Becoming Dual: Measuring the Impact of Gaining Medicaid Coverage For Medicare Beneficiaries *

Gina Li

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Abstract

This paper studies how Medicare and Medicaid – the two largest public health insurance programs in the United States – jointly shape patients' access to healthcare and healthcare spending. Specifically, I estimate the effect of gaining additional Medicaid coverage for Medicare beneficiaries on healthcare utilization. While dual coverage eliminates out-of-pocket costs, thereby increasing demand for healthcare, I identify a countervailing force: providers are less willing to treat dual patients due to lower reimbursement rates and higher administrative burdens associated with Medicaid. Using variation from a substantial expansion in dual-Medicaid eligibility in the state of Connecticut, I find that dual enrollment increases patients' total health care utilization by 51 percent, and that much of this increase is driven by a higher use of the emergency department. At the same time, dual enrollment leads to a 24 percent decline in the number of outpatient physician visits, especially for preventive care. I show that the decline in outpatient care is concentrated among providers with a low share of Medicaid patients. Thus, my findings demonstrate the unintended consequences of policies that increase enrollment in dual-Medicaid among patients without changing provider side constraints regarding their willingness to treat Medicaid patients.

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1 Introduction

Since 1965, Medicare has been the central program providing public health insurance coverage to individuals aged 65 and older and those with disabilities in the United States, covering one-in-five Americans. Medicare beneficiaries face out-of-pocket costs, such as premiums and coinsurance, when receiving healthcare services, with the average Medicare out-of-pocket cost amounting to $5,460 in 2016 (Cubanski et al., 2019). These costs can constitute a substantial financial burden for low-income enrollees. To address this concern, the means-tested Medicaid program – which provides public health insurance coverage to low-income populations – allows eligible Medicare beneficiaries to become dual Medicare-Medicaid enrollees (or "dually enrolled"), covering out-of-pocket costs for these patients. In 2019, 12.2 million individuals were dually enrolled in Medicare and Medicaid, representing 10 percent of the combined Medicare and Medicaid populations. These patients represent some of the most vulnerable people in the country and account for a disproportionate share, 31 percent or $440 billion, of total combined annual Medicare and Medicaid healthcare spending (MACPAC, 2022).

As of 2022, 16 states and the District of Columbia have expanded their Medicaid programs to cover additional Medicare enrollees beyond the federal minimums (NCOA, 2022). These expansions are often lauded as helping seniors access high-quality and affordable healthcare coverage (Lyons, 2020). Yet despite this enthusiasm, there is limited empirical evidence on how dual enrollment affects access to healthcare services for this important and vulnerable population.[1]

In this paper, I offer new evidence on the causal effect of dual enrollment on the healthcare utilization of Medicare beneficiaries. Although policymakers posit that dual enrollment improves healthcare access for low-income individuals, it is not clear that this is the case. While this dual system eliminates out-of-pocket costs for patients, I document and identify a crucial tradeoff: having dual Medicare-Medicaid coverage may reduce the set of providers

[1] This is in stark contrast to the broad literature examining the consequences of Medicaid (e.g. Currie and Gruber (1996b), Finkelstein et al. (2012)) and Medicare coverage (e.g. Finkelstein (2007), Finkelstein and McKnight (2008), Card et al. (2009)).

available and willing to treat them. This is because providers are paid based on Medicaid payment rates when they treat dually enrolled patients, and these rates are often significantly lower than Medicare rates.[2] They also face high administrative hurdles, such as frequent claim denials (Dunn et al., 2021). For both of these reasons, providers may be less willing to treat dually enrolled patients than they are to treat Medicare-only patients.

To identify the causal impact of dual enrollment, I study a substantial dual-Medicaid eligibility expansion in the state of Connecticut in October 2009, which increased dual enrollment in the state by 73 percent. This policy change created both cross-state and within-state variation in dual eligibility, where neighboring states did not experience any policy changes, and regions within Connecticut experienced different treatment intensities based on baseline demographic differences. I use the change in eligibility thresholds in an instrumental variables (IV) framework to isolate the effect of dual enrollment for the marginal Medicare beneficiaries who enrolled due to the expansion.

I use ten years of administrative Medicare claims and enrollment data covering the period from 2006 through 2015. Employing detailed information on healthcare utilization and spending for the same individual over time, I track how individual healthcare utilization changes as people gain dual status. I further use the annual American Community Survey to obtain information on household income by sub-state geographical location (Public Use Microdata Area). I construct an instrument that captures the treatment intensity of the Connecticut policy change, through simulating the share of individuals who are eligible for dual enrollment by sub-state location, based on the pre-policy demographic composition of a local area. This instrument therefore captures cross-state and within-state variation in eligibility for dual enrollment, driven by the policy expansion.

I find that while becoming dually enrolled increases total quarterly healthcare utilization by 51 percent (41 percentage point increase in log spending), patients shift away from physician visits and toward the emergency department (ED). The number of physician visits decreases by 1.0 visit per quarter or 24 percent relative to the sample mean. The decline in

[2] In 2019, Medicaid reimbursement rates were 72 percent of Medicare rates (Zuckerman et al., 2021).

the usage of primary care services drives this decrease, as the probability of having at least one visit to a primary care provider falls by 19 percentage points. The type of care received changes as well, where dual enrollment induces significant declines in preventive care use. In contrast, the probability of having at least one ED visit increases by 8 percentage points for the new dually enrolled. Overall, new dually enrolled patients end up using the ED for healthcare services but are less likely to see a primary care physician. These findings suggest that although Medicaid enrollment (and the associated reduction in out-of-pocket costs faced by Medicare beneficiaries) increases the demand for healthcare services, there is an offsetting force coming from the supply side as physicians become less available.

I formally test this hypothesis, through investigating whether the physicians' reluctance to accept Medicaid patients drives the observed reduction in physician services among dually enrolled patients. First, I study how the effects of dual enrollment vary across providers with different propensities to accept Medicaid as a form of insurance.[3] I show that patients with primary care providers (PCPs) who are least likely to accept Medicaid have a 23 percentage point decline in having any primary care visits in a quarter. At the same time, this effect disappears for individuals with PCPs with a high likelihood of treating Medicaid patients. Furthermore, patients with PCPs unlikely to treat Medicaid patients (presumably the same ones who lose access to their PCP) are more likely to end up in the ED, suggesting substitution from physician services to the ED. Next, I categorize physician specialties by their willingness to accept Medicaid, as measured through the National Ambulatory Medical Care Survey, and show that dual enrollment increases the usage of specialties associated with higher propensities to accept Medicaid patients, such as ophthalmologists and general surgeons. However, the dually enrolled are less likely to visit specialists with a low probability of treating Medicaid patients, such as dermatologists and psychiatrists.

The changes in physician visits suggest that the consequences of becoming dually enrolled might differ by the patient's medical needs. To investigate this conjecture, I estimate how the effect of dual enrollment differs by patient characteristics. I show that those with Social

[3]Specifically, I use Medicare claims and identify the share of a provider's claims that belong to patients with dual status.

Security Disability Insurance experience more pronounced reductions in physician usage than the overall population where they are 8 percentage points less likely to have at least one visit to a specialist. These beneficiaries are more likely to have medical conditions (such as mental illness) treated by doctors with low Medicaid acceptance rates.

Lastly, having documented that dual Medicare-Medicaid enrollment affects healthcare utilization, I ask whether these changes translate into impacts on patient health. The effects on health are theoretically ambiguous; while dual coverage may decrease health through loss of physician access, dual coverage can improve health through non-physician channels. For example, dual enrollment eliminates Medicare-associated financial costs and increases access to non-Medicare Medicaid covered services. I find evidence that average mortality rates were reduced slightly due to the Connecticut expansion. Although this result points to net mortality gains, more work is needed to explore the broader health and welfare consequences, particularly in light of the demand and supply responses documented in this paper.

This paper contributes to several strands of literature. A substantial body of work estimates the effects of Medicaid enrollment and Medicaid expansions on health and healthcare utilization, largely focusing on the previously uninsured (e.g. Finkelstein et al. (2012), Taubman et al. (2014), Wherry and Miller (2016)). In my setting, the Medicaid expansion applies to new enrollees who were already insured under Medicare, making the findings from this existing literature on Medicaid less applicable. Indeed, I find the opposite effect compared to the previous literature; here, Medicaid enrollment decreases physician usage for Medicare beneficiaries as opposed to the increases in access and usage of physician services that the literature has found for the previously uninsured. My results highlight that the experiences of those affected by Medicaid expansion differ by population and baseline insurance coverage.

Providers are responsive to prices and costs, through adjusting the supply of healthcare services (Chen (2014), Clemens and Gottlieb (2014), Haber et al. (2014), Polsky et al. (2015), CMS (2015), Zheng et al. (2017), Callison and Nguyen (2018), Alexander and Schnell (2019), Cabral et al. (2021), Dunn et al. (2021), Hayford et al. (2023)). Notably, for individuals already dually enrolled, Cabral et al. (2021) show that temporary increased payments due to the Affordable Care Act increased usage of physician evaluation and management services and Hayford et al. (2023) illustrate that the dually enrolled in states with more restrictive payment policies saw decreased utilization.[4] I focus on a different margin – patients' shift into dual status – and find that the supply-side drivers are so large that care utilization might decrease upon dual enrollment, despite the reduction in out-of-pocket costs.

More broadly, there is considerably less research on individuals who are covered by both Medicare and Medicaid simultaneously, especially in understanding the effects of dual enrollment itself.[5] Studies that compare the dually enrolled with those enrolled in Medicare-only find that dual status is associated with increased usage and access to medical services (Ozminkowski et al. (1997), Parente and Evans (1998), Rudolph and Haber (2003), Federman et al. (2005), Moon and Shin (2006)), while others (Haber et al. (2014), Cabral et al. (2021)) show the opposite. Given that individuals might select into dual enrollment, I contribute to this literature by using an empirical approach that leverages a plausibly exogeneous policy change as a natural experiment that allows for a causal interpretation of the estimates. Existing studies leveraging quasi-experimental research designs also point to mixed effects with dual coverage increasing physician visits or producing no effect (Roberts et al. (2023), Roberts et al. (2021), Berman (2021b)).[6]

This paper contributes and extends the previous work on the effects of dual enrollment in several dimensions. First, my research design allows me to follow the same individual through time (thus holding individual characteristics fixed) to disentangle the effects of dual enrollment from other concurrent factors that affect utilization. Furthermore, I estimate effects for the newly enrolled, such that these results are generalizable to the policy-relevant

[4]Meanwhile, Roberts and Desai (2021) and Fung et al. (2021) show limited provider responses to the same ACA policy change, suggesting some physicians might not be responsive to transitory payment changes.

[5]Existing studies often use the dually enrolled population as a setting to study a variety of other questions (Basu et al. (2010), McInerney et al. (2017), Gross et al. (2020), Carey et al. (2020), Ding et al. (2021), Neprash et al. (2021)).

[6]Roberts et al. (2021) and Roberts et al. (2023) use a regression discontinuity design around the Medicaid eligibility income threshold and find that the dually enrolled use more physician services. Berman (2021b) focus on the CT expansion finding no effects on the number of outpatient claims. Lastly, Vabson (2014) examines the consequences of losing dual status in Tennessee due to a mandatory dis-enrollment, finding dis-enrollment decreases utilization in outpatient services. The consequences of losing dual status are likely not symmetric with gaining dual status.

populations of interest as states are increasingly expanding their dual-Medicaid programs. Second, I uncover heterogeneous effects depending on the type of service and nature of the provider (e.g. degree of Medicaid acceptance), highlighting the role of the supply-side in determining the usage of care and uncovering mechanisms driving the differential direction of effects. These provider-driven changes in healthcare usage can also produce spillovers onto other forms of care, such as the emergency department. Lastly, my analysis illustrates how the effects of dual enrollment might mask important differences by characteristics of the patient, especially the patient's medical conditions and healthcare needs.

This paper not only provides insights on individuals with dual enrollment in Medicare and Medicaid, but also generates broader implications and lessons for the design of public insurance systems for low-income populations. These programs typically limit out-of-pocket costs for patients, but policymakers impose costs in other ways to lower expenditures, such as low payment rates to providers or frequent claim denials. As this paper shows, the supply-side responses may be so strong that patients have trouble accessing providers upon gaining coverage, even when out-of-pocket costs are no longer a concern. Given these results, government cost-saving measures may affect the quality of care these vulnerable patients receive.

The paper proceeds as follows. Section 2 introduces the background and institutional setting of Medicare, Medicaid, and the dual Medicare-Medicaid program. Section 3 describes the main data set, while section 4 discusses the empirical design and the Connecticut policy change. The effects of Medicaid enrollment are shown in Section 5. Section 6 discusses the implications of these findings while Section 7 concludes.

2 Background and Institutional Setting

2.1 Medicare and Medicaid

The two major public health insurance programs in the United States are Medicare and Medicaid, which have a combined annual spending (as of 2019) of 1.4 trillion dollars, accounting for 37 percent of national health expenditures (CMS, 2019b). Medicare, covering

61.5 million beneficiaries in 2019 (CMS, 2019a), is a federally administered health insurance program that provides coverage to individuals age 65 or over and to individuals with disabilities (through Social Security Disability Insurance (SSDI)). Medicaid, on the other hand, is a state administered health insurance program targeted at low-income populations, with 71.4 million enrollees in the same year (CMS, 2020).

Medicare and Medicaid broadly overlap in covered services for individuals,[7] but differ in out-of-pocket costs to beneficiaries. For Medicare, there are monthly premiums ($135.50 for coverage of medical services in 2019), annual deductibles that have to be met before insurance coverage begins, and coinsurance for specific services. For example, services such as doctor's visits require a $185 annual deductible, followed by a 20 percent coinsurance for each visit. These out-of-pocket Medicare costs can be substantial for the individual; 27 percent of Medicare beneficiaries spent at least 20 percent of their incomes on Medicare premiums and out-of-pocket costs. This was especially pronounced for the lowest-income groups, where the proportion rises to 40 percent for low-income individuals with incomes below 200 percent of the federal poverty line (Schoen et al., 2017). In contrast, since Medicaid serves low-income communities, Medicaid beneficiaries pay very little to no premiums or cost-sharing.

Medicare and Medicaid also differ on payments to providers, which in turn affects providers' willingness to accept a certain type of insurance. Both of these programs largely pay providers on a Fee-for-Service (FFS) basis, where each service to a beneficiary is paid for in accordance to a rate schedule.[8] Medicaid traditionally has lower reimbursement rates. For example in 2019, Medicaid fees were on average 28 percent lower than Medicare fees (Zuckerman et al., 2021). Notably, for primary care, the Medicaid fee was 33 percent lower; a common 15 minute office visit with an established patient was paid a $51.57 rate, while

[7]These services include inpatient hospital care, outpatient hospital care, and physician services. In traditional Medicare, Part A provides inpatient services while Part B includes outpatient services and requires a monthly premium. There is variation in Medicaid coverage across states. Services broadly covered by Medicaid and not Medicare include extended nursing facility care, transportation for medical services, and possibly dental care.

[8]Medicare and Medicaid also operate alternative payment systems: Medicare Advantage and Medicaid Managed Care. This project focuses on 2006-2015, where FFS was more popular for both Medicare and Medicaid. For instance, in 2006, only 12 percent of the dually enrolled were in Medicare Advantage (MMCO, 2018). Furthermore, for the relevant populations in this study (disabled or elderly), state Medicaid programs have historically reserved these groups for FFS.

the corresponding Medicare rate was \$75.32.[9] Furthermore, providers who treat Medicaid enrollees often face substantial administrative burdens due to complicated billing processes for providers seeking payments, such as frequent denials (Dunn et al., 2021).

Given that physicians face lower payments on average for Medicaid services and incur higher administrative costs, fewer physicians choose to accept Medicaid compared to Medicare. For example, out of the 95 percent of physicians in an office-based setting who take new patients, 84 percent reported accepting Medicare, but only 69 percent reported accepting Medicaid (Hing et al., 2015). Furthermore, these self-reported physician acceptance rates likely overstate the acceptance rate as experienced by Medicaid patients seeking doctors. Researchers called 1800 primary and specialist Medicaid providers and found that slightly less than half of the providers could offer appointments (Levinson and General, 2014).

2.2 The Dual Medicare-Medicaid Program

Since the inception of the Medicare and Medicaid programs in 1965, it has been possible to be simultaneously enrolled in both, because eligibility for these programs operates on separate margins. Medicare beneficiaries qualify for Medicaid through having low incomes and assets. In return, Medicaid assists with out-of-pocket costs, including Medicare premiums and cost-sharing. The dual Medicare-Medicaid program has grown over time, with 12.2 million individuals enrolled in 2019 (MMCO, 2020).

Those who are dually enrolled are demographically distinct from the Medicare-only population and are a particularly vulnerable set of individuals. There is geographic dispersion, where dual enrollees are more concentrated in the south and northeast as opposed to the west (Appendix Figure A1). This population is also 32 percent less likely to be non-Hispanic White and is three times more likely to report having poor health than those enrolled only in Medicare (Appendix Figure A2). Given that the dually enrolled population tends to be sicker, they not only account for a large share of beneficiaries (19 percent of Medicare and

[9]The HCPCS code for this service is 99213. The average Medicaid payment is derived from Appendix A.1 (Zuckerman et al., 2021). The Medicare amount is obtained from the CMS 'Search the Physician Fee Schedule', for 2019 for Non-Facility. This price reflects the National Payment Amount; exact Medicare prices varies by geographic location.

14 percent of Medicaid), but an even larger share of spending (34 percent and 30 percent, respectively) (MACPAC, 2022). Furthermore, the per capita Medicare and Medicaid combined spending for dual enrollees was $36.1 thousand, over three times greater than the $10.7 thousand in Medicare per capita spending for Medicare-only beneficiaries (MACPAC (2022), CMS (2019b)).

Financial support for the dually enrolled is provided based on income level, where those with lower incomes and assets qualify for more generous cost assistance. This paper focuses on the 8.0 million (as of 2019) dually enrolled individuals called Qualified Medicare Beneficiaries (QMBs), who have the highest level of poverty and receive complete out-of-pocket cost elimination for Medicare services, including all deductibles, premiums, and other coinsurance.[10] In order to be eligible for QMB, the QMB federal guidelines stipulate that Medicare beneficiaries must have incomes below 100 percent of the Federal Poverty Level (FPL) and assets less than $7,730 for a single individual and $11,600 for a married couple in 2019.

Individual states can choose to have more generous QMB eligibility thresholds. As of 2017, 12 states and the District of Columbia have either removed the asset test or raised the asset threshold, but only Connecticut, Indiana, Maine, and D.C. have increased income eligibility (MACPAC, 2018). In the empirical design, I leverage differential state QMB eligibility generosity. For the rest of this paper, I use the terminology "dually enrolled" to refer to enrollment in the QMB program for simplicity, unless otherwise specified.

When an individual becomes a dual beneficiary, the provider payment system also changes because there are now two insurers paying providers for services. Medicare is considered the primary payer for covered services, while Medicaid is the secondary insurance, filling in the cost gaps of Medicare. Providers first submit their claims to Medicare to pay its share of the service and then the claim is sent to Medicaid.[11] When the claim is sent to Medicaid for

[10] I detail all categories of the dually enrolled population with more information on QMB and other dual types in Appendix A.1, Appendix Table A1, and Appendix A.2. In addition to gaining Medicare cost-elimination, some QMBs also gain access to their state's full Medicaid package, and to non-Medicare Medicaid services.

[11] This also determines how the claims are reported in the administrative data; Medicare administrative claims databases include the full universe of beneficiaries' claims for services covered by Medicare. Thus, the Medicare claims can be used to reliably document patterns in duals' healthcare usage patterns for the types of utilization I focus on.

payment of cost-sharing, individual states do not need to pay the full cost-sharing amount. The vast majority of states opt for the "lesser-of" policy, where Medicaid pays the difference between the Medicaid reimbursement amount and what is already payed by Medicare.

Due to the lesser-of policy, providers can end up receiving less total payment for treating a dually enrolled patient than when the individual is Medicare-only. To illustrate this concept, consider a physician visit, where the Medicare-approved amount is \$100.[12] Assuming that deductibles have been met, Medicare pays \$80 (recall that Medicare coverage is associated with a 20 percent coinsurance). The remaining \$20 that would have been paid by a Medicare-only beneficiary will be sent to Medicaid for payment. If the state Medicaid payment rate is \$80 or less, Medicaid would consider the bill already paid in full, pay nothing else, and the provider would have to accept \$80 as the full payment for the service. If the Medicaid rate is \$90, for example, Medicaid would pay \$10. Medicaid will pay at most \$20 should the Medicaid rate exceed the Medicare rate, which is seldom the case. In addition to the lesser-of policy, high administrative costs associated with filing Medicaid claims (such as frequent claim denials) also prevent providers from seeking or receiving payment even when entitled to such payment (Cabral et al., 2021). In Connecticut in 2009, of the total Medicare cost-sharing portion, Medicaid only covered 11.3 percent for evaluation and management services (Haber et al., 2014).

3 Data

I use administrative Medicare claims and enrollment data from the Centers of Medicare and Medicaid Services (CMS). The CMS data is a 20 percent random sample of Medicare beneficiaries from 2006 through 2015. For each individual, I observe demographics and all Medicare utilization and spending claims through time. In this section, I summarize the creation of key variables for analysis and discuss the sample restrictions, with greater detail documented in Appendix B.

[12] Example adapted from MACPAC Report to the Congress on Medicaid and CHIP, Chapter 4: Medicaid Coverage of Premiums and Cost Sharing for Low-Income Medicare Beneficiaries. It is illegal for providers to ask QMBs to pay for services should Medicaid not pay up to the Medicare amount and providers are subject to sanctions otherwise.

Beneficiary Demographics

This data contains demographic information on the beneficiary, including age, sex, reason for Medicare entitlement (aging or disability), zip code of residence, and date of death. I observe dual enrollment status for each individual each month and produce an indicator for dual enrollment if the individual is enrolled as a dual beneficiary for at least one month in the quarter. I also identify the overall health level, which is used in one of the heterogeneity analyses. This summary measure of health is the number of comorbidities, defined as the number of chronic conditions that an individual has in a calendar year, following Maciejewski and Hammill (2019). One major limitation of Medicare claims is that it does not contain information on income or assets that would allow me to identify each individual's eligibility for dual enrollment. Therefore, I supplement CMS claims with Census data on income and assets, as described in Section 4.

Medicare Spending and Usage

Total Medicare spending is the sum of Medicare paid amounts on inpatient and outpatient services. Inpatient services are services performed in an inpatient setting (excluding Skilled Nursing Facilities), while outpatient services include the sum of spending from physicians, outpatient services such as ED visits, home health, and durable medical equipment.[13] To capture measures of healthcare utilization, I focus primarily on hospitalizations, emergency department (ED) visits, physician visits, and usage of preventive care services.[14] I also classify ED visits into emergent or nonemergent care (Billings et al. (2000), Johnston et al. (2017), Miller (2012), Taubman et al. (2014)), based on whether immediate care within 12

[13]For spending, I focus solely on what Medicare pays for on each claim, and do not include other costs, such as potential copays. This way, spending between the dually enrolled and Medicare-only populations are comparable, since Medicare pays the same amount for each service (conditional on the patient deductible) regardless of the dual status of the individual. What does differ is how much of the individual coinsurance is paid for by Medicaid to providers, but this amount is not included in the spending measure.

[14]In other words, I focus on services from Medicare Part A and Medicare Part B. My data does not contain non-Medicare covered services, including Medicaid-only services such as dental care and transportation. Therefore, I do not capture utilization for non-Medicare covered Medicaid services. However, these services are unlikely to interact with the set of Medicare covered services, which are the focus.

hours was necessary. For physician visit claims, I observe the physician specialty and individual physician identifiers (NPI or National Provider Identifier). I map physician specialties into primary care (General Practice, Internal Medicine, Family Practice, or Geriatrics), while the rest of the physician visits are considered specialist visits (Zhang et al., 2021). Lastly, I identify five measures of preventive care usage: flu shots, mammograms, and for diabetes patients, HbA1c test, lipid test, and retinal eye exam.

Physician Medicaid Acceptance

I categorize physicians into their Medicaid acceptance level or their propensity to accept Medicaid as a form of insurance in two ways. First, I create $PCPMedAccept_i$, a measure of the willingness of individual i's main primary care provider (PCP) to take on a Medicaid patient (see Appendix B.7 for detail on variable construction). Two individuals with similar beneficiary demographics might nonetheless experience different dual enrollment effects, because one individual has a doctor who happens to take Medicaid as a form of insurance, while the other individual has a doctor who does not accept Medicaid. I focus on the PCP given emphasis of the PCP as a key figure in the typical patient's management and coordination of care. Specifically, $PCPMedAccept_i$ is the fraction of the main PCP's Medicare claims that belong to Medicaid patients (specifically, dually enrolled patients, as observed by the dual status in the Medicare claims data), prior to the Connecticut Medicaid expansion. In Appendix Figure A3, I plot the histogram of $PCPMedAccept_i$, where each observation is a patient. The histogram shows that accepting few Medicaid patients is common; over 20 percent of patients have main PCPs where only zero to 5 percent of their claims came from Medicaid patients. The overall mean is 19 percent.

Second, I map physician specialties into three categories, high, medium, and low Medicaid acceptance, based on the fraction of physicians in the specialty who claim to accept Medicaid as a form of payment. These fractions are produced from the National Ambulatory Medical Care Survey (NAMCS). NAMCS is a national survey of office-based physicians in an outpatient setting. Conditional on stating that they are accepting new patients, physicians are asked whether they accepted Medicaid as a form of payment. This mapping is shown in Appendix Table A2; fewer than half of those in dermatology and psychiatry who accept new patients accept new Medicaid patients, while almost all cardiologists and ophthalmologists accept Medicaid.

Sample Restriction and Descriptive Statistics

From the full Medicare data set, I make a series of sample restrictions to arrive at the main sample. The details of the sample restrictions are outlined in Appendix Table A3. First, given that claims are only observed for Fee-For-Service (FFS) Medicare, I restrict to individuals who are always enrolled in FFS (and enrolled in Medicare Part A and Medicare Part B) for all years in the data. Second, for the empirical design, which is described in the next section, I focus on a substantial policy change that occurred in Connecticut. Therefore, I restrict the sample to Connecticut and the surrounding states of Massachusetts, New York, and Rhode Island. Given that the Connecticut policy change occurred in late 2009, this data set allows me to track usage patterns for 3 years pre-policy and 6 years post-policy. The final sample includes 16.4 million individual-quarter level observations across 653,000 unique individuals.[15]

Table 1 shows baseline demographic and Medicare usage and spending averages, split by Medicare-only or dually enrolled, for quarters prior to the policy change at baseline. Panel A makes evident that individuals with dual status are substantially different from those enrolled only in Medicare; this population is more likely to be female and non-White. In particular, they are much younger on average, with only 63 percent aged 65 or older, compared with 93 percent in the sample of beneficiaries enrolled only in Medicare. This gap arises because the dually enrolled are more likely to be entitled to Medicare through Social

[15] As discussed in the previous section, there are several categories of dually enrolled patients and this paper focuses on the QMB duals. I also restrict to individuals who were enrolled in QMB or only in Medicare prior to the Connecticut policy change, because my focus is on transitions from Medicare-only into QMB. This excludes individuals who were ever dually enrolled but not enrolled in QMB (those who were receiving some other type of Medicaid assistance) prior to the policy, removing 12.6 percent of the individual-month observations. This panel of individuals is also unbalanced; individuals enter the sample through Medicare enrollment and leave the sample due to deaths.

Table 1: Summary Statistics

	Medicare-Only	Duals
Panel A: Demographics		
Age 65+	0.93	0.63
SSDI	0.12	0.45
Male	0.43	0.37
White	0.93	0.68
# Comorbidities	2.85	3.45
Panel B: Health Usage & Spending		
Any Hospitalization	0.06	0.09
Any ED	0.09	0.16
# Physician Visits	4.11	4.76
Any Specialist	0.72	0.72
Any Primary Care	0.54	0.60
Total Medicare Spending	2170	3184
Observations	5415307	706040

Source: 2006-2009Q3 CMS FFS (CT, RI, NY, and MA) in 2011 dollars. Each observation is an individual-quarter.

Security Disability Insurance, as opposed to the aging pathway. Those who have dual status also have 21 percent more comorbidities. Given that they have worse health on average, it is perhaps unsurprising that they also use more Medicare services. Panel B of Table 1 presents average utilization and spending for hospitalizations, emergency department visits, and physician visits. The dually enrolled have higher utilization across all of these measures. The average total Medicare spending on inpatient and outpatient services among the dually enrolled is $3,184 in a quarter, which is 47 percent more than that of the population only enrolled in Medicare.

4 Empirical Strategy

4.1 Setup

Consider a model estimating the effect among Medicare recipients of enrolling in Medicaid (becoming dually enrolled) on healthcare spending and usage using the following regression for individual i in geographic location l (Public Use Microdata Area, or PUMA) and quarter

t:

$$Y_{ilt} = \alpha_i + \tau_t + \delta_l + \beta Dual_{ilt} + \nu_{ilt}, \tag{1}$$

where Y_{ilt} includes a set of individual level Medicare spending and usage variables, such as the number of physician visits or the usage of the emergency department, and $Dual_{ilt}$ is an indicator for individual dual enrollment status in quarter t. The coefficient of interest is β, which captures the average effect of dual enrollment on outcomes Y_{ilt}. I control for individual level fixed effects α_i to account for time invariant individual factors that affect health care usage, such as baseline underlying health and preferences for seeking care. Time quarter fixed effects, τ_t, capture time quarter specific usage patterns, while PUMA fixed effects, δ_l, absorb baseline differences across PUMAs in healthcare availability, preferences, and provision.[16]

The main challenge for estimation is that individuals who are dually enrolled are likely different compared with those who are not, in ways unobservable in the data. Even controlling for time, individual, and PUMA specific variables, there are likely other unobserved time-varying factors that affect both propensity to enroll as a dual beneficiary and healthcare usage, such as learning about the Medicaid program or adverse health or income shocks. For example, bad health events can lead to the depletion of resources that affect eligibility or to individuals searching for Medicare cost-saving measures and learning about the dual Medicare-Medicaid program (reverse causation). To overcome these endogeneity concerns, I exploit a change in state dual-Medicaid eligibility through an instrumental variables (IV) design. I first discuss the policy change before turning to the creation of the instrument.

4.2 Connecticut Dual-Medicaid Expansion

In October 2009, Connecticut expanded the income eligibility for the dual-Medicaid (specifically, QMB) program from 100 percent of the Federal Poverty Line (FPL) to 197 percent of the FPL and entirely eliminated the asset test ($4,000 for a single individual or $6,000 for a couple in 2009; see Appendix C.1 for more policy background) (Caswell and Waidmann,

[16] I include both individual FE and PUMA FE, since I allow for individuals to move across PUMAs. 10 percent of individuals move PUMAs across my sample. Fewer than 1 percent move across states.

2017). This expansion led to an immediate increase in dual enrollment that has grown over time. 50,861 individuals in Connecticut were enrolled in the dual (QMB) program as of December 2008, almost a year before the policy change. By December 2010, enrollment jumped to 98,502, and then grew to 142,768 by 2015, increasing 2.8 times since before the policy (MMCO, 2021).

In this paper, I focus on the Connecticut setting because it is an early income expansion state with a large policy change. While the policy affected eligibility both through income and assets, I limit attention to the change in income eligibility due to data constraints in measuring assets. Assets are difficult to capture in the data, and self-reported assets are especially prone to measurement error. Furthermore, there is limited ability of assets alone in shifting eligibility, as shown in the case of New York in the paragraph below. For low-income populations, assets are highly correlated with income, so changing assets without shifting income is unlikely to produce large gains in eligibility and enrollment. Of the older Americans who qualified to become dually enrolled due to income, two-thirds also qualified based on assets and 43 percent had no countable assets (Summer and Thompson, 2004).

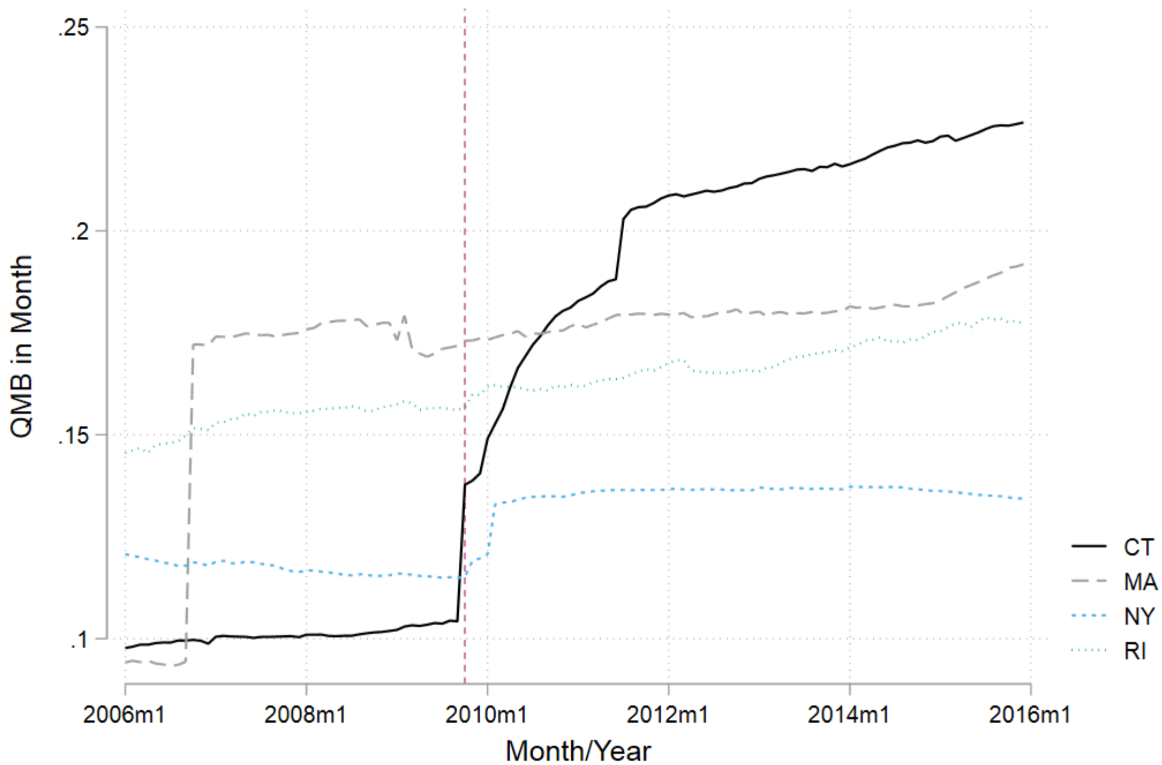
In Figure 1, I graph the fraction of Medicare FFS beneficiaries dually enrolled by month and state for Connecticut and the surrounding states of Massachusetts, Rhode Island, and New York.[17] The neighboring states did not experience any concurrent change in dual-Medicaid income or asset eligibility. Like Connecticut prior to the policy change, all neighboring states had the federal income threshold of 100 percent of FPL, and Massachusetts and Rhode Island had the federal asset limit. New York did eliminate its asset test in April 2008, but this had little, if any, effect on dual enrollment, as shown in this graph.

Figure 1 shows that the Connecticut dual-Medicaid expansion produced an immediate and sustained increase in dual enrollment over time. This is in contrast to the neighboring states, where dual enrollment shares had been broadly steady or perhaps slightly increasing over time.[18] I find that the Connecticut policy change led to a 73 percent increase in dual

[17]Note that in contrast to my main analysis sample, I include all categories of dually enrolled patients to illustrate the size of the overall dually enrolled population relative to all FFS beneficiaries.

[18]There is a noticeable discrete jump in Massachusetts (and a smaller one in New York), despite no changes in eligibility. In Appendix Figure A6, note that the increase in dual enrollment in Connecticut is accompanied

Figure 1: Fraction Dually Enrolled by State



Source: 2006-2015 CMS FFS Claims (CT, NY, RI, NY). This graph shows the fraction of all FFS Medicare beneficiaries enrolled as duals (QMB) by month and state. Note that in contrast to the main sample, I do not restrict to those who were non-QMB dual prior to the policy, to visually illustrate the overall effects of the policy among all FFS Medicare beneficiaries.

enrollment (see Appendix Figures A4, A5, and Appendix C.2).

4.3 Research Design

I create an instrument for individual dual status, $Dual_{ilt}$, called $SimulatedEligibility_{lt}$ to alleviate endogeneity concerns when estimating β from Equation (1). Through an IV design,

by a large decline in the fraction of individuals who are Medicare-only. This is in contrast to Massachusetts and New York, where there were no major changes in the fraction of Medicare-only people around these jumps (Appendix Figures A7 and A8). These figures also show that these states switched individuals into QMB from other types of dually enrolled patients. However, these switches likely do not reflect true changes to individuals' cost-sharing, since they paid very little or nothing before the switch. This further motivates why I restrict the main sample to Medicare-only or QMBs prior to the policy, to not capture shifts from other types of dual status into QMB.

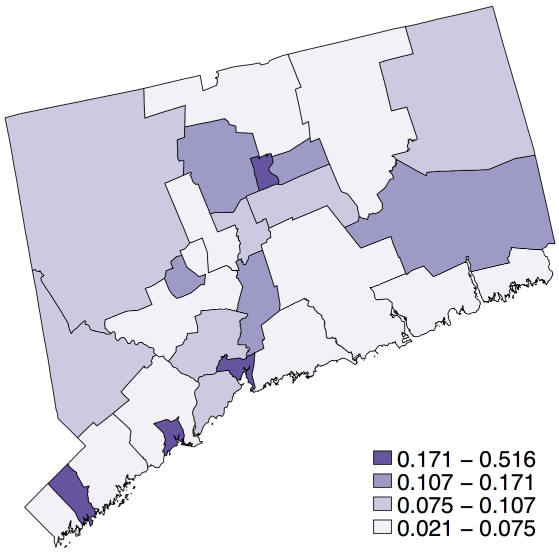
I estimate the causal effect of dual enrollment on healthcare usage for Medicare beneficiaries made eligible for dual enrollment given the policy change. The instrument isolates the portion of dual enrollment that is driven by changes in state eligibility rules, thereby shutting down channels that are driven by endogeneous individual factors, such as worsening health or changing knowledge of the program. The instrument captures changes in the eligibility generosity for dual-Medicaid by simulating the proportion of individuals eligible for dual status based on the laws of the time period.

I leverage two sources of policy-induced variation. First, there is *cross-state* variation in eligibility because Connecticut has a different income eligibility threshold compared with the neighboring states due to the expansion. Second, despite the fact that the dual-Medicaid policy is at the state level, there is *within-state* variation in policy treatment intensity, because of pre-policy characteristics of locations within Connecticut.

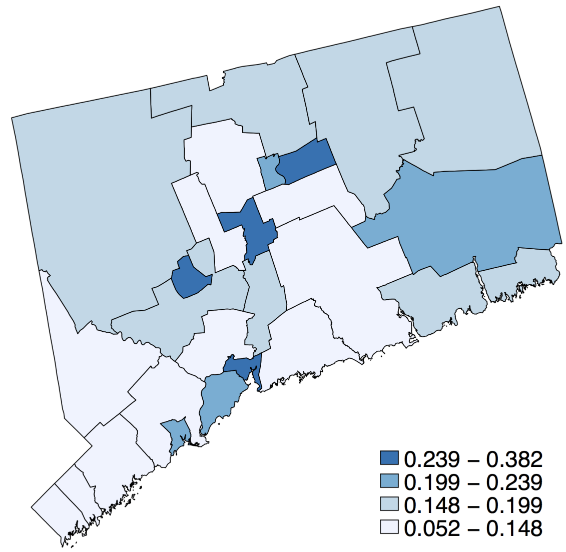
In Figure 2, I map the fraction of Medicare beneficiaries in 2008 who have family incomes below 100 percent of FPL by location within Connecticut in Panel (a). I use the American Community Survey, which I discuss in the next paragraph. Panel (b) shows the fraction with incomes between 100 and 197 percent of FPL in the same year. Before the policy, locations within Connecticut greatly varied in income distribution, with some wealthier areas having poverty rates of less than 10 percent, and others having substantially higher rates. The same locations with high rates of poverty are not necessarily the places with the most people between 100 percent and 197 percent of FPL. I leverage this differential distribution of income prior to the policy; if, for example, a wealthier area had relatively few people between 100 percent and 197 percent of FPL, then the dual-Medicaid expansion would have had less of an impact compared to a lower-income area with a greater concentration of individuals just above the poverty line.

To leverage these sources of variation, I obtain information on individual income and location from the American Community Survey (ACS), since the Medicare claims dataset does not contain income information. The ACS is an annual survey of households conducted by the U.S. Census Bureau and it has several key features that make it useful for this study.

Figure 2: Income Distribution in Connecticut 2008



(a) Fraction Less than 100% FPL



(b) Fraction Between 100 and 197% FPL

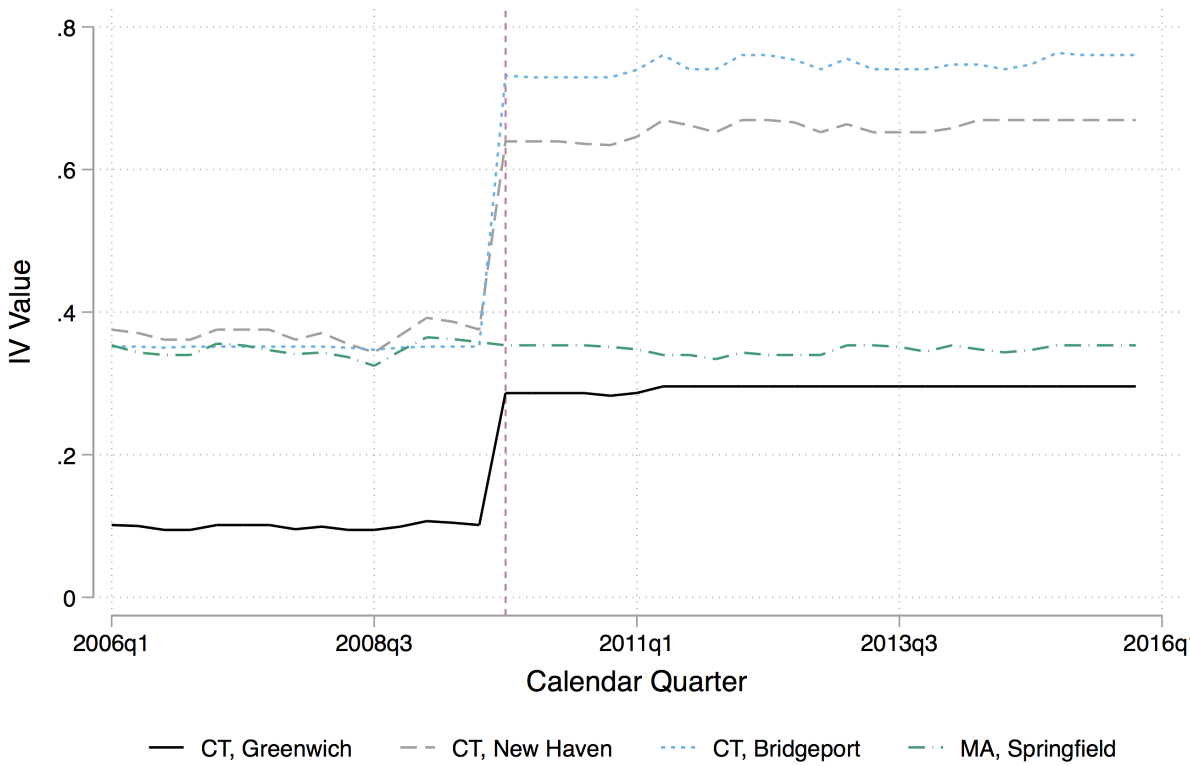
Source: 2008 American Community Survey for Medicare beneficiaries aged 18 and over. These maps depict the fraction of Medicare beneficiaries with family income within a certain range relative to the federal poverty level (FPL).

This dataset allows me to identify sources of income that can be linked within a household, as well as Medicare insurance status. Furthermore, the public use version includes sub-state geographic identifiers, called Public Use Microdata Areas (PUMAs). PUMAs do not cross state boundaries and must contain at least 100,000 individuals. There are 25 PUMAs across Connecticut, for a total of 227 PUMAs across all four states.

To create $SimulatedEligibility_{lt}$, for each PUMA prior to the policy, I take a fixed population of individuals. Using their pre-policy income and marital status, I simulate their income eligibility in each time period given the state's income laws and disregard the asset rules. Specifically, I take Medicare beneficiaries aged 18+ in the 2008 ACS as the fixed base population and inflate income by CPI-U to obtain their inflation-adjusted income through time. Using the state eligibility rules in their state of residence in a given time period, I determine the share of Medicare beneficiaries in a PUMA eligible for dual enrollment given the rules in effect (See Appendix Section D for details).

Figure 3 visually illustrates the instrument by presenting $SimulatedEligibility_{lt}$ across

Figure 3: Instrument Values for Select Locations



Source: 2008 American Community Survey for Medicare beneficiaries aged 18 and over.

select locations and time. For each time period, there is cross-sectional variation in a local area's income distribution; Greenwich, Connecticut, is substantially wealthier compared to New Haven, Connecticut, or Bridgeport, Connecticut, and has a lower simulated fraction eligible for dual enrollment prior to the policy. In fact, Connecticut as a whole is particularly interesting in the stark juxtaposition of highly wealthy areas such as Greenwich where the median household income is $152,577, in contrast to Bridgeport which is located 29 miles away and has a median family income of $46,662 (Census (2019a), Census (2019b)). Following the policy, there is a larger increase in simulated eligibility in Bridgeport compared to New Haven or Greenwich, thus capturing within-state variation. Meanwhile, Springfield, Massachusetts, did not experience any eligibility change, and so the value of the instrument remains flat over time, demonstrating cross-state variation.

For $SimulatedEligibility_{lt}$ to be a valid instrument, it needs to satisfy assumptions, including first stage relevance, monotonicity, independence, and exclusion. I show the first stage in Table 2; the instrument is a strong predictor of individual dual enrollment. Given that no group loses eligibility from the dual-Medicaid eligibility expansion (individuals previously eligible are still eligible), monotonicity is unlikely to be violated. A violation of independence and exclusion is if the instrument, $SimulatedEligibility_{lt}$, is correlated with other factors that might drive health care usage in a PUMA over time.[19]

I perform a balance test of whether the instrument is correlated with possible PUMA-level confounders that might matter for the outcome variables of interest as a check of the exclusion restriction. Specifically, I first predict PUMA-level spending and utilization using the fitted values of a regression of the outcome variable (e.g., average number of physician visits) on PUMA-level demographics. This captures the predicted spending or utilization based on the demographic characteristics of the PUMA. In Appendix Table A4, I show that there is no relationship between the predicted spending and utilization and $SimulatedEligibility_{lt}$.

5 Results

5.1 Main Results

Table 2 presents the coefficient estimates β in equation (1) for a set of Medicare spending and usage outcome variables. While the focus of the discussion will be on the IV results of column (3), I also present the OLS estimates in column (2) for completeness. Dual enrollment increases overall Medicare spending by 51 percent (=exp(0.409)). The increase in total spending shows individuals are using more care on average.

While total Medicare spending increases, the probability of whether an individual has at

[19]Given that the Connecticut dual-Medicaid expansion occurred in the backdrop of the Great Recession, one possible concern is that the recession differentially impacted low-income communities and affected health-care usage over time. However, Social Security is the primary source of income for this population, which is stable across time. Furthermore, I show the balance test holds with inclusion of the local unemployment rate, which proxies for macroeconomic conditions (Appendix Table A4). Another possible concern is that the dual-Medicaid policy produced spillovers onto non-targeted populations, such as those with other forms of insurance. Recent literature do not find evidence of spillovers due to the ACA fee bump for the dually enrolled on non-dual Medicare populations (Cabral et al. (2021)).

Table 2: Effect on Dual Enrollment on Medicare Spending and Usage

Dependent Variable	(1) Mean Dep. Var	(2) OLS	(3) IV
Log(Spending+1)	5.32	0.465	0.409
		(0.019)	(0.150)
Any Spending	0.84	0.058	-0.024
		(0.003)	(0.023)
Any Inpatient	0.06	0.011	0.005
		(0.001)	(0.008)
Any Outpatient	0.84	0.058	-0.024
		(0.003)	(0.023)
Any ED	0.10	0.021	0.083
		(0.001)	(0.018)
# Physician Visits	3.98	0.339	-0.968
		(0.024)	(0.321)
Any Physician Visit	0.83	0.056	-0.025
		(0.003)	(0.021)
Any Specialist	0.73	0.056	0.027
		(0.003)	(0.026)
Any Primary Care	0.56	0.045	-0.185
		(0.003)	(0.049)
Observations	16375484		

Source: 2006-2015 CMS FFS Claims (CT, NY, RI, NY) and 2008 ACS for construction of the instrument. Regressions include controls for quarter FE, individual FE, and PUMA FE. Robust standard errors clustered at the PUMA level in the parentheses. Mean Dep. Var is the mean of the dependent variables for individuals enrolled only in Medicare in CT. "Any" refers to at least one such visit in a quarter or the extensive margin usage. The first stage produces coefficient is 0.254 (s.e. 0.011) with F-statistic of 533.0.

least some Medicare spending (extensive margin) in a quarter is not statistically significant. Furthermore, this point estimate is negative, which is suggestive of even a decreased propensity of having at least some healthcare usage. To explore this further, I break down overall extensive margin spending into spending by setting and find large increases in ED usage. Dual enrollment increases the propensity of having at least one ED visit in a quarter by 8 percentage points, or 83 percent of the mean. However, I do not find statistically significant effects on the share of beneficiaries who have at least some inpatient usage or outpatient spending in the quarter.

In contrast with the large rise in individuals having at least one ED visit, enrolling as a dual beneficiary produces declines in physician visits, as shown in the last four rows of Table 2. On average, individuals have 4.0 visits to physicians in a quarter, and dual enrollment decreases the number of physician visits by 1.0 visits or 24 percent of the mean.[20] These decreases in physician visits are especially prevalent in primary care usage, where dual enrollment decreases the probability of having at least one primary care visit in a quarter by 19 percentage points (33 percent of the mean), with negligible effect on any usage of a specialist.[21]

The decline in physician visits, especially to primary care doctors, suggests that individuals are changing the medical services they receive. I investigate this by estimating the effect of dual enrollment on the usage of different types of preventive care services. Changes in preventive care use provide an indication of how the quality of care might change with dual status. Table 3 shows dual enrollment decreases the receipt of an annual flu shot by 30 percent and the receipt of a mammogram in the past 2 years by 39 percent. Furthermore, dual enrollment is correlated with high rates of diabetes complications compared with individuals with other forms of insurance (Zhang et al., 2009). Given the prevalence of di-

[20]Note that visits with physicians in the ED are included in these measures. In Appendix Table A5, physician visits in the ED are excluded. There is a slightly stronger decrease in total physician visits (29 percent), while the other coefficients remain unchanged.

[21]Furthermore, I investigate whether an individual has an office visit with a new provider or established provider. In Appendix Table A6, I find substantial declines in whether an individual has any new office visits while there is no change in whether an individual has any established office visits. This suggests dually enrolled patients have greater difficulty initiating interactions with new providers.

abetes complications, I focus on diabetes management and find that dual enrollment also decreases diabetes preventive care services across all measures, with drops in HbA1c tests, lipid (cholesterol) tests, and retinal eye exams.

Table 3: Effect of Dual Enrollment on Preventive Care Usage

Dependent Variable	(1) Mean Dep. Var	(2) IV
Panel A. Sample: Age 65+		
Flu Shot	0.62	-0.183
		(0.063)
Observations	3415820	
Panel B. Sample: Women Age 50-74		
Mammogram	0.59	-0.230
		(0.071)
Observations	706532	
Panel C. Sample: Diabetes		
HbA1c Test	0.74	-0.270
		(0.063)
Cholesterol Test	0.80	-0.155
		(0.036)
Retinal Eye	0.67	-0.091
		(0.047)
Observations	1226141	

Source: 2006-2015 CMS FFS Claims (CT, NY, RI, NY) and 2008 ACS for construction of the instrument. Observations at the individual-year level. The relevant samples are labelled; for example, flu shots are estimated only for those aged 65+. Regressions include controls for year FE, individual FE, and PUMA FE. Robust standard errors clustered at the PUMA level in the parentheses. Mean Dep. Var is the mean of the dependent variables for individuals enrolled only in Medicare in CT.

5.2 Mechanisms: Physician Medicaid Acceptance

I examine the role of providers in driving changes in healthcare utilization by exploring how healthcare usage changes when physicians have different propensities to accept Medicaid as a form of insurance ("Medicaid acceptance"). This analysis is motivated by the institutional setting, where providers are less likely to accept patients with Medicaid insurance and receive less payment for treating the dually enrolled compared to those who are Medicare-only. I capture Medicaid acceptance in two ways.

First, I track individuals and their main primary care provider (PCP). Two individuals who are otherwise similar while enrolled only in Medicare might experience very different usage patterns after becoming dually enrolled depending on whether their PCPs accept Medicaid patients. $PCPMedAccept_i$ is a continuous variable that captures the share of claims from the main PCP that belongs to Medicaid (specifically, dual) patients. I interact the indicator for dual enrollment with terciles of $PCPMedAccept_i$ (where, for example, $PCPMedAcceptQ1_i$ refers to the lowest tercile of Medicaid acceptance) to estimate the effects of dual enrollment differentially by the main PCP's Medicaid acceptance level. For individual i in PUMA l in quarter t, I estimate:

$$\begin{aligned} Y_{ilt} = \alpha_i + \tau_t + \delta_l + \theta_1 Dual_{ilt} \cdot PCPMedAcceptQ1_i + \\ \theta_2 Dual_{ilt} \cdot PCPMedAcceptQ2_i + \theta_3 Dual_{ilt} \cdot PCPMedAcceptQ3_i + \epsilon_{ilt}. \end{aligned} \tag{2}$$

I instrument for the interaction terms by the instrument, $SimulatedEligibility_{lt}$, interacted with terciles of $PCPMedAccept_i$. The lowest tercile encompasses values from zero to 8 percent, while the highest tercile includes 21 to 100 percent. Variation in $PCPMedAccept_i$ can arise from differences in provider willingness to contract with Medicaid or differences in likelihood of treating Medicaid patients, even conditional on contracting with Medicaid; thus, the lowest tercile includes PCPs who are unlikely to contract with Medicaid at all or accept Medicaid patients. Furthermore, variation can also reflect differences in location and supply of Medicaid patients in a local area. The inclusion of PUMA FE allows for the comparison between physicians in the same local area. The θ coefficients capture the effect of dual enrollment for an individual whose main PCP had the corresponding tercile of Medicaid acceptance.[22] Differences across the θ coefficients show whether dual enrollment differ by the Medicaid acceptance of the main PCP.

I find that providers most reluctant to treat dually enrolled patients drive declines in primary care usage. The first row of Table 4 shows that the dually enrolled with main PCPs at the lowest tercile of Medicaid acceptance (Q1) have a 23 percentage point decrease (36 percent) in having at least one visit to a PCP. When the main PCP is more accepting of Medicaid, the reduction upon dual enrollment diminishes. For beneficiaries with PCPs at the highest tercile of Medicaid acceptance, there is no statistically significant effect of dual enrollment on primary care usage. Furthermore, Appendix Table A9 shows that the largest declines in preventive care usage occur in settings where the individual has a main PCP who is least likely to accept Medicaid as a form of insurance. This illustrates that PCPs play important roles in preventive care take-up and management of chronic illnesses.

Next, I explore whether the main PCP's Medicaid acceptance has spillover effects onto other types of care in the subsequent rows of Table 4. There are no pronounced effects on the likelihood of having at least one specialist visit upon dual enrollment, and it does not vary by the main PCP's Medicaid acceptance. Access to an individual's main PCP does, however, create spillovers onto the ED. Dual enrollment for those at the lowest tercile of $PCPMedAccept$ increases the likelihood of having at least one visit to the ED by 12 percentage points, suggesting that these individuals are twice as likely to have any visit to the ED. However, for beneficiaries with PCPs at the highest level of Medicaid acceptance, dual enrollment has no statistically significant effect on ED usage. To the extent individuals lose access to their providers due to a lack of Medicaid acceptance, they seek out care from the ED, a setting where individuals cannot be turned away due to insurance status.

I further break down ED visits into categories of emergent or non-emergent care in the bottom rows of Table 4 to understand the nature of these spillover visits. Those with the lowest access to their PCP have an increased likelihood of having at least one emergent ED

[22] As a robustness check, I additionally control for PUMA by post-policy FE, to account for changes in PUMAs that might occur around the policy, with results shown in Appendix Table A7. I also interact Dual with the continuous $PCPMedAccept_i$ variable (Appendix Table A8) for robustness. Both tables show that results are in line with the main analysis.

Table 4: Effect of Dual Enrollment by Main PCP Medicaid Acceptance Level

Dependent Variable	(1) Mean Dep. Var	(2) Dual $\cdot PCPMed$ $AcceptQ1$	(3) Dual $\cdot PCPMed$ $AcceptQ2$	(4) Dual $\cdot PCPMed$ $AcceptQ3$
Panel A. Any Physician Visit				
Primary	0.64	-0.226	-0.073	0.024
		(0.069)	(0.060)	(0.039)
Specialist	0.78	0.023	0.027	0.010
		(0.033)	(0.029)	(0.025)
Observations	7078671			
Panel B. Any ED Visit				
All ED	0.11	0.124	0.114	0.003
		(0.028)	(0.024)	(0.021)
Emergent	0.07	0.057	0.045	0.011
		(0.024)	(0.014)	(0.017)
Non-Emergent	0.04	0.022	0.025	0.002
		(0.022)	(0.016)	(0.012)
Observations	6908818			

Source: CMS 2008-2015 and 2008 ACS, restricted to those with a main PCP (see text for more details on sample restriction). ED outcomes do not include 2015Q4. "Any" refers to at least one such visit in a quarter or the extensive margin usage. IV results from instrumenting Dual interactions with the instrument interacted with Medicaid Acceptance variable(s). Regressions include controls for quarter FE, individual FE, and PUMA FE. Robust standard errors clustered by PUMA in the parentheses.

visit in a quarter by 6 percentage points, while this effect diminishes for the highest tercile of PCP Medicaid acceptance. Furthermore, the point estimates for non-emergent ED care suggest that there is some evidence of spillovers onto non-emergent care, but I cannot reject that there is no statistical difference across estimates.

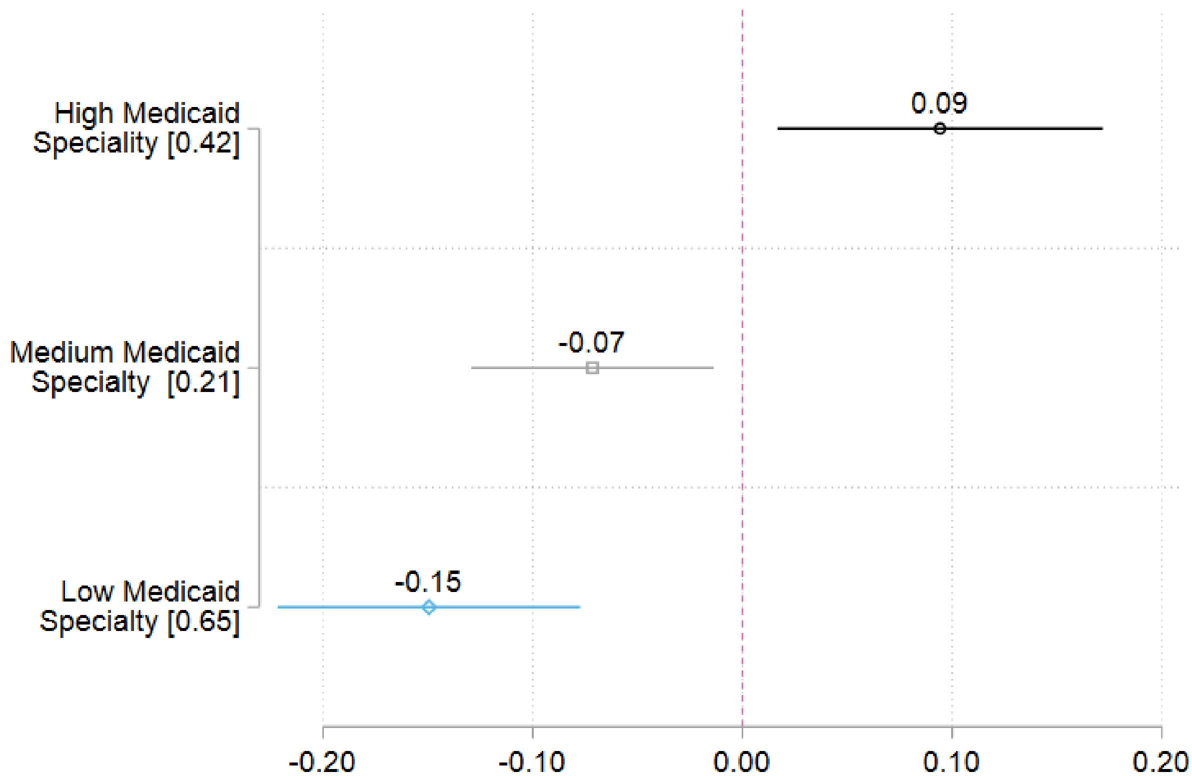
A second way to capture differences in physician Medicaid acceptance is to utilize heterogeneity by physician specialty. In contrast with the previous analysis, I categorize specialties, rather than individual physicians, by the share in the specialty who accept Medicaid. These heterogeneity effects are not based on which physicians the individual sees but rather on the specialists seen, allowing me to also expand beyond PCPs. Furthermore, this measure is derived from a separate data set (NAMCS) and thus captures Medicaid acceptance for all Medicaid patients, as opposed to the fraction of Medicare claims that belong to dually enrolled patients. I separately estimate equation (1) of the effect of dual enrollment on the usage of high, medium, or low Medicaid acceptance specialties. Figure 4 shows that dual enrollment increases the probability that an individual has at least one visit to a high Medicaid acceptance specialty, such as a cardiovascular physician or opthalmologist, by 22 percent. However, the direction of the effect flips for medium and low Medicaid acceptance categories and there is a 23 percent decrease in having at least one visit to a low Medicaid acceptance specialty, such as dermatology and psychiatry.

5.3 Heterogeneity

Given that utilization after dual enrollment differs by Medicaid acceptance, one would expect the consequences of dual enrollment to also differ across characteristics of Medicare beneficiaries. For example, depending on the medical needs of certain patients and their interaction with the healthcare system, enrolling as a dual beneficiary might promote the usage of care for some and decrease the usage for others. In Figure 5, I plot β from Equation (1) for each of the following subgroups: those entitled to Medicare through SSDI, non-White, and those with high (above median) comorbidities.

Overall, the coefficients across all groups are very similar for the outcomes of any hospi-

Figure 4: Effect of Dual Enrollment by Physician Specialty Medicaid Acceptance

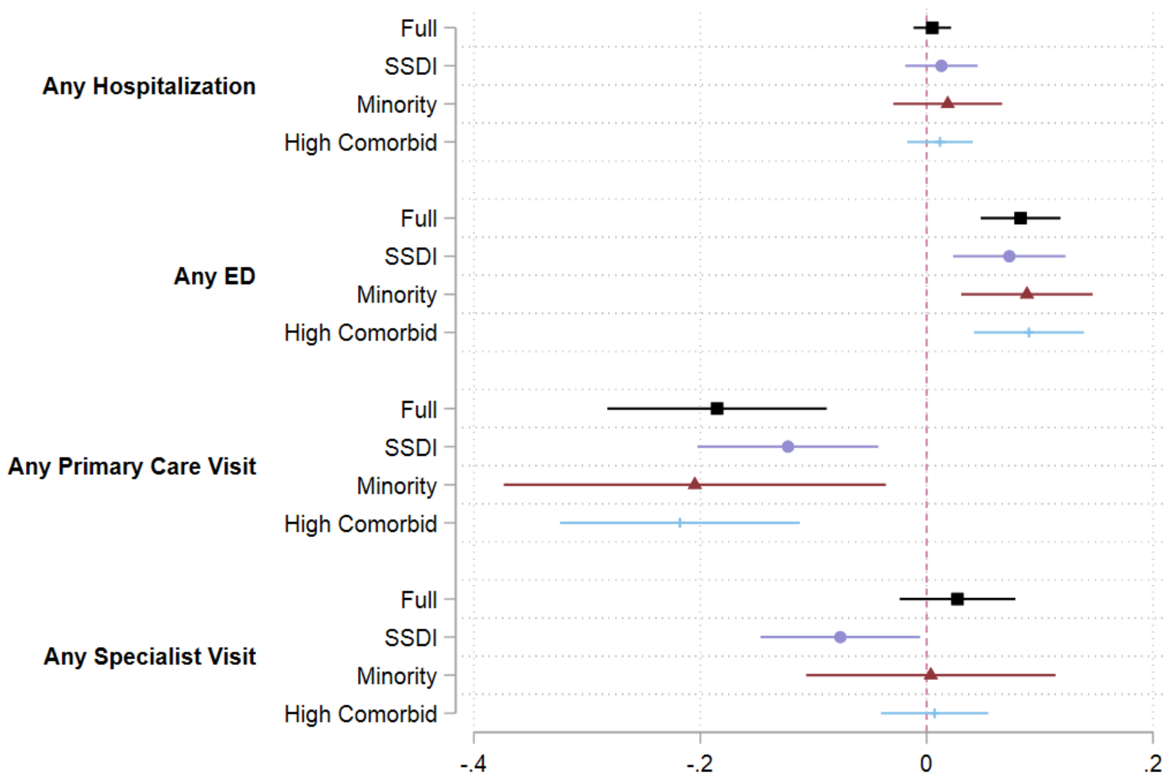


Source: 2006-2015 CMS FFS Claims (CT, NY, RI, NY), the 2008 ACS for construction of the instrument, and 2006-2008 NAMCS for classification of the Medicaid acceptance level by specialty. Each row represents a regression coefficient, with outcome variables of any visit to a High, Medium, or Low Medicaid acceptance specialty. Regressions include controls for quarter FE, individual FE, and PUMA FE. Lines denote 95% confidence intervals with robust standard errors clustered at the PUMA level. Values in the brackets denote mean of the dependent variable.

talization, any ED visit, or any primary care visit. However, SSDI recipients see decreased usage of any specialist care upon dual enrollment by 8 percentage points (12 percent decline), while all other groups, including the full sample, saw no effect. Indeed, as shown in Appendix Table A10, in contrast with the other populations, the SSDI beneficiaries see no effect on overall log Medicare spending (or even suggestive evidence of a decrease), while all other subgroups see overall increases in Medicare spending.

The consequences of dual enrollment differ by healthcare needs and whether providers who treat a particular condition are available to the patient. Those enrolled in SSDI are more

Figure 5: Effect of Dual Enrollment on Medicare Usage Types, Heterogeneity Analysis



Source: 2006-2015 CMS FFS Claims (CT, NY, RI, NY) and 2008 ACS for construction of the instrument. Regressions include controls for quarter FE, individual FE, and PUMA FE. Each row is a regression coefficient on the subsample labelled. The instrument is constructed with the full sample and the same instrument is applied to each subsample. Lines denote 95% confidence intervals with robust standard errors clustered at the PUMA level.

likely to have mental disorders (twice as likely to have depression, four times as likely to have schizophrenia and other psychotic disorders), and less likely to have heart-related diseases (Appendix Table A11). In Appendix Figure A9, I show usage of physician care by specialty, where on the x-axis, the specialties are ordered by increasing Medicaid acceptance. As reflected by the differing chronic illnesses, the SSDI population is less likely to use specialties with high Medicaid acceptance, such as cardiology, and more likely to seek services from psychiatry, which has low Medicaid acceptance.

5.4 Robustness

One potential concern with the results is that PUMAs with greater policy treatment intensity might be systematically different than PUMAs less affected by the policy in a time-varying way that is correlated with healthcare usage, thus violating the exclusion restriction. I construct an alternative instrument called "Demo IV" where the goal is to capture policy treatment intensity without leveraging variation driven by differences in income across sub-state location. I instead leverage differences in income distribution by demographic group prior to the policy, with the idea that different demographic groups might have experienced different policy treatment intensities. Therefore, the purpose of this instrument is to relax the assumption regarding PUMAs, use an alternative source of variation, and test whether the results still hold.

This instrument, Demo IV, is constructed in the same manner as the "simulated instrument variables" methodology (Currie and Gruber, 1996a). This methodology has been used in a variety of settings, including capturing differences in Medicaid laws (DeLeire et al. (2011), Gross and Notowidigdo (2011), Cohodes et al. (2016)), tax subsidy laws (Goda, 2011), asset exemption laws (Mahoney, 2015), and sentencing policies (Liu, 2020). I first partition individuals into pre-determined demographic groups. I then take a fixed national population for each demographic group prior to the policy and run the national population's income through the rules of each state in each time period. Therefore, within a demographic group, the value of the instrument is the same in all states and all PUMAs prior to October 2009. Variation is driven by differential Connecticut policy treatment intensity across demographic groups, given each group's baseline national income distribution and marital status. The identifying assumption is that differences in baseline demographic groups' incomes and marital status are uncorrelated with other unobserved factors that affect the outcomes of interest over time. Note that in contrast to the main instrument, the Demo IV does not rely on assumptions regarding income distributions at the local PUMA-level and offers an alternative source of variation.

My results are robust to relaxing assumptions on the exogeneity of local geographic compositions. I run an analogous set of regressions, replacing PUMA-level controls with the level of variation of this instrument, which occurs at the demographic group by state level. The first stage has an F-statistic of 43.75, suggesting that there is decreased power compared with the main IV.[23] While the Demo IV produces larger standard errors, the estimates are in line with the main results as shown in Appendix Tables A12 and A13; for example, dual enrollment decreases the number of physician visits by 1.2 visits using this instrument as opposed to 1.0 visits in the main results.

Second, I produce event-study Difference-in-Differences (DD) versions of my analysis to complement the IV results and provide an additional check on the instrument validity. Event studies allow me to check for pre-trends, which informs us about the instrument exclusion restriction. If locations show differential trends in dual enrollment or health care usage prior to policy, then this suggests that there might be other factors that are correlated with health care usage outside of dual enrollment, and thus violate the exclusion restriction.

This is a setting where there is a clear policy change at a specific date, so I implement a DD design comparing locations in Connecticut as the treatment with control neighboring states. In this specification, I still control for individual, quarter, and PUMA FE, and the main coefficient of interest is $SimEligDiff_l = SimulatedEligibility_{l,2010} - SimulatedEligibility_{l,2006}$ interacted with each time period (see Appendix F.2 for the full specification and estimation details). $SimEligDiff_l$ captures the difference in the instrument before and after the policy, where individuals in non-Connecticut states will have a value of zero in all time periods. For individuals within Connecticut, this variable captures the size of the population gaining dual status through the income threshold change. In Appendix Figure A10, I graph the coefficients to the event studies for select outcome variables, including dual enrollment (first stage), # of Physician Visits, Any PCP, and Any ED. Overall, areas trended similarly prior to the policy change, before a noticeable change in the point estimates after the policy. These event studies further lend credence to the exclusion restriction assumptions and the

[23]Ideally, the Main IV and the Demographic IV can be combined to leverage an even greater set of variation. The main challenge is data limitation; I am restricted to the 2008 ACS (prior years do not have Medicare status, and later years would be after the policy change). When partitioning on both PUMA and demographics, the sample size within each group becomes very small, making estimates unreliable.

results in the main analysis.

6 Discussion

This paper shows that the consequences of dual enrollment strongly depend on whether the patient sees providers willing to treat Medicaid patients. When the provider does accept Medicaid, this dual system operates as intended. Dual enrollment eliminates cost barriers to healthcare services, and patients can use more medical care. Indeed, individuals who gain dual status are 21 percent more likely to have at least one visit to a physician specialty who is highly likely to treat Medicaid patients. Furthermore, dually enrolled patients receive more care from EDs, where they can receive care without cost-sharing and are guaranteed treatment regardless of insurance status. Low-income individuals and those with poor health report greater difficulty seeking emergency care and increased likelihood of delaying care (Kennedy et al., 2004). Therefore, decreased cost barriers to emergency services may positively impact health to the extent that individuals no longer delay seeking care for medical conditions that require immediate treatment.

When the provider does not treat Medicaid patients, dual enrollment creates unintended barriers to care. For these patients, reduced access to care offsets the benefits of cost protection. These patients are over 30 percent less likely to see a PCP, presumably because their previous PCP dropped them as patients and they did not replace their physician with a new provider. The decline in primary care visits may be particularly concerning for this population, given that increased primary care use has been associated with fewer potentially-preventable hospitalizations among dually enrolled patients with chronic conditions (Oh et al., 2022). PCP visit declines also correspond with a decline in general preventive care use and services for monitoring diabetes, a highly prevalent condition among this population.Loss of physician access also leads to more visits to the ED, a potentially less efficient source of care for avoidable conditions or services that are treatable in an outpatient setting.

Given the various changes to healthcare usage, the natural next question is to understand the overall impact of dual enrollment on health. To do this, I utilize the same policy environment, instrument, and data, and estimate how dual enrollment affects PUMA-level mortality rates through an IV regression (see Appendix G). At the PUMA level, I regress mortality rates on the share of duals with local area controls, and scale the coefficient by the average increase in dual rates due to the expansion. I find a 3.9 percent average reduction in mortality rates in a given PUMA due to the Connecticut policy change.[24] This result suggests that across the periods I study, the benefits of dual enrollment exceed the adverse effects of reduced access to providers who do not accept Medicaid.

While informative of shorter-run effects, this mortality estimate ought to be interpreted with caution. Given that this analysis does not examine longer-run health changes, it is unlikely to capture the full range of mortality consequences. For example, usage changes that potentially lead to adverse health consequences, such as fewer cancer screenings or increased difficulty in finding a PCP, might have a longer time horizon than the time frame captured in the data. Furthermore, the Medicare claims dataset does not contain information on individual or population-level prevalence of physical and mental health issues.[25] Finally, there are a multitude of channels by which dual enrollment affects health; while this paper highlights healthcare access for outpatient services, other factors, such as income effects through elimination of premiums and other out-of-pocket costs (Berman, 2021a), relieving financial burdens (Baicker et al., 2013), and gaining access to non-Medicare Medicaid services such as dental care (Roberts et al., 2022), might affect health as well.[26]

[24]Existing literature on the effect of Medicaid coverage on mortality generally find substantially larger effects; Miller et al. (2021) estimate a 63 percent reduction in mortality for low-income adults aged 55-64 due to the Affordable Care Act Medicaid expansions.

[25]I also investigate how dual enrollment affects diabetes-related Prevention Quality Indicators (PQIs), or hospital admissions that could have been potentially avoided had the individual received outpatient care, developed by the Agency for Healthcare Research and Quality. I examine patients with diabetes and focus on PQI93, which is a composite of short-term diabetes complications, long-term diabetes complications, uncontrolled diabetes, and lower extremity amputation among diabetes patients. Ultimately, I lack statistical power to precisely detect effects since overall PQI93 events are incredibly rare.

[26]This paper focuses on inpatient and outpatient services, while another important component is drug utilization. Appendix Table A6 shows that there is suggestive evidence of increases in Part B physician drug usage.

7 Conclusion

Over 12 million individuals are dually enrolled in Medicare and Medicaid. Despite the size of this population, there has been limited focus on how these two forms of insurance affect healthcare access for this vulnerable population with high healthcare needs. If we only consider the patient demand side, the dual program seemingly improves patient welfare by removing cost barriers. However, dual enrollment also changes provider incentives. Compared to treating Medicare-only patients, physicians receive lower reimbursement on average for treating dually enrolled patients and face other Medicaid-associated costs, such as administrative burdens.

This paper estimates the effect of dual enrollment for the marginal patients who enrolled due to a significant expansion in Connecticut dual-Medicaid eligibility in 2009. Contrary to the notion that dual enrollment will necessarily improve patient access to healthcare, I find that the consequences are heterogeneous. Dual status does increase access to certain services – services where providers are willing to treat dual patients. However, it also decreases access for patients who seek services from providers who presumably prefer to treat patients with other sources of insurance. Indeed, increasing dual enrollment alone without considering physician incentives can lead to unintended consequences of actually decreasing access for some patients.

One alternative design to prevent these unintended consequences is to eliminate reimbursement differences and Medicaid administrative costs. This goal might be accomplished under the existing system by covering dually enrolled beneficiaries through Medigap instead of Medicaid. Medigap is a private supplemental insurance program that covers out-of-pocket Medicare costs after the individual pays premiums. In contrast with this dual system, Medigap pays providers the full cost-sharing amount without the Medicaid-associated administrative barriers; thus, Medigap eliminates the physician supply problem.

I produce back-of-the-envelope estimates and find that the Medicaid program would have to pay substantially more to cover individuals through Medigap than through dual enrollment (see Appendix H for calculation details). Average per capita expenditures for Medicaid under the current system range from \$399 to \$745 per quarter, depending on the fraction of cost-sharing paid by Medicaid. In contrast, average per capita expenditures for covering dually enrolled patients through Medigap plans would cost \$917 to \$1123 per quarter, where the range of estimates reflects possible Medigap premium adjustment given the high-cost nature of this population. The current system, where providers receive less payment for dual patients, reduces costs for the state government. Naturally, ensuring patient access would add to expenditures and there ought to be careful consideration in balancing these additional costs with benefits to patients.

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Appendix

A Background

A.1 Categories of Medicare-Medicaid Duals

Patients with both Medicare and Medicaid coverage or often referred to as "dual-eligibles". It is important to note that despite "eligible" in the name, this refers to individuals enrolled in both programs, not merely eligible for both. Due to possible confusion given the name, the main text refers to "dual-eligibles" as "dually enrolled" or those with "dual status". There are seven mutually exclusive categories of dual-eligibles as outlined in Table A1. All individuals qualify for Medicare through age or disability, but qualify for Medicaid through a variety of state pathways. The first main type of Medicaid that dual-eligibles can receive is through the Medicare Savings Programs (MSP). The MSPs are designed as a Medicare cost assistance program, purely filling in the cost gaps in Medicare. There are four types of MSPs: Qualified Medicare Beneficiary (QMB), Specified Low-Income Beneficiary (SLMB), Qualifying Individuals (QI), and Qualifying Disabled and Working Individuals (QWDI).

All MSPs are subject to an asset test, with individuals of varying levels of poverty qualifying for the different categories of MSPs. I outline the different types of MSPs here:

1. QMB
    - Incomes $\leq$ 100% of FPL and assets less than 3 times the SSI resource test
    - Complete Medicare premium, deductible, and cost-sharing elimination
2. SLMB
    - Incomes between 100% and 120% of FPL and assets less than 3 times the SSI resource test
    - Medicare Part B premium elimination
3. QI
    - Incomes between 121% and 135% of FPL

  - Medicare Part B premium elimination

4. QWDI

  - Disabled workers with income *leq* 200% FPL and assets less than twice the SSI resource test
  - Medicare Part A premium elimination

The difference between SLMB and QI is that the QI program might be capped as states are given a limited set of funds, while anyone who qualifies for SLMB would be eligible. QI is a first-come-first-serve enrolled scheme.

Aside from the MSPs, Medicare beneficiaries might qualify for their state's full Medicaid package, through one of the many other state Medicaid pathways. For seniors and those with disabilities, which are the relevant Medicare eligible populations, there are mandatory and optional pathways states need to have. The mandatory pathway for receiving full Medicaid coverage is through the federal Supplemental Security Income (SSI). Other optional pathways for full Medicaid coverage include covering seniors and those with disabilities and incomes below the poverty level, covering the medically needy, and covering those with Long Term Service and Supports.

Note that the MSPs provide only Medicare cost assistance, but does not provide any additional non-Medicare services. An individual might be simultaneously enrolled in an MSP and in full Medicaid; these individuals receive Medicare cost sharing assistance and additional access to non-Medicare Medicaid services. For example, a person might have Medicare through age, MSP QMB through low income and assets, and full Medicaid through receipt of SSI. For categories of dual-eligibles who receive full Medicaid coverage outside of QMBs (SLMB plus full Medicaid or non-MSP full Medicaid), they pay no more than the Medicaid coinsurance for services covered by both programs, though state payment of Medicare premiums and cost-sharing for other services are up to state discretion. Note that only QMBs and SLMBs might simultaneously receive full Medicaid; QIs and QWDIs cannot also be enrolled in full Medicaid.

Non-QMB individuals in the Medicare Savings Program (SLMB, QI, QWDI) are 17.6% of all duals and those not enrolled in the Medicare Savings Program but receive full Medicaid make up 17.5% of the dual-eligible population. Of the QMBs, 78.4% have full Medicaid and the other 21.6% only receive Medicare cost sharing elimination (MMCO, 2020).

For QMB enrollment, individuals apply through their state Medicaid offices, with generally a 2-4 page form and verification of incomes and assets. When thinking about who enrolls as QMB, take-up in this program is far from complete. It is estimated that about half of eligible QMBs actually enroll (Caswell and Waidmann, 2017). Historically, major barriers to enrollment include lack of knowledge of the program, difficulties with the application process, and complexity in navigating the system (Rudolph and Haber (2003), MACPAC (2017), Roberts et al. (2020)).

A.2 Full Medicaid, Medicaid Managed Care, and Integrated Care Plans

For full Medicaid, states are increasingly moving towards Medicaid Managed Care systems as opposed to Medicaid Fee-for-service. However, the population of this study (Medicare beneficiaries who are seniors or with disabilities), traditionally are excluded from requirements to be enrolled in Medicaid Managed Care.

There has been a long-term acknowledgement that duals suffer from having to navigate two highly complex health insurance systems, and that the lack of coordination can be costly for individuals. To address these concerns, there is increasing interest in "Integrated Care" plans that attempt to combine Medicare and Medicaid, by integrating services, payment of services, and administration. It is important to note that these integrated care plans are mainly aimed at addressing those who are Medicare and full-Medicaid enrolled, and not those who are enrolled just in QMB (or Medicare Savings Programs in general). These plans generally operate under a capitated arrangement where they receive an amount to cover services for duals. Therefore, payment to physicians for duals are more complicated in settings for duals in Medicaid managed care. Common integrated care plans are Program of All-Inclusive Care for the Elderly (PACE), Dual Eligible Special Needs Plans (D-SNP), and Managed Long Term Services and Supports (MLTSS). All three are capitated payment systems. Not all states offer each type of plan.

I next outline enrollment in FFS and managed care in the four states that I study.

Connecticut:

As of 2012, CT is one of three states without Medicaid Managed Care and only has FFS. Furthermore, for aged and disabled individuals (the relevant population for this study) in Medicaid, CT throughout this time period enrolled these patients in FFS.[27] Therefore, since this study focuses on CT individuals, Medicaid Managed Care (including enrollment in plans such as PACE) is not relevant in this study.

Massachusetts:

In Massachusetts, those who have Medicare are excluded from the mandatory Medicaid Managed Care enrollment if they also enroll in Medicaid (Regulation 130 CMR 508.002).[28] However, individuals can choose to enroll in PACE and other managed care/integrated care programs, including One Care and Senior Care Options (SCO). In 2015, 81% of duals in MA are enrolled in FFS Medicaid, so those in managed care are a small share of the dual population.[29]

New York:

In New York, individuals have the option to enroll in Medicaid Managed Care but are not required to do so. In fact, as of December 2017, 76% of the duals are enrolled in FFS Medicaid.[30] The most popular non-FFS arrangement is the Partial MLTC, which only covers long term care arrangements, and medical/hospital services still operate in the standard manner. The fraction of those who are in managed care programs for medical/hospital services are about 5% of all duals in the state.

Rhode Island:

For the majority of this study, RI excluded duals from Medicaid Managed Care.[31] In Novem-

[27] https://www.cga.ct.gov/2015/rpt/2015-R-0010.htm

[28] https://www.mass.gov/regulations/130-CMR-508-masshealth-managed-care-requirements

[29] https://www.bluecrossmafoundation.org/sites/g/files/csphws2101/files/2021-03/Primer_Data_Chartpack_FINAL_1.pdf

[30] https://www.health.ny.gov/health_care/medicaid/redesign/integrated_care/

[31] https://www.cms.gov/Medicare-Medicaid-Coordination/Medicare-and-Medicaid-Coordination/

ber 2013, the Rhody Health Options (RHO) began as an integrated plan accepting the duals.[32] By 2015, the number of duals enrolled in Medicaid Advantage stood at around 20,000.[33]

B Data

Medicare spending and usage come from the CMS 20% 2006-2015 Claims data. For each individual, there are a set of base beneficiary enrollment files, called the Master Beneficiary Summary File (MBSF). Claims are found in individual files based on the who submitted the claim; for this project, I use following claims segments: MedPAR, Outpatient, Carrier, Home Health, and Durable Medical Equipment. In this section, I outline construction of spending, usage, and other beneficiary characteristics variables. I primary follow Curto et al. (2019) for construction of these variables.

B.1 ZIP5 to PUMA

The MBSF contains the ZIP5 code for each patient. I crosswalk ZIP5 to PUMA, which is necessary for identifying the PUMA that each patient lives in (see instrument). I crosswalk from ZIP5 to PUMA via GeoCorr (Geographic Correspondance Engine). Specifically, I use the engine to generate a PUMA (2000) to ZIP/ZCTA crosswalk. Since zip codes tend to be smaller in area than a PUMA, I assign each zip code to the PUMA with the largest AFACT (allocation factor; the fraction of the zip code located in the PUMA) value. Over 70% of the zip codes lie fully within a PUMA and over 95% of zip codes have at least 70% of its population within the PUMA. I successfully crosswalk 99% of individual-quarter observations as detailed in Appendix Table A3. I drop individual-quarters where I am unable to identify the PUMA.

Medicare-Medicaid-Coordination-Office/Downloads/2007StateProfilesRI.pdf

[32]https://eohhs.ri.gov/sites/g/files/xkgbur226/files/2021-03/2016AggregateEQRTechnicalReport.pdf

[33]See Kaiser Family Foundations: Dual Eligible Enrollment in Medicaid Managed Care, by Plan Type

B.2 Total Medicare Spending

Total Medicare spending is defined as the sum of all inpatient and outpatient spending in a quarter. The "Any Total Medicare Spending" variable is an indicator for whether an individual has any total Medicare spending in a quarter.

Total inpatient spending is the total Medicare spending for inpatient services. First, I use all claims found on the MedPAR file, excluding SNFs. For MedPAR, I use the admission date (ADMSN_DT) to define the quarter that the claim belongs to and define total Medicare spending as the sum of the Medicare payment (MDCR_PMT_AMT) and the pass through amount (PASS_THRU_AMT). Furthermore, I also add in spending for claims found in the Carrier file, for services rendered in an inpatient setting (LINE_PLACE_OF_SRVC_CD=21).

Total outpatient spending is defined as the sum of spending from the Carrier file (where place of service is not 21), home health, outpatient, and durable medical equipment.

B.3 Emergency Department Visits

ED visits for the main analysis are identified through the MedPAR (inpatient) and Outpatient files, following the methodology outlined by ResDAC.In particular, I identify claims from the MedPAR file where the Emergency Room Charge Amount (ER_CHRG_AMT) is greater than zero. In the Outpatient files, I look for claims with Revenue Center Codes (REV_CNTR) of 0450-0459, for Emergency Room, or 0981, for Professional fees- Emergency Room. Visits are sum of claims from either MedPAR (inpatient) or the Outpatient file, and I allow for a maximum of one claim of each type in a day.

Total ED spending is the sum of spending from MedPAR, Outpatient, and physician (Carrier) claims where the location of service is 23. The Carrier claim is used only to produce total ED spending amounts and not used to identify ED utilization in the main analysis.

B.4 Classifying ED Events: NYU/Billings Algorithm

The NYU/Billings Algorithm was developed to classify ED visits by identifying whether a certain visit was necessary for treatment at an ED. The original algorithm (Billings et al., 2000) was developed through a team of ED physicians, who classified visits from six hospitals in the Bronx, NY into the following categories using the principle diagnosis code (ICD):

1. Emergent, Not preventable/avoidable (AMI, Intracerebral hemorrhage, respiratory failure, abnormal blood chemistry)
2. Emergent, Preventable/ Avoidable (Diabetes related, asthma related, pneumonia)
3. Emergent, Primary Care Treatable (Salmonella, pain in eye, cysts, heartburn)
4. Non-emergent (warts, carpal tunnel, sinusitis, sunburn, joint pain)
5. Other
   (a) Mental Health Related
   (b) Alcohol Related
   (c) Substance Abuse Related
   (d) Injury
6. Non-classified

The algorithm assigns probability weights to each of the categories.

One difficulty with the original algorithm was that it was developed in 1999; some ICD codes were not classified at the time and as codes are introduced and changed over time, so that a large fraction of diagnosis codes are unclassified by the algorithm. Therefore, I use a patched algorithm developed by Johnston et al. (2017). This version of the algorithm decreases the number of unclassified diagnosis. This algorithm utilizes a mapping of principle diagnosis codes codes into the ED categories and for consistency, I focus on the ICD-9 codes. Given that the CMS claims transitions from ICD-9 to ICD-10 in October 2015, I exclude the last quarter of the sample, 2015Q4, when estimating ED appropriateness.

For my analysis, I map each ED claim in the Carrier file to the associated weights on each of the categories above following the principle ICD-9 diagnosis code. I identify ED visits from the claims in the Carrier file where the location of service is 23. Then, for each principle diagnosis (ICD_DGNS_CD1), I use the patch algorithm to map the ICD code into various categories. Emergent is defined as the sum of weights on (1), (2), (3). Non-emergent is category 4.

The Billings algorithm creates probability weights for whether the diagnosis (ICD code) is emergent or non-emergent. I further create variables that capture whether an individual had any emergent or non-emergent visit in a quarter. Each ED visit (allowing a max of 1 ED visit/day) can have several ICD diagnosis codes and each quarter can contain several ED claims. I first classify ED visits into emergent or non-emergent, by taking the max weight on the emergent or non-emergent categories across all ICD codes in a visit. For example, an individual might have one ED visit with two ICD codes, where the first code places a weight of 0.8 on emergent and 0.2 on non-emergent, and a second ICD code with a weight of 0.4 on emergent and 0.6 on non-emergent. The overall visit would have a weight of 0.8 on emergent and 0.6 on nonemergent. Then, I classify whether the ED visit is considered emergent or non-emergent, by whether the relative weights exceeds a threshold. For the main analysis, my threshold is a weight of 0.5 for either category. For the above example, this visit would be classified as both emergent ($0.8 > 0.5$) and non-emergent ($0.6 > 0.5$). Finally, I define "any emergent/non-emergent" as whether there was at least one such visit in a quarter.

B.5 Physician Visit; Primary and Specialist Care

Physician specialty is obtained from the HCFA code, found in the Carrier claims (PRVDR_SPCLTY variable). From the full set of HCFA available codes, I define the universe of primary and specialty care following Zhang et al. (2021). Specifically, "primary care" is defined as General Practice (01), Internal Medicine (08), Family Practice (11), or Geriatrics (38). Specialist care are the remaining codes of (2-7, 10, 12-31, 33-36, 39-41, 44-48, 62, 64-66, 68, 76-78, 81-86, 90-94, 96, 98). When counting visits, I follow Curto et al. (2019) and allow for a maximum of 1 primary care visit and 1 specialist care visit per day.

The total number of physician visits is the sum of all primary care and specialist care visits in a quarter. Any physician visit is defined as having at least one primary or physician visit.

B.6 Preventive Care Usage

I focus on five preventive care measures: flu shots, mammograms, and for diabetes patients, HbA1c Test, Lipid (Cholesterol) Test, and Retinal Eye Exams. These measures are identified using ICD9 and CPT codes from the claims, following Curto et al. (2019). ICD9 codes shift to ICD10 in the last quarter of 2015 (thus, I miss 2015Q4 preventive care utilization if the claim uses ICD10 codes), I keep the full year 2015 in the main regression analysis. Results are robust to dropping the year 2015 in analysis.

For the relevant population of flu shots and mammograms, I depart from Curto et al. (2019), since my sample includes a broader set of ages. Flu Shots are for all individuals aged 65+ (following U.S. Preventive Services Task Force) and mammograms are for women aged 50-74 (following US Preventive Task Force).[34] All measures are at the annual level. All variables with the exception of mammograms are indicators of receipt of service within the calendar year. The mammogram variable indicates receipt of a mammogram within the last 2 years.

In order to obtain the analysis sample, I first collapsed the individual by quarterly data into individual by year, removing years without a full four quarters. For ages, I took the age by the of the calendar year. For diabetes, I utilized the Chronic Conditions Warehouse's algorithm that identifies if an individual satisfies the requirements for being with diabetes in a calendar year (see the Comorbidity section below for more information). I keep all years after which an individual is first identified as having diabetes treatment, regardless of whether the individual received any treatment in the calendar year.

[34] https://biotech.law.lsu.edu/cphl/Practice/preventive_services.pdf; https://www.uspreventiveservicestaskforce.org/uspstf/recommendation/breast-cancer-screening

B.7 Main PCP Medicaid Acceptance

In Section V, I analyze how the effect of gaining dual status (QMB) differs by the Medicaid acceptance level of the individual's main primary care provider (PCP). Here, I outline in greater detail the creation of the $MedAccept_i$ variable and the associated analysis sample.

1. Identify the main PCP of each patient prior to the October 2009 policy change.

   (a) Sample Restrictions:

      - Restrict analysis to years 2008+. Individual PCPs are identified by the NPI, but the NPI was instituted in May of 2007. Because it might have taken some time for the transition from the previous system, UPIN, to NPI, I begin with 2008.
      - Restrict to individuals who were Medicare-only prior to the policy change and in sample both in 2008 and 2009.
      - Remove individuals who saw no PCPs in 2008Q1 through 2009Q3 or had physicians with missing NPIs.

   (b) Primary Care Provider is a physician NPI where the specialty is primary care. I do not include physicians who treat patients in an inpatient setting.

   (c) Main PCP in a quarter is the PCP with the maximum number of visits in the past calendar year (Kwok, 2019).

   (d) I allow for an individual to have multiple main PCPs in a quarter should there be ties, and allow for individuals to change main PCPs through time, since the Main PCP is defined at the quarter level.

2. For each individual's main PCP, I identify what fraction, λ, of the claims seen by the main PCP are Medicaid (specifically, dually enrolled) patients.

   (a) Overview: For each PCP, count the total number of claims over the 2008Q1 through 2009Q3 (pre-policy) quarters. Count the total number of these claims that come from Medicaid patients. Take the ratio to obtain the λ, the fraction of visits over the pre-policy period that come from Medicaid patients.

- Note that λ is fixed across time for each PCP, and is not the Medicaid acceptance for a given quarter. The reason is that CMS is a panel of patients, not physicians, so I wanted to pool together as many time periods as possible to mitigate the measurement error that might arise just due to a time period having few recorded visits for a PCP.
- Specifically, I define a patient as a Medicaid patient if the individual, at the time of the claim, was dual-eligible with full Medicaid. Specifically, the individual had dual-eligibility of types: QMB-only (variable=1), QMB plus (2), SLMB plus (4), and non-MSP full Medicaid (8). I do not include claims from non duals and partial duals: SLMB Only (3), QDWI (5), QI (6), and Other duals without Medicaid coverage (9). While partial duals technically have Medicaid, I put them in the non-Medicaid category here since they do not receive assistance for cost-sharing.

(b) Remove individuals who have main PCPs where the PCP has fewer than 25 visits across 2008Q1-2009Q3.

3. For each patient, assign a "PCP Medicaid Accepting Likelihood" or "Medicaid Acceptance", $PCPMedAccept_i$ which is the maximum λ across all main PCPs seen in the pre-policy period. The idea is that if an individual had multiple main PCPs across time or within a quarter (ties), they can always go back to a PCP they had once seen.

B.8 Specialty Medicaid Acceptance - NAMCS Linkage

In the main analysis, I link physician specialities to their Medicaid acceptance levels, through acceptance rates obtained in the NAMCS. Unfortunately, the NAMCS specialties and the CMS HCFA specialties do not map perfectly, and I describe my linkage process here.

As described in the previous section, I define the universe of physician visits through Zhang et al. (2021). Then, I utilize the Maryland Medical Care Database (MCBD) -Medicare crosswalk to map from HCFA codes into AMA specialties.[35] Created by the Maryland Health Care Commission, this document contains a mapping of the CMS HCFA specialties and the American Medical Association (AMA) physician specialty types. The reason that I map into AMA specialties is that in the NAMCS, the definitions of each physician specialty is based on AMA specialties. Using this, I create a mapping of each HCFA code into one of 26 AMA specialty categories: Allergy/Immunology (3), Anesthesiology (5), Cardiology (6, 21), Dermatology (7), Endocrinology/Diabetes/Metabolism (46), Emergency Medicine (93), Family/General Practice (1, 8), Geriatrics (27, 38), Internal Medicine (10, 11, 29, 39, 44, 66, 76, 81, 82), Neurological Surgery (14), Neurology (13), Obstetrics/Gynecology (16), Oncology (83, 90, 91, 98), Ophthalmology (18), Orthopedics (20), Otolaryngology (4), Pathology (22), Pediatrics (37), Physical Medicine and Rehab (17, 23, 25), Plastic Surgery (24), Preventive Medicine (84), Psychiatry (26, 86), Radiology (30, 92, 94) Surgery (2, 28, 33, 40, 77, 85), Urology (34), and Other (12, 15, 19, 31, 35, 36, 41, 45, 47, 48, 62, 64, 65, 68, 78, 96).

With this mapping in hand, I map each claim by their HCFA physician codes into each of the 26 types, allowing individuals to have a maximum of 1 visit/day with a physician of each specialist type. Using these categories, I directly match them to one of the 12 NAMCS categories by name. At the end of this process, for each patient claim, I have the NAMCS-defined speciality of the physician.

B.9 Comorbidity

CMS generates information on whether a beneficiary has any of 62 chronic conditions, through its MBSF Chronic Conditions Segment and the MBSF Other Chronic or Potentially Disabling Conditions Segment. These variables are developed through algorithms produced by the Chronic Conditions Warehouse, which go into the claims and identify whether an individual is treated for a particular condition at least a certain number of times in a given time frame (reference period).[36] For example, the algorithm to identify an Acute Myocar-

[35] https://mhcc.maryland.gov/mhcc/pages/home/workgroups/documents/mcdb_payors/MCDB_Payers_Meeting_Speciality_Codes_Crosswalk_20130123_pdf.pdf

[36] https://www2.ccwdata.org/web/guest/condition-categories

dial Infraction is to look in the inpatient claims file for ICD/CPT/HCPCS codes indicating AMIs. Some conditions require more than one claim from certain settings; for arthritis, there needs to be at least 2 claims from a variety of settings over the past two years.

Using these algorithms, the MBSF Chronic Conditions segments show whether an individual, at an annual level, has satisfied the algorithm claim requirements to be considered having a particular condition in the year. I consider an individual as having a certain condition if the end of year indicator is equal to 3, meaning "Beneficiary met claims criteria and had sufficient FFS coverage".

I also calculate the number of comorbidities to summarize overall health, as shown in the summary statistics table. Out of the 62 chronic conditions, I focus on 19 conditions, following Maciejewski and Hammill (2019). The 19 conditions are: Alzheimer/Dementia and related disorders, Arthritis, Atrial Fibrillation, Autism Spectrum Disorder, Cancer (Breast, Lung, Colorectal, Prostate), Chronic Kidney Disease, Chronic Obstructive Pulmonary Disease, Depression, Diabetes, Heart Failure, Ischemic Heart Disease, Hepatitis (Chronic Viral B and C), HIV/AIDs, Hyperlipidemia, Hypertension, Osteoporosis, Schizophrenia and other psychotic disorders, Stroke, or Asthma. The number of comorbidities variable is the sum across these 19 variables.

C Connecticut Policy Change

C.1 Additional Background

The Connecticut QMB expansion came about as part of a broader expansion of the Medicare Savings Program (MSP). The Medicare Savings Programs include an umbrella of Medicaid programs that pay for Medicare premiums and cost-sharing; QMB is the most generous MSP that fully covers all cost-sharing, while those with higher incomes qualify for only premium assistance.

This policy change was the result of state legislative bill H.B. 6146.[37] The purpose

[37] https://www.cga.ct.gov/asp/cgabillstatus/cgabillstatus.asp?selBillType=Bill&bill_num=HB06146&which_year=2009

of the bill was to equalize the eligibility to the Medicare Savings Programs with that of Connecticut's state ConnPACE program. Historically, the state funded a program called ConnPACE, which offered out-of-pocket cost assistance for Medicare beneficiaries' usage of prescription drugs. Only those with low incomes could qualify. Aside from ConnPACE, there exists a federal Low-Income Subsidy (LIS) program, which also offers subsidies to individuals with low incomes for purchasing prescription drugs. Those who qualify for MSP automatically qualify for LIS. The state historically had higher income thresholds (more generous eligibility) for its ConnPACE program compared with the national LIS income limits. As a way to shift costs from CT state funded ConnPACE to the federal LIS program by getting more ConnPACE beneficiaries onto LIS, the bill sought to equalize the eligibility of MSP with that of the ConnPACE program. Therefore, this created an increase in QMB eligibility generosity. See Cohen and Ayers (2009) for more details.

C.2 Size of Policy Change

In this section, I estimate the effect of the policy change on QMB enrollment, isolating the effects for those who transition from Medicare-only into QMB. I use a differences-in-differences design, where the treatment state is CT and the neighboring states are control states, to estimate the size of the QMB enrollment increase for my main sample. Since this project is interested in estimating the effects of transitioning from Medicare-only into QMB dual, I will isolate the size of this transition and not shifts from other types of dual status into QMB. I use my main sample after sample restrictions, as described in Section III.

In Appendix Figure A4 panel (a), I plot the fraction of Medicare beneficiaries enrolled as QMB by calendar quarter in CT and in the neighboring states. Using CT as the treatment state and the neighboring states as the control states, I run a differences-in-differences event study, with coefficients shown in Appendix Figure A4 Panel (b). Prior to the policy change, QMB enrollment in CT remains stable compared to the neighboring states, and after the expansion, there was a 73% increase in QMBs. In the DD analysis, I can also eliminate NY as a comparison control state given its change in asset eligibility, and effects of the CT QMB expansion are nearly identical (see Appendix Figure A5). Excluding NY, QMB enrollment increased by 75.0%.

D Creation of the Instrument

In this section, I outline in greater detail the creation of the main instrument. The purpose of the instrument is to simulate QMB income eligibility for a fixed population pre-policy for each time period and location. The steps to create the instrument are as follows:

1. I take the population of individuals aged 18+ with Medicare in the 2008 American Community Survey as the base fixed population.
    - I choose the 2008 sample and not an earlier year because the ACS does not have Medicare enrollment information prior to 2008.
    - I use the IPUMS (Integrated Public Use Microdata Series) version of the 2008 ACS (Ruggles et al., 2022).
2. The two key income variables are *inctot*, the total individual income in the previous year, and *incearn*, the total earned income in the previous year. For each Medicare individual, I identify their total and earned income, along with the total and earned income of their spouse (their spouse does not have to be a Medicare beneficiary).
3. I obtain inflated-adjusted monthly income for this population for 2006-2015 by dividing annual income by 12 and then inflating incomes by CPI-U.
4. I obtain total countable income for each individual.
    - The QMB program only considers the total income of the individual and the spouse, and not other members of the household. The FPL thresholds are adjusted based on 1 individual or 2 individuals.
    - Certain incomes are disregarded. The program does not count the first $65 of earned income, and only counts 50% of the remaining earned income. Then, $20/month of all income types are not counted (Caswell and Waidmann, 2017).

5. I bring in the monthly QMB eligibility thresholds for CT and the federal thresholds for the surrounding states.

   - Federal Poverty Level guidelines are found from HHS website. [38]

   - In Connecticut, the exact income threshold shifted slightly around 200% of FPL. From 2006 through September 2009, CT was at 100% of FPL. For the subsequent years, this was 197% in October 2009 and 2010, 214% in 2011, 213% in 2012, 207% in 2013, and 211% in 2014 and 2015 (Caswell and Waidmann (2017), Dube (2012), McGreal (2012), OLR (2013), Flowers et al. (2014), Fitzpatrick (2015)). CT implements a new updated FPL each year starting in March, and I take this into account.

6. For each month, I determine if the individual has countable income less than the QMB eligibility thresholds given the marital status.

7. For each PUMA, I calculate the weighted fraction of individuals in the time quarter who qualifies for QMB.

E Testing Instrument Balance

I take the follow steps to test whether the instrument is correlated with PUMA level confounders that matter for the outcomes of interest:

1. Obtain PUMA-level demographics from the ACS.

   - Starting with individual level data, I obtain the following measures at the PUMA level, for the 18+ Medicare population: average age, veteran status, fraction White, fraction Black, fraction Not in the Labor Force, fraction female, fraction Hispanic, fraction with HS or less education, fraction with spouse, fraction with Social Security, fraction with Supplemental Security Income, mean family

[38] https://aspe.hhs.gov/topics/poverty-economic-mobility/poverty-guidelines/prior-hhs-poverty-guidelines-federal-register-references

income, fraction below the poverty line, median family income, log mean family income, and log median family income. I also include, for all 18+ individuals, the unemployment rate.

- The ACS changes the definition of a PUMA in 2012. I utilize the Mable GeoCorr Engine to crosswalk from the new 2012 PUMAs into the pre-2012 PUMA by weighted population (AFACT).
- This produces annual level PUMA demographics for 2008 through 2015. I exclude 2006-2008 because Medicare status is not available prior to 2008.

2. In the CMS claims data, collapse PUMA level spending and utilization information to the annual level.
3. Merge annual PUMA level demographics into the CMS claims data.
4. Regress Medicare spending and usage variables on all the ACS demographic variables, including PUMA and year FE, weighted by the number of beneficiaries in the PUMA and year.
5. Fit predicted Medicare spending and usage
6. Regress predicted Medicare spending and usage on the instrument, including PUMA and year FE, weighted by the number of beneficiaries in the PUMA and year.

F Robustness

F.1 Alternate Demographic IV, Demo IV

The Demo IV is produced in the Survey of Income and Program Participation (SIPP). It is possible to create this instrument in the ACS as well, but I utilize the SIPP to additionally check whether estimates are sensitive to the data source and the baseline year. Using the SIPP, I focus on a baseline national sample of individuals in 2006 with Medicare and aged

18+.[39] The steps for producing the instrument are same as in the main IV; I inflate incomes using CPI-U to all time periods, to obtain incomes through time for a fixed population. For each demographic group (Age 65+ x Sex x White), I estimate the fraction of individuals that would qualify for QMB based on income based on the national eligibility thresholds for each time period. Then, I estimate on the same population the fraction eligible for QMB based on CT income eligibility thresholds for each time period. This instrument varies by the demographic group by state level, and I merge this instrument directly into the CMS claims by the same set of demographic variables and state.

F.2 Differences-in-Differences Event Studies

For the DD event studies, I estimate for individual i in PUMA l and half-year t:[40]

$$Y_{ilt} = \gamma_i + \gamma_t + \gamma_l + \sum_z \delta_z SimEligDiff_l \cdot 1(z = t) + \nu_{ilt}, \tag{3}$$

where the right-hand side includes individual FE, half-year FE, and PUMA FE. $SimEligDiff_l = SimulatedEligibility_{l,2010} - SimulatedEligibility_{l,2006}$, or the difference in the value of the instrument in 2010 (post-policy) and in 2006 (pre-policy). The coefficient of interest is δ_z, which captures the effect of a PUMA going from no individuals eligible for QMB to 100% of individuals eligible for QMB, or the effect for a PUMA where everyone is between 100% to 197% of FPL. The value of this variable is zero for all individuals outside of CT, since there is no difference in the value of the instrument before and after the policy. The outcome variables can either by dual enrollment (first stage) or health care usage and spending variables (reduced form).

G Mortality

In order to estimate the effect of dual enrollment on mortality, I adjust the sample to include all deaths and estimate an alternate specification. For the main sample, I restricted the

[39] In the SIPP, I can identify Medicare status for earlier years, so I am not restricted to 2008. I chose 2006 as the base year to check for the robustness of the base year. I do not use the SIPP to create main IV because I cannot identify geographic location finer than the state level.

[40] These regressions are at the half-year level as opposed to the quarterly level for computational ease. This limitation implies only 20 coefficients that need to be estimated, as opposed to 40.

sample to include only individuals who are present for all three months in a quarter and thus no longer make this restriction. Then, I collapse the sample down to the PUMA by quarter level, focusing on mortality rates by location, average PUMA Dual (QMB) rates, and average PUMA demographic characteristics. I estimate the following specification for PUMA l and quarter t:

$$MortalityRate_{lt} = \tau_t + \tau_l + \beta ShareDual_{lt} + X\theta + \nu_{lt},$$

through an IV model, where I instrument $ShareDual_{lt}$ with my main instrument, $SimulatedEligibility_{lt}$. I include controls for quarter FE τ_t, PUMA FE τ_l, and PUMA level controls X, including share White, share male, and share in age bin (<55, 55-64, 64-74, 74-84, 84+). β is the main coefficient of interest and is the effect of a PUMA going from 0 to 100% dual in a PUMA on PUMA-level mortality rates.

Before discussing the IV results, I first show a visualization of the reduced form:

$$MortalityRate_{lt} = \tau_t + \tau_l + \beta SimulatedEligibility_{lt} + X\theta + \nu_{lt}.$$

Appendix Figure A11 presents a binscatter where the residualized instrument is on the x-axis and the residualized mortality rate is on the y-axis. I only show the Connecticut observations, since variation in share dually enrolled is driven by the policy change, which occurred in Connecticut. The non-Connecticut observations show up as a mass with residualized instrument values around zero. As seen in this figure, increased values of the residualized instrument corresponds with decreased mortality rates, with no clear outliers.

Appendix Table A14 shows the estimated results. In order to interpret the magnitude of the coefficients, the table includes two additional rows: mean mortality rates and mean dual share difference. Mean mortality rates reflect the average quarterly PUMA mortality rates for individuals in CT prior to the CT policy change. Mean Dual Share Diff is the average difference (across time) in the share of individuals who are dual in a CT PUMA before and after the policy change. I take the coefficient estimate, 0.00799, scale it by the mean difference in dual share, 0.06651, and then divide by the mean mortality rate, 0.01354. The interpretation is that the average reduction in PUMA-level mortality rates as a consequence of the CT dual expansion is 3.9%.

H Comparison with Medigap

I first detail the calculation for Medigap expenditures under the current dual (QMB) system. I calculate per-capita average expenditures under the duals (QMB) program as follows:

$$Prem_B + (\overline{CShare_A + CShare_B}) \cdot \delta$$

where $Prem_B$ is the Medicare Part B premium, $\overline{CShare_A + CShare_B}$ is the total average cost-sharing for Parts A and B (including deductibles and coinsurance), and δ is the fraction of cost-sharing covered paid by Medicaid. Under the current system, Medicaid pays for individual Medicare premiums and covers a fraction of Medicare cost-sharing. I take the 2011 monthly Medicare premiums of \$115.40. I do not include Part A premiums since the vast majority of Medicare beneficiaries do not pay Part A premiums, especially this low-income population. I estimate from my data (since Medicare claims contains information on cost-sharing for each claim) that dual enrollment increases Medicare Parts A and B cost-sharing by 30.3%, to \$480.2 (in 2011 dollars) per quarter.

Determining δ is a challenge, since the Medicare claims only shows the cost-sharing liable for each service, and does not show what fraction of the cost-sharing is actually paid by Medicaid. Haber et al. (2014) linked Medicare and Medicaid together and found that in CT in 2009, Medicaid only paid 11% of cost-sharing for office evaluation and management visits. In states with a "full payment" policy, where Medicaid legally pays the full cost-sharing amount, the average fraction actually paid was 83%. The reason this is not 100% is presumably due to factors such as high Medicaid administrative costs. While these estimates are only for a subset of medical services, I take 11% and 83% as the lower and upper bound of δ.

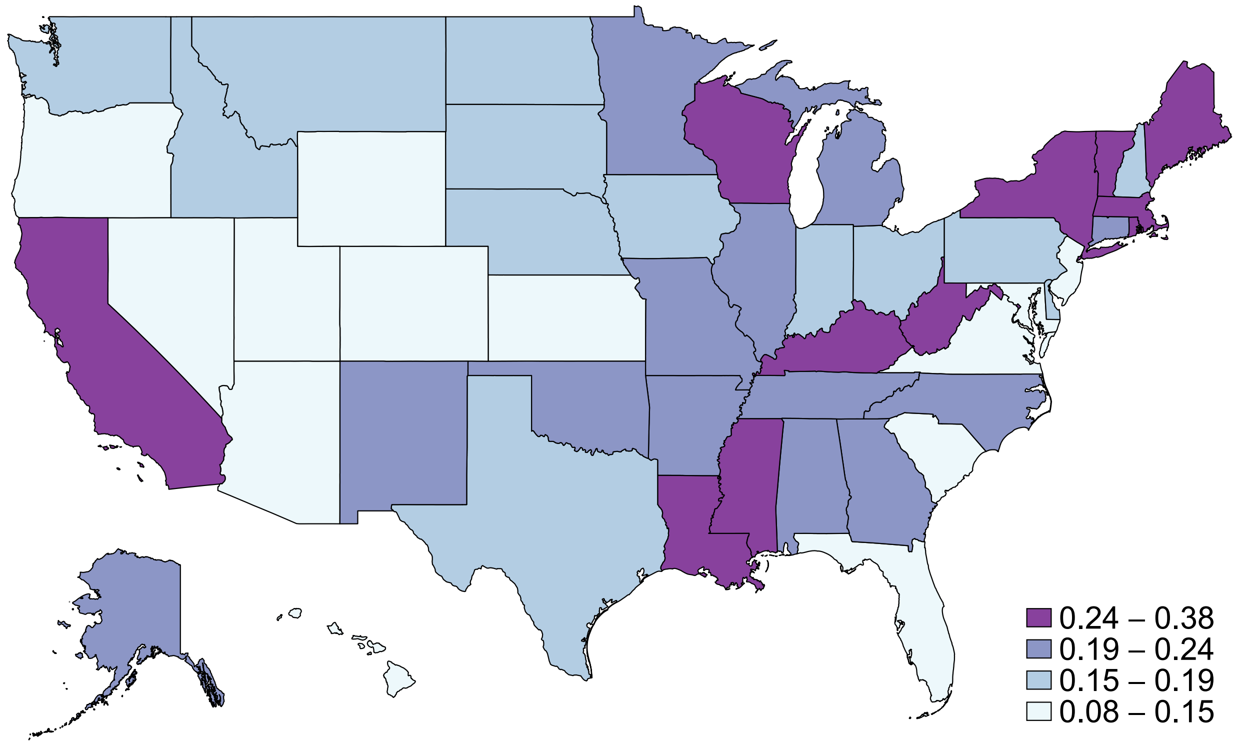
Medigap is a regulated market with set plan features. Medigap Plans C and F most similarly mimic the duals program, since it covers all Medicare hospital and medical insurance cost-sharing. Since Medigap does not cover Medicare premiums, in the alternative policy proposal, Medicaid would only pay Medicare premiums and the Medigap premium. Per-capita average expenditures under Medigap is therefore:

$$Prem_B + Prem_{Medigap}$$

Plan F in CT in 2010 was \$183/month (Huang et al., 2013) or 190.4 deflated to 2011 dollars. The sum of Part B premiums and the purchase of Plan F (assuming historical Plan F rates) totals to \$917/quarter.

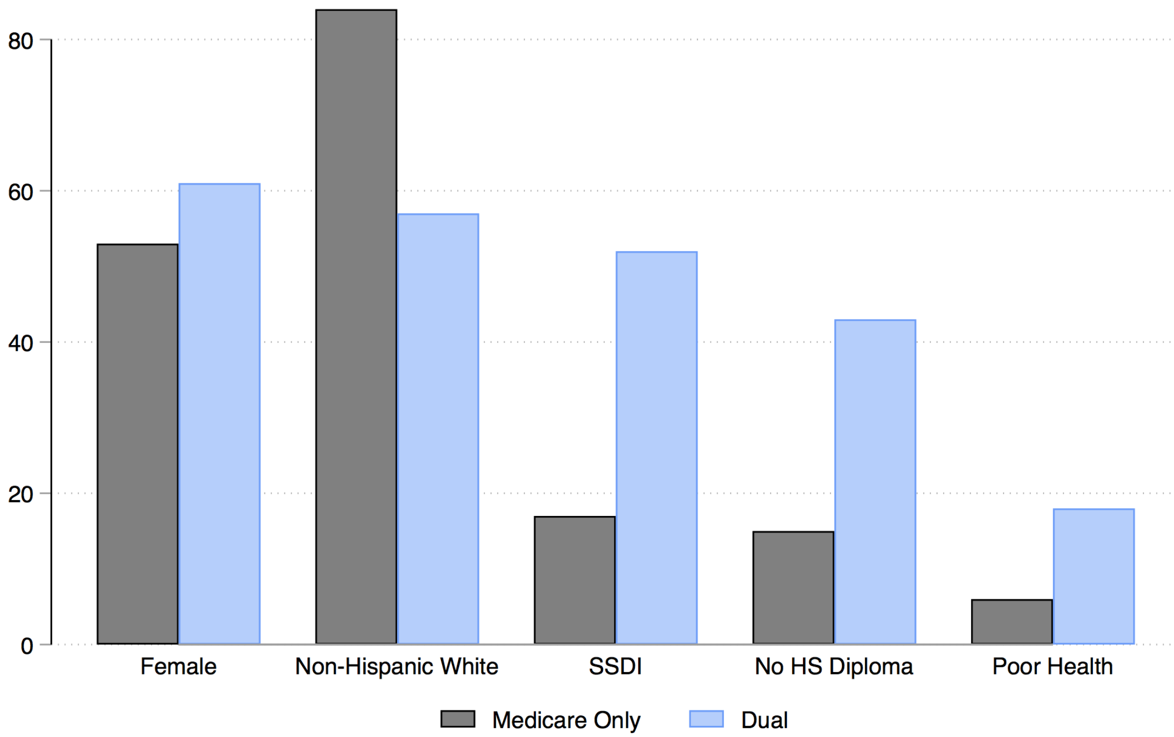
However, that is a lower bound, since true Medigap premiums will likely be higher, given that dual beneficiaries are a high spending population and premiums adjust to patient mix. I take that a 10% increase in Medicare spending leads to a 6% increase in Medigap premiums (Sheingold et al., 2011). In order to understand how Medicare spending would change if the dually enrolled were under Medigap, I need to estimate spending changes if cost-sharing were eliminated and there were no provider supply constraints. I assume that dual patients who have main PCPs with high Medicaid acceptance would mimic spending in the absence of provider constraints. I calculate that duals with high PCP Medicaid acceptance increase Medicare spending by 60%. Medigap premiums would instead be \$258.9, and therefore, the upper bound on expenditures is \$1123/quarter.

Appendix Figure A1: Fraction Dually Enrolled by County, 2014



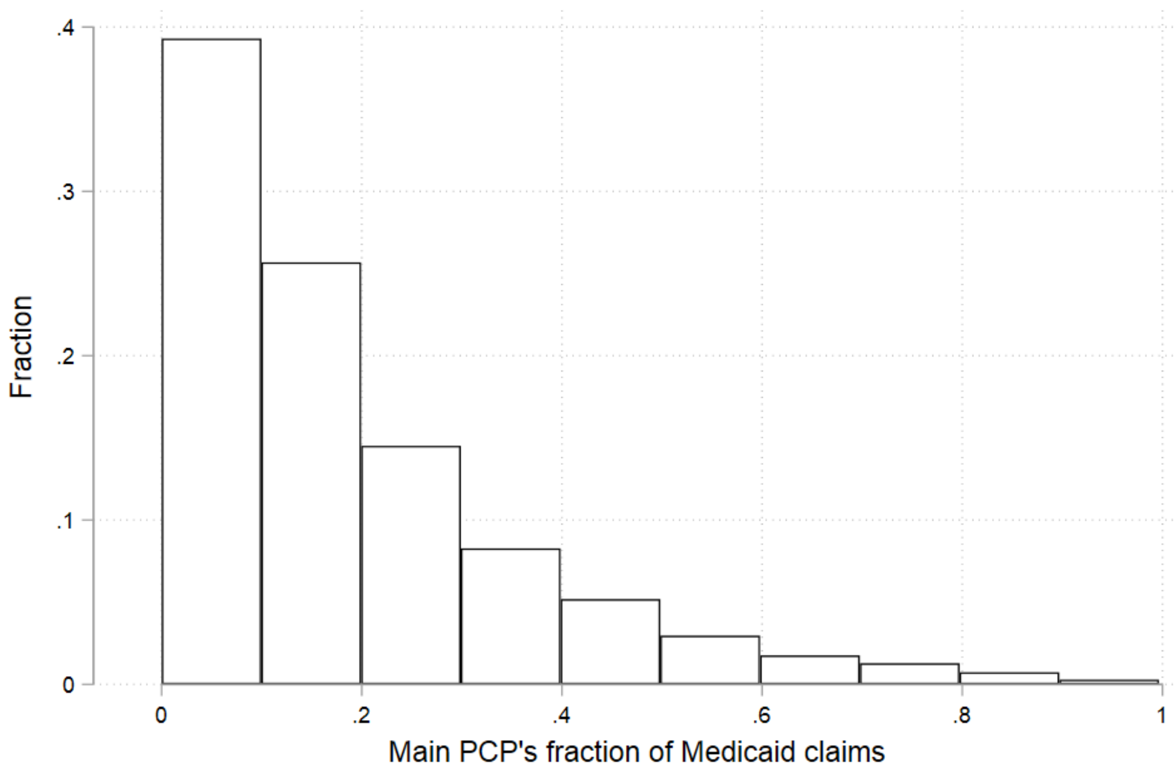
Source: 2014 CMS FFS Claims. The map indicates the fraction of Medicare FFS beneficiaries who are dually enrolled for at least one month in 2014.

Appendix Figure A2: Demographics of Dually Enrolled and Medicare-Only



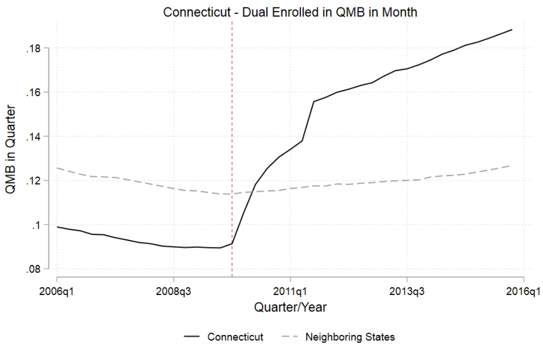
Source: 2018 MEDPAC and MACPAC Data Book: Beneficiaries Dually Eligible for Medicare and Medicaid. Data reflects calendar year 2013. *SSDI* reflects fraction of Medicare beneficiaries who were entitled to Medicare through Social Security Disability Insurance. *Poor Health* is a self-reported health status conducted through the Medicare Current Beneficiary Survey (MCBS).

Appendix Figure A3: Main PCP Medicaid Acceptance Level

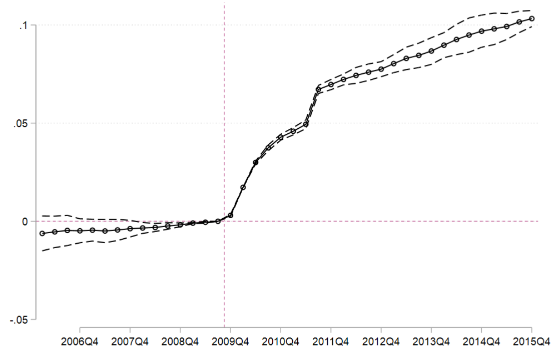


Source: 2008-2015 CMS FFS CMS FFS Claims (CT, NY, RI, NY). This graph plots the distribution of $PCPMedAccept_i$, or the fraction of the main PCP's claims that come from Medicaid patients. Each observation is an individual.

Appendix Figure A4: Connecticut dual-Medicaid Expansion



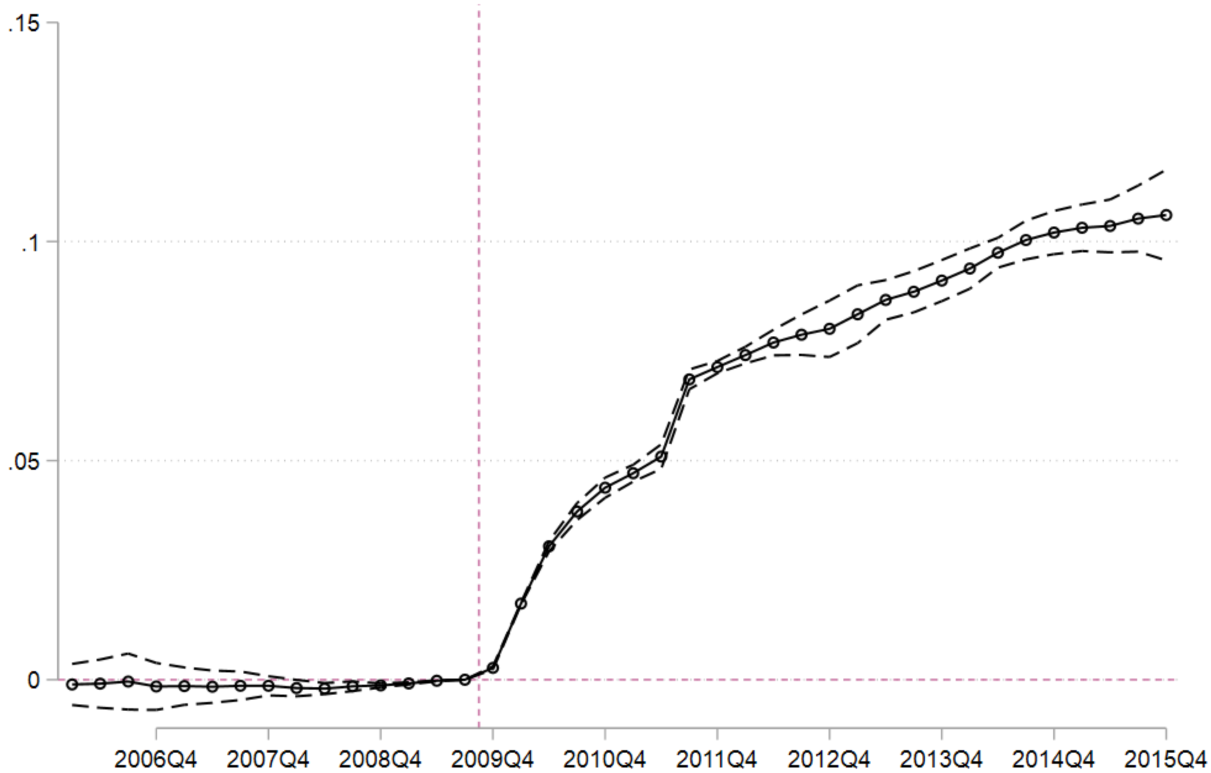
(a) Fraction Enrolled in QMB



(b) Event Study Diff-in-Diff Estimates

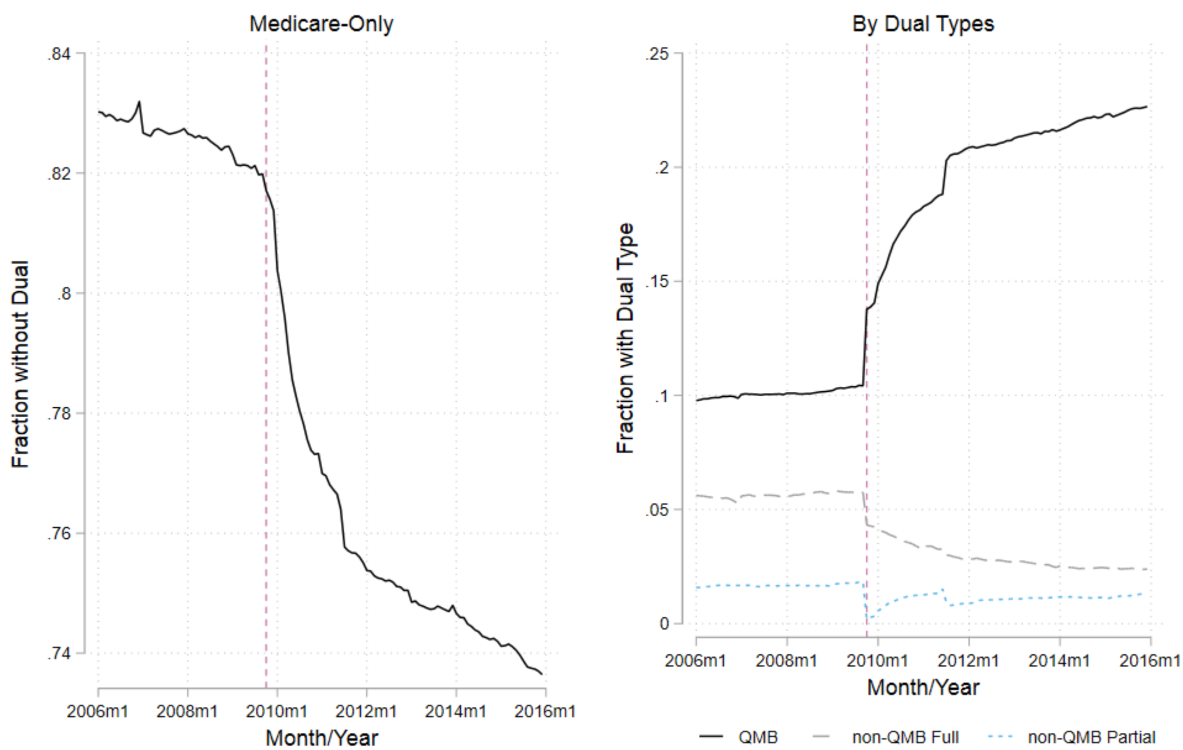
Source: 2006-2015 CMS FFS Claims after sample restrictions. Panel (a) shows raw means of QMB enrollment by time quarter for Connecticut (solid line) and the neighboring states of New York, Massachusetts, and Rhode Island (dashed line). The red vertical dashed line delineates the October 2009 policy change. Panel (b) presents the coefficients of an event study differences-in-differences comparing CT with the neighboring states. For individual i in state s in time t, I regress $QMB_{ist} = \delta_i + \delta_t + \delta_s + \sum_{j=2006Q1}^{2015Q4} \theta_j \cdot CT_s \cdot 1(t = j) + \omega_{ist}$ where the outcome variable is an indicator for individual QMB enrollment and I control for individual FE, time quarter FE, and state FE. The coefficient of interest is θ_j, which captures the effect of being in CT for each time period, relative to the neighboring states. θ_j is shown in Panel (b), where 2009 quarter 3 is the excluded time period. Robust standard errors clustered at the state level.

Appendix Figure A5: Difference-in-Difference for Effect of CT dual-Medicaid Expansion, Excluding New York



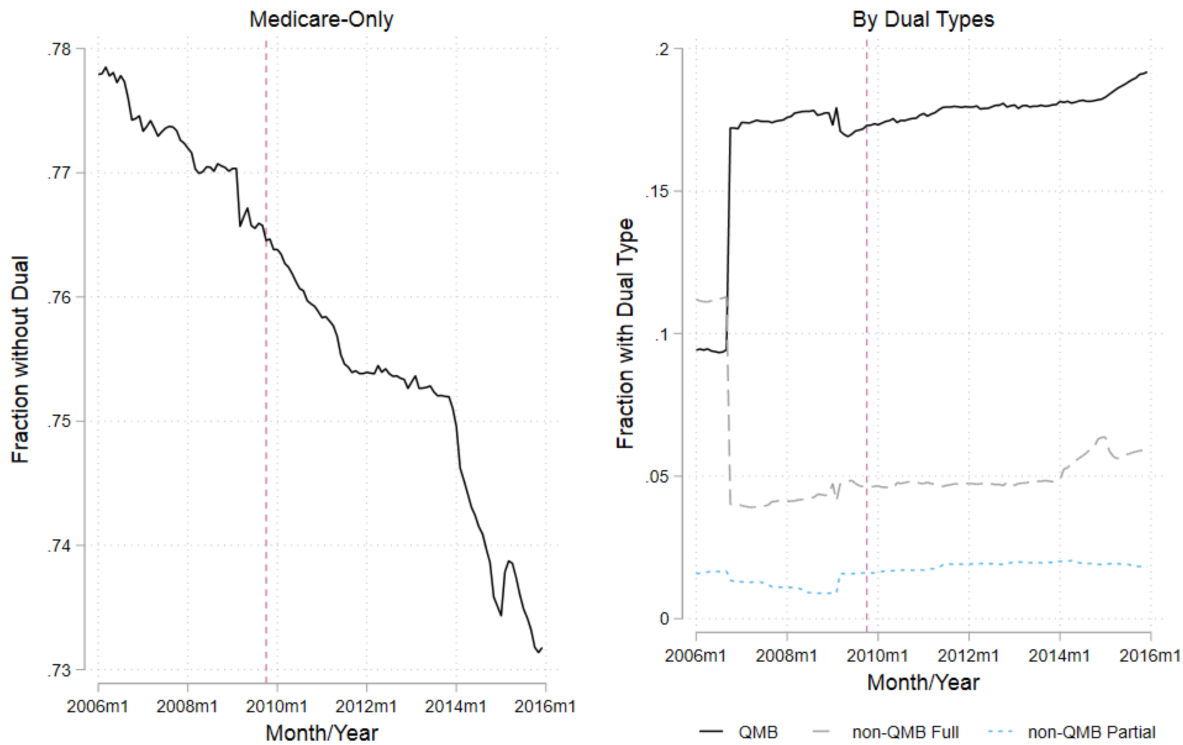
Note: This is a companion DD analysis to Figure A4, excluding New York as a comparison control state.

Appendix Figure A6: Breakdown of Dual-Eligibility Type, Connecticut



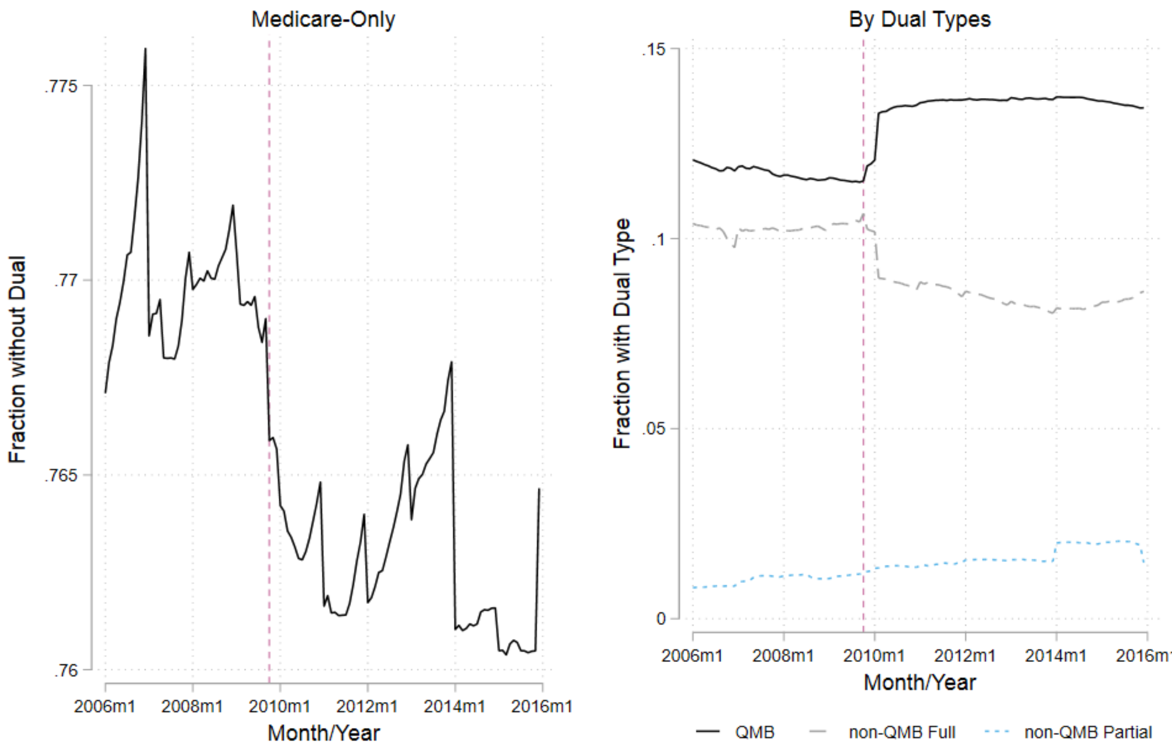
Source: 2006-2015 CMS FFS Claims for CT. Non-QMB full dual refers to individuals who receive full Medicaid through the state, but are not enrolled in QMB. Non-QMB partial dual refers to individuals who only receive Medicare premium assistance. See Appendix A.1 for more details on dual program types.

Appendix Figure A7: Breakdown of Dual-Eligibility Type, Massachusetts



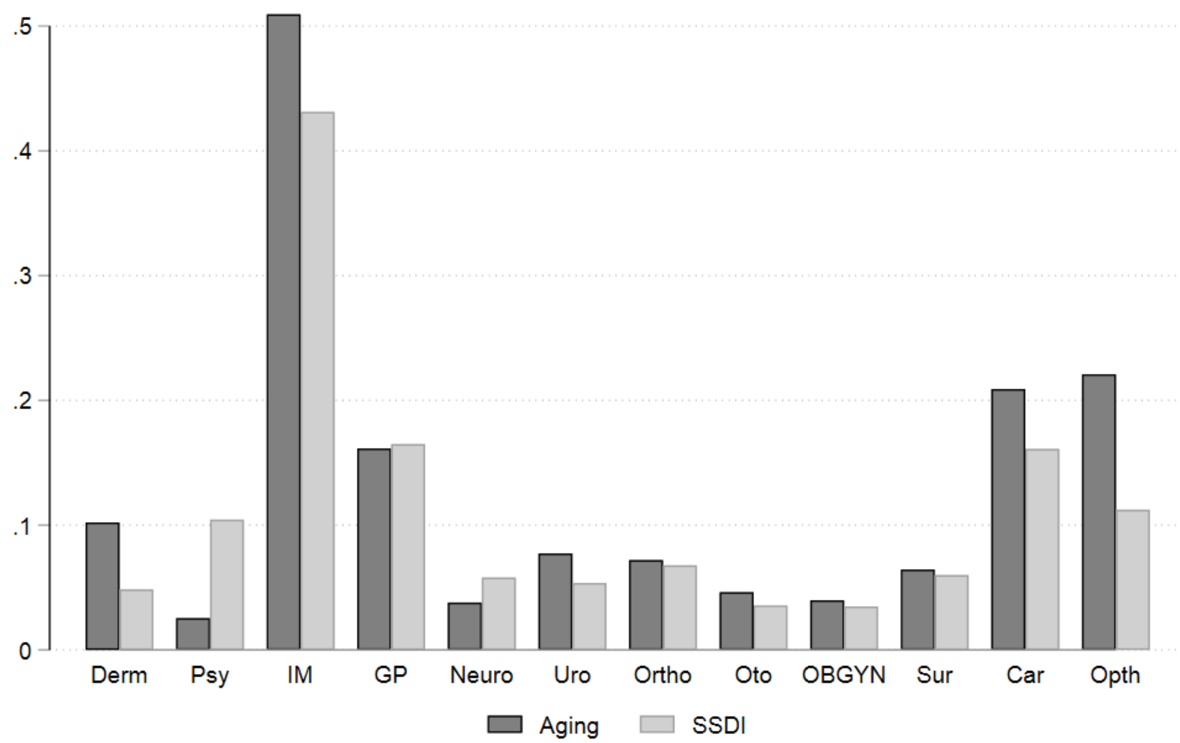
Source: 2006-2015 CMS FFS Claims for MA. Non-QMB full dual refers to individuals who receive full Medicaid through the state, but are not enrolled in QMB. Non-QMB partial dual refers to individuals who only receive Medicare premium assistance. See Appendix A.1 for more details on dual program types.

Appendix Figure A8: Breakdown of Dual-Eligibility Type, New York



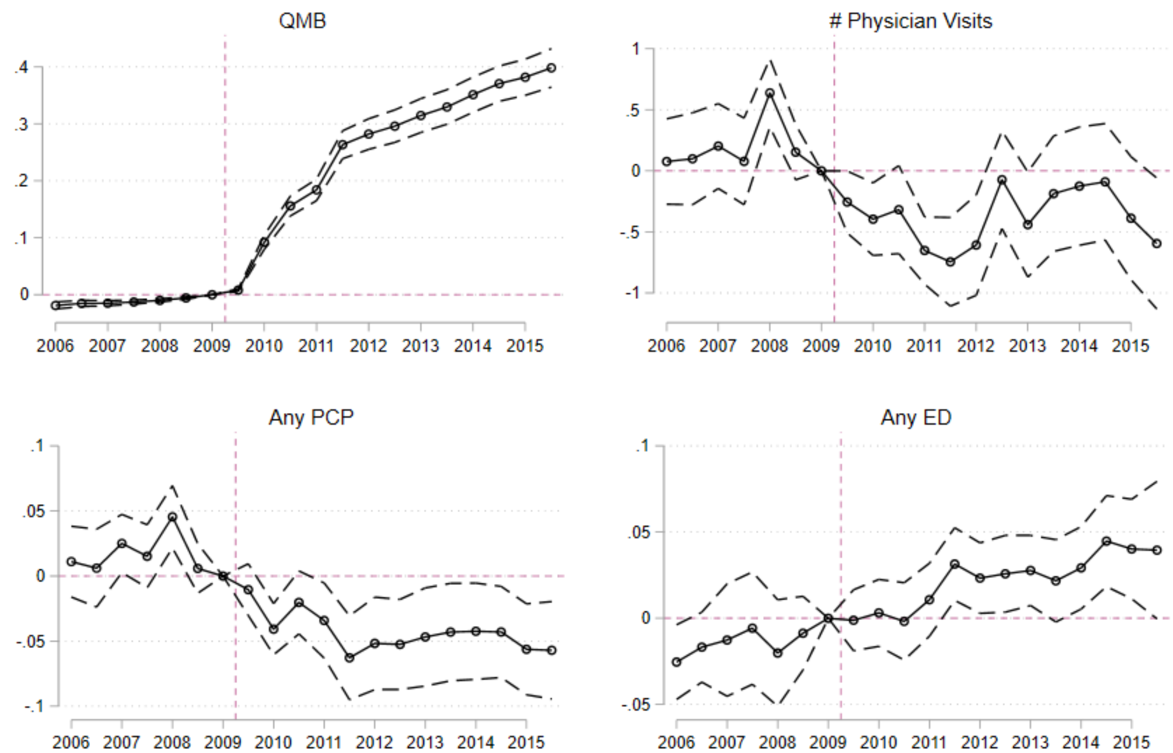
Source: 2006-2015 CMS FFS Claims for NY. Non-QMB full dual refers to individuals who receive full Medicaid through the state, but are not enrolled in QMB. Non-QMB partial dual refers to individuals who only receive Medicare premium assistance. See Appendix A.1 for more details on dual program types.

Appendix Figure A9: Specialty Usage by Medicare Entitlement



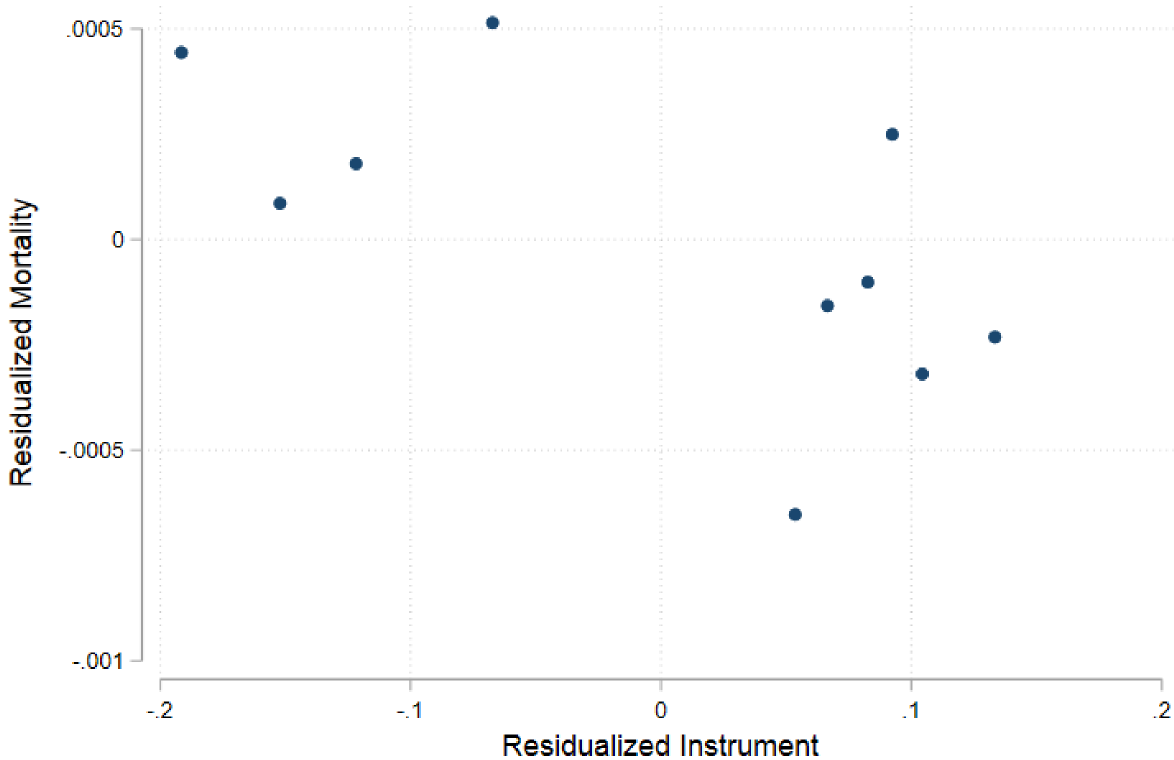
Source: 2006-2009Q3 CMS FFS Claims (CT, NY, RI, NY). Bars show the fraction of individuals who have at least one physician claim in a quarter with physician specialty of each type. SSDI is defined as initial entitlement, so includes individuals over the age of 65. The specialities, listed from left to right, are Dermatology, Psychiatry, Internal Medicine, General/Family Practice, Neurology, Urology, Orthopedics, Otolaryngology, OBGYN, Surgery, Cardiology, and Ophthalmology. The order of the bars are presented from least Medicaid accepting specialties (left) to most Medicaid accepting specialties (right).

Appendix Figure A10: Differences-in-Differences Event Study Versions of the IV



Source: 2006-2015 CMS FFS Claims (CT, NY, RI, NY) and 2008 ACS. Observations are at the individual half-year level. Regressions include controls for half-year FE, individual FE, and PUMA FE. These DD event studies include $SimEligDiff_p^{diff}$ as the main regressor, defined as the difference in the value of the instrument in 2010 and in 2006, or $SimulatedEligibility^{IV}_{p,2010} - SimulatedEligibility^{diff}_{p,2006}$. The excluded time period is the first half-year (Jan-June) of 2009 and standard errors are clustered at the PUMA level.

Appendix Figure A11: Reduced Form Visualization of Mortality Rates on the Instrument, Connecticut



Source: 2006-2015 CMS FFS Claims (CT, NY, RI, NY) and 2008 ACS. Observations are at the PUMA by quarter level. This graph is a binscatter visualization of the reduced form of the mortality rate on the instrument; see Appendix G for specification details. The mortality rate and the instrument are residualized, controlling for quarter FE, PUMA FE, and PUMA level controls (share White, male, and age bin). This graph shows only the Connecticut observations, since variation is driven by the policy induced changes dual rates. Non-Connecticut regions have residualized instrument values clustered in a mass around zero and are not shown in this graph.

Appendix Table A1: Categories of Dual Medicare-Medicaid Patients

Type	Medicaid Type	Income Limit (FPL)	A Premiums	B Premiums	A/B Cost Sharing	Full Medicaid
QMB	Partial	$\leq$ 100%	Yes	Yes	Yes	No
QMB	Full	$\leq$ 100%	Yes	Yes	Yes	Yes
SLMB	Partial	101%-120%	No	Yes	No	No
SLMB	Full	101%-120%	No	Yes	Depends	Yes
QI	Partial	121-135%	No	Yes	No	No
QWDI	Partial	$\leq$ 200%	Yes	No	No	No
Non-MSP	Full	Depends	No	Depends	Depends	Yes

See Appendix A.1 for full discussion. QMB, SLMB, QI, and QWDI are all Medicare Savings Program (MSP) types; the last category refers to dual patients who are non-MSP but have full state Medicaid through a state pathway (such as Supplemental Security Income (SSI), Medically Needy, Special Income Level, etc). The "full" Medicaid type indicates the individual qualifies for full state Medicaid, while "partial" reflects enrollment only in a MSP, with no additional access to Medicaid services. All programs listed have federal asset tests; for QMB, SLMB, and QI, this is three times the SSI resource limit and for QWDI, the asset test is twice the SSI resource limits. QIs and QWDIs cannot be simultaneously receiving full Medicaid coverage. The income and asset qualifications are federal thresholds, but individual states can choose to have more generous eligibility. "Depends" indicates that such coverage might be offered, but this is up to individual state's discretion. For example, some states may not cover Medicare cost-sharing for full dual-eligible SLMBs. Yet, individuals pay no more than the state Medicate costs for Medicare-covered services. See the CMS MMCO "Dual Eligible Individuals - Categories" (https://www.cms.gov/Medicare-Medicaid-Coordination/Medicare-and-Medicaid-Coordination/Medicare-Medicaid-Coordination-Office/Downloads/MedicareMedicaidEnrolleeCategories.pdf) for the most comprehensive description of the dual categories.

Appendix Table A2: Fraction of Physicians who Accept Medicaid by Specialty

Specialty	**Fraction Take Medicaid**	**Medicaid Acceptance Classification**
Dermatology	0.4631	L
Psychiatry	0.4719	L
Internal Med	0.6475	L
General/Family	0.6807	L
Neurology	0.7122	M
Urology	0.7206	M
Orthopedic Surg	0.7428	M
Otolaryngology	0.7479	M
OBGYN	0.7811	H
General Surg	0.8350	H
Cardiovascular	0.8475	H
Ophthalmology	0.8989	H

Note: Derived from the National Ambulatory Medical Care Survey (NAMCS) 2006-2008, which asks physicians who accept new patients whether they accept Medicaid patients. From this survey, specialties are split into Medicaid acceptance terciles.

Appendix Table A3: Sample Restrictions

	Observations	% of Sample
Panel A. Individual - Annual Level		
Full Sample	104,543,192	100%
FFS, Enrolled in A and B, Age $\geq$ 18	52,025,625	49.8%
Dual Status Clearly Defined	51,488,974	49.3%
Non-missing U.S. States	51,286,543	49.1%
Restrict to CT, MA, NY, RI	5,010,542	4.8%
Panel B. Individual - Monthly Level		
Reshape to Monthly	60,126,504	100%
Remove Non-Medicare Months (Joined Medicare/Death)	57,283,668	95.3%
Drop if Ever Non-QMB Dual Prior to Oct 2009	50,040,931	83.2%
Drop Months w/o Full Quarter (Joined/Died in Quarter)	49,603,575	82.5%
Panel C. Individual - Quarterly Level		
Collapse to Quarterly	16,534,525	100%
Matched in Zip/PUMA for IV	16,391,488	99.1%
Singleton Obs. Dropped in Regression	16,375,484	99.0%

Creation of the main sample used for analysis. I begin with a 20% sample of annual individual-level Medicare Claims, 2006-2015 as shown in Panel A. I reshape to individual-monthly level in Panel B in order to remove months without Medicare and those who where ever non-QMB dual. The final unit of analysis is at the individual-quarterly level, as shown in Panel C.

Appendix Table A4: Potential Confounders: Predicted Outcomes Based on Demographics and the IV

	(1) Log(Spending+1)	(2) Any ED	(3) Any Inpatient	(4) # Phys Visits	(5) Any Primary Care	(6) Any Specialist
Instrument	0.0036	0.0021	0.0009	-0.0199	-0.0041	-0.0008
	(0.0046)	(0.0015)	(0.0007)	(0.1002)	(0.0025)	(0.0013)
Observations	1816	1816	1816	1816	1816	1816
Mean Dep. Var	9.080	0.293	0.184	16.321	0.793	0.896

Source: 2008-2015 CMS FFS Claims and 2008-2015 ACS. Each observation is a PUMA-year. This analysis is limited to the year level for years 2008-2015, because the ACS is at the annual level and Medicare status is not collected prior to 2008. Each coefficient is the regression of the fitted value of the outcome at the PUMA level on the instrument controlling for PUMA FE and year FE. The fitted values are obtained from a regression of the PUMA level spending and utilization averages from the claims sample on demographic variables, PUMA FE, and year FE. The demographic variables are produced in the 2008-2015 ACS for the 18+ Medicare population (with the exception of unemployment rate) and includes: average age, mean income, median income, log mean income, log median income, and fraction with each the following characteristics: veteran, White, Black, Not In the Labor Force, female, Hispanic, High School education or less, with spouse, Social Security, Supplemental Security Income, below the poverty line, and unemployment rate for all aged 18+. Robust standard error clustered at the PUMA level in the parentheses.

Appendix Table A5: Effect of Dual Enrollment on Medicare Usage (Removing ED), IV

	(1) # Physician Visits	(2) Any Physician Visit	(3) Any Specialist	(4) Any Primary Care
Dual	-1.109	-0.029	0.007	-0.177
	(0.324)	(0.022)	(0.028)	(0.051)
Observations	16375484	16375484	16375484	16375484
Mean Dep. Var	3.86	0.83	0.72	0.56

Source: 2006-2015 CMS FFS Claims (CT, NY, RI, NY) and 2008 ACS for construction of instrument. In contrast to the results of the main text, these measures of physician visits exclude physician visits that occur in the emergency department. Regressions include controls for quarter FE, individual FE, and PUMA FE. Robust standard errors clustered at the PUMA level in the parentheses.

Appendix Table A6: Effect of Dual Enrollment on Additional Physician-Based Utilization

	(1) Any New Office Visit	(2) Any Established Office Visit	(3) Any Part B Physician Drugs
Dual	-0.156	0.000	0.033
	(0.024)	(0.027)	(0.026)
Observations	16375484	16375484	16375484
Mean Dep. Var	0.155	0.721	0.263

Source: 2006-2015 CMS FFS Claims (CT, NY, RI, NY) and 2008 ACS for construction of instrument. Regressions include controls for quarter FE, individual FE, and PUMA FE. Robust standard errors clustered at the PUMA level in the parentheses. The outcome variables are categorized using the Berenson-Eggers Type of Service Code. A new office visit corresponds to code M1A, an established office visit uses code M1B, while Part B physician drugs use codes D1G, O1D, O1E, O1G, I1E, and I1F. Note that while some Part B drugs can be administered through a durable medical equipment (DME), I focus only on physician-based drugs (therefore using only the Medicare Carrier file as opposed to the DME file) since this paper focuses on physician responses.

Appendix Table A7: Effect of Dual Enrollment by Main PCP Medicaid Acceptance Level, Inclusion of PUMA by Post Policy-Fixed Effects

Dependent Variable	(1) Mean Dep. Var	(2) Dual $\cdot PCPMed$ $AcceptQ1$	(3) Dual $\cdot PCPMed$ $AcceptQ2$	(4) Dual $\cdot PCPMed$ $AcceptQ3$
Panel A. Any Physician Visit				
Primary	0.64	-0.199	-0.050	0.048
		(0.121)	(0.098)	(0.079)
Specialist	0.78	0.080	0.053	0.030
		(0.047)	(0.035)	(0.033)
Observations	7078671			
Panel B. Any ED Visit				
All ED	0.11	0.130	0.112	0.003
		(0.042)	(0.031)	(0.030)
Emergent	0.07	0.012	0.009	-0.021
		(0.035)	(0.027)	(0.024)
Non-Emergent	0.04	0.029	0.029	-0.004
		(0.027)	(0.019)	(0.017)
Observations	6908818			

Source: CMS 2008-2015 and 2008 ACS, restricted to those with main PCP (see text for more details on sample restriction). ED outcomes do not include 2015Q4. "Any" refers to at least one such visit in a quarter or the extensive margin usage. IV results from instrumenting Dual interactions with the instrument interacted with Medicaid Acceptance variable(s). Regressions include controls for quarter FE, individual FE, PUMA FE, and PUMA by post-policy (indicator for post-Oct 2009) FE. Robust standard errors clustered by PUMA in the parentheses.

Appendix Table A8: Effect of Dual Enrollment by Main PCP Medicaid Acceptance Level, Continuous Measure of $MedPCPAccept$

Dependent Variable	(1) Mean Dep. Var	(2) Dual	(3) Dual $\cdot PCPMedAccept$
Panel A. Any Physician Visit			
Primary	0.64	-0.178	0.505
		(0.062)	(0.152)
Specialist	0.78	0.014	0.032
		(0.033)	(0.085)
Observations	7078671		
Panel B. Any ED Visit			
All ED	0.11	0.142	-0.339
		(0.025)	(0.065)
Emergent	0.07	0.063	-0.144
		(0.019)	(0.067)
Non-Emergent	0.04	0.033	-0.088
		(0.020)	(0.044)
Observations	6908818		

Source: CMS 2008-2015 and 2008 ACS, restricted to those with main PCP (see text for more details on sample restriction). ED outcomes do not include 2015Q4. "Any" refers to at least one such visit in a quarter or the extensive margin usage. IV results from instrumenting Dual interactions with the instrument interacted with Medicaid Acceptance variable(s). Regressions include controls for quarter FE, individual FE, and PUMA FE. Robust standard errors clustered by PUMA in the parentheses.

Appendix Table A9: Effect of Dual Enrollment by Main PCP Medicaid Acceptance Level

Dependent Variable	(1) Mean Dep. Var	(2) Dual $\cdot PCPMed$ *AcceptQ*1	(3) Dual $\cdot PCPMed$ *AcceptQ*2	(4) Dual $\cdot PCPMed$ *AcceptQ*3
Panel A. Sample: Age 65+				
Flu Shot	0.67	-0.391	-0.221	-0.150
		(0.110)	(0.063)	(0.064)
Observations	1660823			
Panel B. Sample: Women Age 50-74				
Mammogram	0.75	-0.647	-0.063	-0.108
		(0.161)	(0.149)	(0.095)
Observations	238918			
Panel B. Diabetes				
HbA1c Test	0.76	-0.203	-0.117	-0.004
		(0.107)	(0.058)	(0.058)
Cholesterol Test	0.81	-0.158	-0.127	-0.114
		(0.061)	(0.049)	(0.056)
Retinal Eye	0.68	-0.213	-0.137	-0.095
		(0.090)	(0.074)	(0.062)
Observations	608634			

Source: CMS 2008-2016 and 2008 ACS, restricted to those with main PCP (see text for more details on sample restriction). Observations at the individual year level. The relevant samples are labelled; for example, flu shots are estimated only for those aged 65+. IV results from instrumenting Dual interactions with the instrument interacted with Medicaid Acceptance variable(s). Regressions include controls for year FE, individual FE, and PUMA FE. Robust standard errors clustered by PUMA in the parentheses.

Appendix Table A10: Effect of Dual Enrollment, Heterogeneity Analysis

	(1) Full	(2) Aging	(3) SSDI	(4) Minority	(5) High Comorbid
Panel A: Outcome - Log(Spending+1)					
Dual	0.409	0.583	-0.273	0.661	0.387
	(0.150)	(0.161)	(0.214)	(0.370)	(0.146)
Mean Dep. Var	5.32	5.34	4.98	4.73	6.34
Panel B: Outcome - Any Hospitalization					
Dual	0.005	0.001	0.013	0.019	0.012
	(0.008)	(0.010)	(0.016)	(0.024)	(0.015)
Mean Dep. Var	0.06	0.06	0.07	0.05	0.09
Panel C: Outcome - Any ED Visit					
Dual	0.083	0.082	0.073	0.089	0.090
	(0.018)	(0.019)	(0.025)	(0.029)	(0.025)
Mean Dep. Var	0.10	0.10	0.13	0.10	0.14
Panel D: Outcome - Any Primary Care Visit					
Dual	-0.185	-0.204	-0.123	-0.205	-0.218
	(0.049)	(0.056)	(0.041)	(0.086)	(0.054)
Mean Dep. Var	0.56	0.57	0.47	0.48	0.67
Panel E: Outcome - Any Specialist Care Visit					
Dual	0.027	0.055	-0.076	0.004	0.007
	(0.026)	(0.030)	(0.036)	(0.056)	(0.024)
Mean Dep. Var	0.73	0.74	0.66	0.64	0.85
Observations	16375484	13330009	2981341	1793625	6463808

Source: 2006-2015 CMS FFS Claims (CT, NY, RI, NY) and 2008 ACS for construction of instrument. Regressions include controls for quarter FE, individual FE, and PUMA FE. Each column is a different subsample, with the subsample labelled at the top of the columns. The instrument is constructed with the full sample and the same instrument is applied to each subsample. Robust standard errors clustered at the PUMA level in the parentheses.

Appendix Table A11: Chronic Illness by Medicare Entitlement Type

	Aging	SSDI
Number of Comorbidities	3.09	2.56
Alzheimer's/Dementia	0.16	0.09
Hypertension	0.63	0.44
Stroke/TIA	0.05	0.04
Atrial Fibrillation	0.11	0.05
Asthma	0.04	0.08
Chronic Kidney Disease	0.14	0.12
COPD	0.12	0.13
Depression	0.11	0.23
Diabetes	0.28	0.29
Heart Failure	0.21	0.16
Ischemic Heart Disease	0.40	0.29
Schizophrenia and Other Psychotic Disorders	0.03	0.13
Hyperlipidemia	0.49	0.37
Observations	1601618	436579

Source: CMS FFS 2006-2009Q3. Observations are at the annual level and utilizes the Master Beneficiary Survey File (MBSF)'s Chronic Conditions and Other Chronic or Potentially Disabling Conditions segments.

Appendix Table A12: Demographic IV: Effect of Dual Enrollment on Medicare Spending and Usage

Dependent Variable	(1) Mean Dep. Var	(2) Demo IV
Log(Spending+1)	5.32	0.332
		(1.000)
Any Spending	0.84	-0.027
		(0.097)
Any Inpatient	0.06	-0.006
		(0.031)
Any Outpatient	0.84	-0.027
		(0.097)
Any ED	0.10	0.066
		(0.046)
# Physician Visits	3.98	-1.150
		(1.892)
Any Physician Visit	0.83	-0.034
		(0.103)
Any Specialist	0.73	0.010
		(0.157)
Any Primary Care	0.56	-0.200
		(0.067)
Observations		16265073

Source: 2006-2015 CMS FFS (CT, MA, RI, NY) and 2008 SIPP, observations at the individual-quarter. Regressions include controls for quarter FE, individual FE, and state by demographic group FE. Robust standard errors clustered at the state by demographic group in the parentheses. "Any" refers to at least one such visit in a quarter or the extensive margin usage.

Appendix Table A13: Demographic IV: Effect of Dual Enrollment on Any Physician Visit, by Specialty Type

	(1) High	(2) Medium	(3) Low
Dual	0.074	-0.063	-0.177
	(0.208)	(0.042)	(0.098)
Observations	16265073	16265073	16265073
Mean Dep. Var	0.420	0.210	0.652

Source: 2006-2015 CMS FFS (CT, MA, RI, NY) and 2008 SIPP, observations at the individual-quarter. Regressions include controls for quarter FE, individual FE, and state by demographic group FE. Robust standard errors clustered at the instrument level, or the state by demographic group in the parentheses.

Appendix Table A14: Effect of Dual Share on Mortality, Heterogeneity Analysis

	(1) Mortality Rate
Share Dual	-0.00799 (0.00353)
Observations	9080
Mean Dep. Var	0.01354
Mean Dual Share Diff	0.06651

Source: CMS 2006-2015 and 2008 ACS, with observations at the PUMA by quarter level. Coefficients reflect IV regressions instrumenting $ShareDual_{lt}$ with $SimulatedEligibility_{lt}$. Regressions include controls for share White, share male, share in age bin (54-64, 64-74, 74-84, 85+), quarter FE, and PUMA FE. Mean. Dep. Var refers to mean mortality rates in PUMAs in CT prior to the policy change (October 2009). Mean Dual Share Diff refers to average change in share QMB in PUMAs in CT before and after the policy change. Robust standard errors clustered by PUMA in the parentheses.