decline in hospital use where the OLS regression which did not address selection estimated no change. This implies that the people who opt in to CMC/MLTSS programs are *more* likely to be hospitalized than we'd predict using observable characteristics that are controlled for in the OLS model. This is counterintuitive: the literature for commercial health insurance and Medicare suggests that healthier people opt-in to managed care while sicker individuals remain FFS.

Similar to the analyses of CMC/MLTSS plans together, CMC programs with voluntary enrollment are associated with statistically significant decreases in any hospitalization and potentially avoidable hospitalization in non-metropolitan counties but not metropolitan counties (Table 3.31). CMC plan enrollment is associated with a decrease of 1.8pp, or 10%, in the rate of hospitalization. Enrolling in a CMC plan is associated with a decrease in the rate of PQI of 1pp, or approximately one-third of the baseline rate. As in the CMC/MLTSS program analysis, the coefficients are similar in sign in metro counties but are imprecisely estimated so effects are not statistically significant. Comparing the OLS and IV estimates, patterns are similar to the CMC/MLTSS analyses: OLS estimates are smaller in magnitude than the effects estimated by the IV method, again suggesting that OLS does not adequately account for selection of those more likely to be hospitalized into CMC plans.

The decline in hospitalization associated with CMC/MLTSS enrollment when the two plan types are analyzed together (Table 3.30) is due to this decline in hospitalization associated with CMC enrollment. Coefficients when treatment is MLTSS are relatively large in magnitude, positively signed, and not statistically significant (Table 3.32). MLTSS programs are associated with a significant increase in the rate of PQI in non-metro counties only. Enrollment in an MLTSS plan is associated with an increase in 2.5pp, or nearly doubling of the baseline rate of 2.69%. The magnitude of the coefficient on MLTSS for metropolitan counties is even larger, but is not statistically significant because of the larger standard error of the estimate. Also, the nature of selection appears to be different for the MLTSS programs as compared to the CMC programs. Now, OLS estimates underestimate the effect of MLTSS on hospital use. The coefficients become more positive when IV is used - this is selection in the direction we expected. Healthier individuals, that we'd predict to use hospital care less using observable characteristics in the claims data, enroll in MLTSS plans. Controlling for this selection results in the large increases in hospital use associated with MLTSS that are under-estimated using OLS.

Finally, the overall IV results for the PCCM programs are shown in Table 3.33. In counties with voluntary enrollment, the naive estimate without using IV shows that individuals that enroll in PCCM have lower overall hospitalization rates than those that remain in FFS. However, when accounting for selection using IV, the coefficients are no longer statistically significant. I conclude that enrollment in a PCCM plan is not associated with changes in the rate of any hospitalization or PQI in either metro or non-metro counties.

3.7.6 IV Results - Stratification

As in the DID analyses, for the IV analyses, I stratify by original reason for Medicare entitlement, few and many chronic conditions, long-term care use, and individual chronic conditions. I provide results in a series of tables, for each outcome, metro vs non-metro counties, and plan type (Tables 3.34 - 3.49).

CMC/MLTSS

The IV analyses of CMC/MLTSS showed a modest decrease in hospitalization rates in non-metropolitan counties associated CMC/MLTSS enrollment. This relationship appears to be concentrated among those qualifying for Medicare due to age, those with 4+ chronic conditions, and among beneficiaries that used long-term care (Table 3.34). This pattern is similar for the outcome of PQI in non-metro counties although the noisier IV estimates result in fewer statistically significant effects. The overall patterns in signs and magnitudes of coefficients are also consistent in the metro counties. However, due to the relatively weak instrument in the metropolitan counties, there are not statistically significant effects for the metro counties (Table 3.35).

Stratification by chronic condition reveals declines in any hospitalization and potentially avoidable hospitalization among the all subgroups with the exception of a positive coefficient for beneficiaries with a diagnosis of depression (Table 3.36). Effects were largest among the subgroup of beneficiaries with anemia, with enrollment in a CMC/MLTSS plan associated with a decrease on the rate of any hospitalization of 3.4 percentage points and the rate of PQI of 1.4 percentage points. None of the subgroups examined have statistically significant effects for the metropolitan counties (Table 3.37).

CMC excluding LTC

CMC enrollment was associated with larger declines in hospitalization rates for non-metro counties and insignificant declines for metro counties in the overall sample. Stratifying by beneficiary characteristics show these negative effects were larger for the aged (versus disabled), for beneficiaries with four or more chronic conditions, and for long-term care users in non-metro counties (Table 3.38). Patterns in magnitudes of coefficient are consistent in the metropolitan counties, but due to the lower strength of the instrument in these counties, results are not statistically significant (Table 3.39). These results are very similar to those found when examining CMC/MLTSS as a single treatment.

Looking separately by chronic conditions reveals a statistically significant decrease in the rate of any hospitalization and potentially avoidable hospitalization among most condition groups in non-metro counties. As in the CMC/MLTSS stratification, the largest effects are found among those with a diagnoses of anemia, but effects greater than 2pp are also found for those with diabetes, rheumatoid arthritis, CHF, Alzheimer's disease/dementia and COPD. (Table 3.40). In metro counties, effects are again not statistically significant, but the magnitude of the coefficients are mostly consistent with the findings in non-metro counties with the largest magnitude coefficients among the rheumatoid arthritis, ischemic heart disease, anemia, CHF and COPD subgroups (Table 3.41).

MLTSS

I present stratified results for MLTSS enrollment in Tables 3.42-3.45. The coefficients on MLTSS enrollment for the outcome of any hospitalization are mostly positive, but not statistically significant in the non-metro counties. The estimates of increases in PQI are borderline significant and quite large among the disabled, those with 4+ chronic conditions and those that use LTC. In metropolitan counties, modest increases in the rate of hospitalization and PQI are found among the group with 0-3 chronic conditions. The magnitude of the coefficients are much higher for the group with 4+ chronic conditions, at 0.441 and 0.118 for any hospitalization and PQI respectively, but estimates are imprecise and, therefore, not statistically significant. For both metro and non-metro counties while not statistically significant, it is interesting to note that differences in point estimates between the group that does not use LTC and the group that does suggests that MLTSS enrollment may result in increased hospitalization among people that use LTC while not impacting hospitalization as much among those that do not use LTC services.

The estimates are not statistically significant for most of the subgroups defined by chronic condition in both the non-metro and metro counties (Tables 3.44 and 3.45). The exception is for the outcome of PQI in non-metro counties in the subgroups of beneficiaries with a diagnosis of anemia or depression. For these two subgroups, MLTSS enrollment is associated with increases in the rate of PQI of 5.0 and 3.2 percentage points respectively. It should be noted that the F-statistics for test of instrument strength are quite low in the metro counties when stratifying by chronic condition and that is reflected by the relatively large standard errors for the coefficient estimates.

PCCM

Results in the stratified analyses are consistent with the main IV results for PCCM programs of no statistically significant effects. There is no association between PCCM enrollment and hospitalization using IV methods for the subgroups analyzed for non-metro counties (Tables 3.46 and 3.47) for most subgroups analyzed. There is a statistically significant decline in the rate of overall hospitalization associated with PCCM in the subgroup with few chronic conditions in non-metro counties and also among those with few chronic conditions in metro counties.

In the results stratifying by individual chronic conditions, we find declines in hospitalization rates among those with CHF and COPD in non-metro counties (Table 3.48) and no subgroups in which there are significant findings on PQI. There are also no statistically significant effects for the analyses in metro counties (Table 3.49); however, the the instrument strength is relatively low in the metro county chronic conditions subgroups.

3.7.7 Robustness Checks

Several additional analyses were done as robustness checks. These results are summarized here and detailed in the Appendix.

DID - Addressing sample composition changes

While these main results addressed sample composition changes over time using weighting, I explored two alternative approaches to this problem in the appendix both of which involve restricting the sample.

First, I excluded counties with large changes in the share of duals with FFS Medicare overage during the study time period. This approach, however, turned out to be less useful. In the appendix, I show that when counties with changes in the FFS Medicare enrollment rate of more than 15 percentage points were excluded, over half of treated counties were excluded from the sample (Appendix Table 3.50). Additionally, the lead terms in the DID estimates were statistically significant when analyzing the CMC and MLTSS programs separately providing some evidence that the parallel trends assumption required of DID analyses was violated in this subsample of counties (Appendix Tables 3.52 and 3.53). Because of the loss of generalizability due to omitting such a large share of counties and the inability to control for differences in pre-trends in the counties that remained, this approach was abandoned.

Second, I restricted the sample to individuals that were observed in all ten periods of the data from Q2-2005 to Q4-2012 with FFS Medicare coverage. Again, this is a large sample restriction: the high mortality rate in the dual population, and the expansion of FFS Medicare during the study time period means that this restricted sample is younger, more disabled, and with fewer chronic conditions (at baseline) relative to the main sample (Appendix Table 3.54). With this limitation in mind, I then estimated the DID analyses in the balanced panel. I found that CMC/MLTSS, CMC and MLTSS programs were associated with no change in hospital use. This is consistent with the null findings among the subgroups with 0-3 chronic conditions in the main DID results but not with the overall DID results that showed increases in hospital use associated with all three MMC program types analyzed with DID. This provides some evidence that the changing sample composition over time, and weighting used to address it, did not drive the results found using DID.

Individual fixed effects framework

An alternative to the DID analysis with treatment defined at the county level is an event study framework in which treatment is defined at the individual level and individual fixed effects are used to estimate a within person effect of MMC enrollment. In the appendix, I complete a set of analyses using individual-level fixed effects and instrumental variables where the instrument is the presence of a mandatory enrollment policy in the county to account for potential selection of individuals into MMC. Using this alternative method, I find no effect of CMC/MLTSS, CMC (metro counties only) or MLTSS programs on the overall rate of hospitalization or PQI. These null findings complement the effects of small magnitude I find in the DID results. While the DID results estimate average treatment effects in mandatory enrollment counties, these individual level treatment effects are for the subset of individuals that are compliers and enroll in MMC due to the mandatory enrollment policy. These null findings, therefore, suggest that the DID estimates are robust to this alternative specification given that the null finding and small increases in hospital use in the DID are in fact quite similar.

Mortality as competing risk

A potential concern with both the DID and IV analyses is that observations that die without being hospitalized are coded as zero for the binary outcome of hospitalization. It is possible that enrollment in an MMC plan affects both the risk of hospital use and death and that the two outcome should be analyzed jointly in a competing risk framework. As an alternative to that approach, I investigate the sensitivity of my main results to biases introduced because of death as an alternative outcome by performing two sets of additional analyses in the appendix. First, I repeat the main DID and IV estimation excluding individuals that died during the study period. This means that all observations in this restricted sample were alive for the full quarter. Second, I examine an alternative binary outcome that is coded as 1 if the beneficiary died and/or was hospitalized during the quarter and 0 if they neither died or were hospitalized. Results from these analyses are reported in Tables 3.68-3.81. Results were similar to the main analyses (magnitude of coefficients and statistical significance) giving me confidence that mortality was not driving the main results.

3.8 Discussion

In this study of MMC using national data, I find that the different plan types analyzed have differing effects on hospitalization that vary across subgroups of counties and individuals. I use DID methods to analyze programs with mandatory enrollment policies and IV to analyze counties with voluntary enrollment. Overall, I find that MLTSS programs are associated with small increases in hospital use. CMC programs have mixed effects on hospital use and PCCM programs are not associated with changes in hospital use.

Analyses stratified by individual level characteristics shed light on what groups are most affected by these recent MMC expansions to duals. MLTSS programs are associated with increases in hospitalization and potentially avoidable hospitalization for some subgroups. Using both DID and IV, those individuals with four or more chronic conditions experience larger increases in hospital use due to MLTSS enrollment than do those with 0-3 chronic conditions. The IV analyses also revealed that individuals that previously used LTC experienced increases in hospital use and PQI while those that did not use LTC had much smaller changes in hospital use associated with MLTSS enrollment.

Finally, PCCM enrollment is not associated with changes in hospitalization. This is perhaps not surprising given there is financial incentive to reduce hospital spending and limited ability to do so when Medicaid-paid services remain FFS under this model of MMC.

These findings support the financial incentives plans face in the different managed care models. The large majority of plan costs for CMC plans that exclude LTC services are for Medicare cost-sharing payments. As a result, these plans have a strong financial incentive to decrease hospital use. However, because Medicaid is the second payer for most care that the health plan is responsible for, CMC plans may have limited ability to alter hospital utilization patterns. In contrast, MLTSS plans cover LTC costs in addition to Medicare cost-sharing. As a result, they have a less strong incentive to reduce hospital spending. While MLTSS plans would have higher profits if they reduce hospital costs, if they can save more money by reducing long-term care costs and paying for more hospital care (as second payer), this may blunt the incentive and result in the effects I find.

If the differences in plan type effects are due to incentives related to fragmentation because of the two payers as I hypothesize, it will be interesting to compare results found here with evaluations of the newer Medicare-Medicaid financial alignment initiative demonstrations. In fact, the small effect sizes I find are consistent with the limited evaluations on these newer financial alignment initiative programs. For example, evaluation of an early integrated managed care program in Massachusetts found that there was no effect of the program on hospital readmission rates (Jung et al., 2015). Similarly, an evaluation of the Medicare-Medicaid financial alignment demonstration in South Carolina, while they found sicker beneficiaries remained FFS in this voluntary program, found no improvements in hospitalization rates or other short-term health outcomes (Chen, Yang, and Gajadhar, 2018). A recent overview of the evidence on aligned Medicare-Medicaid plans including the financial alignment initiative and also D-SNP and PACE was commissioned by MACPAC (*Evaluations of Integrated Care Models for Dually Eligible Beneficiaries Key Findings and Research Gaps* 2019). Results from that overview indicate that integrated models generally reduce hospitalization rates but have mixed results with respect to changes in utilization for emergency rooms and long-term care. So while my findings indicate small or no changes in hospitalization rates for the Medicaid-only managed care models that are not integrated, there may be more promise in the integrated models. My study does suggest that Medicaid-only managed care on its own may not produce the reduction in hospital use that is achieved under the newer integrated plans.

While claims data allow me to study the effects of MMC on one important utilization-based outcome, hospitalization, it is important to note that this is just one measure of plan performance. Future studies examining these effects using richer data sources are warranted. For example, survey-based evaluations could evaluate how enrollees perceive quality of care and ease of access to providers under these managed care arrangements. Additionally, newer data sources and improved quality in encounter records for Medicare and Medicaid services provided by health plans will allow for more detailed evaluations of utilization-based outcomes which may be able to determine the mechanisms behind the changes in hospital use I find. One example of this line of research examines primary care visits around MMC transition specific to disabled Medicaid-only beneficiaries in IL in 2011 (Owen et al., 2019). This study finds that MMC enrollees were more likely to have a primary care visit in the year after MMC enrollment, relative to those in a matched control group that remained FFS. However, they were less likely to see the same provider before and after MMC enrollment. This suggests that the additional primary care engagement of MMC may come at the cost of loss of continuity of care. However, this is a single state study of a particular population of Medicaid-only beneficiaries and may not be representative of experiences in other programs or markets.

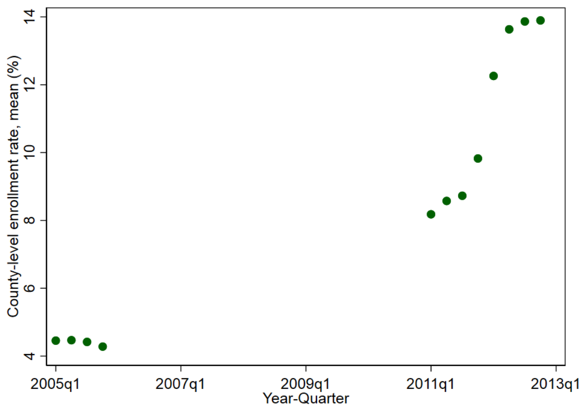
Finally, the differences between the OLS and IV estimates in voluntary counties warrant some discussion. For CMC programs, OLS estimates of no effect of CMC on hospital use but IV estimates of declines in hospital use due to CMC suggests that people more likely to be hospitalized enroll in CMC than remain in FFS. The opposite relationship is found for MLTSS programs: OLS shows no effect or small increases in hospital use due to MLTSS while IV shows larger increases in hospital use, implying those that are less likely to be hospitalized are opting into MLTSS programs. While the MLTSS estimates align with the prevailing conclusions in the literature that healthier people opt into managed care, the CMC results do not. This difference from the literature could have two different explanations. First, it could be driven by the unique group of compliers that are identified by the particular instrument of CMC/MLTSS program enrollment among non-duals. Perhaps individuals that enroll in a CMC/MLTSS program because of CMC/MLTSS penetration at the county level, rather than for some other reason, have different characteristics than the compliers for whom the LATE is identified. Examining other characteristics which are not observed in the claims data, but that could be critical in the decision to join managed care and be hospitalized, such as family caregiving and social supports is key to disentangling this mechanism but beyond the scope of this paper based on claims data only. Second, it could be that healthier duals do select into CMC plans on average and those in poorer health select in to MLTSS plans. Evidence on selection in MMC is mixed in the other studies, more so than in Medicare and commercial markets. Medicare evidence points to less advantageous selection in Medicare Advantage over time [[Author's note: Needs citation]]. And there has been very little evidence to date about how duals with FFS Medicare select or do not select in to MMC programs. So this could be a feature of duals and Medicaid managed care coverage that could be further explored in future studies.

3.9 Conclusions

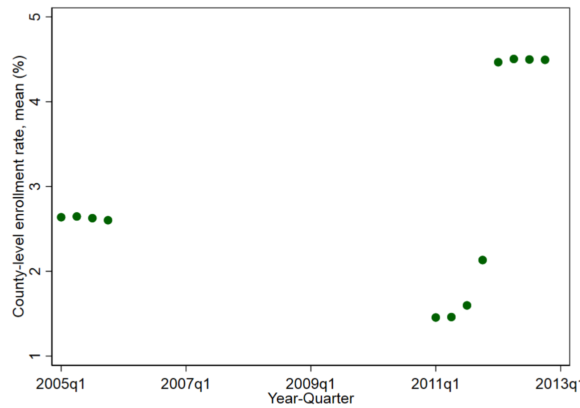
This study uses national data to study the effect of MMC on hospital use for duals. I find that, in the overall sample, MLTSS programs are associated with increases in hospitalization rates, especially among beneficiaries with many chronic conditions. CMC programs are associated with increases in hospital use where enrollment is mandatory and decreases in hospital use where enrollment is voluntary and in the group of compilers for my particular instrument. Finally, PCCM plans in all counties are associated with no changes in hospitalization rates. Policymakers will continue to struggle with how to finance growing Medicaid costs as the population ages and demand for long-term care services increases over time. This study constitutes an important first step in understanding how managed care impacts the dually enrolled, an especially vulnerable and high-cost population of Medicaid beneficiaries.

3.10 Figures

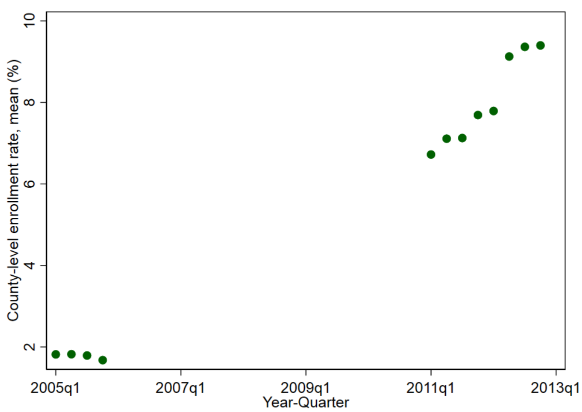
Figure 3.1: County-level Medicaid managed care penetration rates by plan type



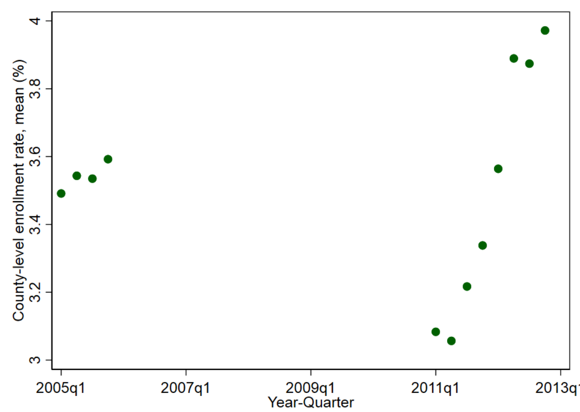
(a) CMC or MLTSS



(b) CMC excl. LTSS



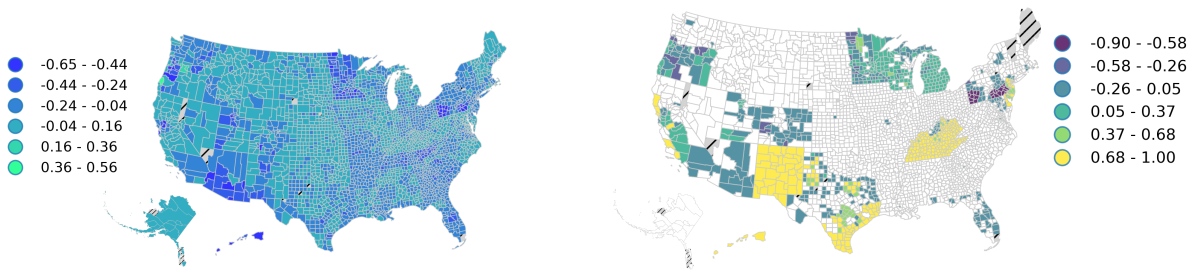
(c) MLTSS



(d) PCCM

Source: MAX/MBSF data. Limited to full-benefit duals with FFS Medicare and valid county codes. Excludes counties from two states: ME and VT and the most rural counties (rural-urban continuum codes 8 and 9).

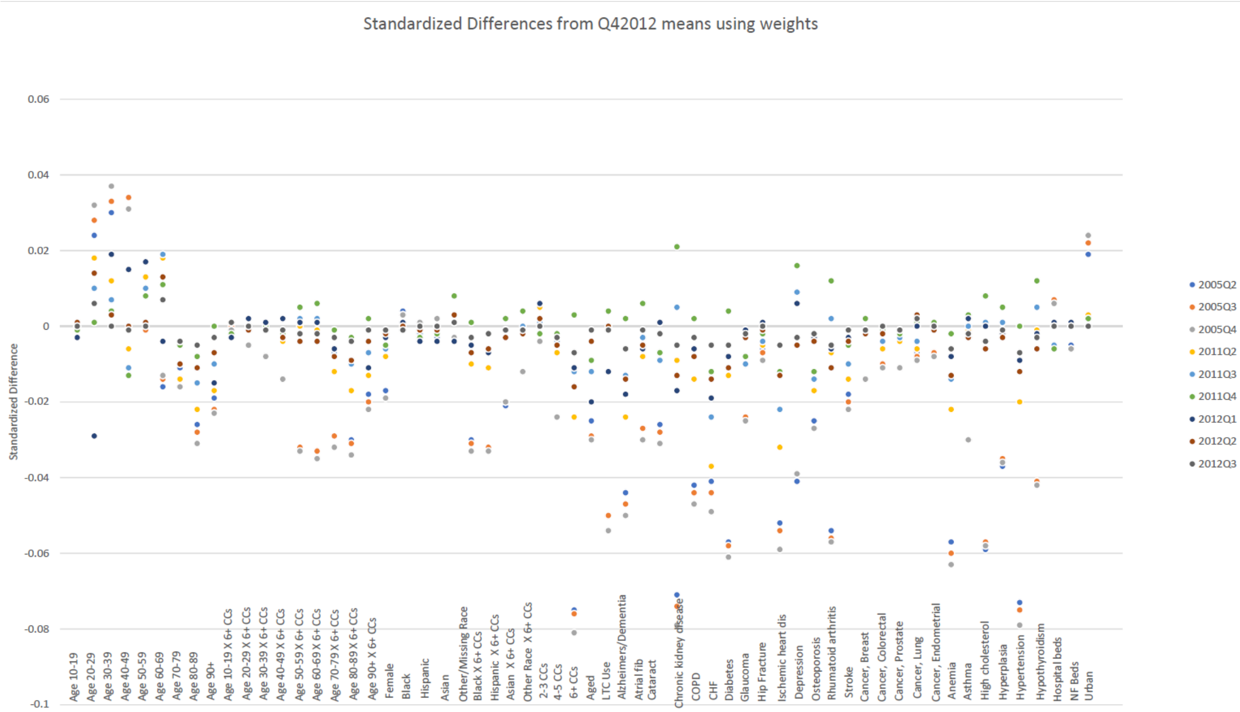
Figure 3.2: Correlation between changes in FFS Medicare and CMC/MLTSS Shares, from Q4-2005 to Q4-2012 changes



(a) FFS Medicare (b) CMC or MLTSS

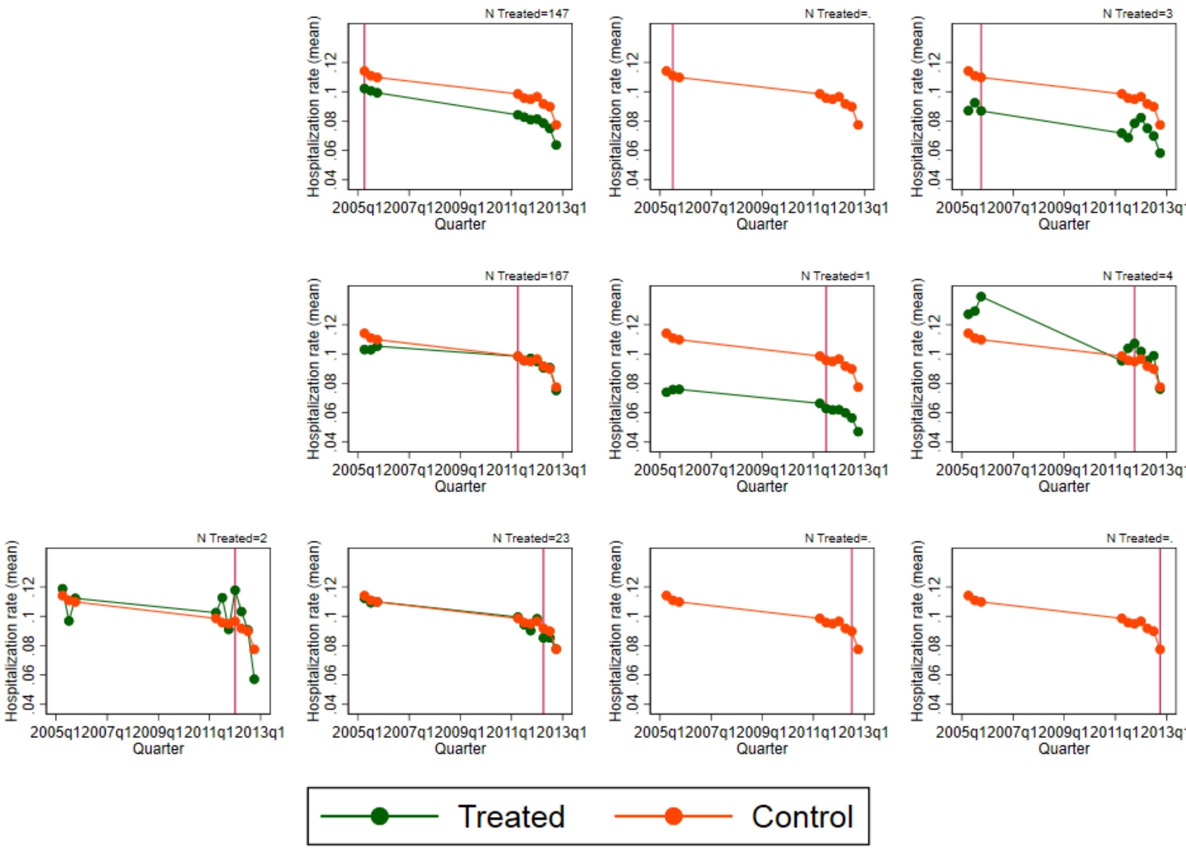
Source: MAX/MBSF data. Limited to full-benefit duals with valid county codes.

Figure 3.3: Standardized differences in means from 2012Q4 of variables used to generate propensity score



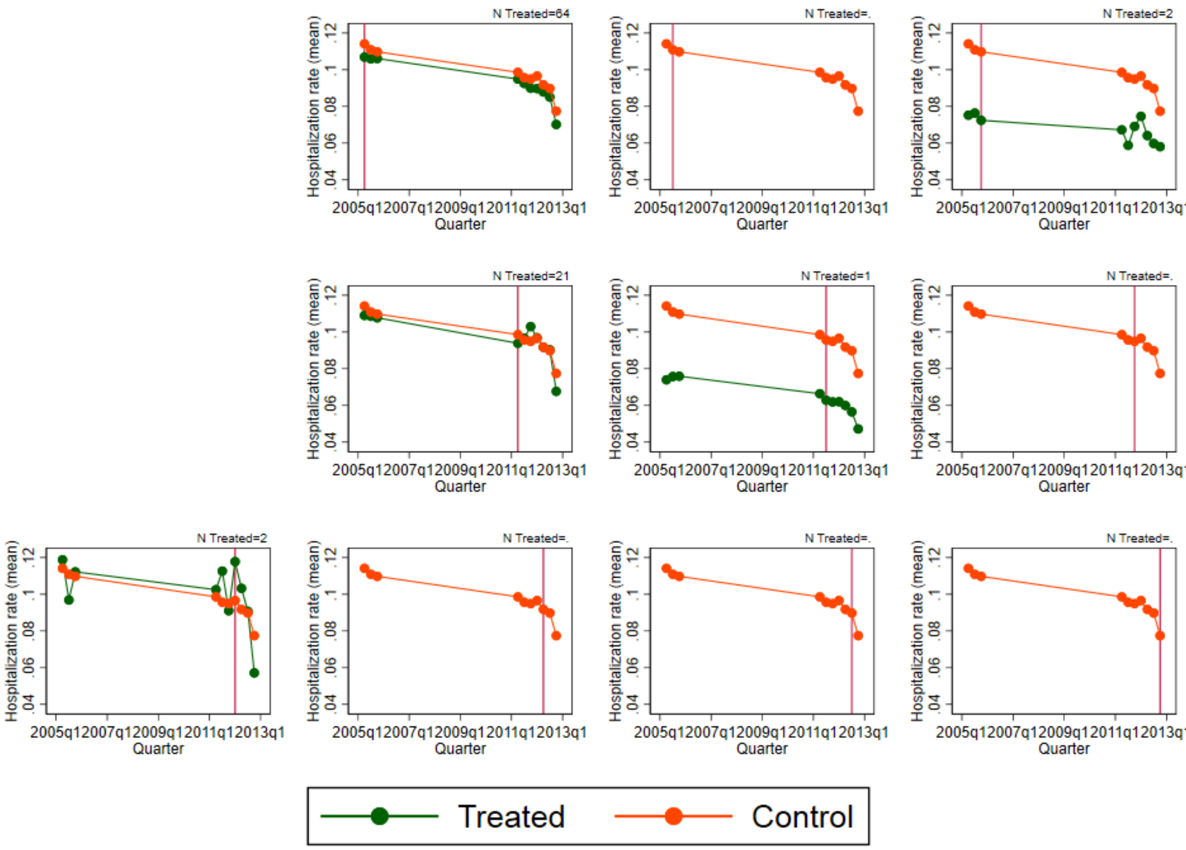
Propensity score weights generated separately for each time period where propensity score estimates Pr(t=Q42012).

Figure 3.4: Plots of pre-trends by MMC start period - CMC or MLTSS



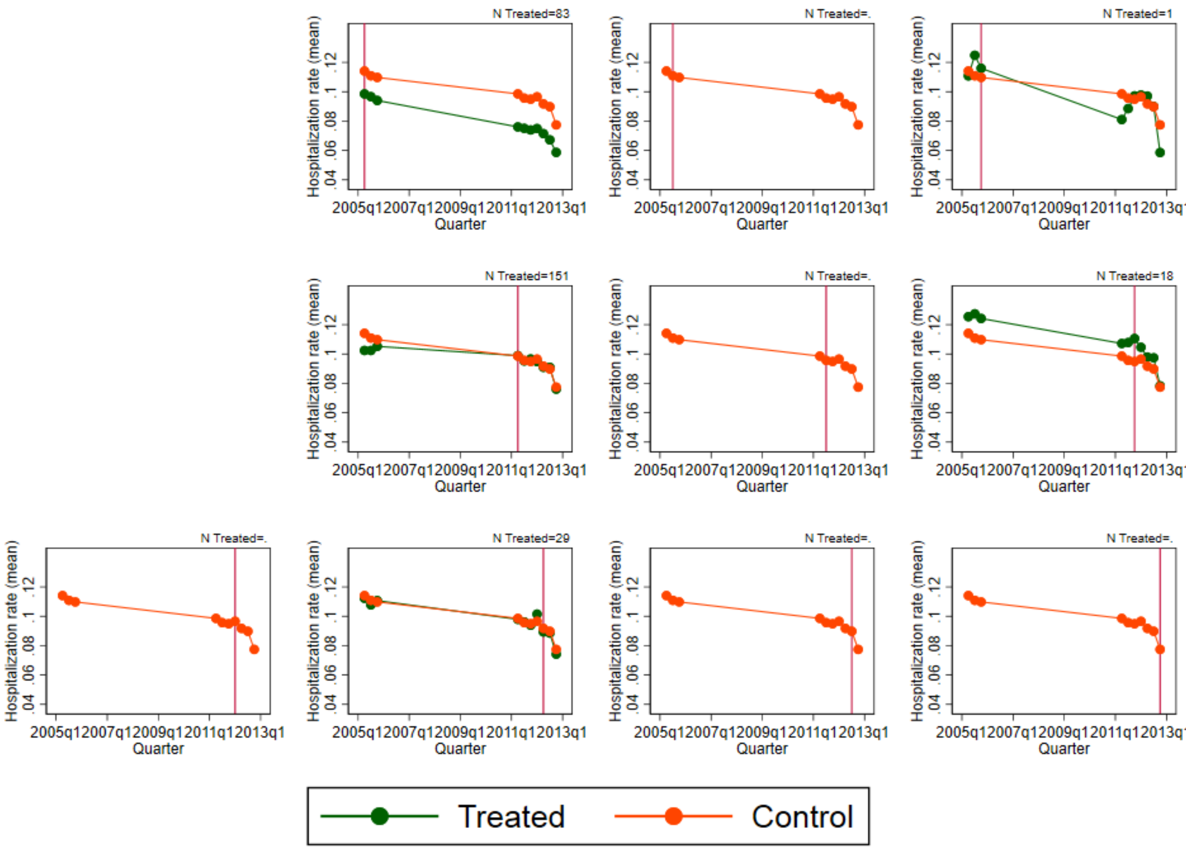
Source: MAX/MBSF data. Limited to full-benefit, FFS Medicare duals. Treatment determination and hospitalization rates calculated at the county level. Red vertical lines indicate first period MMC enrollment observed. N treated in upper right of each plot indicates number of treated counties that had first MMC enrollment observed in that quarter.

Figure 3.5: Plots of pre-trends by MMC start period - CMC excl. LTSS



Source: Source: MAX/MBSF data. Limited to full-benefit, FFS Medicare duals. Treatment determination and hospitalization rates calculated at the county level. Red vertical lines indicate first period MMC enrollment observed. N treated in upper right of each plot indicates number of treated counties that had first MMC enrollment observed in that quarter.

Figure 3.6: Plots of pre-trends by MMC start period - MLTSS



Source: Source: MAX/MBSF data. Limited to full-benefit, FFS Medicare duals. Treatment determination and hospitalization rates calculated at the county level. Red vertical lines indicate first period MMC enrollment observed. N treated in upper right of each plot indicates number of treated counties that had first MMC enrollment observed in that quarter.

3.11 Tables

Table 3.3: Relationship between change in shares FFS Medicare and MMC, by quantile of change in share of FFS Medicare

	1	2	3	4	5
Range Change FFS Medicare	-0.65 - -0.13	-0.13 - -0.07	-0.07 - -0.04	-0.04 - -0.02	-0.02 - 0.56
Change CMC or MLTSS	0.15	0.09	0.07	0.07	0.10
Change CMC	-0.04	0.01	0.01	0.04	0.07
Change MLTSS	0.20	0.08	0.05	0.03	0.03
Change PCCM	0.01	0.00	-0.01	0.01	0.00

Mean changes from Q4 2005 to Q4 2012

Table 3.4: FFS-Medicare and Medicare Managed Care Population Characteristics

	FFS Medicare		Medicare Managed Care	
	Q4-2005	Q4-2012	Q4-2005	Q4-2012
Age, mean	64.5	63.5	72.2	67.0
SD	17.7	17.8	14.0	15.6
Female	62.8	61.1	69.5	64.4
White	54.8	52.7	46.1	40.2
Black	20.1	19.5	22.5	22.4
Hispanic	15.6	16.6	23.6	26.7
Asian	7.2	8.5	6.3	8.9
Other/Unknown Race	2.3	2.7	1.5	1.7
Aged	49.0	44.6	68.8	54.0
Disabled	51.0	55.4	31.2	46.0
LTC Use (t-1)	46.3	48.9	37.6	37.0
CMC/MLTSS Enrolled	8.9	17.1	24.1	34.3
CMC	6.7	7.6	13.9	11.3
MLTSS	2.2	9.6	10.4	23.2
PCCM	2.1	3.4	1.1	1.7
Died	1.8	0.7	2.3	0.6
N	4,976,328	4,674,044	317,211	1,140,327

Source: MBSF-MAX PS-MedPAR files.

Limited to duals enrolled in FFS Medicare with full Medicaid benefits (i.e. full duals)

Table 3.5: Analysis Sample Restrictions

	N	Percent
All duals	77,887,661	
Full-benefit duals	57,772,089	74.17
FFS Medicare	49,556,129	85.78
Valid FIPS code	49,160,137	99.20
Excluding ME and VT	48,592,274	98.84
Excluding RUCC=8,9	47,423,874	97.60
Non-missing data	46,153,253	97.32

Data Source: MAX,MBSF 2005Q2-Q4; 2011Q2-Q4; 2012Q1-Q4

Rural urban continuum code 9= Completely rural or less than 2,500 urban population, not adjacent to a metro area

Table 3.6: Number of treated and control counties DID framework

	Baseline		Mandatory Tx Counties		Ltd control group	
	Treatment	Control	Treatment	Control	Treatment	Control
CMC or MLTSS	895	1,572	347	1,572	347	922
CMC excl. LTSS	508	1,959	90	1,829	90	922
MLTSS	447	2,020	282	1,637	282	922
PCCM	865	1,602	4	1,602	4	922

	Metro Counties		Non-Metro Counties	
	Treatment	Control	Treatment	Control
CMC or MLTSS	203	348	144	574
CMC excl. LTSS	75	348	15	574
MLTSS	143	348	139	574
PCCM	4	348	0	574

Control = counties where enrollment share < 1% all time periods

Baseline = Excludes counties in ME, VT and rural/urban continuum codes 8 and 9

Limited control = Also restricts to no change in Tx status for other plan types

Table 3.7: DID Sample composition changes over time, raw and weighted

	Raw		Weighted	
	Q4-2005	Q4-2012	Q4-2005	Q4-2012
Age, mean	63.5	62.3	62.7	61.8
SD	18.0	18.0	18.0	18.3
Female	62.8	61.2	62.4	61.5
White	59.4	56.5	58.0	58.2
Black	18.9	18.8	18.5	18.7
Hispanic	14.0	15.7	15.0	14.8
Asian	5.2	5.9	5.7	5.5
Other/Unknown Race	2.6	3.1	2.9	2.8
Aged	45.1	40.1	41.9	40.7
Disabled	54.9	59.9	58.1	59.3
LTC Use (t-1)	45.1	50.9	48.7	46.0
0-1 CCs	29.5	26.5	26.5	30.6
2-3 CCs	24.7	22.6	25.3	24.9
4-5 CCs	21.3	20.5	21.5	20.5
6+ CCs	24.5	30.4	26.6	24.0
Metro county	74.5	76.5	76.8	76.8
Hospital beds / 1000	3.6	3.4	3.5	3.5
Nursing facility beds / 1000	0.4	0.4	0.4	0.4
CMC/MLTSS Enrolled	14.6	28.5	14.4	28.1
CMC Enrolled	14.1	26.8	13.8	26.5
MLTSS Enrolled	0.6	1.7	0.6	1.6
PCCM Enrolled	0.1	0.2	0.1	0.3
Hospitalization	10.1	9.1	10.9	7.3
PQI	2.6	2.1	2.7	1.6
Died	1.8	0.7	1.8	0.6
N	2,147,328	2,005,891	1,666,306	1,671,343

Source: MBSF-MAX PS-MedPAR files.

Limited to full-duals enrolled in FFS Medicare.

Excludes individuals living excluded counties (ME, VT, RUCC 8,9, Control group exclusions).

Weighted columns are propensity score weighted to account for sample composition changes over time.

CCs = Chronic conditions; PQI=Potentially avoidable hospitalization.

Table 3.8: Parallel trends exploration, inclusion of leads, CMC/MLTSS

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
CMC/MLTSS, t	0.004	0.002	0.002	0.002	-0.000	-0.001	-0.000	-0.000
	(0.002)*	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
CMC/MLTSS, t+1		0.003		0.001		0.001		0.000
		(0.002)*		(0.001)		(0.001)		(0.000)
CMC/MLTSS, t+2		-0.002		-0.001		-0.001		-0.000
		(0.001)		(0.001)		(0.001)		(0.001)
R2	0.14	0.14	0.15	0.15	0.07	0.07	0.07	0.07
N	3,252,855	3,252,855	10,993,985	10,993,985	3,252,855	3,252,855	10,993,985	10,993,985
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	11.61	11.61	11.69	11.69	3.21	3.21	2.80	2.80
Leads test F-stat		0.078		0.519		0.284		0.593

Regression includes individual and county characteristics and county and quarterly fixed effects.
Individual characteristics are age, sex, race, count chronic conditions,
indicators for each chronic condition, aged (vs disabled), and LTC use.
County characteristics are supply of hospital and nursing facility beds.
Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).
Standard errors clustered by county.
Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
P-value of F-statistic for test of joint significance of lead coefficients reported.
** V2 - Excludes RUCC codes 8,9; generates weights using urban/rural stratification

Table 3.9: Parallel trends exploration, inclusion of leads, CMC excluding LTSS

	Hosp	Hosp	PQI	PQI
CMC, t	0.005	0.002	0.001	0.001
	(0.001)**	(0.001)*	(0.001)	(0.000)
CMC, t+1		0.002		-0.000
		(0.001)		(0.001)
CMC, t+2		0.002		0.001
		(0.001)		(0.001)
R2	0.15	0.15	0.07	0.07
N	8,355,152	8,355,152	8,355,152	8,355,152
Sample	Metro	Metro	Metro	Metro
Mean Outcome	11.69	11.69	2.80	2.80
Leads test F-stat		0.098		0.194

Regression includes individual and county characteristics and county and quarlterly fixed effects.
Individual characteristics are age, sex, race, count chronic conditions,
indicators for each chronic condition, aged (vs disabled), and LTC use.
County characteristics are supply of hospital and nursing facility beds.
Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).
Standard errors clustered by county.
Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
P-value of F-statistic for test of joint significance of lead coefficients reported.
** V2 - Excludes RUCC codes 8,9; generates weights using urban/rural stratification

Table 3.10: Parallel trends exploration, inclusion of leads, MLTSS

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
MLTSS, t	0.004	0.003	0.001	0.002	-0.000	-0.001	-0.001	-0.001
	(0.002)*	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
MLTSS, t+1		0.003		0.001		0.002		0.000
		(0.002)*		(0.002)		(0.001)		(0.001)
MLTSS, t+2		-0.002		-0.003		-0.001		-0.001
		(0.001)		(0.001)**		(0.001)		(0.001)*
R2	0.14	0.14	0.15	0.15	0.07	0.07	0.07	0.07
N	3,201,822	3,201,822	8,181,052	8,181,052	3,201,822	3,201,822	8,181,052	8,181,052
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	11.61	11.61	11.69	11.69	3.21	3.21	2.80	2.80
Leads test F-stat		0.052		0.019		0.149		0.024

Regression includes individual and county characteristics and county and quarlterly fixed effects.
Individual characteristics are age, sex, race, count chronic conditions,
indicators for each chronic condition, aged (vs disabled), and LTC use.
County characteristics are supply of hospital and nursing facility beds.
Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).
Standard errors clustered by county.
Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
P-value of F-statistic for test of joint significance of lead coefficients reported.
** V2 - Excludes RUCC codes 8,9; generates weights using urban/rural stratification

Table 3.11: Overall DID results - CMC/MLTSS

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
CMC/MLTSS	0.008	0.005	0.004	0.002	0.002	0.000	0.001	-0.000
	(0.001)**	(0.002)**	(0.001)**	(0.001)	(0.001)**	(0.001)	(0.000)	(0.000)
R2	0.01	0.14	0.00	0.14	0.00	0.07	0.00	0.06
N	4,209,606	4,209,606	14,280,645	14,280,645	4,209,606	4,209,606	14,280,645	14,280,645
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	11.68	11.68	11.70	11.70	3.24	3.24	2.80	2.80
County,Time FE	X	X	X	X	X	X	X	X
Additional Controls		X		X		X		X
Enrollment rate	71.27	71.27	68.33	68.33	71.27	71.27	68.33	68.33

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).
Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.
Standard errors clustered by county.

Table 3.12: Overall DID results - CMC excluding LTSS

	Hosp	Hosp	PQI	PQI
	(1)	(2)	(1)	(2)
CMC	0.003	0.004	0.001	0.001
	(0.002)*	(0.001)**	(0.001)	(0.001)
R2	0.01	0.15	0.00	0.07
N	11,061,019	11,061,019	11,061,019	11,061,019
Sample	Metro	Metro	Metro	Metro
Mean Outcome	11.70	11.70	2.80	2.80
County,Time FE	X	X	X	X
Additional Controls		X		X
Enrollment rate	62.56	62.56	62.56	62.56

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).
Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.
Standard errors clustered by county.

Table 3.13: Overall DID results - MLTSS

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MLTSS	0.008	0.005	0.005	0.002	0.002	-0.000	0.000	-0.001
	(0.002)**	(0.002)**	(0.002)*	(0.002)	(0.001)*	(0.001)	(0.001)	(0.001)
R2	0.01	0.14	0.00	0.14	0.00	0.07	0.00	0.06
N	4,146,491	4,146,491	10,793,139	10,793,139	4,146,491	4,146,491	10,793,139	10,793,139
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	11.68	11.68	11.70	11.70	3.24	3.24	2.80	2.80
County,Time FE	X	X	X	X	X	X	X	X
Additional Controls		X		X		X		X
Enrollment rate	73.03	73.03	75.79	75.79	73.03	73.03	75.79	75.79

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).
Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.
Standard errors clustered by county.

Table 3.14: Stratified DID results (part 1), Non-Metro Counties, CMC or MLTSS

Any Hospitalization, Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC/MLTSS Program	0.005	0.005	0.003	0.009	0.000	0.002
	(0.002)*	(0.002)**	(0.001)**	(0.002)**	(0.001)	(0.002)
R^2	0.15	0.14	0.03	0.12	0.12	0.14
N	1,554,543	2,655,063	2,130,303	2,079,303	1,965,459	2,244,147
Sub-Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable hospitalization, Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC/MLTSS Program	0.000	0.000	-0.000	0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
R^2	0.07	0.06	0.01	0.06	0.06	0.07
N	1,554,543	2,655,063	2,130,303	2,079,303	1,965,459	2,244,147
Sub-Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC

* $p < 0.05$; ** $p < 0.01$

Table 3.15: Stratified DID results (part 1), Metro Counties, CMC or MLTSS

Any Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC/MLTSS Program	0.001	0.003	0.002	0.003	0.000	0.001
	(0.001)	(0.001)	(0.001)**	(0.002)*	(0.001)	(0.002)
R^2	0.15	0.15	0.04	0.13	0.13	0.15
N	6,008,845	8,271,800	7,066,459	7,214,186	7,325,317	6,955,328
Sub-Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC/MLTSS Program	-0.000	-0.000	0.000	-0.000	-0.000	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
R^2	0.06	0.07	0.01	0.06	0.06	0.06
N	6,008,845	8,271,800	7,066,459	7,214,186	7,325,317	6,955,328
Sub-Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC

* $p < 0.05$; ** $p < 0.01$

Table 3.16: Stratified DID results (part 2), Non-Metro Counties, CMC or MLTSS

Any Hospitalization, Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC/MLTSS	0.007	0.006	0.006	0.008	0.012
	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.003)**
R^2	0.13	0.15	0.15	0.14	0.14
N	2,361,961	1,531,284	1,398,976	1,378,581	1,188,313
Sub-group	Hyper-tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC/MLTSS	0.004	0.006	0.007	0.004	0.010
	(0.003)	(0.003)	(0.004)*	(0.003)	(0.004)*
R^2	0.12	0.13	0.13	0.14	0.13
N	1,073,886	1,234,455	844,149	706,901	823,735
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

Potentially avoidable Hospitalization, Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC/MLTSS	0.001	0.001	-0.000	0.001	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
R^2	0.06	0.07	0.07	0.07	0.07
N	2,361,961	1,531,284	1,398,976	1,378,581	1,188,313
Sub-group	Hyper tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC/MLTSS	-0.002	-0.000	-0.000	-0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
R^2	0.06	0.07	0.06	0.06	0.05
N	1,073,886	1,234,455	844,149	706,901	823,735
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).

CHF=Congestive heart failure; AD=Alzheimers disease; COPD=Chronic obstructive pulmonary disease.

Analysis sample consists of full-benefit duals with FFS Medicare.

Controls for individual and county level characteristics and county and quarterly fixed effects

Table 3.17: Stratified DID results (part 2), Metro Counties, CMC or MLTSS

Any Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC/MLTSS	0.003	0.002	0.002	0.002	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)*
R^2	0.14	0.15	0.16	0.14	0.15
N	8,173,483	5,638,788	5,003,668	4,583,932	4,045,796
Sub-group	Hyper tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC/MLTSS	0.003	0.003	0.004	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
R^2	0.13	0.13	0.14	0.14	0.14
N	4,299,859	4,001,368	2,738,536	2,445,232	2,151,775
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

Potentially avoidable Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC/MLTSS	-0.000	-0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.06	0.07	0.07	0.07	0.07
N	8,173,483	5,638,788	5,003,668	4,583,932	4,045,796
Sub-group	Hyper tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC/MLTSS	-0.000	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.06	0.07	0.06	0.06	0.06
N	4,299,859	4,001,368	2,738,536	2,445,232	2,151,775
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).

CHF=Congestive heart failure; AD=Alzheimers disease; COPD=Chronic obstructive pulmonary disease.

Analysis sample consists of full-benefit duals with FFS Medicare.

Controls for individual and county level characteristics and county and quarterly fixed effects

Table 3.18: Stratified DID results (part 1), Metro Counties, CMC excluding LTSS

Any Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC Program	0.003	0.005	0.003	0.006	0.005	0.005
	(0.002)	(0.002)**	(0.001)**	(0.002)**	(0.001)**	(0.002)*
R^2	0.15	0.15	0.04	0.13	0.12	0.15
N	4,545,821	6,515,198	5,500,492	5,560,527	5,491,973	5,569,046
Sub-Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC Program	0.001	0.001	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.000)**	(0.001)	(0.000)**	(0.001)
R^2	0.06	0.07	0.01	0.06	0.05	0.06
N	4,545,821	6,515,198	5,500,492	5,560,527	5,491,973	5,569,046
Sub-Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC

* $p < 0.05$; ** $p < 0.01$

Table 3.19: Stratified DID results (part 2), Metro Counties, CMC excluding LTSS

Any Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC	0.005	0.005	0.006	0.004	0.007
	(0.001)**	(0.002)**	(0.002)**	(0.002)*	(0.002)**
R^2	0.14	0.15	0.16	0.15	0.15
N	6,282,168	4,315,974	3,811,920	3,494,344	3,119,904
Sub-group	Hyper tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC	0.007	0.008	0.005	0.005	0.005
	(0.003)**	(0.003)**	(0.003)*	(0.003)	(0.003)
R^2	0.14	0.13	0.14	0.15	0.14
N	3,316,582	3,131,747	2,126,833	1,891,925	1,680,365
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

Potentially avoidable Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC	0.001	0.000	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.06	0.07	0.07	0.07	0.07
N	6,282,168	4,315,974	3,811,920	3,494,344	3,119,904
Sub-group	Hyper tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC	0.002	0.001	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
R^2	0.06	0.07	0.06	0.06	0.06
N	3,316,582	3,131,747	2,126,833	1,891,925	1,680,365
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).

CHF=Congestive heart failure; AD=Alzheimers disease; COPD=Chronic obstructive pulmonary disease.

Analysis sample consists of full-benefit duals with FFS Medicare.

Controls for individual and county level characteristics and county and quarterly fixed effects

Table 3.20: Stratified DID results (part 1), Non-Metro Counties, MLTSS

Any Hospitalization, Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
MLTSS Program	0.005	0.005	0.003	0.010	0.000	0.002
	(0.002)*	(0.002)**	(0.001)**	(0.002)**	(0.002)	(0.002)
R^2	0.14	0.14	0.03	0.12	0.12	0.14
N	1,532,336	2,614,155	2,092,784	2,053,707	1,923,660	2,222,831
Sub-Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable hospitalization, Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
MLTSS Program	0.000	-0.000	-0.000	0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)*	(0.001)
R^2	0.07	0.06	0.01	0.06	0.06	0.07
N	1,532,336	2,614,155	2,092,784	2,053,707	1,923,660	2,222,831
Sub-Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC

* $p < 0.05$; ** $p < 0.01$

Table 3.21: Stratified DID results (part 1), Metro Counties, MLTSS

Any Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
MLTSS Program	0.002	0.001	0.002	0.005	-0.002	0.001
	(0.002)	(0.002)	(0.001)**	(0.002)*	(0.001)	(0.002)
R^2	0.15	0.15	0.04	0.13	0.13	0.15
N	4,235,949	6,557,190	5,397,763	5,395,376	5,296,128	5,497,011
Sub-Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
MLTSS Program	-0.001	-0.001	0.000	-0.000	-0.001	-0.003
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)*	(0.001)**
R^2	0.06	0.07	0.01	0.05	0.06	0.06
N	4,235,949	6,557,190	5,397,763	5,395,376	5,296,128	5,497,011
Sub-Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC

* $p < 0.05$; ** $p < 0.01$

Table 3.22: Stratified DID results (part 2), Non-Metro Counties, MLTSS

Any Hospitalization, Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
MLTSS	0.008	0.007	0.006	0.009	0.012
	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.003)**
R^2	0.13	0.15	0.15	0.14	0.14
N	2,332,252	1,509,471	1,381,299	1,362,100	1,173,526
Sub-group	Hyper tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
MLTSS	0.005	0.005	0.008	0.005	0.010
	(0.003)	(0.004)	(0.004)*	(0.003)	(0.004)*
R^2	0.12	0.13	0.13	0.14	0.13
N	1,059,705	1,215,738	835,214	700,104	813,576
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

Potentially avoidable Hospitalization, Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
MLTSS	0.001	0.001	-0.000	0.001	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
R^2	0.06	0.07	0.07	0.07	0.07
N	2,332,252	1,509,471	1,381,299	1,362,100	1,173,526
Sub-group	Hyper tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
MLTSS	-0.002	-0.001	-0.001	-0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
R^2	0.06	0.07	0.06	0.06	0.05
N	1,059,705	1,215,738	835,214	700,104	813,576
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).

CHF=Congestive heart failure; AD=Alzheimers disease; COPD=Chronic obstructive pulmonary disease.

Analysis sample consists of full-benefit duals with FFS Medicare.

Controls for individual and county level characteristics and county and quarterly fixed effects

Table 3.23: Stratified DID results (part 2), Metro Counties, MLTSS

Any Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)
MLTSS	0.004	0.003	0.003	0.004	0.006
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)*
R^2	0.14	0.15	0.16	0.14	0.14
N	6,146,570	4,161,283	3,744,034	3,491,406	2,958,645
Sub-group	Hyper tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
MLTSS	0.004	0.001	0.006	0.003	0.004
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
R^2	0.13	0.13	0.14	0.14	0.13
N	3,160,521	3,195,646	2,076,184	1,834,819	1,698,605
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

Potentially avoidable Hospitalization, Metro Counties

	(1)	(2)	(3)	(4)	(5)
MLTSS	-0.000	0.000	-0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.06	0.07	0.07	0.06	0.06
N	6,146,570	4,161,283	3,744,034	3,491,406	2,958,645
Sub-group	Hyper tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
MLTSS	-0.001	-0.002	-0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
R^2	0.06	0.07	0.06	0.06	0.05
N	3,160,521	3,195,646	2,076,184	1,834,819	1,698,605
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).

CHF=Congestive heart failure; AD=Alzheimers disease; COPD=Chronic obstructive pulmonary disease.

Analysis sample consists of full-benefit duals with FFS Medicare.

Controls for individual and county level characteristics and county and quarterly fixed effects

Table 3.24: Beneficiary characteristics by MMC enrollment

	CMC/MLTSS	CMC	MLTSS	PCCM	FFS
Age, mean	61.7	59.5	65.3	59.0	64.5
SD	17.9	17.4	18.2	17.5	17.8
Female	60.7	59.4	62.9	63.7	62.0
White	47.3	51.3	40.9	53.6	54.2
Black	15.6	14.4	17.5	36.8	20.4
Hispanic	22.4	20.8	24.9	4.6	15.4
Asian	12.2	11.3	13.7	2.4	7.5
Other/Unknown Race	2.5	2.2	3.0	2.5	2.4
Aged	46.3	41.3	54.4	33.5	46.5
Disabled	53.7	58.7	45.6	66.5	53.5
LTSS Use (MAX)	38.1	34.0	44.5	35.4	51.2
Any hospitalization	7.3	6.4	8.6	8.0	9.5
PQI	1.7	1.5	2.0	1.9	2.3
Died	0.5	0.5	0.5	0.6	1.0
0-1 Chronic conditions	34.6	38.8	27.7	30.5	24.9
2-3 conditions	23.1	25.6	19.1	26.4	22.6
4-5 conditions	18.5	18.4	18.6	21.8	21.3
6+ Conditions	23.9	17.1	34.6	21.3	31.2
Metro county	86.7	82.9	92.7	66.0	80.9
Unemployment rate	8.7	8.6	8.9	9.1	7.9
Percent in poverty	17.3	17.3	17.3	18.6	16.6
Income per capita	47,239	38,488	61,227	33,646	41,982
Median income	50,935	48,984	54,054	42,045	49,172
MDs/1000 pop	3.5	2.5	5.0	2.0	3.0
Hospital beds/1000 pop	3.6	3.1	4.4	3.2	3.7
SNF beds/1000 pop	0.2	0.2	0.2	0.1	0.3
N	1,482,454	911,956	570,498	1,261,980	38,929,044

Source: MBSF-MAX PS-MedPAR files. Pooled quarterly data from 2005,2011,2012

Limited to duals enrolled in FFS Medicare with Full Medicaid benefits

Excludes individuals residing in counties with mandatory MMC programs

FFS=1 means no Medicaid managed care CMC, MLTSS, or PCCM enrollment

CMC=Enrolled in a CMC plan, MLTSS not available in county.

MLTSS=Enrolled in either CMC or MLTSS plan, MLTSS available in county.

Table 3.25: Conditional IV Balance

Indep. variable	CMC/MLTSS		CMC		MLTSS		PCCM	
	Coef.	P-value	Coef.	P-value	Coef.	P-value	Coef.	P-value
Age 10-19	-0.005	0.000	-0.005	0.000	-0.001	0.000	0.005	0.000
Age 20-29	-0.002		0.001		-0.002		0.002	
Age 30-39	-0.002		0.000		-0.002		0.004	
Age 40-49	-0.003		-0.001		-0.001		0.003	
Age 50-59	-0.004		-0.001		-0.002		0.005	
Age 60-69	-0.004		-0.002		-0.001		0.004	
Age 70-79	-0.006		-0.005		0.001		0.005	
Age 80-89	-0.008		-0.009		0.002		0.005	
Age 90+	-0.008		-0.009		0.003		0.005	
Female	-0.001	0.004	-0.001	0.203	0.001	0.380	0.000	0.435
Race, Black	-0.001	0.002	0.000	0.001	-0.001	0.001	0.000	0.000
Hispanic	-0.000		-0.001		0.000		0.001	
Asian	0.000		0.001		-0.001		-0.001	
Other/Unknown	-0.001		-0.001		0.001		0.001	
2-3 Chronic cond.	-0.000	0.685	0.001	0.462	-0.002	0.276	0.000	0.572
4-5	-0.001		0.002		-0.003		0.001	
6+	-0.001		0.002		-0.003		0.001	
Aged	0.002	0.000	0.001	0.019	-0.000	0.949	-0.001	0.000
LTC Use (t-1)	0.001	0.007	-0.000	0.924	0.001	0.417	-0.001	0.006
AD/dementia	-0.001	0.197	-0.004	0.002	0.003	0.001	-0.001	0.000
Atrial fibrillation	0.000	0.938	-0.002	0.151	0.002	0.042	0.000	0.635
Cataract	0.001	0.000	0.002	0.076	0.000	0.889	0.000	0.766
Chronic kidney dis.	0.001	0.104	-0.002	0.312	0.002	0.119	-0.001	0.005

Table 3.25: Continued from previous page

Indep. variable	CMC/MLTSS		CMC		MLTSS		PCCM	
	Coef.	P-value	Coef.	P-value	Coef.	P-value	Coef.	P-value
COPD	0.001	0.000	0.003	0.001	-0.001	0.063	0.000	0.120
CHF	-0.001	0.014	0.000	0.935	-0.001	0.211	-0.000	0.890
Diabetes	-0.002	0.000	-0.004	0.003	0.002	0.075	0.000	0.188
Glaucoma	0.000	0.776	-0.001	0.278	0.001	0.129	-0.000	0.887
Hip fracture	-0.000	0.460	-0.001	0.726	0.001	0.646	0.001	0.106
Ischemic heart dis.	0.001	0.000	0.002	0.083	-0.001	0.273	0.000	0.054
Depression	0.001	0.029	-0.000	0.738	0.001	0.039	-0.000	0.456
Osteoporosis	-0.002	0.000	-0.004	0.009	0.003	0.077	0.001	0.242
Rheum. arthritis	0.000	0.942	0.001	0.690	-0.001	0.723	0.002	0.159
Stroke	-0.000	0.493	0.001	0.411	-0.000	0.359	0.000	0.297
Breast cancer	-0.000	0.167	-0.001	0.085	0.001	0.125	-0.000	0.461
Colorectal cancer	-0.000	0.605	-0.001	0.336	0.001	0.203	0.000	0.421
Prostate cancer	-0.000	0.359	-0.001	0.023	0.001	0.000	0.001	0.028
Lung cancer	0.001	0.235	-0.000	0.596	0.001	0.121	0.000	0.612
Endometrial cancer	0.000	0.902	0.001	0.586	0.000	0.780	-0.000	0.656
Anemia	0.000	0.874	0.002	0.564	-0.001	0.532	-0.001	0.017
Asthma	-0.001	0.045	-0.001	0.681	-0.001	0.582	0.001	0.173
High cholesterol	0.001	0.019	0.001	0.440	-0.000	0.936	-0.001	0.119
Enlarged prostate	-0.004	0.000	-0.009	0.005	0.005	0.061	0.001	0.328
Hypertension	0.001	0.050	0.000	0.825	0.001	0.160	-0.000	0.016
Hyperthyroidism	0.001	0.006	0.001	0.295	-0.001	0.514	-0.000	0.025

Limited to counties with voluntary enrollment programs

Table 3.26: IV - Endogeneity of treatment exploration, CMC/MLTSS

	MMC=1 Hosp.	MMC=1 PQI	MMC=0 Hosp.	MMC=0 PQI
Z=Share CMC/MLTSS non-duals	-0.004	-0.004	-0.002	-0.001
	(0.011)	(0.006)	(0.001)	(0.001)*
	[0.70]	[0.48]	[0.08]	[0.01]
R^2	0.14	0.07	0.14	0.07
N	197,866	197,866	7,206,014	7,206,014
Sample	Non-Metro	Non-Metro	Non-Metro	Non-Metro

* $p < 0.05$; ** $p < 0.01$

	MMC=1 Hosp.	MMC=1 PQI	MMC=0 Hosp.	MMC=0 PQI
Z=Share CMC/MLTSS non-duals	0.010	0.003	-0.001	-0.001
	(0.006)	(0.003)	(0.002)	(0.001)
	[0.08]	[0.27]	[0.49]	[0.25]
R^2	0.14	0.06	0.14	0.06
N	1,284,588	1,284,588	29,138,253	29,138,253
Sample	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Table 3.27: IV - Endogeneity of treatment exploration, CMC

	MMC=1 Hosp.	MMC=1 PQI	MMC=0 Hosp.	MMC=0 PQI
Z=Share CMC non-duals	-0.005	-0.003	-0.003	-0.002
	(0.014)	(0.007)	(0.001)**	(0.000)**
	[0.74]	[0.70]	[0.00]	[0.00]
R^2	0.14	0.07	0.14	0.07
N	156,363	156,363	7,380,159	7,380,159
Sample	Non-Metro	Non-Metro	Non-Metro	Non-Metro

* $p < 0.05$; ** $p < 0.01$

	MMC=1 Hosp.	MMC=1 PQI	MMC=0 Hosp.	MMC=0 PQI
Z=Share CMC non-duals	0.005	0.007	-0.004	-0.001
	(0.011)	(0.006)	(0.004)	(0.001)
	[0.62]	[0.28]	[0.33]	[0.41]
R^2	0.14	0.06	0.14	0.06
N	755,593	755,593	29,748,889	29,748,889
Sample	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Table 3.28: IV - Endogeneity of treatment exploration, MLTSS

	MMC=1 Hosp.	MMC=1 PQI	MMC=0 Hosp.	MMC=0 PQI
Z=Share MLTSS non-duals	0.044	0.021	0.006	0.004
	(0.038)	(0.014)	(0.003)*	(0.001)**
	[0.25]	[0.16]	[0.03]	[0.00]
R^2	0.16	0.06	0.14	0.07
N	41,503	41,503	7,242,717	7,242,717
Sample	Non-Metro	Non-Metro	Non-Metro	Non-Metro

* $p < 0.05$; ** $p < 0.01$

	MMC=1 Hosp.	MMC=1 PQI	MMC=0 Hosp.	MMC=0 PQI
Z=Share MLTSS non-duals	0.003	-0.003	0.011	0.002
	(0.005)	(0.002)	(0.008)	(0.002)
	[0.51]	[0.16]	[0.14]	[0.18]
R^2	0.15	0.06	0.14	0.06
N	528,995	528,995	30,901,546	30,901,546
Sample	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Table 3.29: IV - Endogeneity of treatment exploration, PCCM

	MMC=1 Hosp.	MMC=1 PQI	MMC=0 Hosp.	MMC=0 PQI
Z=Share PCCM non-duals	0.003	-0.002	-0.002	-0.000
	(0.007)	(0.004)	(0.001)	(0.001)
	[0.67]	[0.61]	[0.15]	[0.33]
R^2	0.15	0.07	0.14	0.07
N	428,975	428,975	7,416,862	7,416,862
Sample	Non-Metro	Non-Metro	Non-Metro	Non-Metro

* $p < 0.05$; ** $p < 0.01$

	MMC=1 Hosp.	MMC=1 PQI	MMC=0 Hosp.	MMC=0 PQI
Z=Share PCCM non-duals	-0.004	-0.003	-0.005	-0.001
	(0.007)	(0.003)	(0.003)	(0.001)
	[0.60]	[0.36]	[0.14]	[0.42]
R^2	0.15	0.07	0.14	0.06
N	833,005	833,005	31,478,005	31,478,005
Sample	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Table 3.30: Overall IV results - CMC/MLTSS, Non-metro and Metro Counties

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share CMC/MLTSS non-duals	0.215				
	(0.028)**				
CMC/MLTSS enrolled		-0.002	-0.012	-0.000	-0.008
		(0.001)	(0.004)**	(0.001)	(0.002)**
N	7,403,880	7,403,880	7,403,880	7,403,880	7,403,880
F-test IV	60.03				
Sample	Non-metro	Non-metro	Non-metro	Non-metro	Non-metro
N Counties	1,315	1,315	1,315	1,315	1,315
Mean Outcome		9.98	9.98	2.69	2.69

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share CMC/MLTSS non-duals	0.070				
	(0.018)**				
CMC/MLTSS enrolled		0.001	-0.014	0.002	-0.010
		(0.002)	(0.027)	(0.001)*	(0.009)
N	30,422,841	30,422,841	30,422,841	30,422,841	30,422,841
F-test IV	14.74				
Sample	Metro	Metro	Metro	Metro	Metro
N counties	1,058	1,058	1,058	1,058	1,058
Mean Outcome		9.33	9.33	2.14	2.14

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with Voluntary Enrollment or no program. Controls for individual and county level characteristics and county and quarter fixed effects. Standard errors clustered by county. Mean outcome = mean in control group (FFS enrolled).

Table 3.31: Overall IV results - CMC excluding LTSS, Non-metro and Metro Counties

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share CMC non-duals	0.199				
	(0.026)**				
CMC excl. LTSS enrolled		-0.003	-0.018	-0.002	-0.010
		(0.002)*	(0.005)**	(0.001)**	(0.003)**
N	7,536,522	7,536,522	7,536,522	7,536,522	7,536,522
F-test IV	58.61				
Sample	Non-metro	Non-metro	Non-metro	Non-metro	Non-metro
N Countiles	1,315	1,315	1,315	1,315	1,315
Mean Outcome		9.94	9.94	2.67	2.67

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share CMC non-duals	0.083				
	(0.012)**				
CMC enrolled		0.000	-0.045	0.002	-0.007
		(0.002)	(0.054)	(0.001)*	(0.012)
N	30,504,482	30,504,482	30,504,482	30,504,482	30,504,482
F-test IV	48.58				
Sample	Metro	Metro	Metro	Metro	Metro
N Counties		1,098	1,098	1,098	1,098
Mean outcome		9.35	9.35	2.14	2.14

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with Voluntary Enrollment or no program. Controls for individual and county level characteristics and county and quarter fixed effects. Standard errors clustered by county. Mean outcome = mean in control group (FFS enrolled).

Table 3.32: Overall IV results - MLTSS, Non-metro and Metro Counties

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share MLTSS non-duals	0.211				
	(0.033)**				
MLTSS enrolled		0.003	0.030	0.004	0.025
		(0.002)	(0.016)	(0.001)**	(0.007)**
N	7,284,220	7,284,220	7,284,220	7,284,220	7,284,220
F-test IV	40.78				
Sample	Non-metro	Non-metro	Non-metro	Non-metro	Non-metro
N Countiles	1,315	1,315	1,315	1,315	1,315
Mean Outcome		9.97	9.97	2.69	2.69

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share MLTSS non-duals	0.094				
	(0.013)**				
MLTSS enrolled		0.006	0.132	0.003	0.030
		(0.003)*	(0.075)	(0.001)*	(0.017)
N	31,430,541	31,430,541	31,430,541	31,430,541	31,430,541
F-test IV	50.56				
Sample	Metro	Metro	Metro	Metro	Metro
N Counties		1,117	1,117	1,117	1,117
Mean outcome		9.39	9.39	2.16	2.16

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with Voluntary Enrollment or no program. Controls for individual and county level characteristics and county and quarter fixed effects. Standard errors clustered by county. Mean outcome = mean in control group (FFS enrolled).

Table 3.33: Overall IV results - PCCM, Non-metro and Metro Counties

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share PCCM non-duals	0.053				
	(0.006)**				
PCCM enrolled		-0.005	-0.029	0.001	-0.008
		(0.001)**	(0.021)	(0.000)*	(0.010)
N	7,845,837	7,845,837	7,845,837	7,845,837	7,845,837
F-test IV	80.04				
Sample	Non-metro	Non-metro	Non-metro	Non-metro	Non-metro
N Countiles	1,315	1,315	1,315	1,315	1,315
Mean Outcome		9.93	9.93	2.66	2.66

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share PCCM non-duals	0.046				
	(0.011)**				
	[0.00]				
PCCM enrolled		-0.006	-0.101	-0.000	-0.015
		(0.001)**	(0.087)	(0.000)	(0.023)
N	32,311,010	32,311,010	32,311,010	32,311,010	32,311,010
F-test IV	19.49				
Sample	Metro	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with Voluntary Enrollment or no program. Controls for individual and county level characteristics and county and quarter fixed effects. Standard errors clustered by county. Mean outcome = mean in control group (FFS enrolled).

Table 3.34: IV results, Stratified Part 1, CMC/MLTSS Non-Metro

Any hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC/MLTSS enrolled	-0.024	-0.007	0.000	-0.008	-0.005	-0.024
	(0.007)**	(0.004)	(0.002)	(0.008)	(0.003)	(0.010)*
N	2,932,025	4,471,855	3,649,340	3,754,540	3,505,458	3,898,422
F-test IV	53.73	62.46	64.28	54.64	69.26	52.94
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC/MLTSS enrolled	-0.011	-0.006	-0.001	-0.009	-0.004	-0.016
	(0.004)*	(0.002)**	(0.001)	(0.004)*	(0.001)**	(0.006)*
N	2,932,025	4,471,855	3,649,340	3,754,540	3,505,458	3,898,422
F-test IV	53.73	62.46	64.28	54.64	69.26	52.94
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Table 3.35: IV results, Stratified Part 1, CMC/MLTSS Metro

Any hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC/MLTSS enrolled	-0.131	0.009	0.003	-0.103	-0.009	-0.062
	(0.067)*	(0.018)	(0.009)	(0.065)	(0.015)	(0.064)
N	14,610,736	15,946,557	14,630,627	15,926,666	15,697,209	14,860,084
F-test IV	10.59	16.86	15.73	13.24	16.38	10.60
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

Potentially avoidable hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC/MLTSS enrolled	-0.048	-0.005	-0.004	-0.043	-0.002	-0.041
	(0.024)*	(0.006)	(0.002)*	(0.023)	(0.004)	(0.027)
N	14,610,736	15,946,557	14,630,627	15,926,666	15,697,209	14,860,084
F-test IV	10.59	16.86	15.73	13.24	16.38	10.60
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with voluntary enrollment.

Table 3.36: IV results, Stratified Part 2, CMC/MLTSS Non-Metro

Any hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC/MLTSS enrolled	-0.009	-0.011	-0.013	-0.013	-0.006
	(0.006)	(0.006)	(0.008)	(0.007)	(0.008)
N	4,220,991	2,599,729	2,444,243	2,381,472	2,194,601
F-test IV	57.05	61.03	58.23	55.57	56.50
Sub-group	Hyper-tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC/MLTSS enrolled	-0.034	0.002	-0.020	0.006	-0.014
	(0.012)**	(0.010)	(0.014)	(0.032)	(0.009)
N	2,003,250	2,000,859	1,667,271	1,366,055	1,460,931
F-test IV	54.16	55.33	53.06	45.00	64.99
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC/MLTSS enrolled	-0.008	-0.007	-0.009	-0.011	-0.008
	(0.003)*	(0.003)*	(0.004)*	(0.004)*	(0.005)
N	4,220,991	2,599,729	2,444,243	2,381,472	2,194,601
F-test IV	57.05	61.03	58.23	55.57	56.50
Sub-group	Hyper-tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC/MLTSS enrolled	-0.014	-0.009	-0.017	-0.013	-0.013
	(0.008)	(0.005)	(0.010)	(0.020)	(0.006)*
N	2,003,250	2,000,859	1,667,271	1,366,055	1,460,931
F-test IV	54.16	55.33	53.06	45.00	64.99
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Table 3.37: IV results, Stratified Part 2, CMC/MLTSS Metro

Any hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC/MLTSS enrolled	-0.059	-0.045	-0.065	-0.069	-0.125
	(0.050)	(0.037)	(0.053)	(0.055)	(0.075)
N	17,981,770	12,113,399	10,908,236	9,973,784	9,569,441
F-test IV	12.57	13.56	13.62	14.08	13.18
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC/MLTSS enrolled	-0.137	-0.009	-0.124	-0.047	-0.064
	(0.100)	(0.031)	(0.108)	(0.163)	(0.052)
N	9,845,553	7,748,948	6,446,879	5,432,665	4,788,155
F-test IV	11.26	16.12	12.06	6.61	18.02
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC/MLTSS enrolled	-0.024	-0.011	-0.029	-0.026	-0.043
	(0.017)	(0.013)	(0.022)	(0.018)	(0.026)
N	17,981,770	12,113,399	10,908,236	9,973,784	9,569,441
F-test IV	12.57	13.56	13.62	14.08	13.18
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC/MLTSS enrolled	-0.061	-0.012	-0.057	-0.051	-0.021
	(0.034)	(0.012)	(0.046)	(0.070)	(0.022)
N	9,845,553	7,748,948	6,446,879	5,432,665	4,788,155
F-test IV	11.26	16.12	12.06	6.61	18.02
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Table 3.38: IV results, Stratified Part 1, CMC excluding LTSS Non-Metro

Any hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC enrolled	-0.035	-0.013	-0.002	-0.021	-0.004	-0.041
	(0.006)**	(0.004)**	(0.002)	(0.007)**	(0.002)	(0.009)**
N	3,804,265	5,728,129	4,746,008	4,786,385	4,638,951	4,893,441
F-test IV	86.82	93.21	92.98	88.76	101.44	83.82
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

Potentially avoidable hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC enrolled	-0.015	-0.007	-0.001	-0.013	-0.003	-0.021
	(0.003)**	(0.002)**	(0.001)	(0.004)**	(0.001)**	(0.005)**
N	3,804,265	5,728,129	4,746,008	4,786,385	4,638,951	4,893,441
F-test IV	86.82	93.21	92.98	88.76	101.44	83.82
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with voluntary enrollment.

Table 3.39: IV results, Stratified Part 1, CMC excluding LTSS Metro

Any hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC enrolled	-0.125	-0.032	-0.022	-0.215	-0.036	-0.101
	(0.082)	(0.031)	(0.013)	(0.147)	(0.036)	(0.107)
N	15,736,809	17,382,934	15,921,933	17,197,810	17,114,330	16,005,413
F-test IV	36.21	47.02	57.35	30.96	52.94	39.60
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

Potentially avoidable hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
CMC enrolled	-0.032	-0.008	-0.004	-0.061	-0.005	-0.023
	(0.022)	(0.005)	(0.001)**	(0.039)	(0.007)	(0.026)
N	15,736,809	17,382,934	15,921,933	17,197,810	17,114,330	16,005,413
F-test IV	36.21	47.02	57.35	30.96	52.94	39.60
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with voluntary enrollment.

Table 3.40: IV results, Stratified Part 2, CMC excluding LTSS Non-Metro

Any hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC enrolled	-0.019	-0.014	-0.026	-0.022	-0.014
	(0.005)**	(0.005)**	(0.007)**	(0.006)**	(0.006)*
N	5,428,722	3,350,713	3,153,609	3,061,651	2,779,571
F-test IV	91.61	96.12	91.52	90.70	92.61
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC enrolled	-0.043	-0.014	-0.030	-0.031	-0.025
	(0.010)**	(0.008)	(0.012)*	(0.025)	(0.008)**
N	2,541,480	2,538,287	2,112,230	1,698,369	1,860,359
F-test IV	88.16	87.21	87.12	75.77	107.68
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

Potentially avoidable hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC enrolled	-0.011	-0.009	-0.011	-0.013	-0.010
	(0.003)**	(0.002)**	(0.004)**	(0.004)**	(0.004)*
N	5,428,722	3,350,713	3,153,609	3,061,651	2,779,571
F-test IV	91.61	96.12	91.52	90.70	92.61
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC enrolled	-0.019	-0.013	-0.020	-0.025	-0.014
	(0.006)**	(0.005)**	(0.008)*	(0.016)	(0.005)**
N	2,541,480	2,538,287	2,112,230	1,698,369	1,860,359
F-test IV	88.16	87.21	87.12	75.77	107.68
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with Voluntary Enrollment.

Table 3.41: IV results, Stratified Part 2, CMC excluding LTSS Metro

Any hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC enrolled	-0.139	-0.134	-0.159	-0.210	-0.258
	(0.109)	(0.097)	(0.115)	(0.144)	(0.162)
N	19,411,812	13,114,854	11,777,475	10,718,839	10,164,579
F-test IV	35.05	32.05	40.15	28.05	30.14
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC enrolled	-0.298	-0.037	-0.311	-0.117	-0.201
	(0.191)	(0.067)	(0.213)	(0.171)	(0.151)
N	10,542,806	8,521,893	6,868,924	5,807,469	5,170,015
F-test IV	33.59	38.37	31.73	19.06	29.53
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

Potentially avoidable hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)
CMC enrolled	-0.034	-0.032	-0.042	-0.055	-0.070
	(0.027)	(0.023)	(0.034)	(0.033)	(0.043)
N	19,411,812	13,114,854	11,777,475	10,718,839	10,164,579
F-test IV	35.05	32.05	40.15	28.05	30.14
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
CMC enrolled	-0.082	-0.005	-0.089	-0.019	-0.053
	(0.050)	(0.012)	(0.064)	(0.037)	(0.041)
N	10,542,806	8,521,893	6,868,924	5,807,469	5,170,015
F-test IV	33.59	38.37	31.73	19.06	29.53
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with Voluntary Enrollment.

Table 3.42: IV results, Stratified Part 1, MLTSS Non-Metro

Any hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
MLTSS enrolled	0.029	0.022	0.002	0.018	-0.010	0.096
	(0.027)	(0.014)	(0.008)	(0.032)	(0.010)	(0.046)*
N	3,588,248	5,383,799	4,444,880	4,527,166	4,353,689	4,618,356
F-test IV	51.07	41.86	49.70	39.38	54.49	39.77
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

Potentially avoidable hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
MLTSS enrolled	0.019	0.017	0.004	0.032	0.007	0.053
	(0.012)	(0.005)**	(0.002)*	(0.015)*	(0.003)	(0.024)*
N	3,588,248	5,383,799	4,444,880	4,527,166	4,353,689	4,618,356
F-test IV	51.07	41.86	49.70	39.38	54.49	39.77
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with voluntary enrollment.

Table 3.43: IV results, Stratified Part 1, MLTSS Metro

Any hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
MLTSS enrolled	0.158	0.075	0.033	0.441	0.057	0.188
	(0.118)	(0.045)	(0.011)**	(0.240)	(0.046)	(0.195)
N	17,003,161	18,063,402	16,740,364	18,326,199	18,337,507	16,729,056
F-test IV	27.74	33.81	57.34	20.26	89.20	8.48
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

Potentially avoidable hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
MLTSS enrolled	0.036	0.014	0.004	0.118	0.010	0.027
	(0.036)	(0.008)	(0.001)**	(0.066)	(0.009)	(0.056)
N	17,003,161	18,063,402	16,740,364	18,326,199	18,337,507	16,729,056
F-test IV	27.74	33.81	57.34	20.26	89.20	8.48
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with voluntary enrollment.

Table 3.44: IV results, Stratified Part 2, MLTSS Non-Metro

Any hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
MLTSS enrolled	0.001	-0.029	0.025	0.038	0.007
	(0.027)	(0.027)	(0.026)	(0.033)	(0.037)
N	5,134,350	3,162,006	2,966,404	2,881,543	2,637,247
F-test IV	40.79	32.41	41.88	41.90	37.86
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
MLTSS enrolled	0.060	0.037	-0.009	-0.014	0.079
	(0.035)	(0.027)	(0.028)	(0.026)	(0.056)
N	2,407,507	2,375,256	2,004,684	1,603,682	1,760,844
F-test IV	36.50	45.56	49.70	44.46	31.76
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

Potentially avoidable hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
MLTSS enrolled	0.020	0.021	0.019	0.016	0.020
	(0.013)	(0.011)	(0.014)	(0.014)	(0.017)
N	5,134,350	3,162,006	2,966,404	2,881,543	2,637,247
F-test IV	40.79	32.41	41.88	41.90	37.86
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
MLTSS enrolled	0.050	0.032	0.005	0.016	0.061
	(0.019)**	(0.011)**	(0.018)	(0.011)	(0.032)
N	2,407,507	2,375,256	2,004,684	1,603,682	1,760,844
F-test IV	36.50	45.56	49.70	44.46	31.76
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with Voluntary Enrollment.

Table 3.45: IV results, Stratified Part 2, MLTSS Metro

Any hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)
MLTSS enrolled	0.262	0.276	0.297	0.497	0.594
	(0.177)	(0.169)	(0.178)	(0.248)*	(0.292)*
N	20,610,691	13,971,209	12,516,675	11,347,378	10,951,286
F-test IV	29.04	23.40	29.95	16.10	11.30
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
MLTSS enrolled	0.571	0.095	0.693	0.280	0.635
	(0.256)*	(0.163)	(0.344)*	(0.333)	(0.350)
N	11,264,724	8,806,273	7,322,022	6,176,319	5,414,507
F-test IV	16.64	25.52	16.30	9.20	29.13
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

Potentially avoidable hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)
MLTSS enrolled	0.057	0.066	0.069	0.125	0.157
	(0.048)	(0.044)	(0.060)	(0.061)*	(0.085)
N	20,610,691	13,971,209	12,516,675	11,347,378	10,951,286
F-test IV	29.04	23.40	29.95	16.10	11.30
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
MLTSS enrolled	0.144	-0.000	0.188	0.024	0.175
	(0.073)*	(0.031)	(0.113)	(0.080)	(0.101)
N	11,264,724	8,806,273	7,322,022	6,176,319	5,414,507
F-test IV	16.64	25.52	16.30	9.20	29.13
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with Voluntary Enrollment.

Table 3.46: IV results, Stratified Part 1, PCCM Non-Metro

Any hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
PCCM enrolled	-0.004	-0.054	-0.020	-0.096	-0.086	0.018
	(0.027)	(0.022)*	(0.011)	(0.038)*	(0.020)**	(0.033)
N	3,078,833	4,767,004	3,906,756	3,939,081	3,742,009	4,103,828
F-test IV	93.29	75.27	85.52	65.88	71.37	78.01
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
PCCM enrolled	-0.007	-0.009	-0.003	-0.027	-0.013	-0.001
	(0.015)	(0.009)	(0.004)	(0.019)	(0.007)	(0.017)
N	3,078,833	4,767,004	3,906,756	3,939,081	3,742,009	4,103,828
F-test IV	93.29	75.27	85.52	65.88	71.37	78.01
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Table 3.47: IV results, Stratified Part 1, PCCM Metro

Any hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
PCCM enrolled	-0.030	-0.140	-0.057	-0.152	-0.010	-0.119
	(0.077)	(0.101)	(0.021)**	(0.171)	(0.030)	(0.141)
N	18,099,774	19,453,703	17,983,595	19,569,882	19,709,655	17,843,822
F-test IV	17.34	23.32	25.82	15.81	21.86	20.30
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)	(6)
PCCM enrolled	-0.004	-0.011	-0.000	-0.023	0.012	-0.007
	(0.028)	(0.021)	(0.002)	(0.050)	(0.007)	(0.038)
N	18,099,774	19,453,703	17,983,595	19,569,882	19,709,655	17,843,822
F-test IV	17.34	23.32	25.82	15.81	21.86	20.30
Sample	Aged	Disabled	0-3 CCs	4+ CCs	No LTC	LTC Use

* $p < 0.05$; ** $p < 0.01$

Exclusions: Limited to counties with voluntary enrollment.

Table 3.48: IV results, Stratified Part 2, PCCM Non-Metro

Any hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
PCCM enrolled	-0.071	-0.072	-0.048	-0.085	-0.135
	(0.030)*	(0.034)*	(0.033)	(0.041)*	(0.053)*
N	4,458,325	2,752,346	2,593,590	2,496,151	2,282,850
F-test IV	68.42	61.57	72.26	64.81	59.21
Sub-group	Hyper-tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
PCCM enrolled	-0.060	-0.136	-0.161	-0.098	-0.162
	(0.042)	(0.056)*	(0.058)**	(0.066)	(0.062)**
N	2,108,659	2,101,590	1,733,218	1,408,912	1,513,159
F-test IV	70.20	74.95	71.68	76.24	69.56
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable hospitalization - Non-Metro Counties

	(1)	(2)	(3)	(4)	(5)
PCCM enrolled	-0.018	-0.015	-0.006	-0.036	-0.027
	(0.014)	(0.016)	(0.018)	(0.021)	(0.025)
N	4,458,325	2,752,346	2,593,590	2,496,151	2,282,850
F-test IV	68.42	61.57	72.26	64.81	59.21
Sub-group	Hype-r tension	High cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
PCCM enrolled	-0.017	-0.031	-0.052	-0.037	-0.028
	(0.023)	(0.027)	(0.033)	(0.039)	(0.037)
N	2,108,659	2,101,590	1,733,218	1,408,912	1,513,159
F-test IV	70.20	74.95	71.68	76.24	69.56
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Table 3.49: IV results, Stratified Part 2, PCCM Metro

Any hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)
PCCM enrolled	-0.160	-0.195	-0.169	-0.273	-0.329
	(0.142)	(0.155)	(0.167)	(0.236)	(0.291)
N	19,060,159	12,806,574	11,544,414	10,525,516	10,138,588
F-test IV	14.38	13.89	14.42	13.95	13.36
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
PCCM enrolled	-0.182	-0.215	-0.339	-0.165	-0.241
	(0.205)	(0.183)	(0.320)	(0.222)	(0.234)
N	10,507,957	8,375,169	6,867,888	5,919,139	5,093,675
F-test IV	13.79	22.18	13.65	19.53	19.10
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

Potentially avoidable hospitalization - Metro Counties

	(1)	(2)	(3)	(4)	(5)
PCCM enrolled	-0.031	-0.058	-0.041	-0.072	-0.071
	(0.042)	(0.052)	(0.055)	(0.071)	(0.090)
N	19,060,159	12,806,574	11,544,414	10,525,516	10,138,588
F-test IV	14.38	13.89	14.42	13.95	13.36
Sub-group	Hyper-tension	High Cholesterol	Diabetes	Rheumatoid arthritis	Ischemic heart dis.
	(6)	(7)	(8)	(9)	(10)
PCCM enrolled	-0.042	-0.009	-0.075	-0.036	-0.054
	(0.057)	(0.039)	(0.103)	(0.075)	(0.089)
N	10,507,957	8,375,169	6,867,888	5,919,139	5,093,675
F-test IV	13.79	22.18	13.65	19.53	19.10
Sub-group	Anemia	Depression	CHF	AD/ Dementia	COPD

* $p < 0.05$; ** $p < 0.01$

3.12 Appendix

3.12.1 DID Validity

As noted in the main text, there are several potential threats to validity of the DID parallel trends assumption. In the main results, I address two of these problems directly: changes in the control group due to expansions of other MMC plan types and changes due to Medicare managed care expansions over time. I address the sample composition changes due to Medicare managed care over time using propensity score weighting. This method allows me to balance the sample on observable characteristics over time. I've explored several alternatives to this preferred DID approach below.

3.12.2 DID - Alternative to weighting 1 - excluding counties with large decline in FFS Medicare rate

The first alternative approach I explored was excluding counties with large changes in the share of duals that had FFS Medicare coverage from 2005 to 2012. Using a cut-off of 15 percentage points, this results in the exclusion of approximately 20% of counties that were included in the main DID analyses. However, this excludes many more counties with MMC programs than control counties: over half of treated counties in the CMC/MLTSS analyses are dropped.

With this sample restriction, I repeated the parallel trends check of including leads. Results for each of the three managed care types are tabulated below.

Table 3.50: Treated and control counties, DID excluding counties with Medicare managed care expansion

	Main DID Sample		FFS Medicare Change Restr.	
	Treatment	Control	Treatment	Control
CMC or MLTSS	347	972	146	932
CMC excl. LTSS	90	972	49	932
MLTSS	282	972	119	932
PCCM	4	994	0	956

	Metro Counties		Non-Metro Counties	
	Treatment	Control	Treatment	Control
CMC or MLTSS	85	327	61	560
CMC excl. LTSS	38	327	11	560
MLTSS	59	327	60	560
PCCM	0	327	0	560

Control = counties where enrollment share $< 1\%$ all time periods

FFS Medicare Change restriction = Excludes counties with more than 10 pp decline in rate of FFS Medicare coverage among full benefit duals 2005 to 2012.

Table 3.51: Parallel trends exploration, inclusion of leads, CMC/MLTSS

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
CMC/MLTSS, t	0.000	-0.001	-0.002	-0.000	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)*
CMC/MLTSS, t+1		0.004		-0.001		0.001		0.001
		(0.001)*		(0.002)		(0.001)		(0.001)
CMC/MLTSS, t+2		-0.003		-0.002		-0.001		-0.002
		(0.002)		(0.003)		(0.001)		(0.001)
R2	0.14	0.14	0.15	0.15	0.07	0.07	0.07	0.07
N	3,306,662	3,306,662	7,697,388	7,697,388	3,306,662	3,306,662	7,697,388	7,697,388
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	11.06	11.06	11.02	11.02	3.17	3.17	2.71	2.71
Leads test F-stat		0.028		0.504		0.358		0.248

Regression includes individual and county characteristics and county and quarlterly fixed effects.
Individual characteristics are age, sex, race, count chronic conditions,
indicators for each chronic condition, aged (vs disabled), and LTC use.
County characteristics are supply of hospital and nursing facility beds.
Excludes counties in with ¿15 pp change in Medicare FFS Share
Standard errors clustered by county.
Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
P-value of F-statistic for test of joint significance of lead coefficients reported.

Table 3.52: Parallel trends exploration, inclusion of leads, CMC

	Hosp	Hosp	PQI	PQI
CMC, t	0.004	-0.000	0.001	-0.001
	(0.002)*	(0.001)	(0.001)	(0.001)
CMC, t+1		0.003		0.002
		(0.002)		(0.001)
CMC, t+2		0.005		0.001
		(0.003)		(0.001)
R2	0.15	0.15	0.07	0.07
N	6,644,831	6,644,831	6,644,831	6,644,831
Sample	Metro	Metro	Metro	Metro
Mean Outcome	11.02	11.02	2.71	2.71
Leads test F-stat		0.017		0.035

Regression includes individual and county characteristics and county and quarlterly fixed effects.
Individual characteristics are age, sex, race, count chronic conditions,
indicators for each chronic condition, aged (vs disabled), and LTC use.
County characteristics are supply of hospital and nursing facility beds.
Excludes counties in with ¿15 pp change in Medicare FFS Share
Standard errors clustered by county.
Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
P-value of F-statistic for test of joint significance of lead coefficients reported.

Table 3.53: Parallel trends exploration, inclusion of leads, MLTSS

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
MLTSS, t	0.000	-0.001	-0.005	-0.001	-0.002	-0.002	-0.004	-0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)**	(0.001)**
MLTSS, t+1		0.005		-0.003		0.002		0.001
		(0.002)**		(0.002)		(0.001)		(0.001)
MLTSS, t+2		-0.006		-0.004		-0.003		-0.002
		(0.002)**		(0.002)		(0.001)**		(0.001)*
R2	0.14	0.14	0.15	0.15	0.07	0.07	0.07	0.07
N	3,280,005	3,280,005	6,465,244	6,465,244	3,280,005	3,280,005	6,465,244	6,465,244
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	11.06	11.06	11.02	11.02	3.17	3.17	2.71	2.71
Leads test F-stat		0.001		0.000		0.024		0.001

Regression includes individual and county characteristics and county and quarlterly fixed effects.
Individual characteristics are age, sex, race, count chronic conditions,
indicators for each chronic condition, aged (vs disabled), and LTC use.
County characteristics are supply of hospital and nursing facility beds.
Excludes counties in with ¿15 pp change in Medicare FFS Share
Standard errors clustered by county.
Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
P-value of F-statistic for test of joint significance of lead coefficients reported.

While the lead terms analyzing CMC/MLTSS programs are not statistically significant in either group of counties (Table 3.51), this is not the case for the CMC or MLTSS program analyses (Tables 3.52 3.53). In the case of CMC programs in metro counties, the coefficient on CMC in the current period is zero and both lead terms are positive, showing that all of the effect observed in the DID specification is due to increasing hospitalization rates in the counties that take up treatment prior to the policy change. While effects are smaller for the outcome of PQI, the same pattern is present. As similar result occurs for the MLTSS program analyses.

I explored whether using different cutoff values for the exclusion criteria of “too much” Medicare managed care expansion would result in more convincing evidence of parallel trends in the unweighted data; however, the sample size of treated counties got too small. Therefore, because the parallel trends assumptions required for DID to yield causal estimates appear to be violated with this approach, I did not continue to pursue this approach.

3.12.3 DID - Alternative to weighting 2 - balanced panel of beneficiaries

As an alternative robustness check to address changing sample composition over time, I constructed another sample which should be balanced over time. I identified individuals that were observed in all time periods of the study data from 2005-2012, with FFS Medicare coverage for that entire time, and that do not move between a metro and non-metro county. I re-estimated the DID analyses on this balanced panel of individual-level observations. This is a selected sample: duals that are alive and maintain coverage in both programs for the entire study period from 2005-2012 are younger and healthier at baseline than the average dual eligible. In non-metro and metro counties, this balanced panel includes 19.2% and 19.0% of all duals in the main analysis sample respectively. Sample characteristics are shown in Table 3.54 below, stratified by county of residence metropolitan status.

In this limited sample, the average age in 2005 is 58 and a larger share of this sample was originally eligible for Medicare due to disability than in the overall sample of duals. We can also see that in 2005, approximately 36% of individuals had 0-1 chronic conditions compared to only 28% in the full DID sample. As this sample ages, we can observe an increase in LTC use and the number of chronic conditions. We also can see an increase in MMC enrollment over time in both groups of counties. The mean hospitalization rate is much lower than in the overall sample and by construction, mortality is zero until the last period.

Next, I report the DID regressions including leads to assess if there is evidence of the parallel trends assumption in this restricted sample (Tables 3.55-3.57).

Table 3.54: DID Sample Characteristics - limited to balanced panel of individuals

	Metro		Non-Metro	
	Q4-2005	Q4-2012	Q4-2005	Q4-2012
Age, mean	58.8	65.8	58.0	65.0
SD	16.9	16.9	16.8	16.8
Female	61.4		61.3	
White	51.7		70.7	
Black	19.0		15.4	
Hispanic	18.9		8.1	
Asian	8.1		0.6	
Other/Unknown Race	2.3		5.1	
Aged	38.4		32.2	
Disabled	61.6		67.8	
LTC Use (t-1)	42.6	56.7	43.5	57.7
0-1 Chronic Conds.	36.0	22.7	38.5	24.5
2-3 Chronic Conds.	27.5	22.3	28.2	23.8
4-5 Chronic Conds.	20.3	21.6	19.5	21.7
6+ Chronic Conds.	16.2	33.5	13.8	30.0
Metro county	100.0	100.0	0.0	0.0
Hospital beds /1000	3.5	3.4	3.7	3.7
Nursing facility beds / 1000	0.3	0.3	0.9	0.9
CMC/MLTSS Enrolled	13.4	35.7	0.8	17.4
CMC Enrolled	13.1	34.5	0.7	14.1
MLTSS Enrolled	0.3	1.2	0.2	3.3
PCCM Enrolled	0.1	0.2	0.1	0.0
Any Hospitalization	6.2	8.6	5.9	8.5
PQI	1.0	2.0	1.2	2.5
Died	0.0	0.6	0.0	0.7
N	553,788	553,788	181,263	181,263

Source: MBSF-MAX PS-MedPAR files.

Limited to full-duals enrolled in FFS Medicare.

Excludes individuals living excluded counties (ME, VT, RUCC 8,9, Control group exclusions).

Limited to individuals with observations 2005-2012 all periods

Table 3.55: Inclusion of Leads, CMC or MLTSS, Limited to balanced panel of individuals

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
CMC/MLTSS, t	-0.002	-0.003	-0.001	-0.000	-0.002	-0.002	-0.001	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)**	(0.001)*	(0.000)*	(0.000)
CMC/MLTSS, t+1		0.004		-0.001		0.001		-0.001
		(0.002)*		(0.001)		(0.001)		(0.001)
CMC/MLTSS, t+2		-0.004		-0.001		-0.002		-0.000
		(0.002)*		(0.001)		(0.001)		(0.001)
R2	0.11	0.11	0.11	0.11	0.05	0.05	0.05	0.05
N	1,394,645	1,394,645	4,230,581	4,230,581	1,394,645	1,394,645	4,230,581	4,230,581
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	6.49	6.49	6.90	6.90	1.19	1.19	1.10	1.10
Leads test F-stat		0.028		0.621		0.148		0.011

Regression includes individual and county characteristics and county and quarlterly fixed effects.
Individual characteristics are age, sex, race, count chronic conditions,
indicators for each chronic condition, aged (vs disabled), and LTC use.
County characteristics are supply of hospital and nursing facility beds.
Excludes individuals not observed all periods
Standard errors clustered by county.
Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
P-value of F-statistic for test of joint significance of lead coefficients reported.

Table 3.56: Inclusion of Leads, CMC, Limited to balanced panel of individuals

	Hosp	Hosp	PQI	PQI
CMC, t	0.002	0.001	-0.001	-0.000
	(0.001)*	(0.001)	(0.000)	(0.001)
CMC, t+1		0.002		-0.001
		(0.002)		(0.001)
CMC, t+2		0.001		0.000
		(0.001)		(0.001)
R2	0.11	0.11	0.05	0.05
N	3,247,749	3,247,749	3,247,749	3,247,749
Sample	Metro	Metro	Metro	Metro
Mean Outcome	6.90	6.90	1.10	1.10
Leads test F-stat		0.393		0.337

Regression includes individual and county characteristics and county and quarlterly fixed effects.
Individual characteristics are age, sex, race, count chronic conditions,
indicators for each chronic condition, aged (vs disabled), and LTC use.
County characteristics are supply of hospital and nursing facility beds.
Excludes individuals not observed all periods
Standard errors clustered by county.
Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
P-value of F-statistic for test of joint significance of lead coefficients reported.

Table 3.57: Inclusion of Leads, MLTSS, Limited to balanced panel of individuals

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
MLTSS, t	-0.002	-0.004	-0.002	0.000	-0.002	-0.002	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)**	(0.001)*	(0.001)	(0.001)
MLTSS, t+1		0.005		-0.002		0.002		-0.001
		(0.002)**		(0.001)		(0.001)		(0.001)
MLTSS, t+2		-0.005		-0.002		-0.002		-0.001
		(0.002)**		(0.001)		(0.001)**		(0.001)
R2	0.11	0.11	0.11	0.11	0.05	0.05	0.05	0.05
N	1,378,032	1,378,032	3,187,706	3,187,706	1,378,032	1,378,032	3,187,706	3,187,706
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	6.49	6.49	6.90	6.90	1.19	1.19	1.10	1.10
Leads test F-stat		0.001		0.182		0.028		0.060

Regression includes individual and county characteristics and county and qualrterly fixed effects.
Individual characteristics are age, sex, race, count chronic conditions,
indicators for each chronic condition, aged (vs disabled), and LTC use.
County characteristics are supply of hospital and nursing facility beds.
Excludes individuals not observed all periods
Standard errors clustered by county.
Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
P-value of F-statistic for test of joint significance of lead coefficients reported.

Examining CMC/MLTSS, none of the tests of joint significance of the leads term indicate that the null hypothesis that they are zero is rejected. Similar to the weighted results in the full sample, the coefficient on CMC/MLTSS program in period t does not change substantially with the inclusion of the lead terms. These results are consistent when analyzing CMC and MLTSS separately as well. However, in the main results, I estimated positive coefficients on the MLTSS program period t terms with and without the lead terms for the outcome of any hospitalization. However, in this limited sample, in the non-metro counties, I estimate negative coefficients. Also in non-metro counties for the outcome of hospitalization, the coefficients on the lead terms are statistically significant, but of different signs (signs match those in the main results). These differences for the MLTSS analysis in non-metro counties should be considered in interpreting the DID MLTSS results presented next.

Finally, the results of the main DID specifications are tabulated below.

Table 3.58: Overall DID results, CMC or MLTSS, Limited to balanced panel of individuals

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
CMC/MLTSS Program	0.004	-0.001	0.002	-0.001	-0.000	-0.002	0.000	-0.001
	(0.001)**	(0.002)	(0.001)*	(0.001)	(0.001)	(0.001)**	(0.000)	(0.000)
R2	0.01	0.12	0.00	0.12	0.00	0.05	0.00	0.05
N	1,812,630	1,812,630	5,537,880	5,537,880	1,812,630	1,812,630	5,537,880	5,537,880
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	6.51	6.51	6.86	6.86	1.18	1.18	1.09	1.09
County,Time FE	X	X	X	X	X	X	X	X
Additional Controls		X		X		X		X
Enrollment rate	73.31	73.31	68.62	68.62	73.31	73.31	68.62	68.62

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
Limited to individuals with observations each period (10 quarters 2005,2011,2012)
Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.
Standard errors clustered by county.

Table 3.59: Overall DID results, CMC, Limited to balanced panel of individuals

	Hosp	Hosp	PQI	PQI
CMC Program	-0.000	0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
R2	0.00	0.12	0.00	0.05
N	4,309,364	4,309,364	4,309,364	4,309,364
Sample	Metro	Metro	Metro	Metro
Mean Outcome	6.86	6.86	1.09	1.09
County,Time FE	X	X	X	X
Additional Controls		X		X
Enrollment rate	63.73	63.73	63.73	63.73

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
Limited to individuals with observations each period (10 quarters 2005,2011,2012)
Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.
Standard errors clustered by county.

Table 3.60: Overall DID results, MLTSS, Limited to balanced panel of individuals

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
MLTSS Program	0.004	-0.002	0.004	-0.002	-0.000	-0.002	0.001	-0.001
	(0.001)**	(0.001)	(0.001)**	(0.002)	(0.001)	(0.001)**	(0.000)	(0.001)
R2	0.01	0.12	0.00	0.12	0.00	0.05	0.00	0.05
N	1,791,875	1,791,875	4,234,539	4,234,539	1,791,875	1,791,875	4,234,539	4,234,539
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	6.51	6.51	6.86	6.86	1.18	1.18	1.09	1.09
County,Time FE	X	X	X	X	X	X	X	X
Additional Controls		X		X		X		X
Enrollment rate	74.95	74.95	75.08	75.08	74.95	74.95	75.08	75.08

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
Limited to individuals with observations each period (10 quarters 2005,2011,2012)
Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.
Standard errors clustered by county.

As in the main results, adding in controls decreases the magnitudes of the coefficients on CMC/MLTSS programs in most cases (Table 3.58. But unlike in the main results, CMC/MLTSS programs are associated with no change in the rate of any hospitalization (main results there was an increase in hospital use). There is also a small decease in PQI in non-metro counties due to CMC/MLTSS programs in this restricted sample.

This finding of no effect is consistent in the analysis of CMC programs that exclude LTC (Table 3.59). And the pattern of positive coefficients without the controls but negative coefficients with the controls appears to be driven by the MLTSS programs. Table 3.60 shows that in this restricted sample, with the preferred specification, there are no changes in hospitalization rates with the introduction of MLTSS programs and a slight decline in the rate of PQI in non-metro counties.

Recall that in the main paper results, CMC/MLTSS, CMC and MLTSS were all associated with increase in hospital use and no change in PQI using DID methods. However, these increases were concentrated among the beneficiaries with 4+ chronic conditions (versus fewer). This selected sample of 20% of individuals from the main sample is younger, has fewer chronic conditions and lower hospital use at baseline than the population of duals examined in the main results. With that in mind, these DID analyses using the balanced panel are consistent with the *stratified* results in the main sample finding little effect of MMC on hospital use among those with 0-3 chronic conditions.

3.12.4 Alternative to DID - Individual-level fixed effects

In the DID analyses, treatment is assigned at the county level and an average treatment effect is estimated for mandatory enrollment counties. An alternative approach is an event study framework where treatment is assigned at the individual level. To address selection, I use the county-level mandatory enrollment policy as an instrument to account for selection at the individual level into MMC programs. Specifically, I generate an indicator variable, Policy_{ct} that is equal to 1 if there is a mandatory MMC program in county c at time t and

0 otherwise. Then I estimate the following specification using two stage least squares:

$$\text{Stage 1: } \text{MMC}_{ict} = \text{Policy}_{ct} + \gamma_1 * I_i + \gamma_2 * T_t + \epsilon_{ict}$$

$$\text{Stage 2: } Y_{ict} = \hat{\text{MMC}}_{ict} + \gamma_1 * I_i + \gamma_2 * T_t + \epsilon_{ict}$$

Because treatment assignment is at the individual level, I include individual level fixed effects $\gamma_1 * I_i$. Therefore, the variation used to identify the treatment effect comes from individuals switching between FFS and MMC. Rather than estimating an average treatment effect as in the main DID results, this estimates a LATE for individuals that enroll in MMC due to the mandatory enrollment policy in their county.

Results of this event study style estimation are tabulated for each of the plan types and groups of counties (non-metro and metro) that had mandatory programs in the following tables.

Recall that in the main DID analyses, I found that mandatory CMC/MLTSS programs were associated with small increases in hospitalization rates of 0.4 and 0.2 percentage points for non-metro and metro counties respectively. In the individual fixed effects regression without using IV, in non-metro counties, individuals experience a small decline in hospitalization rates associated with CMC/MLTSS enrollment. However, using the instrument controls for selection. The coefficient changes from -0.003 to 0.001 with the use of the instrument. This suggests that there is some remaining selection in the within person estimates without the IV. Controlling for that selection using the county mandatory CMC/MLTSS enrollment policy as an instrument to predict individual level CMC/MLTSS enrollment yields estimates essentially no effect of CMC/MLTSS on the rate of any hospitalization or PQI in non-metro and metro counties (Table 3.61). For the group of individuals that opt in to CMC/MLTSS due to mandatory enrollment policies, there appears to be no relationship between MMC enrollment and hospital use.

Next, we turn to the examination of CMC and MLTSS programs separately. CMC

Table 3.61: Event Study - CMC/MLTSS, Non-Metro Counties

	First stage	Hosp. No IV	Hosp. IV	PQI No IV	PQI IV
Mand. CMC/MLTSS	0.824				
	(0.029)**				
CMC/MLTSS enrolled		-0.003	0.001	-0.001	-0.001
		(0.001)*	(0.002)	(0.000)*	(0.001)
N	8,524,240	8,524,240	8,412,391	8,524,240	8,412,391
F-test IV	828.02				
Sample	Non-Metro	Non-Metro	Non-Metro	Non-Metro	Non-Metro

	First stage	Hosp. No IV	Hosp. IV	PQI No IV	PQI IV
Mand. CMC/MLTSS	0.690				
	(0.058)**				
CMC/MLTSS enrolled		-0.000	-0.002	0.000	-0.001
		(0.001)	(0.001)	(0.000)	(0.001)
N	37,629,013	37,629,013	37,165,730	37,629,013	37,165,730
F-test IV	143.00				
Sample	Metro	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Additional controls are time varying individual characteristics (LTC use, chronic conditions), county characteristics, (supply hospital and nursing facility beds), and individual and quarter fixed effects. Standard errors clustered at county level.

programs that exclude LTC in metro counties are not associated with changes in hospital use using this alternative method (Table 3.62). Finally, this method results in similar null findings for MLTSS programs (Table 3.63) with precisely estimated zero coefficients in the non-metro counties and negative but not significant effects for any hospitalization in the metro counties.

So while I found small increases in hospitalization using DID (treatment assigned at the county level), I find no association between hospitalization and MMC enrollment using this alternative method. The two methods identify slightly different effects when mandatory enrollment is not enforced for every beneficiary in the county, as is the case. Recall from

Table 3.62: Event Study - CMC, Metro Counties

	First stage	Hosp. No IV	Hosp. IV	PQI No IV	PQI IV
Mandatory CMC	0.492				
	(0.102)**				
CMC Enrolled		0.001	-0.001	0.000	-0.001
		(0.001)	(0.002)	(0.000)	(0.001)
N	37,629,013	37,629,013	37,165,730	37,629,013	37,165,730
F-test IV	23.37				
Sample	Metro	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Additional controls are time varying individual characteristics (LTC use, chronic conditions), county characteristics, (supply hospital and nursing facility beds), and individual and quarter fixed effects. Standard errors clustered at county level.

Tables 3.12 and 3.13 that average county level enrollment rates ranged from 62.5% in metro counties for CMC programs to 75.7% in non-metro county MLTSS programs among counties with "mandatory" enrollment policies. Therefore, these event study style models estimate the effect for people induced to enroll in MMC due to the policy while the DID estimates estimate the average treatment effect for everyone in the county. The null finding, while not the same as the small increases found in the DID results, reassures us that the small effects found in for these mandatory programs are not driven by violations of the DID methods assumptions.

3.12.5 Additional IV estimation

Examining of unconditional exogeneity of the instrument

To investigate whether the instrument, share of MMC enrollment by plan type among non-disabled, non-elderly Medicaid-only beneficiaries, is unrelated to health outcomes, I present the same sample characteristics, separately for individuals in counties with the values of the IV above and below the median. Tables 3.64 - 3.67 show differences unconditional on the

Table 3.63: Event Study - MLTSS, Non-Metro Counties

	First stage	Hosp. No IV	Hosp. IV	PQI No IV	PQI IV
Mand. MLTSS	0.886				
	(0.016)**				
MLTSS Enrolled		-0.004	-0.000	-0.002	-0.001
		(0.002)**	(0.002)	(0.001)**	(0.001)
N	8,524,240	8,524,240	8,412,391	8,524,240	8,412,391
F-test IV	2944.56				
Sample	Non-Metro	Non-Metro	Non-Metro	Non-Metro	Non-Metro

	First stage	Hosp. No IV	Hosp. IV	PQI No IV	PQI IV
Mand. MLTSS	0.844				
	(0.017)**				
MLTSS Enrolled		-0.001	-0.003	0.000	-0.000
		(0.001)	(0.002)	(0.000)	(0.001)
N	37,629,011	37,629,011	37,165,727	37,629,011	37,165,727
F-test IV	2423.39				
Sample	Metro	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Additional controls are time varying individual characteristics (LTC use, chronic conditions), county characteristics, (supply hospital and nursing facility beds), and individual and quarter fixed effects. Standard errors clustered at county level.

other observable characteristics. Large standardized differences for race, aged vs disabled, and metropolitan county for plan types CMC/MLTSS, MLTSS, and PCCM indicate that there is not unconditional balance on covariates across high and low values of the instrument.

3.12.6 Exploring censoring due to death, DID & IV

In the main analyses, I include individuals that died during the quarter. My estimated effects of MMC on hospitalization could be biased if inclusion of these individuals results in censoring of the data and people that died have different treatment effects than those that did not die. To investigate this, I repeated the main DID and IV analyses two ways. First, I exclude individuals that died in the quarter and re-estimated the effects. Second, I created a new binary outcome that =1 if (Died or Hospitalized) and =0 if neither. I tabulate the two sets of results below.

Table 3.64: CMC/MLTSS IV Balance

	IV< Median	IV>Median	Std. diff.
Age, mean	63.3	64.7	0.1
SD	18.0	17.7	
Female	63.2	61.4	-3.7
White	60.8	49.6	-22.7
Black	25.0	18.0	-17.1
Hispanic	9.2	19.4	29.4
Asian	2.3	10.5	33.7
Other/Unknown Race	2.6	2.4	-0.8
Aged	41.0	48.8	15.8
Disabled	59.0	51.2	-15.8
Medicaid LTSS Use (t-1)	49.7	47.6	-4.2
Any hospitalization	9.9	9.0	-3.2
PQI	2.5	2.1	-2.9
Died	1.1	0.9	-2.5
0-1 Chronic conds.	26.2	25.2	-2.3
2-3 Chronic conds.	23.6	22.4	-2.9
4-5 Chronic conds.	21.6	21.1	-1.1
6+ Chronic conds.	28.6	31.2	5.8
Metro county	62.3	89.4	66.8
Unemployment rate, AHRF	7.9	8.0	0.1
Percent in poverty, AHRF	18.0	16.0	-0.5
Income per capita, AHRF	34,160.7	45,081.1	1.0
Median income, AHRF	42,730.4	52,219.0	1.1
MDs/1000 pop	2.0	3.3	0.8
Hospital beds/1000 pop	3.6	3.5	-0.0
Nursing facility beds/1000 pop	0.5	0.2	-0.4
N	13,395,294	32,763,157	-0

Source: MBSF-MAX PS-MedPAR files. Pooled quarterly data from 2005,2011,2012
Limited to duals enrolled in FFS Medicare with Full Medicaid benefits

Table 3.65: CMC excl LTSS IV Balance

	IV< Median	IV>Median	Std. diff.
Age, mean	64.2	64.4	0.0
SD	17.8	17.7	
Female	62.3	61.5	-1.6
White	52.8	53.0	0.4
Black	21.1	19.1	-4.8
Hispanic	16.4	16.5	0.3
Asian	6.6	9.6	10.8
Other/Unknown Race	3.1	1.8	-8.5
Aged	46.0	47.1	2.1
Disabled	54.0	52.9	-2.1
Medicaid LTSS Use (t-1)	48.5	47.9	-1.1
Any hospitalization	9.5	9.1	-1.3
PQI	2.2	2.1	-0.6
Died	0.9	1.0	1.2
0-1 Chronic conds.	25.2	25.8	1.2
2-3 Chronic conds.	22.4	23.1	1.7
4-5 Chronic conds.	21.0	21.5	1.1
6+ Chronic conds.	31.3	29.7	-3.6
Metro county	78.7	84.3	14.5
Unemployment rate, AHRF	8.1	7.9	-0.1
Percent in poverty, AHRF	17.5	15.8	-0.4
Income per capita, AHRF	44,236.4	39,665.3	-0.4
Median income, AHRF	48,332.1	50,555.3	0.2
MDs/1000 pop	3.2	2.6	-0.3
Hospital beds/1000 pop	3.8	3.3	-0.3
Nursing facility beds/1000 pop	0.3	0.3	-0.1
N	22,623,505	23,534,946	-0

Source: MBSF-MAX PS-MedPAR files. Pooled quarterly data from 2005,2011,2012
Limited to duals enrolled in FFS Medicare with Full Medicaid benefits

Table 3.66: MLTSS IV Balance

	IV< Median	IV>Median	Std. diff.
Age, mean	64.0	65.0	0.1
SD	17.9	17.5	
Female	62.2	61.3	-1.9
White	55.6	46.5	-18.2
Black	21.7	16.3	-13.8
Hispanic	13.3	24.0	27.7
Asian	7.4	9.9	8.9
Other/Unknown Race	2.1	3.4	7.9
Aged	44.9	50.5	11.1
Disabled	55.1	49.5	-11.1
Medicaid LTSS Use (t-1)	48.4	47.8	-1.2
Any hospitalization	9.4	9.0	-1.2
PQI	2.3	2.0	-1.9
Died	1.1	0.7	-3.7
0-1 Chronic conds.	26.0	24.3	-4.1
2-3 Chronic conds.	23.4	21.3	-4.9
4-5 Chronic conds.	21.5	20.6	-2.3
6+ Chronic conds.	29.1	33.8	10.3
Metro county	77.3	91.7	40.5
Unemployment rate, AHRF	7.8	8.5	0.4
Percent in poverty, AHRF	16.5	16.9	0.1
Income per capita, AHRF	37,932.1	51,391.9	0.9
Median income, AHRF	48,122.7	52,677.5	0.5
MDs/1000 pop	2.4	4.1	0.8
Hospital beds/1000 pop	3.4	3.9	0.2
Nursing facility beds/1000 pop	0.3	0.2	-0.3
N	32,549,469	13,608,982	-0

Source: MBSF-MAX PS-MedPAR files. Pooled quarterly data from 2005,2011,2012
Limited to duals enrolled in FFS Medicare with Full Medicaid benefits

Table 3.67: PCCM IV Balance

	IV< Median	IV>Median	Std. diff.
Age, mean	64.8	63.5	-0.1
SD	17.5	18.2	
Female	61.1	63.1	4.2
White	49.6	58.0	16.8
Black	18.0	23.2	12.9
Hispanic	18.6	13.1	-14.9
Asian	11.1	3.6	-29.1
Other/Unknown Race	2.7	2.1	-4.0
Aged	49.1	42.7	-12.8
Disabled	50.9	57.3	12.8
Medicaid LTSS Use (t-1)	48.2	48.2	-0.1
Any hospitalization	8.7	10.1	4.5
PQI	2.0	2.4	2.6
Died	0.8	1.2	3.5
0-1 Chronic conds.	25.2	25.9	1.6
2-3 Chronic conds.	22.7	22.9	0.4
4-5 Chronic conds.	21.5	20.9	-1.3
6+ Chronic conds.	30.6	30.3	-0.6
Metro county	84.3	77.2	-18.3
Unemployment rate, AHRF	8.3	7.5	-0.4
Percent in poverty, AHRF	16.4	16.8	0.1
Income per capita, AHRF	44,982.8	37,129.1	-0.7
Median income, AHRF	52,074.6	45,401.5	-0.8
MDs/1000 pop	3.2	2.5	-0.4
Hospital beds/1000 pop	3.6	3.5	-0.0
Nursing facility beds/1000 pop	0.3	0.3	0.1
N	28,111,185	18,047,266	0

Source: MBSF-MAX PS-MedPAR files. Pooled quarterly data from 2005,2011,2012
Limited to duals enrolled in FFS Medicare with Full Medicaid benefits

Table 3.68: Excluding Beneficiaries that Died - DID Overall, CMC/MLTSS

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
CMC/MLTSS	0.006	0.003	0.004	0.002	0.001	-0.000	0.000	-0.000
	(0.001)**	(0.002)*	(0.001)**	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
R2	0.01	0.14	0.00	0.14	0.00	0.06	0.00	0.06
N	4,171,318	4,171,318	14,166,468	14,166,468	4,171,318	4,171,318	14,166,468	14,166,468
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	11.02	11.02	11.11	11.11	3.03	3.03	2.64	2.64
County,Time FE	X	X	X	X	X	X	X	X
Additional Controls		X		X		X		X
Enrollment rate	71.26	71.26	68.37	68.37	71.26	71.26	68.37	68.37

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.

Excludes individuals that died during the quarter.

Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).

Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.

Standard errors clustered by county.

Table 3.69: Outcome=Died or Hospitalized - DID Overall, CMC/MLTSS

	Hosp or Died	Hosp or Died	Hosp or Died	Hosp or Died
CMC/MLTSS Program	0.011	0.007	0.006	0.003
	(0.002)**	(0.002)**	(0.001)**	(0.001)*
R2	0.01	0.14	0.01	0.14
N	4,209,606	4,209,606	14,280,645	14,280,645
Sample	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	12.45	12.45	12.47	12.47
County,Time FE	X	X	X	X
Additional Controls		X		X
Enrollment rate	71.27	71.27	68.33	68.33

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.

Outcome = died and/or hospitalized.

Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).

Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.

Standard errors clustered by county.

Table 3.70: Excluding Beneficiaries that Died - DID Overall, CMC

	Hosp	Hosp	PQI	PQI
CMC Program	0.003	0.004	0.001	0.001
	(0.002)*	(0.001)**	(0.001)	(0.000)
R2	0.00	0.14	0.00	0.06
N	10,969,845	10,969,845	10,969,845	10,969,845
Sample	Metro	Metro	Metro	Metro
Mean Outcome	11.11	11.11	2.64	2.64
County,Time FE	X	X	X	X
Additional Controls		X		X
Enrollment rate	62.63	62.63	62.63	62.63

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
Excludes individuals that died during the quarter.
Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).
Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.
Standard errors clustered by county.

Table 3.71: Outcome=Died or Hospitalized - DID Overall, CMC

	Hosp or Died	Hosp or Died
CMC Program	0.003	0.004
	(0.001)*	(0.001)**
R2	0.01	0.15
N	11,061,019	11,061,019
Sample	Metro	Metro
Mean Outcome	12.47	12.47
County,Time FE	X	X
Additional Controls		X
Enrollment rate	62.56	62.56

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.

Outcome = died and/or hospitalized.

Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).

Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.

Standard errors clustered by county.

Table 3.72: Excluding Beneficiaries that Died - DID Overall, MLTSS

	Hosp	Hosp	Hosp	Hosp	PQI	PQI	PQI	PQI
MLTSS Program	0.006	0.003	0.004	0.002	0.001	-0.000	0.000	-0.001
	(0.001)**	(0.002)*	(0.002)*	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R2	0.01	0.14	0.00	0.14	0.00	0.06	0.00	0.06
N	4,108,664	4,108,664	10,705,971	10,705,971	4,108,664	4,108,664	10,705,971	10,705,971
Sample	Non-Metro	Non-Metro	Metro	Metro	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	11.02	11.02	11.11	11.11	3.03	3.03	2.64	2.64
County,Time FE	X	X	X	X	X	X	X	X
Additional Controls		X		X		X		X
Enrollment rate	73.03	73.03	75.78	75.78	73.03	73.03	75.78	75.78

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
Excludes individuals that died during the quarter.
Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).
Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.
Standard errors clustered by county.

Table 3.73: Outcome=Died or Hospitalized - DID Overall, MLTSS

	Hosp or Died	Hosp or Died	Hosp or Died	Hosp or Died
MLTSS Program	0.011	0.007	0.007	0.003
	(0.002)**	(0.002)**	(0.002)**	(0.002)
R2	0.01	0.14	0.00	0.14
N	4,146,491	4,146,491	10,793,139	10,793,139
Sample	Non-Metro	Non-Metro	Metro	Metro
Mean Outcome	12.45	12.45	12.47	12.47
County,Time FE	X	X	X	X
Additional Controls		X		X
Enrollment rate	73.03	73.03	75.79	75.79

Mean Outcome = Baseline rate (control group, Q2-2005) in percentage.
Outcome = died and/or hospitalized.
Weighted using inverse propensity score weights where propensity score is Pr(t=Q42012).
Additional controls are age, sex, race, reason for entitlement, LTC use, chronic conditions, supply hospital and nursing facility beds, and county and quarter fixed effects.
Standard errors clustered by county.

Comparing these tables to the main results shows that censoring due to death does not drive the main findings. For the DID analyses, point estimates are slightly smaller when individuals that died are excluded (Table 3.68 and larger when the outcome is died and/or hospitalized 3.69 but in both cases, the main finding, that CMC/MLTSS programs are associated with small changes in the rate of any hospitalization but no change in PQI is consistent across all three specifications. A similar pattern is found for the CMC and MLTSS programs evaluated separately.

IV analyses examining mortality are tabulated below.

Table 3.74: Excluding Beneficiaries that Died - IV Overall, CMC/MLTSS

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share CMC/MLTSS non-duals	0.217				
	(0.028)**				
CMC/MLTSS enrolled		-0.002	-0.013	-0.000	-0.008
		(0.001)	(0.004)**	(0.001)	(0.002)**
N	7,318,189	7,318,189	7,318,189	7,318,189	7,318,189
F-test IV	60.20				
Sample	Non-metro	Non-metro	Non-metro	Non-metro	Non-metro

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share CMC/MLTSS non-duals	0.071				
	(0.018)**				
CMC/MLTSS enrolled		0.003	-0.024	0.002	-0.011
		(0.002)	(0.027)	(0.001)**	(0.009)
N	30,131,878	30,131,878	30,131,878	30,131,878	30,131,878
F-test IV	14.69				
Sample	Metro	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Estimated using 2SLS. Includes controls for individual level char, county and quarter FE

Limited to individuals residing in voluntary counties and counties with no program.

Excludes individuals that died during the quarter.

Table 3.75: Outcome=Died or Hospitalized - IV Overall, CMC/MLTSS

	First stage	No IV, Died or Hosp	IV, Died or Hosp
Z=Share CMC/MLTSS non-duals	0.215		
	(0.028)**		
CMC/MLTSS enrolled		-0.002	-0.008
		(0.001)	(0.004)
N	7,403,880	7,403,880	7,403,880
F-test IV	60.03		
Sample	Non-Metro	Non-Metro	Non-Metro

	First stage	No IV, Died or Hosp	IV, Died or Hosp
Z=Share CMC/MLTSS non-duals	0.070		
	(0.018)**		
CMC/MLTSS enrolled		0.002	-0.015
		(0.002)	(0.026)
N	30,422,841	30,422,841	30,422,841
F-test IV	14.66		
Sample	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Estimated using 2SLS. Includes controls for individual level char, county and quarter FE

Limited to individuals residing in voluntary counties and counties with no program.

Table 3.76: Excluding Beneficiaries that Died - IV Overall, CMC

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share CMC non-duals	0.200				
	(0.026)**				
CMC enrolled		-0.003	-0.019	-0.002	-0.011
		(0.002)*	(0.005)**	(0.001)**	(0.002)**
N	7,450,092	7,450,092	7,450,092	7,450,092	7,450,092
F-test IV	58.73				
Sample	Non-metro	Non-metro	Non-metro	Non-metro	Non-metro

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share CMC non-duals	0.083				
	(0.012)**				
CMC enrolled		0.000	-0.044	0.002	-0.007
		(0.002)	(0.053)	(0.001)**	(0.011)
N	30,211,090	30,211,090	30,211,090	30,211,090	30,211,090
F-test IV	48.56				
Sample	Metro	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Estimated using 2SLS. Includes controls for individual level char, county and quarter FE

Limited to individuals residing in voluntary counties and counties with no program.

Excludes individuals that died during the quarter.

Table 3.77: Outcome=Died or Hospitalized - IV Overall, CMC

	First stage	No IV, Died or Hosp	IV, Died or Hosp
Z=Share CMC non-duals	0.199		
	(0.026)**		
CMC enrolled		-0.004	-0.014
		(0.001)**	(0.005)**
N	7,536,522	7,536,522	7,536,522
F-test IV	58.61		
Sample	Non-Metro	Non-Metro	Non-Metro

	First stage	No IV, Died or Hosp	IV, Died or Hosp
Z=Share CMC non-duals	0.083		
	(0.012)**		
CMC enrolled		-0.001	-0.040
		(0.002)	(0.055)
N	30,504,482	30,504,482	30,504,482
F-test IV	48.58		
Sample	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Estimated using 2SLS. Includes controls for individual level char, county and quarter FE

Limited to individuals residing in voluntary counties and counties with no program.

Table 3.78: Excluding Beneficiaries that Died - IV Overall, MLTSS

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share MLTSS non-duals	0.210				
	(0.033)**				
MLTSS enrolled		0.002	0.027	0.005	0.024
		(0.002)	(0.015)	(0.001)**	(0.006)**
N	7,198,737	7,198,737	7,198,737	7,198,737	7,198,737
F-test IV	40.65				
Sample	Non-metro	Non-metro	Non-metro	Non-metro	Non-metro

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share MLTSS non-duals	0.094				
	(0.013)**				
MLTSS enrolled		0.006	0.126	0.003	0.028
		(0.003)*	(0.075)	(0.001)*	(0.016)
N	31,121,005	31,121,005	31,121,005	31,121,005	31,121,005
F-test IV	50.67				
Sample	Metro	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Estimated using 2SLS. Includes controls for individual level char, county and quarter FE

Limited to individuals residing in voluntary counties and counties with no program.

Excludes individuals that died during the quarter.

Table 3.79: Outcome=Died or Hospitalized - IV Overall, MLTSS

	First stage	No IV, Died or Hosp	IV, Died or Hosp
Z=Share MLTSS non-duals	0.211		
	(0.033)**		
MLTSS enrolled		0.003	0.028
		(0.002)	(0.016)
N	7,284,220	7,284,220	7,284,220
F-test IV	40.78		
Sample	Non-Metro	Non-Metro	Non-Metro

	First stage	No IV, Died or Hosp	IV, Died or Hosp
Z=Share MLTSS non-duals	0.094		
	(0.013)**		
MLTSS enrolled		0.005	0.135
		(0.004)	(0.079)
N	31,430,541	31,430,541	31,430,541
F-test IV	50.56		
Sample	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Estimated using 2SLS. Includes controls for individual level char, county and quarter FE

Limited to individuals residing in voluntary counties and counties with no program.

Table 3.80: Excluding Beneficiaries that Died - IV Overall, PCCM

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share PCCM non-duals	0.054				
	(0.006)**				
PCCM enrolled		-0.004	-0.015	0.001	-0.004
		(0.001)**	(0.020)	(0.000)*	(0.009)
N	7,757,069	7,757,069	7,757,069	7,757,069	7,757,069
F-test IV	80.65				
Sample	Non-metro	Non-metro	Non-metro	Non-metro	Non-metro

	First stage	No IV, HOSP	IV, HOSP	No IV, PQI	IV, PQI
Z=Share PCCM non-duals	0.047				
	(0.011)**				
PCCM enrolled		-0.005	-0.104	0.000	-0.015
		(0.001)**	(0.089)	(0.000)	(0.024)
N	31,994,063	31,994,063	31,994,063	31,994,063	31,994,063
F-test IV	19.57				
Sample	Metro	Metro	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Estimated using 2SLS. Includes controls for individual level char, county and quarter FE

Limited to individuals residing in voluntary counties and counties with no program.

Excludes individuals that died during the quarter.

Table 3.81: Outcome=Died or Hospitalized - IV Overall, PCCM

	First stage	No IV, Died or Hosp	IV, Died or Hosp
Z=Share PCCM non-duals	0.053		
	(0.006)**		
PCCM enrolled		-0.006	-0.048
		(0.001)**	(0.021)*
N	7,845,837	7,845,837	7,845,837
F-test IV	80.04		
Sample	Non-Metro	Non-Metro	Non-Metro

	First stage	No IV, Died or Hosp	IV, Died or Hosp
Z=Share PCCM non-duals	0.046		
	(0.011)**		
PCCM enrolled		-0.007	-0.101
		(0.001)**	(0.077)
N	32,311,010	32,311,010	32,311,010
F-test IV	19.49		
Sample	Metro	Metro	Metro

* $p < 0.05$; ** $p < 0.01$

Estimated using 2SLS. Includes controls for individual level char, county and quarter FE

Limited to individuals residing in voluntary counties and counties with no program.

BIBLIOGRAPHY

1115 Demonstration Federal Evaluation & Meta-Analysis. URL: https://www.medicaid.gov/medicaid/section-1115-demo/evaluation-reports/federal-evaluation-and-meta-analysis/index.html (visited on 10/08/2019).

2005 National Summary of State Medicaid Managed Care Programs (Sept. 2006). Tech. rep. Program Descriptions as of June 30, 2005. Finance, Systems, and Budget Group, Centers for Medicare & Medicaid Services.

AHRQ - Quality Indicators. URL: http://www.qualityindicators.ahrq.gov/Modules/PQI_TechSpec_ICD09_v60.aspx (visited on 08/07/2018).

Aizer, Anna, Janet Currie, and Enrico Moretti (Aug. 2007). "Does Managed Care Hurt Health? Evidence from Medicaid Mothers". In: *Review of Economics & Statistics* 89.3, pp. 385–399.

Angrist, Joshua D. and Jorn-Steffen Pischke (2009). *Mostly Harmless Econometrics.* Princeton, N.J.: Princeton University Press.

Baicker, Katherine, Michael E. Chernew, and Jacob A. Robbins (Dec. 2013). "The spillover effects of Medicare managed care: Medicare Advantage and hospital utilization". In: *Journal of Health Economics* 32.6, pp. 1289–1300.

Baiocchi Michael, Cheng Jing, and Small Dylan S. (Mar. 2014). "Instrumental variable methods for causal inference". In: *Statistics in Medicine* 33.13, pp. 2297–2340.

Basu, Anirban, Norma B. Coe, and Cole G. Chapman (2018). "2SLS versus 2SRI Appropriate methods for rare outcomes and/or rare exposures". In: *Health Economics* 0.0, pp. 1–19.

Brega, Angela G. et al. (Sept. 2005). "Racial and Ethnic Disparities in the Outcomes of Elderly Home Care Recipients". In: *Home Health Care Services Quarterly* 24.3, pp. 1–21.

Byrd, Vivian L.H. and Allison Hedley Dodd (Aug. 2015). *Assessing the Usability of Encounter Data for Enrollees in Comprehensive Managed Care 2010-2011.* Brief 22. Mathematica Policy Research.

Carlson, Barbara Lepidus et al. (Feb. 2007). "Effects of Cash and Counseling on Personal Care and Well-Being". In: *Health Services Research* 42.1p2, pp. 467–487.

Chen, Brian K., Y. Tony Yang, and Rachelle Gajadhar (Nov. 2018). "Early evidence from South Carolina's Medicare-Medicaid dual-eligible financial alignment initiative: an observational study to understand who enrolled, and whether the program improved health?" In: *BMC Health Services Research* 18.

Coe, Norma B. and Courtney Harold Van Houtven (Sept. 2009). "Caring for Mom and Neglecting Yourself? The Health Effects of Caring for an Elderly Parent". In: *Health Economics* 18.9, pp. 991–1010.

Colello, Kirsten J. and Scott R. Talaga (July 2015). *Who Pays for Long-Term Services and Supports? A Fact Sheet*. Tech. rep. R43483. Congressional Research Service.

Condition Categories - Chronic Conditions Data Warehouse. URL: `https://www.ccwdata.org/web/guest/condition-categories` (visited on 04/07/2019).

Coughlin, Rebecca et al. (Sept. 2017). *Money Follows the Person Demonstration: Overview of State Grantee Progress, January to December 2016*. Tech. rep. Cambridge, MA: Mathematica Policy Research.

Creditor, Morton C. (Feb. 1993). "Hazards of Hospitalization of the Elderly". In: *Annals of Internal Medicine* 118.3, pp. 219–223.

Currie, Janet and John Fahr (Jan. 2005). "Medicaid managed care: effects on children's Medicaid coverage and utilization". In: *Journal of Public Economics*. Tax and Transfer Programs for Low-Income People 89.1, pp. 85–108.

Data Book: Beneficaries dually eligible for Medicare and Medicaid (Jan. 2018). Tech. rep. MedPAC and MACPAC.

Deb, Partha, Edward C. Norton, and Willard G. Manning (2017). *Health Econometrics Using Stata*. First edition. Stata press.

Dong, Jing, Harold Pollack, and R. Tamara Konetzka (2018). "Effects of Long-Term Care Setting on Spousal Health Outcomes". In: *Health Services Research* 1.9.

Duggan, Mark (Dec. 2004). "Does contracting out increase the efficiency of government programs? Evidence from Medicaid HMOs". In: *Journal of Public Economics* 88.12, pp. 2549–2572.

Duggan, Mark and Tamara Hayford (2013). "Has the Shift to Managed Care Reduced Medicaid Expenditures? Evidence from State and Local-Level Mandates". In: *Journal of Policy Analysis and Management* 32.3, pp. 505–535.

Eicheldinger, Celia and Arthur Bonito (2008). "More Accurate Racial and Ethnic Codes for Medicare Administrative Data". In: *Health Care Financing Review* 29.3, pp. 27–42.

Eiken, Steve (Sept. 2016). *Medicaid 1915(c) waiver data based on the CMS 372 report, 2012-2013*. Tech. rep.

Eiken, Steve et al. (May 2018). "Medicaid Expenditures for Long-Term Services and Supports in FY 2016". In: p. 154.

Evaluations of Integrated Care Models for Dually Eligible Beneficiaries Key Findings and Research Gaps (July 2019). Issue Brief. Wahsington, DC: Medicaid and CHIP Payment Access Commission.

Experton, Bettina et al. (Apr. 1999). "How does managed care manage the frail elderly?: The case of hospital readmissions in fee-for-service versus HMO systems". In: *American Journal of Preventive Medicine* 16.3, pp. 163–172.

Feng, Zhanlian et al. (July 2011). "Growth Of Racial And Ethnic Minorities In US Nursing Homes Driven By Demographics And Possible Disparities In Options". In: *Health Affairs* 30.7, pp. 1358–1365.

Feng, Zhanlian et al. (May 2019). *Analysis of Pathways to Dual Eligible Status: Final Report.* Final Report. RTI International, p. 46.

Foundation, Kaiser Family (Feb. 2012). *Medicaid Managed Care: Key Data, Trends, and Iusses*. Issue Brief. Washington, DC: Henry J. Kaiser Family Foundation.

Garrett, Bowen, Amy J. Davidoff, and Alshadye Yemane (Apr. 2003). “Effects of Medicaid Managed Care Programs on Health Services Access and Use”. In: *Health Services Research* 38.2, pp. 575–594.

Garrido, Melissa M. et al. (Oct. 2014). “Methods for Constructing and Assessing Propensity Scores.: EBSCOhost”. In: *Health Services Research* 49.5, pp. 1701–1720.

Glied, Sherry (Jan. 2000). “Managed Care”. In: *Handbook of Health Economics*. Handbook of Health Economics 1, pp. 707–753.

Gonçalves, Judite, France Weaver, and R. Tamara Konetzka (July 2018). “Measuring State Medicaid Home Care Participation and Intensity Using Latent Variables”. In: *Journal of Applied Gerontology*, p. 0733464818786396.

Grabowski, David C. (Feb. 2006). “The Cost-Effectiveness of Noninstitutional Long-Term Care Services: Review and Synthesis of the Most Recent Evidence”. In: *Medical Care Research and Review* 63.1, pp. 3–28.

— (Dec. 2007). “Medicare and Medicaid: Conflicting Incentives for Long-Term Care”. In: *Milbank Quarterly* 85.4, pp. 579–610.

— (Jan. 2009). “Special Needs Plans And The Coordination Of Benefits And Services For Dual Eligibles”. In: *Health Affairs* 28.1, pp. 136–146.

Grabowski, David C. et al. (May 2017). “Passive Enrollment Of Dual-Eligible Beneficiaries Into Medicare And Medicaid Managed Care Has Not Met Expectations”. In: *Health Affairs* 36.5, pp. 846–854.

Gruber, Jonathan (Nov. 2017). “Delivering Public Health Insurance through Private Plan Choice in the United States”. In: *Journal of Economic Perspectives* 31.4, pp. 3–22.

Harrington, Charlene, Joshua M. Wiener, and MaryBeth Musumeci (Oct. 2017). *Key Issues in Long-Term Services and Supports Quality*. KFF Issue Brief.

Health and Retirement Study 1998-2016 Core, Exit, and Helper Files public use dataset. Tech. rep. Produced and distrubted by the University of Michigan with funding from the National Institute on Aging (grant number NIA U01AG009740). Ann Arbor, MI, (2016).

Heckman, James J, Sergio Urzua, and Edward Vytlacil (Aug. 2006). "Understanding Instrumental Variables in Models with Essential Heterogeneity". In: *The Review of Economics and Statistics* 88.3, pp. 389–432.

Herring, Bradley and E. Kathleen Adams (Apr. 2011). "Using HMOs to serve the Medicaid population: what are the effects on utilization and does the type of HMO matter?" In: *Health Economics* 20.4, pp. 446–460.

Herzog, A. R. and R. B. Wallace (May 1997). "Measures of cognitive functioning in the AHEAD Study". In: *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences* 52 Spec No, pp. 37–48.

Hinton, Elizabeth et al. (Dec. 2019). *10 Things to Know about Medicaid Managed Care*. Issue Brief. Washington, DC: Henry J. Kaiser Family Foundation, p. 10.

Jacobson, Gretchen, Anthony Damico, and Tricia Neuman (Nov. 2018). *A Dozen Facts About Medicare Advantage*. Data Note. Washington DC: Henry J. Kaiser Family Foundation, p. 13.

Jorm, AF (1994). "A short form of the Informant Questionnaire on Cognitive Decline in the Elderly (IQCODE): development and cross-validation - download.php". In: *Psychological Medicine* 24, pp. 145–153.

Jung, Hye-Young et al. (Oct. 2015). "Integrated Medicare and Medicaid managed care and rehospitalization of dual eligibles". In: *The American Journal of Managed Care* 21.10, pp. 711–717.

Kaestner, Robert, Lisa Dubay, and Genevieve Kenney (Apr. 2005). "Managed care and infant health: an evaluation of Medicaid in the US". In: *Social Science & Medicine* 60.8, pp. 1815–1833.

Kane, Robert L. et al. (Dec. 2007). *Managed Long-term Care and the Rebalancing of State Long Term Support Systems*. Topic Paper 3.

Kaye, H. Stephen, Charlene Harrington, and Mitchell P. LaPlante (Jan. 2010). “Long-Term Care: Who Gets It, Who Provides It, Who Pays, And How Much?” In: *Health Affairs* 29.1, pp. 11–21.

Kelley, Amy S. et al. (Nov. 2015). “The Burden of Health Care Costs for Patients With Dementia in the Last 5 Years of Life”. In: *Annals of Internal Medicine* 163.10, pp. 729–736.

Kim, Hyunjee et al. (Nov. 2017). “Comparing Care for Dual-Eligibles Across Coverage Models: Empirical Evidence From Oregon”. In: *Medical Care Research and Review*.

Kitchener, Martin, Helen Carrillo, and Charlene Harrington (Nov. 2003). “Medicaid Community-Based Programs: A Longitudinal Analysis of State Variation in Expenditures and Utilization”. In: *INQUIRY: The Journal of Health Care Organization, Provision, and Financing* 40.4, pp. 375–389.

Kitchener, Martin et al. (July 2005). *Medicaid 1915(c) Home and Community-Based Service Programs: Data Update. 2005.* Issue Brief. Kaiser Commission on Medicaid and the Uninsured.

Konetzka, R. Tamara, Sarita L. Karon, and D. E. B. Potter (June 2012). “Users Of Medicaid Home And Community-Based Services Are Especially Vulnerable To Costly Avoidable Hospital Admissions”. In: *Health Affairs* 31.6, pp. 1167–1175.

Konetzka, R. Tamara and Rachel M. Werner (Oct. 2009). “Review: Disparities in Long-Term Care: Building Equity Into Market-Based Reforms”. In: *Medical Care Research and Review* 66.5, pp. 491–521.

Langa, Kenneth M. et al. (Nov. 2018). *Langa-Weir Classification of Cognitive Function (1995 Onward).* Tech. rep. Ann Arbor, MI: Survey Research Center, Institute for Social Research, University of Michigan.

Lewis, Elizabeth et al. (2017). “The Growth of Managed Long-Term Services and Supports Programs: 2017 Update”. In: p. 70.

Libersky, Jenna et al. (June 2017). *Managed Long-Term Services and Supports Design Supplement: Interim Outcomes Evaluation*. Tech. rep. Baltimore, MD: Mathematica Policy Research.

Libersky, Jenna et al. (Jan. 2018). *Medicaid 1115 Demonstration Interim Evaluation Report Managed Long-Term Service and Supports*. Tech. rep. Mathematica Policy Research.

Lipson, Debra (Oct. 2018). *End of the Drought: New Measures for Assessing the Quality of Managed Long-Term Services and Supports*. URL: https://www.mathematica-mpr.com/commentary/end-of-the-drought-new-measures-for-assessing-the-quality-of-managed-long-term-services-and-supports (visited on 02/12/2019).

Manning, Willard G. et al. (1987). "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment". In: *The American Economic Review* 77.3, pp. 251–277.

Maslow, Katie and Joseph G. Ouslander (Feb. 2012). *Measurement of potentially preventable hospitalizations*. White Paper. Long-term Quality Alliance, p. 92.

McCall, Nelda and Jodi Korb (1997). "Utilization of Services in Arizona's Capitated Medicaid Program for Long-Term Care Beneficiaries". In: *Health Care Financing Review* 19.2, pp. 119–134.

Medicare and Medicaid Services, Centers for (Mar. 2019). *MAX General Information*. URL: https://www.cms.gov/Research-Statistics-Data-and-Systems/Computer-Data-and-Systems/MedicaidDataSourcesGenInfo/MAXGeneralInformation.html (visited on 08/13/2019).

MedPAC and MACPAC (Jan. 2018). *Data book: Beneficiaries dually eligible for Medicare and Medicaid*. Tech. rep.

Meyers, David J., Vincent Mor, and Momotazur Rahman (Jan. 2018). "Medicare Advantage Enrollees More Likely To Enter Lower-Quality Nursing Homes Compared To Fee-For-Service Enrollees". In: *Health Affairs* 37.1, pp. 78–85.

Miller, Edward Alan and William G. Weissert (Sept. 2000). “Predicting Elderly People’s Risk for Nursing Home Placement, Hospitalization, Functional Impairment, and Mortality: A Synthesis”. In: *Medical Care Research and Review* 57.3, pp. 259–297.

Miller, Nancy A. and Adele Kirk (Jan. 2016). “Predicting State Investment in Medicaid Home- and Community-Based Services, 2000–2011”. In: *Journal of Aging & Social Policy* 28.1, pp. 49–64.

Mor, Vincent et al. (June 2004). “Driven to Tiers: Socioeconomic and Racial Disparities in the Quality of Nursing Home Care”. In: *Milbank Quarterly* 82.2, pp. 227–256.

Office, Congressional Budget (June 2013). *Rising Demand for Long-Term Services and Supports for Elderly People*. Tech. rep. Congressional Budget Office.

Owen, Randall et al. (Oct. 2019). “Utilization of and Relationships With Primary Care Providers During the Transition to Medicaid Managed Care”. In: *Journal of Disability Policy Studies*.

Patel, Yash M. and Stuart Guterman (2017). *The Evolution of Private Plans in Medicare*. Issue Brief. Commonwealth Fund.

Peebles, Victoria et al. (Dec. 2017). *HCBS Claims Analysis Chartbook: Final Report*. Tech. rep. Mathematica Policy Research.

Rahman, Momotazur et al. (Oct. 2015). “High-Cost Patients Had Substantial Rates Of Leaving Medicare Advantage And Joining Traditional Medicare”. In: *Health Affairs* 34.10, pp. 1675–1681.

RAND HRS Longitudinal File 2016 (May 2019). Tech. rep. Produced by the RAND Center for the Study of Aging, with funding from the National Institute on Aging and the Social Security Administration. Santa Monica, CA.

Research, Mathematica Policy (2019). *Medicaid Managed Care Enrollment and Program Characteristics, 2017*. Tech. rep. Washington, DC: Centers for Medicare &Medicaid Services, p. 500.

Rosenbaum, Paul R. and Donald B. Rubin (Apr. 1983). “The central role of the propensity score in observational studies for causal effects”. In: *Biometrika* 70.1, pp. 41–55.

Sansoni, J et al. (2013). “Caregivers of Alzheimer’s patients and factors influencing institutionalization of loved ones: some considerations on existing literature”. In: *Ann Ig* 25, pp. 235–246.

Saucier, Paul, Brian Burwell, and Kerstin Gerst (Apr. 2005). *The Past, Present, and Future of Managed Long-Term Care*. Tech. rep.

Saucier, Paul et al. (July 2012). *The Growth of Managed Long-Term Services and Supports (MLTSS) Programs: A 2012 Update*. Tech. rep. Centers for Medicare &Medicaid Services.

Schulz, Richard and Lynn M. Martire (May 2004). “Family Caregiving of Persons With Dementia: Prevalence, Health Effects, and Support Strategies”. In: *The American Journal of Geriatric Psychiatry* 12.3, pp. 240–249.

Schwartz, Margot L. (June 2018). *Comparing the Quality of Home Health Agencies That Serve Traditional Medicare Versus Medicare Advantage Beneficiaries*. Paper presentation.

Shaughnessy, Peter W., Robert E. Schlenker, and David F. Hittle (1994). “Home Health Care Outcomes Under Capitated and Fee-for-Service Payment”. In: *Health Care Financing Review* 16.1, pp. 187–222.

Skira, Meghan M. (Feb. 2015). “Dynamic Wage and Employment Effects of Elder Parent Care”. In: *International Economic Review* 56.1, pp. 63–93.

Smith, David Barton et al. (Sept. 2007). “Separate And Unequal: Racial Segregation And Disparities In Quality Across U.S. Nursing Homes”. In: *Health Affairs* 26.5, pp. 1448–1458.

Sparer, Michael (Sept. 2012). *Medicaid managed care: Cost, access and quality of care*. Research Synthesis Report 23. Robert Wood Johnson Foundation.

Terza, Joseph V., Anirban Basu, and Paul J. Rathouz (May 2008). “Two-stage residual inclusion estimation: Addressing endogeneity in health econometric modeling”. In: *Journal of Health Economics* 27.3, pp. 531–543.

Thach, Nga T. and Joshua M. Wiener (May 2018). *An Overview of Long-Term Services and Supports and Medicaid: Final Report*. Tech. rep. Washington DC: U.S. Department of Health et al., p. 34.

Toseef, Mohammad Usama, Gail A. Jensen, and Wassim Tarraf (July 2019). "Is enrollment in a Medicaid health maintenance organization associated with less preventable hospitalizations?" In: *Preventive Medicine Reports* 16.

Wallace, Steven P. et al. (Mar. 1998). "The Persistence of Race and Ethnicity in the use of Long-Term Care". In: *The Journals of Gerontology: Series B* 53B.2, S104–S112.

Walsh, Edith G. and William D. Clark (2002). "Managed Care and Dually Eligible Beneficiaries: Challenges in Coordination". In: *Health Care Financing Review* 24.1, pp. 63–82.

Walsh, Edith G. et al. (May 2012). "Potentially Avoidable Hospitalizations of Dually Eligible Medicare and Medicaid Beneficiaries from Nursing Facility and Home- and Community-Based Services Waiver Programs". In: *Journal of the American Geriatrics Society* 60.5, pp. 821–829.

Watts, Molly O'Malley and MaryBeth Musumeci (Jan. 2018). *Medicaid Home and Community-Based Services: Results from a 50-state survey of enrollment, spending, and program policies*. Tech. rep. Washington, DC: Kaiser Family Foundation.

Wenzlow, Audra, Steve Eiken, and Kate Sredl (June 2016). *The Evolution of Medicaid Expenditures for Long-Term Services and Supports, FY 1981-2014*. Tech. rep. Truven Health Analytics.

Wieland Darryl et al. (Apr. 2015). "Hospitalization in the Program of All-inclusive Care for the Elderly (PACE): Rates, Concomitants, and Predictors". In: *Journal of the American Geriatrics Society* 48.11, pp. 1373–1380.

Wysocki, Andrea et al. (June 2014). "The Association between Long-Term Care Setting and Potentially Preventable Hospitalizations among Older Dual Eligibles". In: *Health Services Research* 49.3, p. 778.

Wysocki, Andrea et al. (Jan. 2019). *Design Supplement: Final Outcomes Evaluation*. Tech. rep. Mathematica Policy Research.

Wysocki Andrea et al. (Jan. 2014). "Hospitalization of Elderly Medicaid Long-Term Care Users Who Transition from Nursing Homes". In: *Journal of the American Geriatrics Society* 62.1, pp. 71–78.

Yao, Nengliang et al. (Aug. 2016). "Geographic Concentration Of Home-Based Medical Care Providers". In: *Health Affairs* 35.8, pp. 1404–1409.

Yao, Nengliang (Aaron) et al. (2018). "Use of Home-Based Medical Care and Disparities". In: *Journal of the American Geriatrics Society* 66.9, pp. 1716–1720.

Zuckerman, Stephen, Niall Brennan, and Alshadye Yemane (Aug. 2002). "Has Medicaid Managed Care Affected Beneficiary Access and Use? - Stephen Zuckerman, Niall Brennan, Alshadye Yemane, 2002". In: *INQUIRY: The Journal of Health Care Organization, Provision, and Financing* 39.3, pp. 221–242.