Becoming Dual: Measuring the Impact of Gaining Medicaid Coverage for Medicare Beneficiaries Appendix

Gina Li [*]

June 2023

I Background

I.A 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:

*Stanford University, ginali@stanford.edu

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)).

I.B 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.[1] Therefore, since this study focuses on CT individuals, Medicaid Managed Care (including enrollment in plans such as PACE) is not relevant in this study.

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

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).[2] 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.[3]

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.[4] 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.[5] In November 2013, the Rhody Health Options (RHO) began as an integrated plan accepting the duals.[6] By 2015, the number of duals enrolled in Medicaid Advantage stood at around 20,000.[7]

II 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

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

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

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

[5] `https://www.cms.gov/Medicare-Medicaid-Coordination/Medicare-and-Medicaid-Coordination/Medicare-Medicaid-Coordination-Office/Downloads/2007StateProfilesRI.pdf`

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

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

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.

II.A 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.

II.B 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.

II.C 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.

II.D 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.

II.E 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.

II.F 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).[8] 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.

II.G 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.

[8] `https://biotech.law.lsu.edu/cphl/Practice/preventive\_services.pdf`; `https://www.uspreventiveservicestaskforce.org/uspstf/recommendation/breast-cancer-screening`

(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.

II.H 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.[9] Created by the Maryland Health Care Commission, this document contains a mapping of the CMS HCFA specialties and the

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

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.

II.I 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).[10] For example, the algorithm to identify an Acute Myocardial Infraction is to look in the inpatient claims file for ICD/CPT/HCPCS codes indicating

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

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.

III Connecticut Policy Change

III.A 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.[11] The purpose

[11] `https://www.cga.ct.gov/asp/cgabillstatus/cgabillstatus.asp?selBillType=Bill&bill_num=`

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.

III.B 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

HB06146&which_year=2009

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%.

IV 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. [12]
   - 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.

V 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.

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

- 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 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.

VI Robustness

VI.A 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+.[13] 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.

VI.B Differences-in-Differences Event Studies

For the DD event studies, I estimate for individual i in PUMA l and half-year t:[14]

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

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

[13] 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.

[14] 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.

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).

VII 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 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%.

VIII 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:

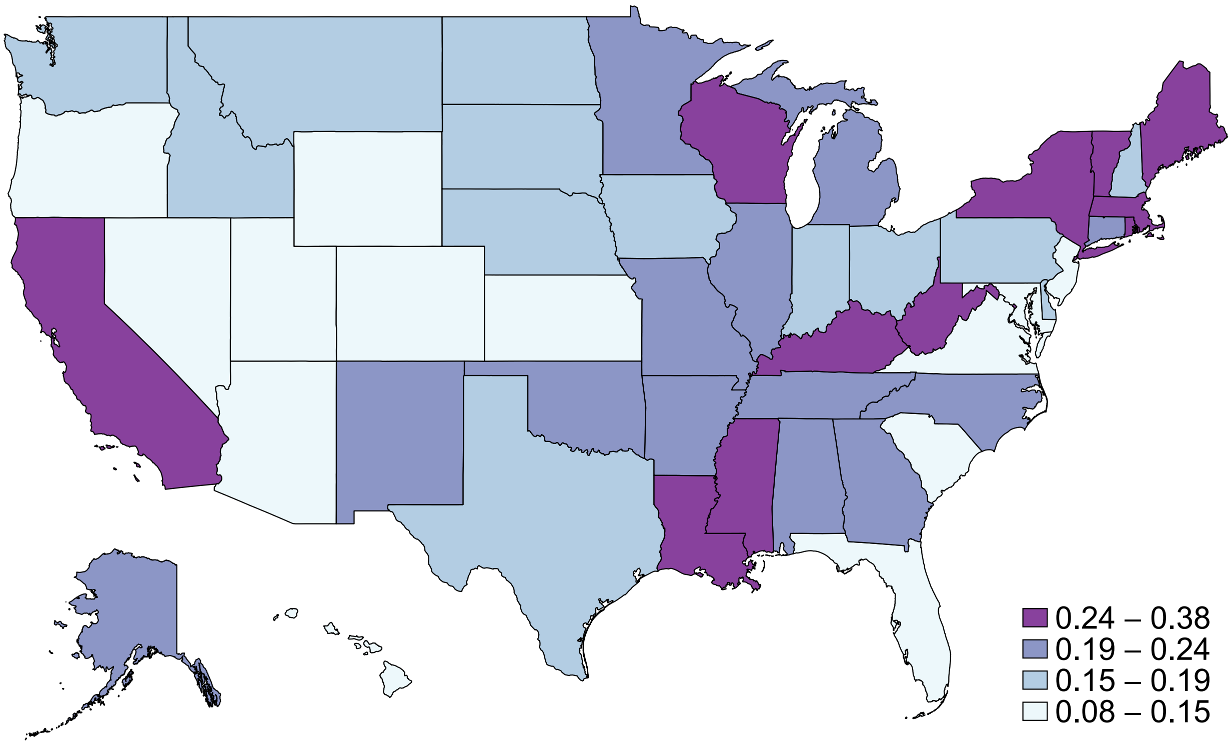
$$Prem_B + Prem_{Medigap}$$

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

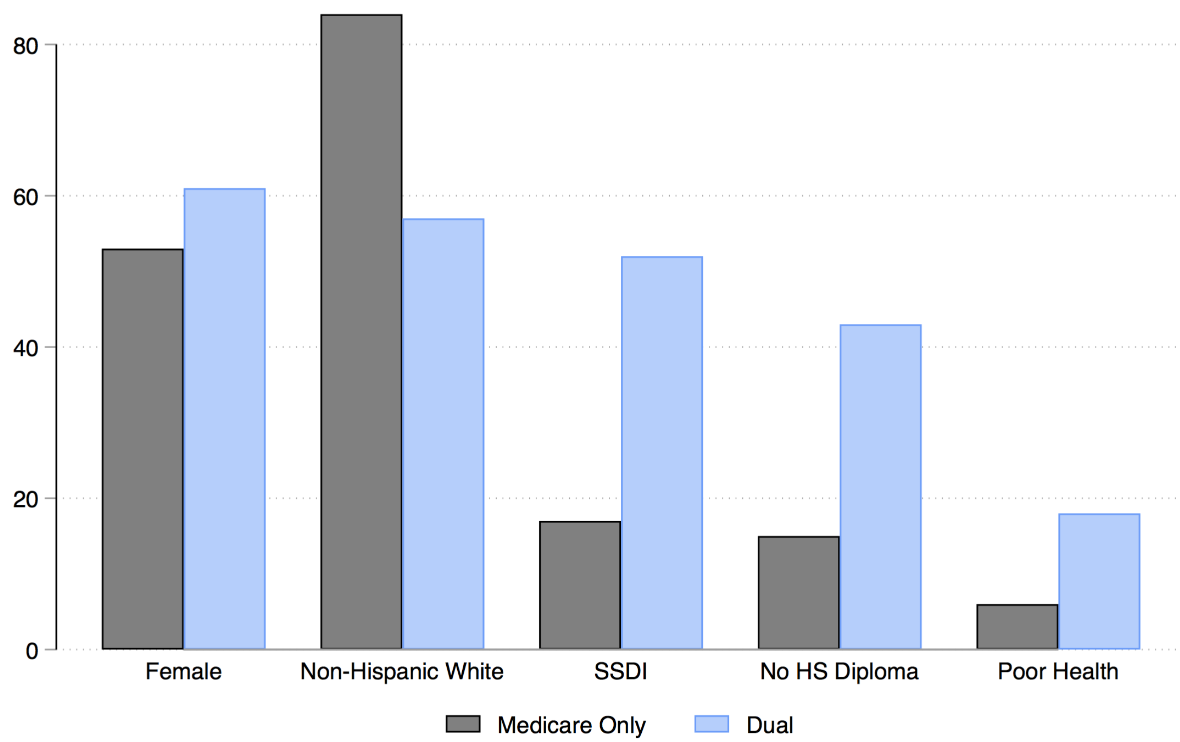
(Sheingold et al., 2011). In order to understand how Medicare spending would change if the dually enrolled were under Medigap, I need to estimate spending changes if cost-sharing were eliminated and there were no provider supply constraints. I assume that dual patients who have main PCPs with high Medicaid 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



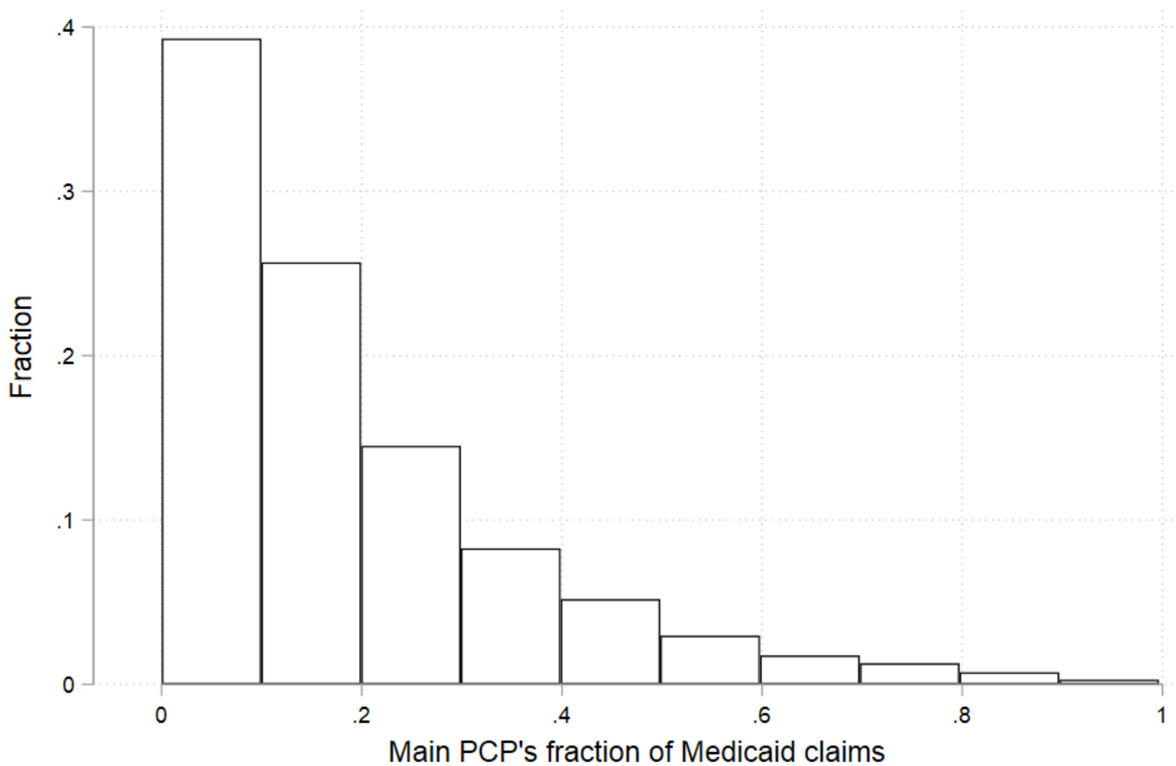
Source: 2014 CMS FFS Claims. The map indicates the fraction of Medicare FFS beneficiaries who are dually enrolled for at least one month in 2014.

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



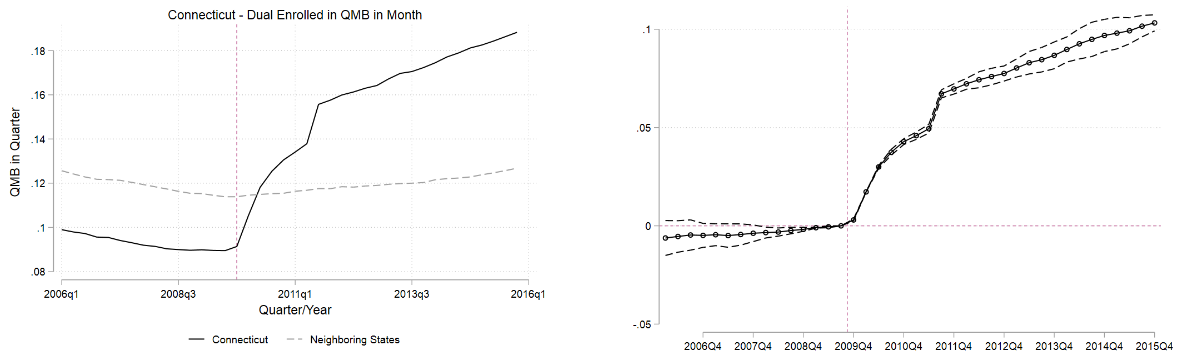
Source: 2018 MEDPAC and MACPAC Data Book: Beneficiaries Dually Eligible for Medicare and Medicaid. Data reflects calendar year 2013. *SSDI* reflects fraction of Medicare beneficiaries who were entitled to Medicare through Social Security Disability Insurance. *Poor Health* is a self-reported health status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

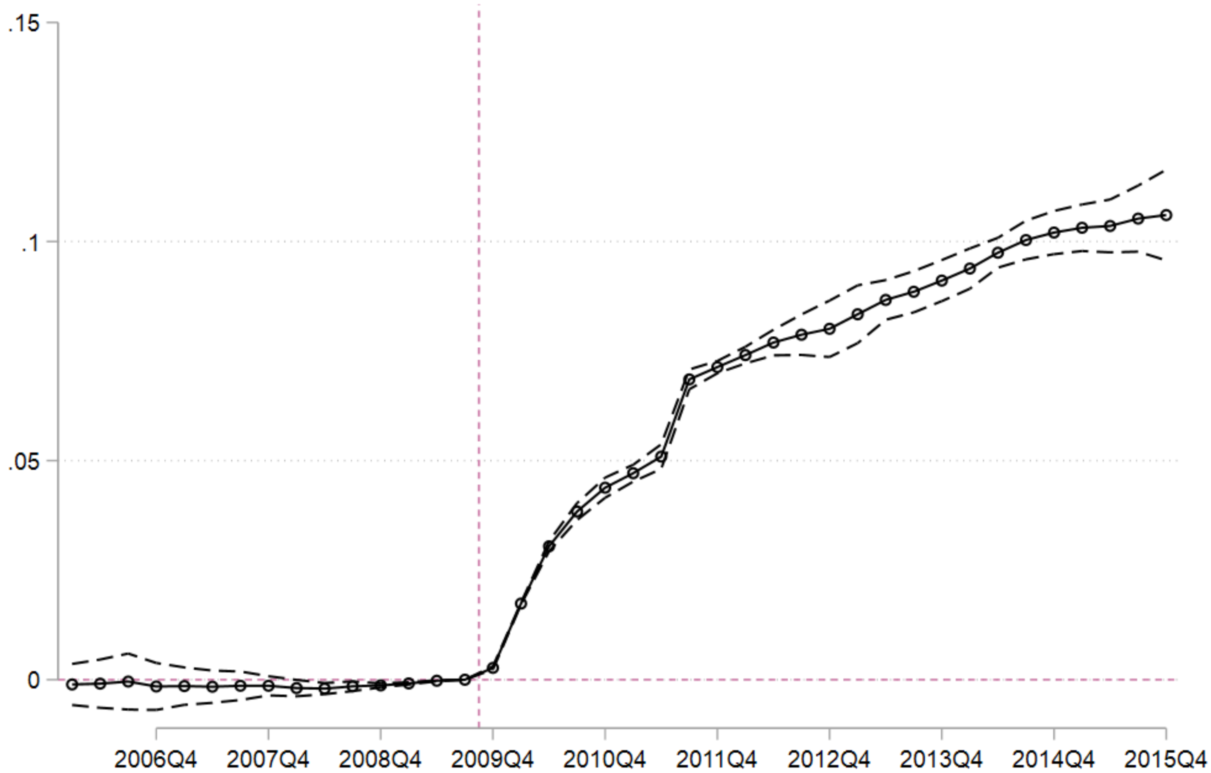


(a) Fraction Enrolled in QMB

(b) Event Study Diff-in-Diff Estimates

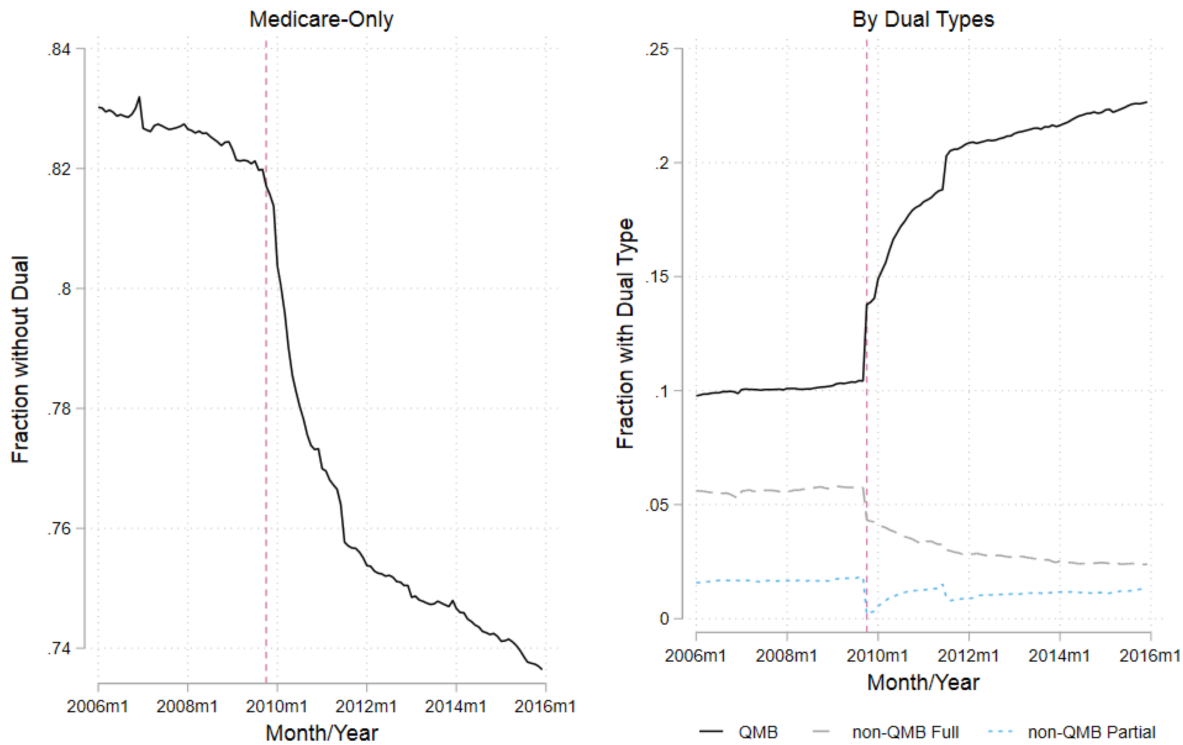
Source: 2006-2015 CMS FFS Claims after sample restrictions. Panel (a) shows raw means of QMB enrollment by time quarter for Connecticut (solid line) and the neighboring states of New York, Massachusetts, and Rhode Island (dashed line). The red vertical dashed line delineates the October 2009 policy change. 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



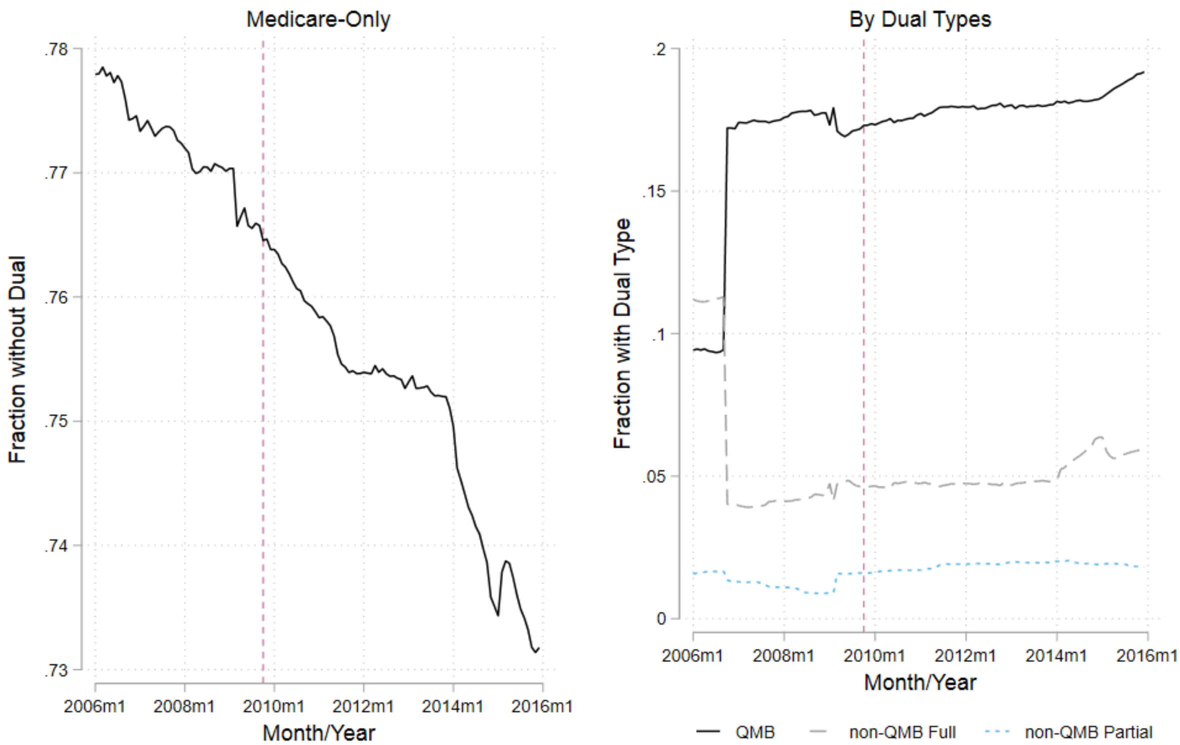
Note: This is a companion DD analysis to Figure A4, excluding New York as a comparison control state.

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



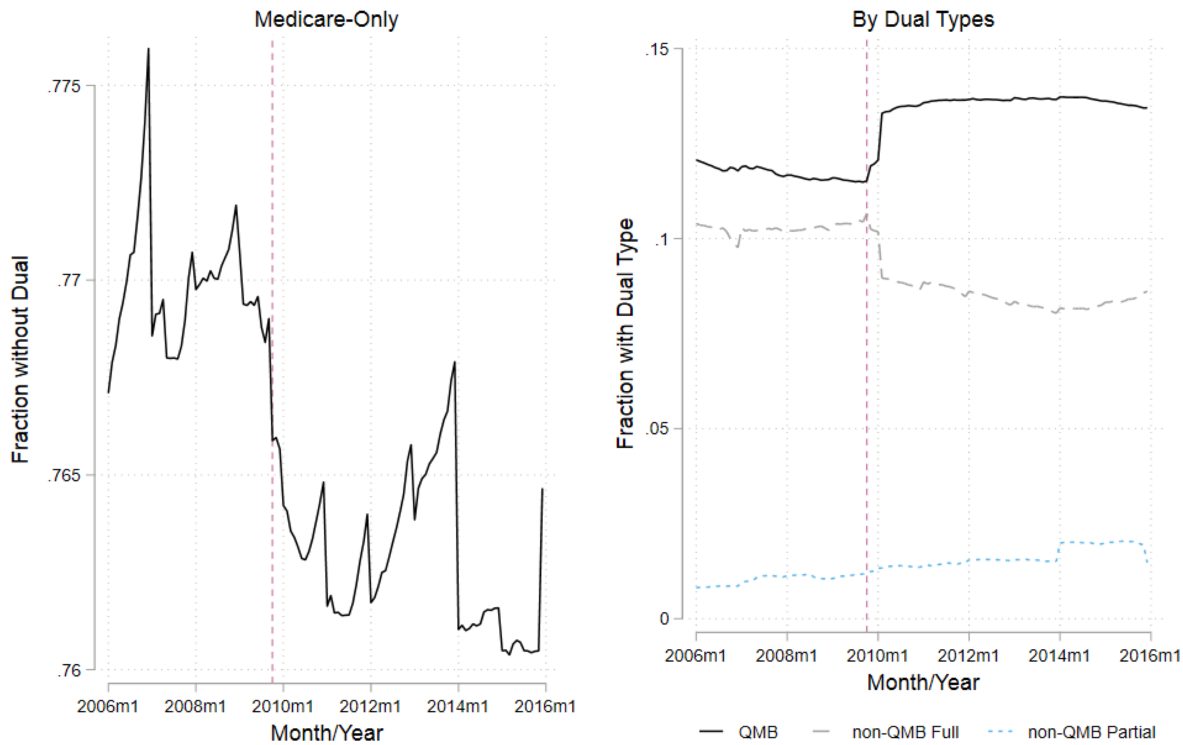
Source: 2006-2015 CMS FFS Claims for CT. Non-QMB full dual refers to individuals who receive full Medicaid through the state, but are not enrolled in QMB. Non-QMB partial dual refers to individuals who only receive Medicare premium assistance. See Appendix I.A for more details on dual program types.

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



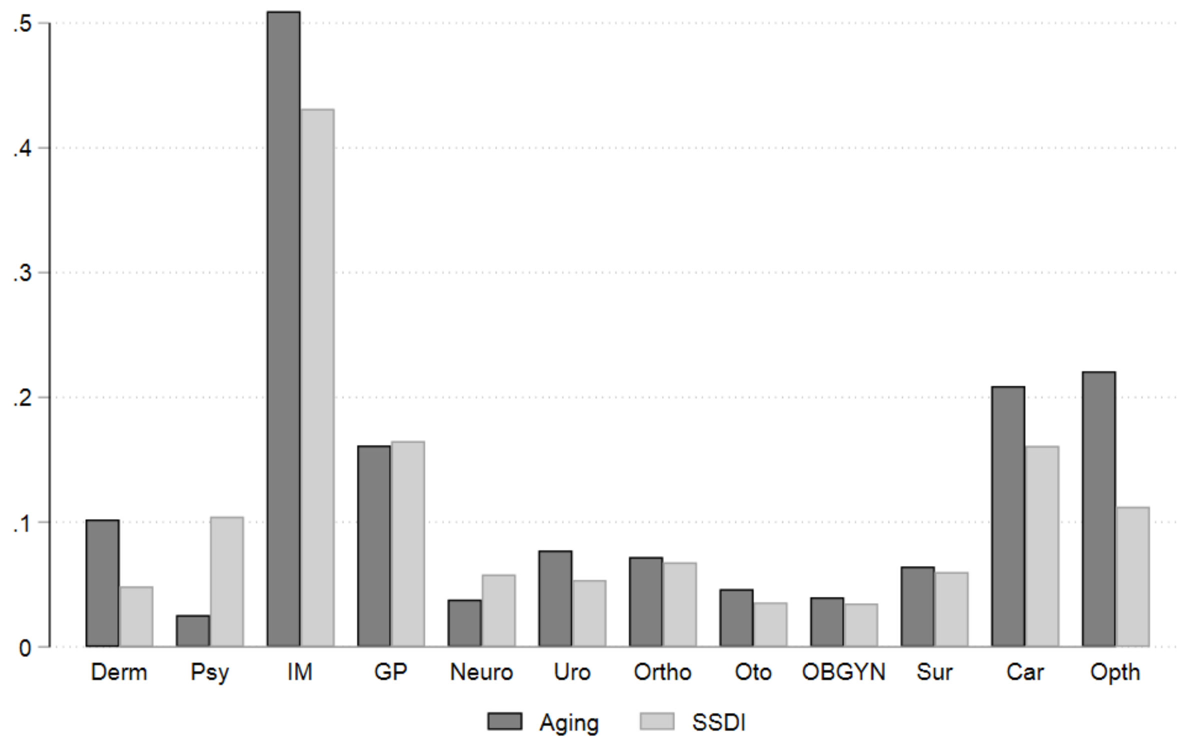
Source: 2006-2015 CMS FFS Claims for MA. Non-QMB full dual refers to individuals who receive full Medicaid through the state, but are not enrolled in QMB. Non-QMB partial dual refers to individuals who only receive Medicare premium assistance. See Appendix I.A for more details on dual program types.

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



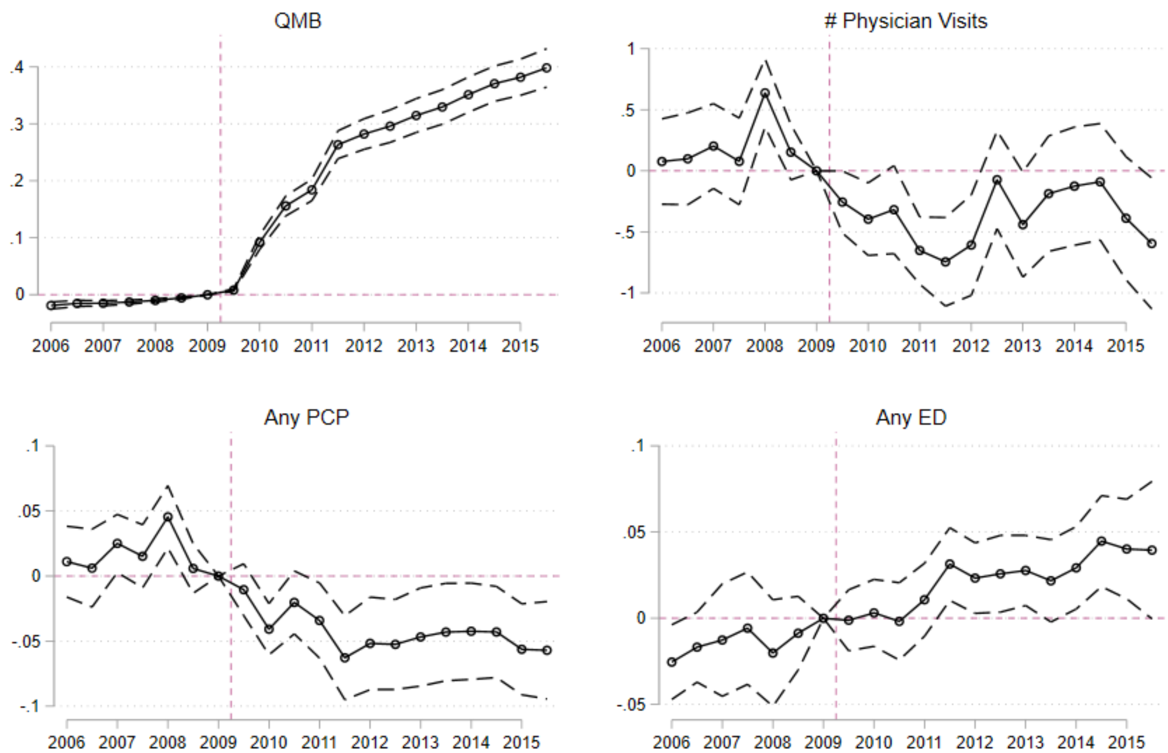
Source: 2006-2015 CMS FFS Claims for NY. Non-QMB full dual refers to individuals who receive full Medicaid through the state, but are not enrolled in QMB. Non-QMB partial dual refers to individuals who only receive Medicare premium assistance. See Appendix I.A for more details on dual program types.

Appendix Figure A9: Specialty Usage by Medicare Entitlement



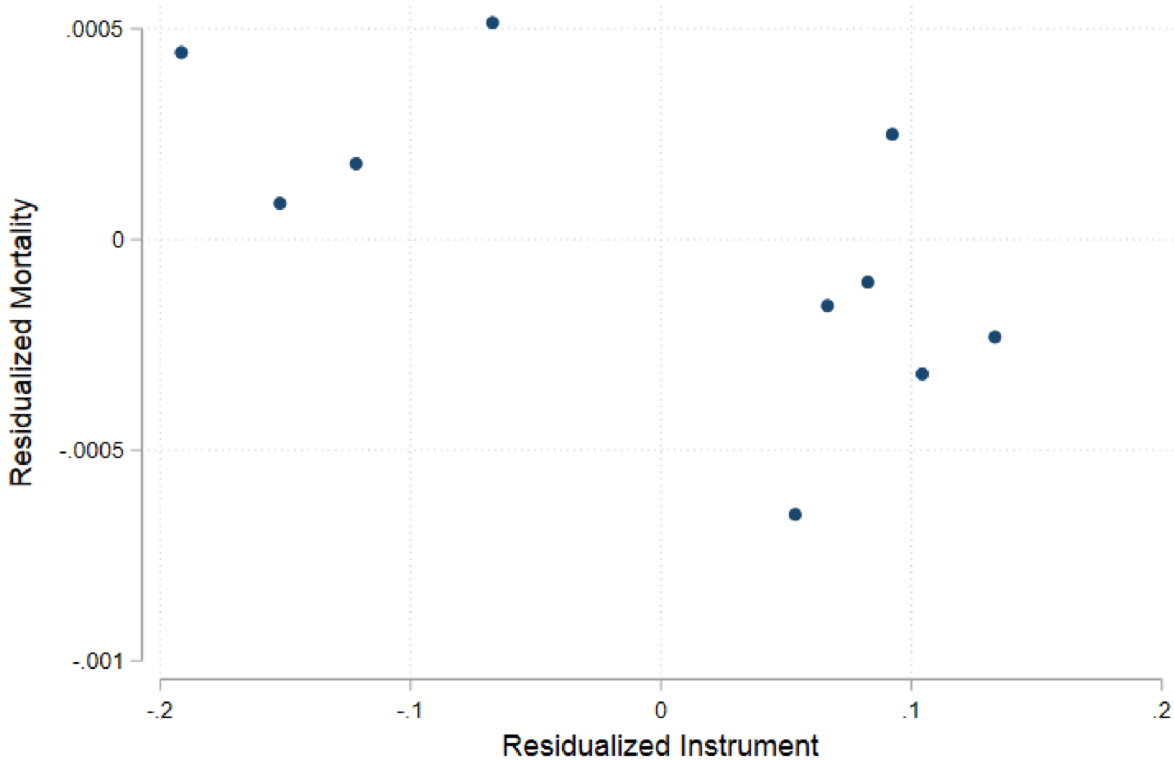
Source: 2006-2009Q3 CMS FFS Claims (CT, NY, RI, NY). Bars show the fraction of individuals who have at least one physician claim in a quarter with physician specialty of each type. SSDI is defined as initial entitlement, so includes individuals over the age of 65. The specialities, listed from left to 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 $SimulatedEligibility_{p,2010}^{IV} - SimulatedEligibility_{p,2006}^{diff}$. 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 VII 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 I.A 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 $\cdot PCPMed$ *AcceptQ1*	(3) Dual $\cdot PCPMed$ *AcceptQ2*	(4) Dual $\cdot PCPMed$ *AcceptQ3*
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.

References

Billings, J., Parikh, N., and Mijanovich, T. (2000). Emergency department use in new york city: a substitute for primary care? *Issue Brief (Commonwealth Fund)*, (433):1–5.

Caswell, K. J. and Waidmann, T. A. (2017). Medicare savings program enrollees and eligible non-enrollees. *MACPAC*.

Cohen, R. and Ayers, N. (2009). Medicare savings program and the medicare part d drug assistance. `https://www.cga.ct.gov/2009/rpt/2009-R-0097.htm`. Accessed: 2021-11-9.

Curto, V., Einav, L., Finkelstein, A., Levin, J., and Bhattacharya, J. (2019). Health care spending and utilization in public and private medicare. *American Economic Journal: Applied Economics*, 11(2):302–32.

Dube, N. (2012). Medigap insurance. `https://www.cga.ct.gov/2012/rpt/pdf/2012-R-0082.pdf`. Accessed: 2021-11-2.

Fitzpatrick, M. (2015). Olr backgrounder: Medicaid eligibility. `https://www.cga.ct.gov/2013/rpt/2013-R-0016.htm`. Accessed: 2021-11-2.

Flowers, L., Buettgens, M., and Dev, J. (2014). Transitioning from medicaid expansion programs to medicare: Making sure low-income medicare beneficiaries get financial help.

Haber, S., Zheng, N. T., Hoover, S., and Feng, Z. (2014). Effect of state medicaid payment policies for medicare cost sharing on access to care for dual eligibles. *Final Report. https://www. macpac. gov/wp-content/uploads/2015/01/Medicaid-Payment-for-Cost-Sharing. pdf. Accessed May*, 5:2017.

Huang, J. T., Jacobson, G. A., Neuman, T., Desmond, K. A., and Rice, T. (2013). Medigap: Spotlight on enrollment, premiums, and recent trends. *The Henry J Kaiser Family Foundation*.

Johnston, K. J., Allen, L., Melanson, T. A., and Pitts, S. R. (2017). A “patch” to the nyu emergency department visit algorithm. *Health services research*, 52(4):1264–1276.

Kwok, J. (2019). How do primary care physicians influence healthcare? evidence on practice styles and switching costs from medicare. Technical report, Working Paper.

Maciejewski, M. L. and Hammill, B. G. (2019). Measuring the burden of multimorbidity among medicare beneficiaries via condition counts and cumulative duration. *Health services research*, 54(2):484–491.

MACPAC (2017). Medicare savings programs: New estimates continue to show many eligible individuals not enrolled. *Issue brief*.

McGreal, R. (2012). Medicaid state plan amendment. `https://www.medicaid.gov/sites/default/files/State-resource-center/Medicaid-State-Plan-Amendments/Downloads/CT/CT-12-017-ltr.pdf`. Accessed: 2021-11-2.

MMCO (2020). Data analysis brief: Medicare-medicaid dual enrollment 2006 through 2019.

OLR (2013). Medicaid — eligibility, administration, and provider participation. `https://www.cga.ct.gov/2013/rpt/2013-R-0016.htm`. Accessed: 2021-11-2.

Roberts, E. T., McGarry, B. E., and Glynn, A. (2020). Cognition and take-up of the medicare savings programs. *JAMA Internal Medicine*, 180(11):1529–1531.

Rudolph, N. and Haber, S. G. (2003). Evaluation of qualified medicare beneficiary (qmb) and specified low-income medicare beneficiary (slmb) programs.

Ruggles, S., Flood, S., Goeken, R., Schouweiler, M., and Sobek, M. (2022). Ipums usa: Version 12.0 [american community survey]. `https://doi.org/10.18128/D010.V12.0`. Minneapolis, MN: IPUMS.

Sheingold, S., Shartzer, A., and Ly, D. (2011). Variation and trends in medigap premiums. *US Department of Health and Human Services Assistant Secretary of Planning and Evaluation, Office of Health Policy*, page 4.

Zhang, J., Chen, Y., Einav, L., Levin, J., and Bhattacharya, J. (2021). Consolidation of primary care physicians and its impact on healthcare utilization. *Health Economics*.