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Are Medicaid And Medicare Patients Treated Equally?*

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3/24/25

Abstract

We examine whether Medicaid recipients receive the same health care services as those on Medicare. We track the services provided to the same individual as they age into Medicare from Medicaid at age 65. Cost sharing remains negligible across the insurance switch, implying that changes in care utilization reflects supply-side factors. Utilization increases by about 20 percent upon switching to Medicare. We find that 60 to 90 percent of the increase in office visits is explained by physicians averse to accepting Medicaid patients. This analysis provides new evidence that Medicaid's smaller provider network plays a large role in limiting utilization.

JEL: I13 - Health Insurance, Public and Private, I14 - Health and Inequality

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1 Introduction

Medicaid represents the largest government transfer program to low-income individuals in the United States, reaching close to $880 billion in spending in fiscal year 2023, up from $550 billion in 2015. The average Medicaid enrollee receives over $8 thousand dollars of services per year, which is a significant portion of their total income considering Medicaid enrollees earn on average about $20 thousand dollars per year.[1] The program is an important determinant of low-income individuals' overall consumption levels and has been shown to increase overall well-being, financial security, and decrease mortality (Finkelstein et al. (2012), Baicker et al. (2013), Baicker et al. (2014), Brown et al. (2019), Finkelstein et al. (2019), Goodman-Bacon (2021), and Miller et al. (2021)). While there are many proponents of the Medicaid program,[2] it is considered by some to be of lower quality than typical private insurance and Medicare, the other large public insurance program.[3] For instance, fewer providers accept Medicaid, resulting in a smaller network of available physicians (Berman et al. (2002), Cunningham and O'Malley (2008), Long (2013), and Dunn et al. (2024)). However, there is limited empirical evidence showing patients ultimately receive different care than those on Medicare. Our study addresses this question by assessing whether Medicaid recipients would have received different care had they been on Medicare.

To assess this question, we examine the population who age into traditional Medicare from fee-for-service (FFS) Medicaid at 65 between 2011 and 2014, using a 100 percent sample of Medicaid enrollees from the CMS eXtract (MAX) data and match this with CMS Medicare FFS data. These individuals transition from Medicaid coverage to "dual-enrolled," where Medicare is the primary payer and Medicaid the secondary payer. This event-study methodology solves three potential identification concerns that exist when comparing service provision across payers. First, it avoids insurance selection concerns, as those switching off of Medicaid into Medicare do so only because of their change in age. Primarily, these individuals did not choose to separate from Medicaid coverage. Second, it allows us to track the same individual's health service provision around a short time window, which controls for health status. Third, we can abstract from potential differences in out-of-pocket prices, as most of these patients face little to no out-of-pocket payments for their care on either side of the event date, which helps to isolate supply side factors.[4]

[1]The medical expenditures estimate comes from the author's analysis of the Medical Expenditure Panel Survey data for Medicaid enrollees ages 60-64 from 2019. Appendix Section B shows this calculation for years 2006-2019 and expenditures are roughly $7.6k (in 2011 dollars) when averaged over all those years. The average income calculation comes from the author's analysis of the American Community Survey for the years 2018-2020 for individuals 55-64 years old.

[2]For example, Rachel West, "Expanding Medicaid in All States Would Save 14,000 Lives Per Year" Center for American Progress, October 24, 2018, and Sparer, Michael. "The Best Replacement for Obamacare Is Medicaid," *The New York Times*, March 18, 2017

[3]For example, Gottlieb, Scott "Medicaid Is Worse Than No Coverage at All," *Wall Street Journal*, March 10, 2011.

[4]Changes in insurance plan generosity are known to impact service utilization (see Newhouse (1993) and Shigeoka (2014).) If patients have unmet or latent demand, then the supply curve shifts out, we interpret the associated

A priori, there are plausible reasons that service provision could differ between the two insurance programs. Medicare has a substantially larger provider network than Medicaid, which gives Medicare patients access to more providers than on Medicaid. The literature points to many factors driving low Medicaid acceptance rates among providers, including low reimbursements (see Alexander and Schnell (2019)), high administrative hassle, and issues with managed care plans (see Dunn et al. (2024)). Furthermore, numerous studies show that providers respond to higher reimbursements by providing more care.[5] However, to our knowledge, there is no causal empirical evidence documenting how the care a patient receives differs across these two important public programs for a wide variety of services.[6] Our paper provides the first precise estimate by linking together administrative data from both programs and looking at a comprehensive set of medical care services.

Beyond highlighting the differences between these two massive government programs, the quasi-experiment in our paper also contributes to the broader understanding of economic theory regarding the importance of supply and the role of access in health care. There has been considerable interest in measuring how changes in out-of-pocket payments impact care (Newhouse, 1993; Brot-Goldberg et al., 2017). Our paper provides a setting where out-of-pocket payments are held fixed, but reimbursements change. As discussed below, we find results similar in magnitude to Newhouse (1993), highlighting the relative importance of supply side factors. Furthermore, our setting allows us to credibly disentangle the mechanisms driving these supply factors. For example, doctors could be changing their behavior due to reimbursement changes, they could be referring within their organization more, or this could be driven by access to new physicians. Understanding these mechanisms can be important for policy, as the levers to adjust these vary (e.g. payment reform versus prior authorizations versus network adequacy). We find stark evidence that access is an important driver of these supply side factors, which relates to papers like (Buitrago-Gutiérrez et al., 2024; Gruber and McKnight, 2016) which show how narrow networks impact care, but in different settings.

We use two different types of utilization measures to quantify how treatment differs between the two insurers. First, we look at visits, which is a concrete measure of utilization, but is limited in its measurement of service intensity (e.g., a simple lab test versus MRI would both count as one visit). Second, we use the average Medicare price for a service as a proxy for relative value units (RVUs) as in Dunn et al. (2013) and Dunn et al. (2017). This utilization measure better captures changes in service intensity than visits, but is potentially noisier than visit counts. Because Medicare and Medicaid often cover different services (e.g. Medicare has much more limited coverage of nursing

increase in care as a supply response.

[5]See Clemens and Gottlieb (2014), Brekke et al. (2017), Cabral et al. (2025), and Dunn and Shapiro (2018).

[6]Card et al. (2008) explores the effect of becoming eligible for Medicare, but their population is coming from a mix of insurance types before turning 65. Li (2023) examines the impact of becoming dual eligible from having only *Medicare* coverage, whereas we are examining the effect of becoming dual eligible from having just *Medicaid* coverage. Cabral et al. (2025) focus on E&M services.

home care than Medicaid), we focus on outpatient services, and in particular, on services that span both Medicaid and Medicare coverage which we refer to as "core services."[7]

We find that these two measures of utilization produce similar results. Total core services utilization increases by 20 percent upon switching to Medicare from Medicaid. This increase is driven by many different categories of care including evaluation & management, imaging, procedures, and tests. The number of office visits (both primary care and specialist combined) increase by about 1.4 visits per year per individual, which represents about a 24 percent increase. To put this figure in perspective, it is approximately half of the magnitude of an uninsured individual receiving Medicaid coverage based on the Oregon Health Insurance Experiment (Baicker et al., 2013) and roughly the same magnitude as going from 50% coinsurance to no cost sharing in the RAND Health Insurance Experiment (Newhouse, 1993).[8] As an important robustness check using entirely different data, we show these results are consistent with the repeated cross-section analysis using the publicly available MEPS, which show a 30 percent increase in the number of office visits.[9] While the utilization effects are large, the more pronounced change in utilization comes from access to new providers. The probability of having a new patient visit with a primary care provider or a specialist increases by about 60 percent. The access to new providers and subsequent care may be especially important given that differences in provider practice styles and skill levels have been well documented in the literature (e.g., Chan et al. (2022), Chandra et al. (2011), Cutler et al. (2019), and Molitor (2018)).

Using definitions of high and low value care similar to Brot-Goldberg et al. (2017), we find statistically significant increases in seven of nine measures of high-value care, and no statistically significant changes in the three measures of low-value care (or the other two high-value measures) upon switching to Medicare. These results are consistent with external evidence suggesting that quality of treatment is generally lower for Medicaid relative to Medicare.[10] Our results contrast with studies who use cost-sharing (demand side) variation and find reductions in both high and low value care (Newhouse, 1993; Brot-Goldberg et al., 2017).

Prior to analyzing how the treatment and provider mix changes, we conduct several robustness checks. Our primary concern is ensuring that our specification is not merely capturing mechanical differences in the Medicare and Medicaid data sets or reflecting missing information. To assess this,

[7]Core services includes physicians visits, outpatient services like labs, procedures/surgeries, and testing. Core services does not include inpatient services, drugs, home health, long-term care, and skilled nursing. Our results are likely a lower bound for the change in overall utilization, as this calculation focuses on a narrower set of services for identification and measurement issues. For example, our core services measure excludes inpatient services, but we find inpatient stays actually increase upon turning 65.

[8]The Oregon Experiment found Medicaid coverage caused an increase of 2.7 office visits, a 50 percent increase relative to the baseline.

[9]Although we cannot track a panel of individuals using the MEPS data, as in our main analysis, we can control for observable characteristics. The MEPS data does sample people across two years, however, we do not have enough power to do any analyses if we subset our sample to those who turn 65 across sample years and are on Medicaid in the MEPS.

[10]Goldman et al. (2007) uses cross sectional data comparing hospitals with high share of Medicaid patients versus lower shares, Oostrom et al. (2017) compare the outpatient waiting times for Medicaid and privately insured patients, Landon et al. (2007) compare Medicaid HMO enrollees and commercially insured HMO enrollees.

we run a couple alternative specifications. First, we run a specification on a subset of data where utilization can be accurately tracked both before and after turning 65 with just Medicaid claims. The results show a percent increase in utilization that closely aligns with that observed using the full data set. This exercise provides strong evidence that the utilization effect is not due to differences between the Medicare and Medicaid data sources at the threshold. Second, we conduct a placebo test on the combined Medicare-Medicaid data by examining if the number of injuries or poisonings changes across the threshold. This placebo group is arguably cleaner than some other conditions, such as heart disease, where an increase in testing and screening (related to supply factors) may lead to additional diagnoses. We also test for changes in non-deferrable conditions used in Card et al. (2009). We find no impact on the number of injuries, poisonings, or non-deferrable conditions. We also run several other robustness exercises. This includes checking that our specification does not inadvertently capture effects associated with turning 65, running specifications that include alternative time controls and time-window requirements around the age-65 threshold, as well as alternative samples of dual-enrolled individuals.[11] Our results are qualitatively unchanged across these different specifications and populations.

We spend the latter part of our study exploring the mechanisms behind this increase in care, as well as assessing any implications for quality of care. We explore a few possible mechanisms, (1) that new utilization is driven by access to providers who do not take new Medicaid patients; (2) that physicians seen before and after the patient ages into Medicare are increasing their service intensity, which we refer to as the intensive margin; and (3) that physicians appear to be referring more within their group. The first mechanism would be consistent with additional supply due to extensive margin changes: more providers are willing to see these patients when on Medicare. The second and third mechanisms are more suggestive of an individual provider's supply response, if more care is provided as the patient's insurance changes.

First, we examine whether the change in utilization is attributable to new providers that patients may not have had access to through Medicaid. We construct two novel measures of Medicaid aversion. One we refer to as "Medicaid averse," based on whether that provider ever uses a "new patient visit" CPT code in a given year, and the other, "non-Medicaid-accepting," using whether a provider ever sees a Medicaid patient in the 100% MAX claims data.[12] The less strict definition is more encompassing of Medicaid aversion but can only be applied to providers who use an E&M CPT code. The stricter definition can be applied to a broader range of services but will miss access effects at providers that are less apt to take Medicaid patients, but still see some Medicaid patients. We find that 90% of the gap in primary care E&M office visits and 60% of the gap in specialist office visits between Medicaid and Medicare is attributable to Medicaid-averse providers. Non Medicaid-

[11] This includes a specification on a subset of dual-enrolled patients who are partially covered by Medicaid (i.e., individuals in the Qualified Medicare Benficiary Program (QMB)) as well as a subset that drops patients ever in nursing homes.

[12] This second measure is combined with survey measures from SK&A data.

accepting providers account for approximately one third of the total gap in core services utilization. We verify these effects using variation in Medicare and Medicaid acceptance rates across U.S. states. States with lower Medicaid acceptance rates and higher Medicare acceptance rates tend to have larger differences in service provision between Medicaid and Medicare. We run a similar cross-state analysis using variation in the gap between Medicare and Medicaid fees. We find larger effects in those states with higher fee gaps, but the results are much less precise.[13]

Next, we explore the intensive margin, tracking changes in service provision by patient-provider pairs. Here we focus on office and outpatient E&M services where the National Provider Identifier (NPI) is more likely to represent a single physician. We find that the intensive margin accounts for 10% of the difference in office and outpatient E&M RVUs and a negligible portion of the gap in the all E&M category and office visits between Medicaid and Medicare. To explore the referral mechanism further, we run a similar intensive margin analysis at the Tax Identification Number (Tax-ID) level, which captures the physician's broader organization. Results are significantly larger than at the NPI level which suggest that within-organization referrals increase upon the patient switching to Medicare.

The large role of provider access suggests that patients have unmet demand under Medicaid.[14] There is a literature focusing on how Medicaid patients have limited access to providers, and our results build on those papers by showing that this lack of access may be limiting the amount of care provided. To explore the implications of this lack of access further, we check whether these providers who do not accept Medicaid are higher quality. We assess two types of physician quality measures: (1) Medicare's quality payment program data which are measures of clinical quality, and (2) Medicare claims data with detailed information on locations of providers and patients to construct a quality measure based on revealed preferences. Based on both metrics, we find evidence that Medicaid providers are lower quality, on average, than non-Medicaid-accepting providers.

Our paper relates to a recent literature trying to better understand the role of health plans and the effects on patient care, outside of solely cost-sharing effects (e.g., Geruso et al. (2023) and Abaluck et al. (2021)). These papers show that health plan assignments impacts the care patients receive and ultimately the outcomes of that care. Our paper also documents how changes in health insurance can have large impacts on patient care, even when there is no cost sharing. We show these changes occur more generally between the two largest public health insurance programs in the United States. In addition, our results suggest that access to providers, or the insurance network,

[13]The fee gap is highly correlated with our measures of Medicaid acceptance, consistent with other research such as Alexander and Schnell (2019) and Dunn et al. (2024), but the estimates are less precise for utilization for the dual population we are studying. Results become larger and more precise when limiting the analysis to state without "lessor-of" policies, which pay providers the full Medicare reimbursement level.

[14]One concern is that the utilization changes between Medicaid and Medicare are transitory if providers are withholding care and waiting for patients to turn 65 or if patients have pent up demand. In those cases, we would expect to see a dip in the months before turning 65, a big increase at 65, that then dissipates. That we observe no such dynamics suggests that this is a sustained increase in care.

plays a large role in limiting the care that Medicaid patients receive. While there is considerable research on insurance networks generally, there is limited evidence on how networks impact the care patients receive (Buitrago-Gutiérrez et al., 2024).

Indeed, there is strong evidence that obtaining Medicare coverage has important consequences for both utilization and health outcomes, although their is uncertainty regarding what causes this effect. Card et al. (2008) and Card et al. (2009) examine how utilization and health outcomes change at age 65 and find an increase in utilization and a drop in mortality. These studies do not track individuals as they age into Medicare (i.e., do not include individual fixed effects), but instead rely on a regression-discontinuity design at age 65. The design compares the impact of attaining Medicare on utilization relative to under-65 individuals on a mix of insurance types. In contrast, our study focuses on Medicaid which controls for patient-demand side effects due to cost-sharing. The focus on the Medicaid population sheds some light on a puzzle presented in Card et al. (2009). Specifically, Card et al. (2009) find that the magnitude of the mortality decline that they observe at age 65 cannot be explained by the uninsured gaining insurance, as the uninsured population is too small relative to their estimated mortality decline. They hypothesize that the mortality decline must be explained by the remaining private and Medicaid populations. Our paper confirms that the treatment received by the Medicaid enrollees turning 65 increases substantially as they gain Medicare coverage, providing support for their hypothesis, especially in light of the work by Abaluck et al. (2021) demonstrating how health insurance plans may affect mortality.

2 Background and Descriptive Analysis

Medicaid currently covers around 21 percent of the U.S. population, while Medicare covers around 18 percent.[15] Our study focuses on individuals enrolled in Medicaid who switch insurance plans by aging into Medicare at age 65. These individuals continue to receive Medicaid as a secondary payer when they age into Medicare, and so are known as "dually-eligible" since they are covered by both public health programs. In 2019, there were 7.7 million individuals on Medicaid who qualified for Medicare because of aging into the Medicare system.[16] Under this program, Medicare acts as the primary payer for preventative, primary, acute services and prescription drugs while Medicaid provides secondary coverage for Medicare premiums and other out-of-pocket costs as well as primary coverage for long-term care services. This means the reimbursement providers receive for these individuals more closely resembles Medicare prices, though individuals on Medicaid who age into the Medicare system at 65 continue to face little to no premiums or out-of-pocket

[15] "U.S. Health Care Coverage and Spending," Congressional Research Services, (2023). https://sgp.fas.org/crs/misc/IF10830.pdf

[16] "Data Analysis Brief: Medicare-Medicaid Dual Enrollment 2006 through 2019," CMS Medicare-Medicaid Coordination Office https://www.cms.gov/files/document/medicaremedicaiddualenrollmenteverenrolledtrendsdatabrief.pdf

costs.[17] [18]

The sample period assessed in this study occurs before the Medicaid expansion from the Affordable Care Act.[19] Prior to the ACA, low income was not sufficient to qualify for Medicaid in all states, however, states could apply for Section 1115 waivers to expand Medicaid to other populations, such as low income individuals.[20] There were a number of pathways to Medicaid eligibility for those under 65 years old. States were required to cover those qualified for Supplemental Security Income (SSI) through a disability, as well required to cover pregnant women. States could also choose to cover other populations, such as working disabled individuals whose income is too high for SSI and those with high medical expenses, such as long-term care services or chemotherapy. In our treatment sample, 64 percent qualify for Medicaid because of SSI Cash Assistance, another 25 percent qualify because of disability or medical need (even if not receiving SSI), and 7 percent are enrolled through section 1115 waivers.[21]

One subtlety is that disabled individuals may also be eligible for Social Security Disability Insurance (SSDI). To qualify for SSDI, one needs to be disabled and have a sufficient work history, as opposed to SSI where the individual needs to be disabled and have sufficiently low income. Individuals enrolled in SSDI are eligible for Medicare after a 24 month waiting period.[22] Therefore, our sample of Medicaid individuals consists of those who qualify for SSI, but either do not qualify for SSDI or are in the 24-month waiting period.[23] We do use those individuals younger than 65, on Medicare through SSDI (or another channel, such as having end-stage renal disease), as a way to check for discontinuities in care at age 65.

2.1 Medical Care Panel Survey (MEPS)

We begin our analysis using data from the nationally-representative Medical Care Panel Survey (MEPS). The MEPS dataset is publicly available and has been used across a wide variety of studies,

[17] Approximately a third of dual-eligibles are known as “partial-duals” who have incomes and assets not quite low enough to qualify for full Medicaid services. While these individuals are not eligible for Medicaid-only services (such as long-term care services), they do receive Medicaid coverage for Medicare premiums and cost-sharing.

[18] Due to “lesser of” policies it is also common that neither the enrollee nor Medicaid pay for the remaining out-of-pocket costs when Medicare is the primary payer, which still leaves out-of-pocket costs close to zero. Under lesser of policies, after Medicare pays the state as the primary payer, then Medicaid pays the lower amount of Medicare’s cost sharing or the difference between Medicare’s fee schedule and Medicaid’s fee schedule, reducing the total amount paid relative to non-dual Medicare enrollees.

[19] Our sample includes data from 2011 to 2014. However, since we require patients to be in the sample for 12 months prior to switching to Medicare, our sample excludes individuals who were only on Medicaid in 2014—the first year of Medicaid expansion.

[20] “Federal Requirements and State Options: Eligibility” MACPAC, 2017 FactSheet https://www.macpac.gov/wp-content/uploads/2017/03/Federal-Requirements-and-State-Options-Eligibility.pdf

[21] Table A1 presents summary statistics for our sample.

[22] “Supplemental Security Income for People with Disabilities: Implications for Medicaid” KFF, 2021 ‘‘https://www.kff.org/medicaid/issue-brief/supplemental-security-income-for-people-with-disabilities-implications-for-medicaid/

[23] While we do not observe SSDI information in our data, our sample of individuals likely do not have a sufficient work history to qualify for SSDI, or else they would have Medicare prior to turning 65, which we would observe.

making it a good resource for an initial assessment of spending across age groups.[24] It is also a useful benchmark in terms of validating our results with the data from Centers of Medicare and Medicaid Services (CMS), which is used in our main analysis.

The top panel of Figure 1 shows total health care spending per capita by payer for Medicaid beneficiaries between the ages of 60 and 70 taken from the MEPS data.[25] The plot represents repeated cross sections (by age) of the 5,008 individuals in the MEPS data from 2006-2019 who are enrolled in Medicaid and under 65 years old, or dual-eligible and over 65 years old. As individuals age from 64 to 65, medical care spending transitions from mainly Medicaid to mainly Medicare. Total spending increases, as the decline in Medicaid spending compensates for the increase in new Medicare spending. In total, dual-eligible individuals with Medicare as the primary payer (that is, those over 65) receive approximately, \$5,000 more medical-care spending, or an approximately 50 percent increase, relative to those on Medicaid alone and younger than 65.

Part of the difference between Medicaid and Medicare spending is the price of the service, so it is possible to spend more, while patients are receiving the same treatments. Spending may also increase due to more utilization. The bottom panel of Figure 1 shows that there is a substantial increase in utilization, based on the number of office and outpatient visits.[26] The increase is from about 9.5 visits to around 12.5 visits, or about a 30 percent increase.

These spending and utilization patterns across age reveal potential differences across Medicaid and Medicare primary payers, providing important evidence of how these patient populations are treated differently. However, there are a number of limitations of using this readily available data. First, the MEPS data represent repeated cross sections of individuals, meaning that we are comparing different individuals on each side of the age 65 cutoff between Medicaid and Medicare.[27] Regression techniques can be used to control for differing observable patient attributes on each side of the age-65 threshold but, ultimately it is impossible to control for unobserved health differences that could bias results.[28] Second, the MEPS data represent information over the course of a year for an individual. It is conceivable that spending patterns could be trending within this one-year window, especially for sicker individuals. Finally, MEPS does not provide as granular information as contained in the claims data to understand how provider networks and specific treatments change for individuals across the threshold. All of these drawbacks from the MEPS data can be addressed

[24]For example, the MEPS website lists over 1,000 publications using the MEPS data since year 2000. See `https://meps.ahrq.gov/mepsweb/data_stats/publications.jsp`

[25]For this analysis the data covers the years 2006 to 2019. For ages 60-64, we include all individuals under 65 who are enrolled in Medicaid but not Medicare. For ages 65-70, we include all individuals enrolled in both Medicaid and Medicare. In Appendix Section B, we test sensitivity to dropping individuals in Medicaid Managed Care or Medicare Advantage, which better matches the CMS data sample. The results do not change.

[26]We focus on office and outpatient visits as they are the most frequently reported, while inpatient and ER visits would introduce additional noise. In addition, office and outpatient better aligns with our definition of core services.

[27]There are only 112 panel observations (that is, the same individual surveyed twice) in the MEPS data where we see a given individual age from Medicaid into Medicare.

[28]Including demographic controls shows similar results to those shown in Figure 1. Results are shown in appendix tables A4 and A5.

using the more granular and comprehensive CMS data used in our main analysis.

2.2 Healthcare Effectiveness Data and Information Set (HEDIS)

For a descriptive assessment of quality differences between Medicaid and Medicare, we use the Healthcare Effectiveness Data and Information Set (HEDIS). This publicly-available cross-sectional dataset, consists of dozens of quality metrics for millions of enrollees across insurance types. The National Committee for Quality Assurance (NCQA) which defines the HEDIS measures claims that HEDIS is among the most widely used performance measurement tool in health care.[29] For each measure in the HEDIS where both Medicare and Medicaid data are collected we average scores across all years of the data.[30] For example, 54% of women age 50-74 in Medicaid had received a breast cancer screening in the prior two years, compared to 70% of women in Medicare. In addition, we average across multiple measures that fall roughly in the same disease category to avoid double-counting, for example there are 8 measures for Initiation and Engagement of Alcohol and Other Drug Abuse or Dependence Treatment, while just one for breast cancer screening.[31]

Figure 2 presents a scatterplot at the aggregated disease level, where the Medicaid score is on the vertical axis and the Medicare average is on the horizontal axis. For those measures below the 45 degree line, Medicare is better, while above the 45 degree line Medicaid scores better. Medicare scores better on breast cancer screening, diabetes control, cardiovascular disease (i.e. adherence to beta blockers after a heart attack, adherence to statins). Medicaid is better than Medicare on drug and alcohol related care, including follow-up after drug related ER and hospital visits, and initiation and engagement of alcohol and other drug abuse dependence treatment. The two types of insurance are close on follow-up after mental health related visits to the ER and hospital, speaking with a provider about physical activity, and various preventative measures for COPD.

In general, we find that most of the disease conditions fall at or below the 45-degree line, indicating Medicare is typically of higher quality. However, these data have similar drawbacks as the MEPS data. The data are cross-sectional and therefore may be conflating quality with heterogeneous patient characteristics. In the claims data, we are able control for unobserved variation in patient characteristics using patient fixed effects. Another issue is that the Medicare population used in the HEDIS data includes those with positive out-of-pocket costs, meaning that cost-sharing varies between the Medicaid and Medicare patients in this data.

[29]See `https://www.ncqa.org/`. All measures and their underlying methodologies are available here: `https://www.ncqa.org/hedis/measures/`

[30]The HEDIS data are yearly measures and different measures were collected in different years. For this exercise, we use the years 2001 to 2020. There were 11 measures in the 2001 data which had both Medicare and Medicaid listed. That number grew to 39 by 2020. For each measure, we take an unweighted average, across years, for all years where each payer type contributes data. For Medicare, we take an unweighted average across PPOs and HMOs.

[31]In the appendix, Table A6 present results at the measure level.

3 CMS Data

We use health insurance claims data from two sources, both from Centers for Medicare & Medicaid Services (CMS). The first is the CMS eXtract (MAX) data, which is a 100 percent sample of Medicaid enrollees for the years 2011 through 2014. We also have Medicare fee-for-service claims for all these Medicaid enrollees who enroll in traditional Medicare. These data sets are both high frequency, highly granular at the service code level, and importantly, allow us to track individuals as the they age into Medicare.

Each state and the District of Columbia reports Medicaid enrollee eligibility, service utilization, and payment information to the Medicaid Statistical Information System (MSIS). The CMS compiles the MAX from Medicaid Statistical Information System (MSIS) each calendar year. The MAX files contain fee-for-service (FFS) claims and encounter data from managed care organizations (MCO) and contains claims information for all services covered by Medicaid, including physician and hospital providers. The 100 percent MAX data covered 75 million enrollees in 2013. Each year more than 1.5 billion claim or encounter lines are recorded. Our analysis focuses on Medicaid FFS claims as payment information is only available for these enrollees.[32]

CMS Medicare FFS data includes individuals over the age of 65 and some individuals below 65 with certain disabilities. The data provide complete information on insurance claims for services covered by parts A and B of Medicare. Both the Medicare and Medicaid FFS claims contain enrollment information, dates (admission and discharge), diagnosis codes, procedure codes, national provider codes, and payment information.

As Medicare reimburses providers at a substantially higher rate than Medicaid, it is important to separate utilization changes (that is, quantity) from the price. We define quantity as the mean Medicare price for each service (i.e., CPT code) we observe. This is similar in spirit to a Relative Value Unit or RVU, which is used by Medicare to proxy for the amount of effort for a particular procedure. As a slight abuse of terminology, we will refer to the mean Medicare price for a claim as an RVU.[33]

To construct our primary sample, we first use the MAX annual summary data to identify beneficiaries who switch from Medicaid fee-for-service coverage to Medicaid-Medicare dual coverage upon turning 65. We use this list of beneficiaries to pull claims from both the Medicaid MAX database and the Medicare database. We then stack and harmonize the claims from each source for each beneficiary. The resulting dataset includes comprehensive information of diagnoses, procedures,

[32]In Appendix Section B we explore how the managed care and fee for service populations differ in the MEPS data. We also estimate whether expenditures and visits increase including these other populations. While results are somewhat smaller in magnitude when including managed care and Medicare Advantage, they are still economically and statistically significant.

[33]For example, suppose we observe one Medicaid patient and one Medicare patient receiving CPT code X which has an average Medicare price of $100. Also, suppose the observed prices were $50 and $150 for these Medicaid and Medicare patients, respectively. Then our methodology would imply that both utilized 100 RVUs of care, but the prices of each services were 0.5 and 1.5 respectively. This is similar to what is done in Dunn et al. (2013).

payments, and providers as beneficiaries move from Medicaid to dual coverage. We exclude nine states (CA, FL, ID, KS, NY, RI, TX, UT, and HI) from our analysis based on a combination of missing and/or likely inaccurate data based on CMS data validation reports.[34]

We pull Medicaid claims from both the MAX inpatient file and MAX OT file. We pull Medicare claims from the inpatient, outpatient, carrier office, and home health files. We find that the place of service and service type information is not consistent across datasets (for example, a physician visit in a hospital setting might be categorized as a physician visit in one dataset and an outpatient visit in another). Therefore, most of our analysis classifies services based on the Restructured BETOS Classification System (RBCS) which is based on procedure codes. This classification system is released by CMS to group procedures into clinically meaningful service categories and has been used by many studies to classify utilization (e.g., Fuchs et al. (2004), Song et al. (2010), and Badinski et al. (2023)). RBCS includes three hierarchical levels of classification: 8 major categories, 53 subcategories, and 162 families. We focus on four RBCS categories which we refer to as "core services:" evaluation and management (E&M), procedures, imaging, and tests. These represent common services that span both Medicaid and Medicare. We exclude categories such as occupational therapy (which are not covered by Medicaid), home health services (which are not covered by Medicare), and dialysis services (which are covered by Medicare for individuals under the age of 65).[35] Additional details on data construction are presented in Appendix Section A.

For the main analyses, we sum spending, visits, and RVUs to the person-month level. In our main specification, we keep individuals who we observe 6 months of continuous enrollment before and after turning 65. We present robustness checks requiring only 2 months or 12 months of continuous enrollment and results are similar. We drop any person-months which are in the top 0.5% of spending or RVUs, though results are similar without dropping outliers or windsorizing.

Table 1 provides summary statistics for our primary sample, representing enrollee-months in the window of 12 months prior and after turning 65. There are noticeable differences in spending and utilization between those individuals below and above the age of 65. The data show an increase of \$1,092 in annual "core" spending per enrollee in the over-65 group relative to the under-65 group, around \$91 monthly (i.e., \$281 − \$190) multiplied by 12. This is around a 50 percent increase in

[34]We exclude CA and NY because we are missing data for these states. We exclude ID, HI, RI due to insufficient sample size. We exclude KS and UT because CMS's data validation reports indicate that a large portion of dual enrollment data is missing. We exclude TX because the validation reports suggest that a high percentage of crossover claims and procedure codes are missing, and there is an implausibly large increase in placebo utilization measures. We exclude FL because the validation reports suggest that a high percentage of crossover claims are missing and there is an implausibly large (> 50%) decrease in utilization in the post period.

[35]There are eight BETOS major categories. We include (1) imaging, (2) tests, (3) procedures, and (8) E&M in core. We exclude four categories: (4) anesthesia, (5) durable medical equipment, (6) treatments, (7) other. We include 5 subcategories of (8) E&M: behavioral health, care coordination, observation care services, office/outpatient service, and opthalmological services. Within the (8) E&M category, we exclude critical care services, miscellaneous E&M, home services, hospital, nursing facilities, emergency services, and inpatient services We exclude treatments because they include services, such as dialysis, which are not consistently covered between Medicaid and Medicare. We exclude emergency E&M services because we do not not have a comprehensive and consistent mapping of place of service for non-E&M emergency services. Results are not sensitive to including these categories.

spending. The data show that about half of this increase in spending stems from prices effects, as the number of RVUs increase by about 564 per year (or 18 percent).[36] The average enrollee has about 1.45 more visits (about .648 more primary care visits and 0.804 more specialist visits), sees 3.3 more providers, and has 18 more procedure codes per year when on Medicare compared to Medicaid alone. The increase in visits observed is similar to that observed in the MEPS data shown in Figure 1.[37]

4 Estimation

We estimate an event-study model around one year window of time before and after individuals turn 65. As explained above, we examine a subset of the Medicaid and Medicare population—those who are enrolled in traditional Medicaid and age into traditional Medicare with Medicaid as the secondary payer (i.e., dual enrolled). While the providers' reimbursements change over this threshold due to the change in payer, the individual's out-of-pocket costs remain close to zero since Medicaid acts as the secondary payer in the post-65 period.

The key identifying assumption is that an individual has similar health status a few months before and after turning 65, implying that demand for healthcare services remains fixed across the event date. The remaining variation is attributable to supply-related factors, namely access to providers who do not accept Medicaid as well as changes to the financial incentives of providers who do accept Medicaid. Unlike a regression discontinuity design which compares *different* people across a threshold, the panel structure of our data allows us to track changes for the same person. This reduces potential omitted-variable bias due to unobserved characteristics specific to an individual patient.

In our main specification, we estimate monthly coefficients, which allows us to flexibly visualize the impact of turning 65. Our baseline specification is the following:

$$y_{it} = \sum_{r=M-}^{r=-2} \delta_r + \sum_{r=0}^{r=M+} \delta_r + \tau_m + \tau_y + \gamma_i + \epsilon_{it} \tag{1}$$

Where y_{it} is a measure of health care utilization for individual i in event-month t. Some of the key measures include the number of visits, the number of providers, and the number of procedures.[38] While these measures are straightforward to interpret, they do not capture differences in treatment intensity. For example, a simple blood test and a complicated imaging procedure are each counted as

[36] Total RVUs and total spending in the post period differ because we use a broader sample of claims when constructing RVUs, so the mean payments may differ in the RVU calculation and our sample.

[37] The MEPS estimate is a somewhat larger in levels because office and outpatient is a broader category than primary and specialist visits. However, in percentage terms, our results are quite similar and the qualitative story is consistent.

[38] A visit is defined as an encounter with a provider in a given day.

one visit. Therefore, we also include a measure in RVUs, which weighs the intensity of utilization. The variables τ_m and τ_y represent vectors of calendar-month and calendar-year fixed effects.[39] Patient fixed effects, γ_i, control for differences in composition across the threshold. In our main specification, we require that individuals are in our sample for 6 months before and after turning 65.[40] Standard errors are clustered at the individual level.

Our main variables of interest are the indicator variables for the number of months before or after an individual's 65^{th} birth date (i.e., δ_r). The key assumption of our identification strategy is that the only variable that changes across the age 65 threshold is insurance coverage. However, since our treatment variable is defined on age, we need to account for trends associated with aging. For this reason, we superimpose a line which is fitted to the trend in the pre-treatment period onto the visualizations of the estimates δ_r. To the extent that the pre-trends would have continued linearly after turning 65, the impact of turning 65 is captured by the coefficient estimates minus any pre-trend. As we show in the next section, there are only negligible pre-treatment trends for our treated sample.

For some analyses, we include a single post-65 indicator, rather than a vector of event-time indicators, which allows us to better summarize results when including interactions, exploring heterogeneity, or presenting robustness checks. To ensure that a single indicator represents the average difference in our outcome variables after removing pre-trends we use the imputation method presented in Borusyak et al. (2022). This method consists of four steps. First, fit a model of the dependent variable on the untreated unit-years, which in our case is the time before turning 65. Next, use the fitted model to predict the counterfactual outcome for those turning 65, capturing the pre-trend and any other fixed effects and controls ($\widehat{y_{it}}$). Then, take the difference between the counterfactual predicted outcome and the observed outcome $y_{it} - \widehat{y_{it}}$. This yields the unit-time specific treatment effect. Finally, regress the unit-time specific treatment effects on the treatment variable, which creates an average over the unit-time specific treatment effects. Formally, we estimate:

$$y_{it} = \alpha \times r + \gamma_i + \tau_m + \tau_y + \epsilon_{it} \qquad \text{if } r \in \{-12, -1\} \tag{2}$$

$$y_{it} - \widehat{y_{it}} = \mathbb{1}(Post_{it})\beta + \epsilon_{it} \tag{3}$$

where equation 2 is estimated using only the pre-treated units, and equation 3 is estimated using all of the units. r is a linear time trend which is extrapolated into the post period when predicting $\widehat{y_{it}}$. Then as equation 3 makes clear, the pre-trend is differenced out. β is our coefficient of interest and it represents the average of the post treatment δ_r from equation 1, after subtracting out any pre-trend, month fixed effects, and person fixed effects.

[39]As discussed in Dobkin et al. (2018); Borusyak et al. (2022), we cannot separately identify year-month fixed effects and event time, hence we include month and year fixed effects separately.

[40]In principle, the restriction that we have a balanced panel for 6 months before and after turning 65, along with individual fixed effects should limit the amount that compositional differences are driving our results.

There are a few potential identification concerns. First, it may be that Medicaid data is lower quality or missing some claims or information. To test for this, we explore how RVUs change for injuries and poisonings, and separately non-deferrable conditions defined by Card et al. (2009). These conditions are unlikely to be influenced by supply factors, thus arguably a cleaner placebo group than some other conditions, such as heart disease, where an increase in testing and screening (related to supply factors) may lead to additional treatment and diagnoses. We find no effect of these categories, where we would not expect to see much of an effect.

A potential drawback of the specification above is that it does not control for effects specific to turning 65, beyond the effect of switching to Medicare. Some treatment guidelines change at 65, for instance a higher dosage influenza vaccine is recommended to individuals over the age of 65. Additionally, some important life events, such as retirement, may occur at this age, although studies such as Card et al. (2008) find no discontinuous impact of turning 65 on being employed. To control for age-65 effects, we assess individuals who were dual enrolled prior to turning 65. We refer to this population who were enrolled in Medicare prior to turning 65 as "always dual," while our treatment sample who get Medicare when they turn 65 are referred to as "new duals." These individuals are eligible for Medicare before turning 65 because they are disabled or have end-stage renal disease. Hence, they remain on Medicare (with Medicaid as the secondary payer) before and after turning 65. We estimate the same regressions as above with the "always duals" to explore the age 65 effect. For the most part, we see few breaks from the under-65 pre-trend for this population, except in places where we know treatment guidelines change.[41]

We use the "always dual" individuals as a control group and estimate an analysis similar to a difference-in-differences design. However, the "always dual" population is sicker and so they often have much starker pre-trends. Therefore, we allow these groups to have different pre-trends in our event study design, as our goal is to difference out any age-65 effects from the "new dual" population.[42] Formally, we estimate:

[41] Medicare covers a "Welcome to Medicare" visit within the first twelve months of being enrolled in Medicare. This would not be accounted for with our "always dual" control population. However, it is almost never billed for in our "new dual" sample, likely because this population already has a lot of interaction with the health care system.

[42] The interpretation of this specification is *not* that the "new duals" would have followed the "always duals" trends in the absence of Medicare (as is usually the case in a difference-in-differences design), but rather we are differencing out the age 65 effect the "always duals" exhibit, while continuing the "new dual" pre-trend into the post period.

$$y_{it} = \sum_{r=M-}^{r=-2} \delta_r + \sum_{r=0}^{r=M+} \delta_r + \alpha \times \mathbb{1}(ND_i) \times r + \tau_m + \tau_m \times \mathbb{1}(ND_i) + \tau_y + \tau_y \times \mathbb{1}(ND_i) + \gamma_i + \epsilon_{it} \tag{4}$$

$$\text{if } r \in \{-12, -1\} \ \& \ \mathbb{1}(ND_i) = 1 \text{ or}$$

$$r \in \{-12, 12\} \ \& \ \mathbb{1}(ND_i) = 0$$

$$y_{it} - \widehat{y_{it}} = \beta \mathbb{1}(Post_{it}) + \epsilon_{it} \tag{5}$$

where equation 4 is estimated on just control units—"new duals" (ND) at age 64 and "always duals" (AD) at ages 64 and 65. A standard difference-in-differences design would include solely event-time controls, δ_r, estimated on the AD units. The δ_r terms flexibly capture any pre-trend for the AD units. The addition of the pre-period new-dual linear pre-trend ($\mathbb{1}(ND_i) \times r$) allows for differences in the pre-trends between the ND and AD groups. That is, δ_r controls for level effects between the treatment and control groups, as in a standard difference-in-differences model, and $\alpha \times \mathbb{1}(ND_i) \times r$ captures the differences in pre-trends for the two groups. The main estimate, β, captures the average difference between the pre-period and the post-period for the ND group, after differencing out the ND pre-trend and any level differences (e.g., age-65 effects) from the AD group.

4.1 Results

Figure 3 shows the event-study coefficients from Equation 1 estimated on visits to primary-care (upper panel) and specialist (lower panel) physicians. The reference period is two-months prior to turning 65. The blue dashed line depicts the pre-period trend. The results show very small pre-period trends for both sets of physicians. Prior to aging into Medicare, the coefficient estimates are approximately zero. The figure also shows no obvious dip prior to turning 65, which would have indicated that individuals are waiting until turning 65 to receive care. Primary care and specialist visits both increase after switching onto Medicare at the month at which the individual turns 65. Primary-care visits increase by about 0.05 visits per month and specialist visits increase by 0.07 per month, in total about 1.4 more visits per year per individual. This represents a 24% increase in the number of visits. In percentage terms, these results are roughly in line with what we find in the MEPS which also shows a significant increase.[43]

The magnitude of this effect is large. To place the result in context, the magnitude of our estimate is approximately equal to going from 50% coinsurance to no cost sharing in the RAND

[43] See Appendix Table A5. In absolute terms, we actually find a larger increase in the MEPS, however, in the MEPS data we use all office and outpatient visits, which is a broader set of services than primary and specialist visits. Hence, these numbers are similar in percentage terms, but not in the absolute number of visits.

experiment (Newhouse (1993)). The effect is about half the effect based on the Oregon Health Insurance Experiment (Finkelstein et al. (2012)), which assessed the impact of going on Medicaid from being uninsured. The Oregon study found the increase to be 2.7 visits, or around a 50 percent increase relative to the baseline.

Figure 4 shows the results for RVUs, which take into account the intensity of service provision. Here we assess core services, as well as the underlying subcategories. The upper right panel shows that core RVUs increase by about 55 RVUs per month upon turning 65, representing about a 20% increase above the pre-65 mean.[44] The increase in core services occurs across all the sub-categories of core services, as shown in the lower panels of Figure 4. Evaluation and management (EM) services increase by about 25 RVUs per month, imaging services increase by around 10 RVUs per month, procedures increase by over 10 RVU per month. Tests increase by approximately 7 RVUs per month, however this specific category appears to have an upward pre-trend.

To check the validity of our study design, we next estimate our baseline event-study model (1) on the sample of "always dual" individuals—the sample of individuals who do not switch plans at 65. Figure 5 shows the event-study plots for core utilization, measured in RVUs, for this "always-dual" population.[45] There are two main takeaways from this figure. First, the estimates show a smooth upward trend in utilization for all utilization measures over the time horizon, consistent with health deteriorating more quickly for the "always dual" population than our "new dual" population.[46] It is for this reason we allow our treatment and control groups to have different pre-trends in our difference-in-differences analysis. The second takeaway is that, in contrast to the observed dynamics for newly eligible duals, we do not see a discontinuous jump at age 65. This suggests that our main results are not due to other events at age 65, such as changes in treatment guidelines.

Table 2 summarizes these results, for the treated group (column 1), the control group (column 2), and the difference-in-differences strategy (column 3). The new dual estimates match those from Figures 3 and 4. In Figure 3, the primary care visits coefficients are all between 0.05 and 0.1, which is consistent with the coefficient of 0.0529. Individuals receive 0.0529 additional primary care visits per month on average after turning 65, or about 0.64 more per year. It is worth pointing out that pretrends are differenced out of these regression coefficients. For example, in Figure 4 the Tests RVU coefficients tend to be between 5-10, but are only about 4-6 RVUs above the pre-trend line on average, hence the coefficient of 5.26, which is well below the coefficients in Figure 4 before netting out the pre-trends. The "always dual" coefficients are often not statistically significant, and if they are, they are always much smaller in magnitude than the "new dual" coefficients.

[44] Event time 0 is smaller, likely because birth dates can be mid-month. Hence, some of that month's utilization may be when an individual was only on Medicaid.

[45] In Appendix Figure A1 we show analogous estimates for primary care and specialist visits.

[46] This may be due to the fact that this "always dual" population is sicker, for example many in this population would have qualified due to end-stage renal disease or amyotrophic lateral sclerosis (ALS).

The difference-in-differences estimates are almost identical to estimates using just the new-dual sample, we find that core RVUs increase by approximately 54 RVUs per month—a 21 percent increase in service utilization. The increase is spread across BETOS categories: E&M, imaging, procedures, and tests. We also see a 1.3 per month increase in the number of distinct procedure codes, a 15 percent increase from the pre-period mean. The number of new patient primary care and specialist visits increase by 0.00492 and 0.0178 per month, respectively.[47] This is arguably the most striking of the estimates as the percent increase is substantial with new primary care and specialist visits increasing by about 60 percent each, relative to the baseline. This finding relates to one of the key differences in how treatment differs across Medicaid and Medicare patients — the access to providers. This is a point we return to in detail in the following sections.

For nearly all of the estimates, column (1) closely matches the estimates we find by applying the difference-in-differences in column (3), demonstrating the robustness of the findings. As discussed above, the potential improvement in applying a difference-in-differences strategy is exemplified by the case of the flu vaccine. In particular, the CDC recommends that individuals over age 65 receive a stronger flu vaccine. In the last two rows of Table 2 we see that the RVUs for vaccines are higher in the post period for the "always dual" control group. This is an age 65 effect, likely due to the difference in medical guidelines at age 65. Our treatment and control groups are receiving a stronger vaccine. In practice we want to difference that out, which is what our "difference-in-differences" strategy does. The difference-in-differences coefficient of 0.619 is fairly similar to the difference between the coefficients for new duals and always duals. Reassuringly, we see no change in the number of flu vaccines given (flu vaccine visits) for the always-dual group, suggesting that the increase in RVUs is due to RVUs per visit (the change in guidelines for a stronger vaccine) and not more visits, which we wouldn't expect to change at 65 for the control group. In contrast, our new dual population is twice as likely to have a flu vaccine in the post-period, suggesting a large change in utilization due to the change in insurance and not due to turning 65.

Tables A7, A8, and A9 in the appendix provide estimates of the more granular BETOS categories underlying these four groupings. There is no single type of service that is responsible for the increase in utilization across the age threshold, as the estimates show increases across a wide range of types of services. There are 27 BETOS subcategories we keep, and 16 of them have statistically significant increases in RVUs. This suggests that the breadth of increases in utilization are fairly uniform. Likewise, we only observe 3 cases out of 27 which have positive and statistically significant increases in RVUs in the control group and in these mostly smaller in magnitude than for the treated group.

We next assess whether the quality of care changes as the individual ages into Medicare. We draw from the basic idea of Brot-Goldberg et al. (2017) who divide a subset of services into high- and low-value care treatments. High-value treatments include preventative care visits, psychiatry

[47] We define new patient visits as visits using the CPT codes 99201, 99202, 99203, 99204, 99205, which a provider bills if it is their first time seeing a particular patient.

visits, vaccines, and HBA1C tests for diabetes patients. We also break preventative care into various categories based on the U.S. Preventive Services Taskforce recommendations for preventative care. Low-value treatments include CT scan of sinuses, imaging for uncomplicated headache, and imaging for back pain.

Table 3 shows the results of this exercise. Service utilization increases for all high-value treatments except for HBA1C test on diabetes patients. While we do find positive effects for some of these measures in our control group, these effects are often much smaller in magnitude than the results for our treatment group. We find no effect on low-value services. Our quality results contrast with studies who use cost-sharing (demand side) variation and find reductions in both high and low value care (Newhouse, 1993; Brot-Goldberg et al., 2017).

4.2 Robustness

We consider a number of alternative specifications and subsamples to test the robustness of our results. We begin by performing two tests to address the possibility that our results are driven by mechanical differences between the Medicare and Medicaid data sets. First, we examine a measure of utilization using only Medicaid claims for those states and procedures where Medicaid data provides a clear measure of utilization pre- and post-65. More precisely, we examine procedures that have at least a 90% match rate between Medicare claims and Medicaid crossover claims for the 10 states with the highest overall match rate. Recall that a Medicaid crossover claim occurs for dual Medicare-Medicaid enrollees when Medicare does not cover the full balance of a claim and the claim is sent to Medicaid to cover the remaining balance. These crossover claims will not be observed when Medicare covers the full cost of a claim or in many "lesser of" states where no additional funds are collected if Medicare pays above the Medicaid rate in the state. However, in several states and for some procedures, crossover claims are consistently observed and can be used to measure utilization post-65 using solely Medicaid claims data. Therefore, for the select set of state-procedure combinations analyzed in this robustness check, we can rerun the event study using only Medicaid data. Figure A2 present event study plots for the subset of state-procedure combinations that have a high degree of crossover claims. The effects are small because of the limited sample of procedures. However, in percentage terms, we find that the treatment effect here is about 25%, relative to the pre-period mean. Similar results are observed when limiting the analysis to the 5 states with the highest match rate, shown in Figure A3.

As a second test, we run a placebo exercise that assesses injuries and poisonings across the threshold. These conditions are arguably a cleaner placebo group than some other conditions, such as heart disease, where an increase in testing and screening (related to supply factors) may lead to additional diagnoses or preventative care may reduce disease onset. In a separate table, we also use the non-deferrable conditions used by Card et al. (2009). Table 4 presents results for any core E&M

claims in a person-month for the injury and poisoning categories defined by the American Academy of Professional Coders based on ICD-9 codes.[48] Table 5 shows the results for the Card et al. (2009) measures.[49] Reassuringly, in both cases we only find one condition with a difference-in-differences coefficient that is statistically significant. This is roughly in line with what one would expect from chance and contrasts sharply with the statistically significant increases in nearly every category in Table 2. These null results are not due to low power since statistically significant results are obtained with much less common conditions, as shown in Table 3.

We next consider the robustness of our results to different subsets of dual-enrolled individuals. First, we consider the subset of our newly-dual enrollees covered under the full-benefit Qualified Medicare Beneficiary (QMB), also known as QMB Plus. These individuals receive all benefits available to a QMB (i.e., full cost-sharing coverage for both Medicare A and B), as well as all benefits available under their state's Medicaid plan. While other Medicaid beneficiaries also tend to have no cost sharing, the benefits vary more than the QMB population.[50] This population makes up 53 percent of our sample. Examining effects for the QMB population alone is an important check that our results are not driven by any change in out-of-pocket expenses for services not covered by Medicare. Figure A5 shows the baseline event-study plots for this group. The results from this subset of the dual-enrolled population are almost identical to the full-sample results. Second, we address the concern is that the dual-enrolled population is more likely to be in a nursing home or other living facility, as it is a population that mainly qualifies through disability. Indeed, about 15% of both our "new dual" and "always dual" population have at least one day in a nursing or long-term care facility covered by Medicaid.[51] Table A12 presents results dropping that population and results are nearly identical, or even slightly larger.

We then explore the robustness of our results to different specifications. First, we consider an alternative set of calendar-time fixed effects. As discussed by Dobkin et al. (2018) and Borusyak et al. (2022), event-time coefficients cannot be separately identified from calendar month-year fixed effects in a model with no "never-treated" group. In our baseline specification we include calendar-month and calendar-year fixed effects. Table A10 explores both dropping the calendar-month and

[48]The American Academy of Professional Coders has 18 categories, we drop the category for complications from surgical and medical care, which does increase as individuals age into Medicare, but that may be because they are getting more care generally. We just present results for E&M, however there are increases in treatment categories like imaging for these conditions. We think that imaging may be more reimbursement elastic, and therefore not a proper placebo category.

[49]We do not include asthma or chronic airway obstruction (COPD) from the set of conditions in Card et al. (2009), because hospitalizations for these conditions are considered preventable with proper primary care in AHRQ's preventable hospitalization indicators (McDermott and Jiang, 2020), suggesting that much of the care received is preventative services.

[50]For the non-QMB population, state specific benefits apply, which often capture cost sharing, but not always. Importantly, around 40 states have "lesser-of" policies during our period of study, where out-of-pocket costs are not typically paid by dual Medicare-Medicaid enrollees.

[51]We do not have nursing facility or long-term care claims, but do have an indicator for the number of days in a nursing facility in the annual person level files. Conditional on having at least 1 day in a nursing facility, the majority of individuals in our data spend most of the year in a facility.

calendar-year fixed effects. Another concern is that the Affordable Care Act was implemented in 2014, which could potentially impact our study, such as through Medicaid expansion. We view this as unlikely because someone in our sample would have needed to be enrolled in Medicaid in 2013 to be in our sample (e.g., they could not have qualified for Medicaid solely due to Medicaid expansion). Nevertheless, Table A10 also shows that results are robust to dropping individuals who are 65 at any point in 2014. Second, we explore changing the imposed restriction on the time window of enrollment. In our main specification we restrict the sample to individuals with 6 months of enrollment both before and after turning 65. In Table A11, we change the requirement to 2 months and 12 months. We also try a specification where we drop the person fixed effects, but use a 12 month restriction. The person fixed effects help to control for composition changes. With a 12 month restriction we have a fully balanced panel so there are no changes in composition. Results are all robust.

Finally, there is a concern that our results may be driven by a few states, as data quality and how Medicaid is administered varies across states. We do two analyses to check for this. First, Figure A4 plots the coefficients from an analysis where we drop one state at a time. The density of coefficients are not very wide, and not close to zero. In Table A13, we re-run our main analysis by region. While this cuts our sample size considerably, so coefficients are noisier, we still see large increases in all 4 regions. These two sets of results provide evidence that no individual state or region of the country is driving our results.

5 Mechanisms

In this section, we explore several mechanisms that may be driving our results. First, we explore the role physician access plays in the change in utilization between Medicaid and Medicare. While there is considerable evidence that physicians are less likely to accept Medicaid patients (Polsky et al. (2015), Candon et al. (2018), Alexander and Schnell (2019)), less is known about how that impacts the care Medicaid patients receive. Second, we explore whether the change in utilization is attributable to intensive margin effects (the same provider supplying more services). Finally, we explore whether these increases are related to additional referrals and whether these increases correlate directly with differences in state-level reimbursement rates across the two insurers.

5.1 Role of Expanded Access

Measuring whether a patient has access to a particular provider is not straightforward, and thus we examine a couple of different measures. While much of the literature focuses on physician surveys Decker (2012) or patient surveys Alexander and Schnell (2019), we build on this dimension by also using the universe of Medicaid claims to measure access. First, we measure access to a provider based on whether that provider (i.e., National Provider Identifier (NPI)) ever uses a "new patient visit" CPT code on a Medicaid claim using the full Medicaid MAX data each calendar year. We define providers that do not bill a new Medicaid patient visit CPT code in the calendar year as "Medicaid averse." Second, we define providers as "Non-Medicaid-Accepting" if the NPI is not associated with any (or only a few) Medicaid patients.[52]

These two Medicaid access measures have trade-offs. The first measure plausibly does a more accurate job identifying whether this provider is seeing new Medicaid patients, which more cleanly captures access from the Medicaid patient's perspective. However, this measure only applies to a subset of the data, as many specialties, including non-physician providers like labs and imaging, may not use the new-patient CPT codes. We can capture a broader universe of providers and services with the Medicaid-accepting measure, but it captures whether a provider sees any Medicaid patients, rather than if they are accepting new patients. Both measures may understate Medicaid aversion (and overstate Medicaid access), as a provider may not be willing to see a particular Medicaid patient, at a particular moment in time, even if they do see some throughout the year.

5.1.1 Utilization at Medicaid-Averse Providers

As described above, we define Medicaid-averse providers as providers who do not see a new Medicaid patient in a given year, based on the provider's National Provider Identifier (NPI) and observing a new-patient visit CPT code. We first consider new E&M patient visits. New-patient visits represent a small subset of care, but are an important component of utilization since they indicate the start of a new patient-physician relationship. Moreover, our measure of Medicaid-aversion is particularly informative about new patient dynamics. These are providers that are open to seeing new patients, but averse to seeing new Medicaid patients. In this way, this metric most directly captures the change in network access associated with newly enrolling in Medicare.

Figure 6 plots the monthly mean number of new patient primary care (top panel) and new patient specialist visits (bottom panel), broken out by Medicaid-averse and non-Medicaid-averse providers. Over 75% of the increase in primary-care new-patient visits is associated with Medicaid-averse physicians. For specialists, about half of the increase can be traced to Medicaid-averse physicians.

[52] We utilize three dataset to define being Medicaid-accepting. First, MDPPAS data which provides summary annual information of physicians based traditional Medicare Fee-For-Service (FFS) claims 100% sample. The MDPPAS contains a number of summary variables for each physician NPI, including the number of claim lines in the sample. This helps define a universe of providers who see Medicare patients. The second dataset is the 100% sample of Medicaid MAX claims. This tells us whether a particular provider saw any Medicaid patients. Finally, we use the SK&A Database. The SK&A physician database is a comprehensive database of physicians based on a telephone survey of physician offices. The survey data includes an indicator of whether the physician office, associated with a particular physician, accepts Medicaid or not. Using the MAX claims and MDPPAS database, we first compute the ratio of Medicaid claims to Medicaid plus Medicare claims over the period 2012-2013. We then identify physicians who reported to SK&A that they did not accept Medicaid patients. We then define not Medicaid-accepting as physicians that satisfy either (1) less than 1% of claims are Medicaid or (2) less than 2% of claims are Medicaid and they are flagged as non-Medicaid in the SK&A data.

While new patient visits provide a more direct measure of changes in access, they only represent a small fraction of care—the initial visit. Follow-up visits are not accounted for. Figure 7 plots all primary care and specialist visits, broken out by Medicaid-averse and non-Medicaid-averse providers. For both primary care physicians and specialists, the average number of monthly visits increases by around 25% in the post period. As the pink region of these plots shows, the utilization bumps are highly accounted for by Medicaid-averse physicians. Specifically, Medicaid-averse physicians account for roughly 90% of the increase in primary care visits and 60% of the increase in specialist visits.[53] That these percentages are larger than the effects on new-visits shown in Figure 6 is consistent with our intuition that solely focusing on new-visits may understate the role of access.

5.1.2 Utilization at Non-Medicaid-Accepting Providers

Next, we use the stricter definition of Medicaid access described above—those providers that are "non-Medicaid-accepting." This definition allows us to measure a broader set of services than the prior section. Figure A6 depicts service utilization, measured in RVUs, for both core and E&M services over the 24 month event window. The pink bars represent those services performed by non-Medicaid-accepting providers while the blue bars represent those services provided by all other providers. By construction, Medicaid-accepting physicians provide close to 100% of patient services prior to turning 65. Slightly more than 50% of the total increase in core services—those services above the dashed black line—are attributable to non-Medicaid-accepting providers. We find a similar pattern for E&M, with nearly 30% of the total increase attributable to non-Medicaid-accepting providers. We also compute this decomposition for primary care and specialist visits, depicted in Figure A7. For primary care visits, about half of the increase is associated with non-Medicaid-accepting. For specialist visits, these providers account for about one-third of the increase.[54]

5.1.3 State-level variation in provider acceptance rates

We exploit the geographic variation in Medicaid and Medicare acceptance rates across U.S. states, to further test whether Medicare's larger provider network size plays a role in driving the increase in care received. Given our findings above, one would expect smaller differences in service provision between Medicaid and Medicare in those states where Medicaid and Medicare acceptance rates are similar. That is, one would expect smaller increases in utilization between Medicaid and Medicare in those states where where Medicaid acceptance rates are higher and Medicare acceptance rates are lower. We use two measures of the state-level insurance acceptance rate. The first measure

[53] These are less than the pink area above the dashed line in the post period as it accounts for the pre-period usage of Medicaid-averse providers.

[54] The difference between Figures 7 and A7 is due to the Medicaid-accepting definition being more strict than Medicaid averse, 90% of primary care visits are due to Medicaid averse providers, while only about half is due to non-Medicaid accepting providers.

is from publicly available estimates from MACPAC (2021) using data from the National Electronic Health Records Survey, a survey of physicians. The survey asks whether physicians are accepting new patients by insurance status. Second, we compute state-by-specialty Medicaid acceptance rates by checking whether a provider in that state-speciality ever billed a new-patient CPT code in the 100% Medicaid claims data.[55]

To test the correlation of acceptance rates with the change in service utilization, we run the following specification:

$$y_{it} = \beta \mathbb{1}(Post_{it}) + \delta \mathbb{1}(Post_{it}) \times Accept_s + \tau_m + \tau_y + \tau_i + \epsilon_{it} \tag{6}$$

where y_{it} are our outcome measures (visits, RVUs, etc.) For this analysis we include person fixed effects, calendar month and year fixed effects, and use the "new dual" sample where we rely on the fact that there are minimal pre-trends in these outcomes.

$Accept_s$ is our measure of acceptance rates. When using the data from MACPAC (2021), the acceptance rates are at the state-level and we include the Medicare and Medicaid acceptance rates separately in the regression. When using the claims based measure of the acceptance rate, $Accept_s$ varies at the state-specialty level. When we use the acceptance variable constructed from the claims data, we change the unit of observation to the patient-specialty-month level (rather than patient-month) and construct measures of visits at this level. For the patient-specialty-month regressions, we include both state and specialty fixed effects.[56]

The acceptance rate interacted with the post variable tests whether states(-specialties) with higher acceptance rates have larger differences in utilization as patients turn 65. For these results we cluster at the state level for the regressions using the survey based acceptance rates and the state-specialty level for the claims based acceptance rate regressions.[57]

Table 6 shows results using the MACPAC (2021) state level acceptance rates.[58] On average, a one percentage point increase in Medicare acceptance rates is correlated with a 0.008 larger increase primary care visits, consistent with patients having more access using more care. Bringing the Medicare acceptance rate down to the Medicaid acceptance rate (about 10 percentage points) would lead to about .08 fewer monthly primary care visits, which is about one-third of the pre-period mean. A one percentage point increase in Medicaid acceptance rates is correlated with a 0.002 smaller increase primary care visits, suggesting that places with more access to Medicaid

[55]We cannot compute a similar measure for Medicare, because we only have a 5% sample of Medicare claims, outside of this matched population.

[56]For the survey based measure, we include both Medicare and Medicaid acceptance rates separately as this is more general than including the difference in rates. However, similar results are obtained using the gap in acceptance rates between Medicare in Medicaid. See appendix table A14. For the claims based measure we only measure Medicaid acceptance rates. We cannot measure Medicare acceptance rates because we only have a 5% sample (outside the Medicaid-matched population.

[57]We also drop states with fewer than 300 enrollees. Results are similar, but noisier, if we include all states.

[58]Table A15 presents results for RVUs which are similar, but noisier, as RVUs are a noisier measure than visits.

see smaller differences in service provision with Medicare (their access expands less when turning 65). Similar results hold with specialist visits. A 10 percentage point increase in the state-level Medicaid acceptance rate would lead to a 0.028 smaller increase in specialist visits per month across the threshold, about 11% of the pre-period mean. Results are especially strong for new-patient visits with specialists. A 10 percentage point increase in state Medicaid acceptance rates would reduce the increase in care across the threshold by 0.01 visits, about one-third for the pre-period mean and more than half of the overall increase in new-patient visits with specialists we see in Table 2.

Table 7 presents results using the state-specialty level acceptance rates constructed using the claims data. The pre-period mean for visits is 0.031, which is smaller than in Table 2 because the data are at the patient-month-specialty level, rather than the patient-month level. The results suggest that a 10 percentage point increase in Medicaid acceptance at the state-specialty level is associated with a 0.0025 smaller increase in visits for that specialty when an individual ages into Medicare. This is roughly 8 percent of the pre-period mean in visits at the specialty level. Findings for new-patient visits are similar, where state-specialties that have higher Medicaid acceptance rates have smaller increases in care for those who age into Medicare.

5.1.4 Quality of Medicaid Accepting Providers

Our results suggest that access to new providers is a key factor in the difference in utilization across insurers. The welfare implications of these findings depend on whether these providers are higher quality. In this section we test for differences in quality between those providers who accept and do not accept Medicaid. This builds on work by Perloff et al. (1995) and Geissler et al. (2016) who have shown that physicians who accept Medicaid are more likely to have graduated from lower ranked medical schools, more likely to have graduated from foreign medical schools, and less likely to be board certified. We assess quality differences between Medicaid-accepting and non-Medicaid-accepting providers using two different proxies for provider quality. First, we use Medicare's quality payment program data to explore whether providers who accept Medicaid patients score worse on Medicare quality metrics than those who do not. Second, we use a discrete choice model to determine the willingness to travel by a Medicare patient to a provider in the Medicare data. Importantly, both of these datasets measure quality based on Medicare claims only, so differences in access across payers should not be driving results.

Medicare's quality payment program data were collected as part of the merit-based incentive payment system which began in 2017. We use the data from 2017, which is the first year the data were collected. The data is at the provider level and contain an aggregated score as well as specific quality measures (e.g. the share of women receiving breast cancer screenings, influenza immunization rates, or screening for future fall risk). We focus on the specific quality metrics rather than the aggregated score since the latter includes variation which may be correlated with taking Medicaid, such as extra points for treating dual-eligible patients and billing electronically.

Providers choose between six to ten (out of hundreds) of specific measures to report. They then receive "achievement points" based on their decile and where they are in that decile for each score. Our data contain only the achievement points for each metric and not the raw score.[59] As all providers must provide at least 6 scores, the score we focus on is the sum of the highest six scores submitted. However, Table A18 in the appendix presents results for the five most commonly submitted quality measures like "screening for tobacco use" or "pneuomococcal vaccination," and results qualitatively are similar. For this exercise we focus on small providers, as large providers have more ability to adjust scores in ways that are less likely to be reflective of individual physician skills, both because they have more measures to choose from and because they can choose to submit as an individual or a group.

The first row of Table 8 presents the quality payment program measure results. The coefficient we present corresponds to an indicator for whether the provider takes Medicaid meaning that they are "Medicaid-accepting" as defined above. Under all three specifications, accepting Medicaid is negatively associated with a provider's quality score. The score we focus on is the sum of the highest six scores submitted, so the top score achievable is 60 points. A coefficient of -1.43 indicates a provider who accepts Medicaid scores about about 1.4 deciles worse on one out of the six quality metrics or 0.2 deciles worse on each of the 6 metrics. Quality measures are constructed using only Medicare claims, so the interpretation of this result is that providers who also take Medicaid appear to have lower quality scores among their Medicare populations. Table A18 in the appendix presents results for the five most commonly submitted quality measures like "screening for tobacco use" or "pneuomococcal vaccination." It also provides a wider range of variation in the set of controls included. The sum of clinical quality scores measure is quite robust to controls.

Our second measure of quality is based on the estimated revealed-preference of patients, which has been used in the health economics literature as a distinct measure of quality (e.g., Romley and Goldman (2011) and Garthwaite et al. (2022)). The basic idea is to model the utility of patients for visiting different providers, controlling for observable characteristics (e.g., distance), in order to isolate the revealed-preference quality of each physician. We estimate a simple discrete-choice model, which relies on standard methods applied in the industrial organization literature.

The revealed-preference quality measure is estimated using a 5% sample of the Medicare claims data, which is based on the Medicare FFS population. Importantly, the Medicare FFS population does not face the same restrictive network of Medicaid enrollees. Therefore, we observe the revealed-preference of Medicare patients choosing between physicians that accept Medicaid and those that do not. We assume patients select among physicians of the same specialty type, so the estimates are run separately by physician specialty. The methodology yields one quality measure per physician.

[59]There are fractional points given for where the provider is within the decile. For example, if the provider was half-way between the 5th and 6th decile for a particular measure, they would receive 5.5 points. Because the deciles differ in width, the mapping from raw score (i.e. 95% of patients received a breast cancer screening) to decile is not linear.

Additional details of the methodology are provided in the appendix section D.

The results using the revealed preference quality measure are shown in the second row of Table 8. Across all three specifications we find that those physicians that accept Medicaid have systematically lower quality measures than those that do not. More concretely, physicians whose Medicare patients are willing to travel further are less likely to take Medicaid patients.

5.2 Intensive Margin Effects

We next explore the extent to which the increase in utilization is due to an increase in services within an existing patient-NPI pair, which we refer to as the intensive margin. To quantify the intensive margin effect we perform a regression-based analysis similar to the main regressions, but at the more granular patient-provider level:

$$y_{ipt} = \beta \mathbb{1}(\text{Post}_{it} = 1) + \tau_m + \tau_y + \gamma_{ip} + \epsilon_{ipt} \tag{7}$$

where y_{ipt} denotes the utilization of individual i with provider p in month t, and we include fixed-effects at the individual-provider level γ_{ip}. Given the inclusion of provider-patient fixed effects, identification is based solely on individuals who have some exposure to a given physician both before and after aging into Medicare. For this regression, we rely on the lack of pre-trends in our main analysis without the control group and do not include a term which differences out the pre-trend.[60] The coefficient of interest in this specification is β, which reflects the difference in utilization, for a given individual-provider pair, when the individual is enrolled in Medicare versus when they are enrolled only in Medicaid. As our goal is to measure within physician changes in utilization, we focus on E&M services and physicians visits, in particular office visits, which are more likely to be performed by a single individual.[61]

Results are shown in Table 9. E&M office and outpatient increase by 0.83 RVUs within a patient-NPI pair. The total intensive margin effect is found by multiplying by this effect by the average number patient-NPI pairs, which is labeled as "mean unique physicians" in the table. This implies that about 1.6 (8.3×1.95) additional RVUs are due to the intensive margin. This is about 10% of the 16 increase in E&M office and outpatient RVUs shown in Table 2. The intensive margin effects are smaller and insignificant for E&M RVUs and the number of primary-care and specialist

[60] Requiring an individual sees the same provider both before and after turning 65 creates a mechanical within-year trend. If someone has a follow-up, it will likely be soon after the initial visit, so we see a lot of December visits, with January follow-ups in this subsample. We see fewer follow-up visits say 8 or 9 months apart. Hence, there is a mechanical upward pre-trend and downward post-trend in this sample, so we do not think pre-trend adjustment would be credibly capturing aging effects for this specific analysis.

[61] The Medicare data includes both a physician and an organization NPI, while the Medicaid data often provides just one NPI, which could be either an organization or physician NPI. We use the more complete information in Medicare to capture the NPI information that corresponds to the Medicaid data. Both the physician and organization NPI's arguably do not capture the complete decision of the firm, which may take place at the system or tax identifier level.

visits. Overall, the results suggest that the intensive margin is playing a relatively small role in driving the increase in E&M services, especially for office visits where the NPI is more likely a single physician. This result shows that the change in utilization between Medicare and Medicaid is likely not driven by billing intensity or upcoding, as one would expect to see large increases in within-provider utilization.

5.3 Role of Referrals

We next examine the role of referrals by repeating the intensive analysis but broadening the definition of provider from the NPI to the Tax Identification Number (Tax ID) level. The Tax ID may include multiple NPIs in a provider group or firm. Larger total effects with this definition would suggest that additional utilization is occurring within a provider organization beyond an individual NPI. This would be consistent with a provider being more likely to refer to other providers in the same organization after a patient ages into Medicare.

Table 10 shows the intensive margin results using the Tax-ID rather than the NPI. The role of intensive margin effects at the Tax ID level can be computed by multiplying the coefficient estimate by the number of unique Tax IDs. The intensive margin at the Tax-ID level accounts for 21.2 additional core RVUs (5.94 RVUs per organization $\times$ 3.56 organizations per patient), or 39% of the increase in total core RVUs upon switching to Medicare. Importantly, these results are larger than simply scaling the intensive-margin NPI effects by the number of NPIs per organization. The intensive margin at the Tax ID level accounts for 4.23 additional E&M office and outpatient RVUs (2.3×1.84), which is over twice as large as the intensive margin E&M office and outpatient effect measured at the NPI level (1.6 RVUs).

The contrast with the NPI-level results are even more stark for all E&M RVUs and primary-care and specialist visits. For primary and specialist visits, the tax-id level effect is .05 additional visits ($.03 \times 1.7$) which is about one-half of the 0.11 additional monthly visits we find in Table 2. We found almost no increase in visits at the NPI level. While we do not have a measure of outside-of-organization referral behavior, this analysis suggests that within-organization referrals may play a role in driving the increase in utilization upon switching to Medicare.

5.4 Financial Incentives

Finally, we look at the role of financial incentives as they have been found to impact service utilization directly, beyond accepting insurance. For instance, higher fees may incentivize existing Medicaid-accepting physicians to perform more services (i.e., the intensive margin). An analysis of direct financial incentive effects is complicated of the process by which providers are reimbursed for dual-enrolled individuals. For non-dual Medicaid enrollees, Medicaid is the sole payer and the fees are determined by a fee schedule set at the state level. As mentioned above, Medicaid typically pays the full amount with limited cost sharing. However, for dual-enrolled individuals, Medicare pays the amount covered by insurance (e.g., 80 percent of the allowed amount for a physicians visit) and the remaining coinsurance amount is passed to Medicaid. Typically, secondary insurers would pay the balance (e.g., the 20 percent coinsurance). Most states in the U.S. have "lesser of" policies, which ensure that Medicaid does *not* contribute to reimbursements to providers exceeding the Medicaid fee schedule for duals. In particular, under "lesser of" policies, Medicare pays the primary portion while Medicaid would only cover the gap between the Medicare payment (e.g. 80%) and the Medicaid fee schedule. For the purposes of our paper, this means that the fee gap between Medicare-only enrollees and Medicaid-only enrollees may be very different than the fee gap between Medicaid-only enrollees and duals. Complicating the dual fee structure further, Medicaid will pay providers based on the Medicaid fee structure when enrollees are in the deductible range and lesser-of policies may vary by the type of provider.

Despite the complex reimbursement schedule for dual-enrolled individuals, we perform a simple analysis that tests whether states with higher gaps in reimbursement rates (i.e., fees) have larger differences in utilization between Medicare and Medicaid. Specifically, we exploit the geographic variation in Medicaid and Medicare reimbursements across states, similar to the analysis in Section 5.1.3. We construct a measure of the fee gap using claims, by regressing the reimbursement rate on state-by-payer dummies (e.g. Medicare, Medicaid) and procedure code fixed effects. Table A16 presents the results. The signs are consistent with states with bigger fee gaps seeing bigger changes in utilization, however, the results are not statistically significant. To demonstrate the importance of lesser-of policies, Table A17 presents similar results keeping only states that do not have lesser-of policies (e.g. those where Medicaid pays the entire cost-share for duals). Results are much larger in magnitude and statistically significant on primary care visits and total visits, however, this analysis is limited to only a handful of states.

6 Conclusion

We track individuals on Medicaid as they age into the Medicare program at 65, becoming dual enrolled. We document that spending rises by about 50 percent and service utilization increases by 20 percent upon switching to insurance to Medicare. The increase in health care utilization is driven by many different categories of care including evaluation & management, imaging, procedures, and tests. We find the magnitude of these effects to be large, roughly half the effect of gaining Medicaid insurance (from being uninsured) based on the Oregon Health Insurance Experiment.

Overall, we present evidence that Medicare and Medicaid patients are not treated equally. This raises important questions related to the quantity and quality of care received in the largest public insurance programs in the U.S. As mentioned previously, Card et al. (2009) find evidence of a large mortality decline at age 65 as individuals age into Medicare (from all forms of insurance and being uninsured), but they argue that it cannot be explained by the uninsured gaining insurance, as the magnitude of the mortality decline is too large. We find that the uninsured gaining insurance is not the only important change at age 65, as we show that Medicaid enrollees aging into Medicare leads to significantly more treatment, potentially contributing to improved health outcomes. Our findings motivate future research on the health outcome effects of this change in insurance.

In addition, we are able to provide some evidence about why these differences in care exists. We find little evidence of changes in utilization within a patient-physician pair between Medicaid and Medicare, and some evidence of an increase in referrals within an organization upon switching to Medicare. However, a majority of the increase appears to be driven by providers who do not accept Medicaid or those who are "Medicaid-averse." This indicates that Medicare's larger network size likely plays a significant role in explaining the utilization difference between Medicare and Medicaid. To the extent that these providers are higher quality (and we find some suggestive evidence of this), this may also mean that Medicare patients are receiving higher quality care.

This study has implications for Medicaid design, and more broadly, major public health insurance programs, which is particularly relevant in light of the work by Einav and Finkelstein in their recent book "We've Got You Covered" (Einav and Finkelstein (2023)). In their book, the authors propose a solution to improve U.S. healthcare: implementing universal basic health insurance coverage for everyone. However, determining what that basic coverage is and measuring the implications is challenging.[62] Namely, our findings show that supply-side factors play an important role in the cost, quantity, and quality of services provided. In the case of Medicaid these supply-factors appear to dissuade physicians from seeing patients and limiting the care they provide.

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[62]Unlike other goods in the economy where consumers purchase goods at market price, the price in health care markets determines the set of goods and services available and administered to patients.

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Table 1: Summary Statistics for Utilization Measures

	(1) Under-65		(2) Over-65	
	mean	sd	mean	sd
Core Spending	190	434	281	561
Core RVUs	259	620	306	652
E&M RVUs	107	365	128	376
Office and Outpatient E&M RVUs	53	91	70	110
Imaging RVUs	51	217	61	222
Procedures RVUs	61	337	71	351
Tests RVUs	40	142	46	146
Primary Care Visits	0.256	0.564	0.310	0.618
New Patient Visit, Primary	0.008	0.093	0.013	0.117
Number of Providers, Primary	0.437	0.729	0.560	0.869
Specialists Visits	0.237	0.585	0.304	0.676
New Patient Visit, Specialist	0.030	0.179	0.048	0.230
Number of Providers, Specialist	0.785	1.616	0.943	1.802
Number of Procedure Codes	8.368	13.637	9.876	15.159
Any Inpatient	0.012	0.111	0.017	0.129
Any Emergency	0.072	0.258	0.080	0.271
Unique Individuals	22,436		22,436	
Person-Months	249,051		267,902	

Notes: This table presents summary statistics for our measures of utilization at the enrollee-month level. The averages include months when our enrollees received no care. Providers are identified by their NPI number. Procedure codes are referring to CPT4 codes.

Table 2: Regression Results: Impact of Turning 65 on Utilization

	New Dual Pre-Period Sample Mean	(1) New Dual	(2) Always Dual	(3) Diff-in-Diff
Core Spending	190	89.62***	3.556	89.08***
		(3.398)	(3.528)	(4.817)
Core RVUs	259	54.01***	3.059	53.82***
		(4.528)	(3.789)	(5.837)
E&M RVUs	107	24.18***	3.237+	24.92***
		(2.164)	(1.708)	(2.785)
Office and Outpatient E&M RVUs	53	16.31***	0.814	15.13***
		(0.663)	(0.497)	(0.819)
Imaging RVUs	51	12.25***	1.841+	10.12***
		(1.639)	(1.114)	(1.959)
Procedures RVUs	61	12.33***	-2.523	14.07***
		(2.608)	(2.449)	(3.486)
Tests RVUs	40	5.256***	0.504	4.709**
		(1.121)	(0.945)	(1.447)
Primary Care Visits	.256	0.0529***	0.00633*	0.0452***
		(0.00404)	(0.00294)	(0.00496)
New Patient Visit, Primary	.008	0.00556***	0.000180	0.00492***
		(0.000723)	(0.000557)	(0.000891)
Number of Providers, Primary	.437	0.107***	0.00914*	0.100***
		(0.00564)	(0.00436)	(0.00705)
Specialists Visits	.237	0.0626***	0.000237	0.0627***
		(0.00434)	(0.00331)	(0.00541)
New Patient Visit, Specialist	.03	0.0178***	0.000220	0.0178***
		(0.00142)	(0.00118)	(0.00180)
Number of Providers, Specialist	.785	0.153***	0.00206	0.153***
		(0.0129)	(0.00976)	(0.0161)
Number of Procedure Codes	8.37	1.116***	-0.0152	1.279***
		(0.0841)	(0.0617)	(0.106)
Flu Vaccine RVUs	.225	0.811***	0.151***	0.619***
		(0.0223)	(0.0239)	(0.0330)
Flu Vaccine Visits	.013	0.0158***	0.000919	0.0139***
		(0.000725)	(0.000701)	(0.00101)
Calendar Time Fixed Effects		Month, Year	Month, Year	Month, Year × Treatment
Person Fixed Effects		Yes	Yes	Yes
Number of Enrollees		22269	49417	71686
Person-Months		516953	1152616	1669569

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each row and column present results of a different regression. The outcome variable is listed in the first column and we present coefficient estimates for the "post" turning 65 years old indicator. Standard errors clustered at the patient level are in parentheses below the coefficient estimate. The unit of observation is a patient-month. The first two columns are estimated using equations 2 and 3. "New dual" refers to our treatment group, individuals whose insurance changes at 65. "Always duals" are our control group. They were dual enrolled in Medicare before and after turning 65. These regressions include patient fixed effects, calendar-month and calendar-year fixed effects, and difference out any pre-trends. The third column is a difference-in-differences specification which uses the "always duals" as the control group. The third column is estimated using equations 4 and 5, and includes patient fixed effects, calendar-month and calendar-year fixed effects, and differences out pre-trends separately for the treatment and control groups. "Procedures RVUs" refers to RVUs for the BETOS category of procedures, which is a subset of all types of service. "Number of procedure codes" refers to the number of distinct CPT4 procedure codes in a month, which can include BETOS categories for procedures, as well as other categories like tests, imaging, office visits, etc.

Table 3: High and Low Value Care

	New Dual Pre-Period Sample Mean	(1) New Dual	(2) Always Dual	(3) Diff-in-Diff
High Value:				
Preventative Care RVU	2.43	3.784***	0.838***	2.973***
		(0.141)	(0.204)	(0.247)
Any Preventative Care	.092	0.0462***	0.00555***	0.0417***
		(0.00199)	(0.00160)	(0.00251)
Any Cancer Screening	.003	0.00552***	0.0000852	0.00572***
		(0.000454)	(0.000524)	(0.000676)
Any Depression Screening	0.00000750	0.000195***	0.000106	0.000112
		(0.0000386)	(0.0000680)	(0.0000698)
Any Alcohol Misuse Screening	0.00000370	0.000135***	-0.0000782	0.000180***
		(0.0000261)	(0.0000552)	(0.0000535)
Psychiatry Visits	.014	0.0104***	-0.00221*	0.0125***
		(0.00113)	(0.00102)	(0.00145)
Flu Vaccine Visits	.013	0.0158***	0.000918	0.0139***
		(0.000725)	(0.000701)	(0.00101)
Primary Care Visits (Diabetes)	.256	0.0587***	0.00593**	0.0536***
		(0.00302)	(0.00212)	(0.00364)
Any HBA1C Test (Diabetes)	.07	-0.000795	0.00187*	-0.000309
		(0.00143)	(0.000911)	(0.00166)
Low Value:				
Any CT of Sinuses	0.00032470	0.000104	0.000185*	-0.0000502
		(0.000128)	(0.0000914)	(0.000156)
Any Imaging for Uncomplicated Headache	.004	-0.000743	-0.000304	-0.000492
		(0.000460)	(0.000270)	(0.000527)
Any Imaging for Back Pain	.009	-0.000568	0.0000996	-0.000855
		(0.000745)	(0.000463)	(0.000865)
Calendar Time Fixed Effects		Month, Year	Month, Year	Month, Year × Treat
Person Fixed Effects		Yes	Yes	Yes
Number of Enrollees		22269	49417	71686
Person-Months		516953	1152616	1669569

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each row and column present results of a different regression. The outcome variable is listed in the first column and we present coefficient estimates for the "post" turning 65 years old indicator. Standard errors clustered at the patient level are in parentheses below the coefficient estimate. The unit of observation is a patient-month. The first two columns are estimated using equations 2 and 3. "New dual" refers to our treatment group, individuals whose insurance changes at 65. "Always duals" are our control group. They were dual enrolled in Medicare before and after turning 65. and include patient fixed effects, calendar-month and calendar-year fixed effects, and difference out any pre-trends. The third column is a difference-in-differences specification which uses the "always duals" as the control group. The third column is estimated using equations 4 and 5, and includes patient fixed effects, calendar-month and calendar-year fixed effects, and differences out pre-trends separately for the treatment and control groups. The primary care visits for diabetes patients and any Hb1ac visits for diabetes patients are run on a restricted sample of patients with diabetes, all other results use the full sample of data.

Table 4: Placebo: Injuries and Poisonings E&M

	New Dual Pre-Period Sample Mean	(1) New Dual	(2) Always Dual	(3) Diff-in-Diff
Any Fractures	.003	0.000400	-0.000172	0.000379
		(0.000458)	(0.000397)	(0.000592)
Any Dislocation	0.00053380	0.000176	-0.00000435	0.000183
		(0.000153)	(0.000135)	(0.000201)
Any Sprains And Strains Of Joints	.002	0.000478	0.0000360	0.000342
		(0.000391)	(0.000304)	(0.000487)
Any Intracranial Injury	0.00016420	-0.0000494	-0.0000684	-0.0000314
		(0.0000701)	(0.0000781)	(0.000101)
Any Internal Injury Of Thorax, Abdomen, And Pelvis	0.00002610	0.0000303	0.0000266	0.00000981
		(0.0000568)	(0.0000255)	(0.0000609)
Any Open Wounds	.002	0.00123***	-0.000176	0.00129**
		(0.000316)	(0.000275)	(0.000411)
Any Injury To Blood Vessels	0.00000750	0.0000191	-0.0000293	0.0000325
		(0.0000156)	(0.0000305)	(0.0000324)
Any Late Effects Of Injuries, Poisonings	0.00004850	0.0000167	0.000112*	-0.0000724
		(0.0000616)	(0.0000437)	(0.0000759)
Any Superficial Injury	0.00055990	-0.0000360	-0.0000317	-0.0000912
		(0.000187)	(0.000151)	(0.000236)
Any Contusion With Intact Skin	0.00097800	0.000384+	-0.00000866	0.000460
		(0.000229)	(0.000214)	(0.000306)
Any Crushing Injury	0.00002240	-0.0000364	0.00000329	-0.0000550
		(0.0000402)	(0.0000282)	(0.0000540)
Any Effects Of Foreign Body Entering	0.00009710	0.0000522	0.0000219	0.0000220
		(0.0000684)	(0.0000572)	(0.0000874)
Any Burns	0.00025760	0.0000291	-0.0000290	0.0000330
		(0.000136)	(0.000108)	(0.000173)
Any Injury To Nerves And Spinal Cord	0.00039570	0.000315+	0.000241	0.000114
		(0.000164)	(0.000149)	(0.000218)
Any Poisoning By Drugs, Medicinal And Biological	0.00007840	-0.0000765	-0.0000294	-0.0000405
		(0.0000648)	(0.0000531)	(0.0000837)
Any Toxic Effects Of Substances Chiefly Nonmedicinal	0.00005970	0.0000534	0.0000286	0.0000217
		(0.0000537)	(0.0000543)	(0.0000748)
Any Other And Unspecified Effects	0.00021280	0.000218*	0.0000889	0.000100
		(0.000105)	(0.0000838)	(0.000131)
Calendar Time Fixed Effects		Month, Year	Month, Year	Month, Year × Treat
Person Fixed Effects		Yes	Yes	Yes
Number of Enrollees		22269	49417	71686
Person-Months		516953	1152616	1669569

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each row and column present results of a different regression. The table presents coefficient estimates for the "post" turning 65 years old indicator. The dependent variable in these regressions is a binary indicator variable for any claims in that patient-month with the condition listed in the first column. Standard errors clustered at the patient level are in parentheses below the coefficient estimate. The unit of observation is a patient-month. The first two columns are estimated using equations 2 and 3. "New dual" refers to our treatment group, individuals whose insurance changes at 65. "Always duals" are our control group. They were dual enrolled in Medicare before and after turning 65. These regressions include patient fixed effects, calendar-month and calendar-year fixed effects, and difference out any pre-trends. The third column is a difference-in-differences specification which uses the "always duals" as the control group. The third column is estimated using equations 4 and 5, and includes patient fixed effects, calendar-month and calendar-year fixed effects, and differences out pre-trends separately for the treatment and control groups.

Table 5: Placebo: Non-Deferrable Conditions

	New Dual Pre-Period Sample Mean	(1) New Dual	(2) Always Dual	(3) Diff-in-Diff
Obstructive Chronic Bronchitis	.005	0.000724	0.000193	0.000440
		(0.000553)	(0.000360)	(0.000653)
Respiratory Failure	.001	0.000291	0.000217	0.0000981
		(0.000300)	(0.000214)	(0.000365)
AMI of other inferior wall	0.00003730	-0.0000304	0.0000177	-0.0000206
		(0.0000462)	(0.0000423)	(0.0000611)
AMI of other anterior wall	0.00004480	-0.0000360	0.0000142	-0.0000581
		(0.0000472)	(0.0000234)	(0.0000512)
Intracerebral Hemorrhage	0.00025010	0.000164+	0.0000672	0.000102
		(0.0000986)	(0.0000672)	(0.000120)
Fracture of neck of femur	0.00017920	0.000191	0.000161+	0.000115
		(0.000135)	(0.0000941)	(0.000160)
Cerebral artery occlusion, unspecified	.003	0.000591	0.000214	0.000417
		(0.000400)	(0.000269)	(0.000477)
Convulsions unknown cause	.005	0.000567	-0.000494	0.00149*
		(0.000541)	(0.000396)	(0.000660)
Calendar Time Fixed Effects		Month, Year	Month, Year	Month, Year × Treat
Person Fixed Effects		Yes	Yes	Yes
Number of Enrollees		22269	49417	71686
Person-Months		516953	1152616	1669569

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each row and column present results of a different regression. The table presents coefficient estimates for the "post" turning 65 years old indicator. The dependent variable in these regressions is a binary indicator variable for any claims in that patient-month with the condition listed in the first column. The definition of non-deferrable conditions are from Card et al. (2009), though we drop asthma and COPD as these conditions are considered preventable by McDermott and Jiang (2020). Standard errors clustered at the patient level are in parentheses below the coefficient estimate. The unit of observation is a patient-month. The first two columns are estimated using equations 2 and 3. "New dual" refers to our treatment group, individuals whose insurance changes at 65. "Always duals" are our control group. They were dual enrolled in Medicare before and after turning 65. These regressions include patient fixed effects, calendar-month and calendar-year fixed effects, and difference out any pre-trends. The third column is a difference-in-differences specification which uses the "always duals" as the control group. The third column is estimated using equations 4 and 5, and includes patient fixed effects, calendar-month and calendar-year fixed effects, and differences out pre-trends separately for the treatment and control groups.

Table 6: Cross-state variation in acceptance rates measured with survey data

	(1) Primary Care All Visits	(2) Primary Care New-Patient Visits	(3) Specialists All Visits	(4) Specialists New-Patient Visits	(5) Total Physician Visits
Post=1	-0.503*	0.00193	0.0312	-0.00613	-0.471
	(0.235)	(0.0164)	(0.158)	(0.0324)	(0.351)
Post=1 × State Medicaid Accept. Rate	-0.216+	-0.0205	-0.278*	-0.104**	-0.495**
	(0.113)	(0.0142)	(0.117)	(0.0260)	(0.155)
Post=1 × State Medicare Accept. Rate	0.808*	0.0221	0.284	0.118*	1.092*
	(0.325)	(0.0286)	(0.227)	(0.0453)	(0.477)
Pre-Period Mean	0.260	0.008	0.243	0.031	0.503
Mean Medicaid Accept. Rate	0.780	0.780	0.780	0.780	0.780
Mean Medicare Accept. Rate	0.889	0.889	0.889	0.889	0.889
Person Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Enrollees	19242	19242	19242	19242	19242
Person-Months	447207	447207	447207	447207	447207

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each column presents results of a different regression estimated using equation 6. The outcome variable is listed in the header and we present coefficient estimates for the "post" turning 65 years old indicator, as well as an interaction between the post indicator and Medicare and Medicaid acceptance rates, derived from MACPAC (2021). Standard errors clustered at the state level are in parentheses below the coefficient estimates. The unit of observation is a patient-month and the sample for this regression is only the "new dual" population.

Table 7: Cross-state-speciality variation in acceptance rates measured with claims data

		Primary Care + Specialist Visits		
	Visits	Visits	New Visits	New Visits
Post	0.02167***	0.02017***	0.00153***	0.00154***
	(0.00257)	(0.00244)	(0.00029)	(9e-05)
Post x Medicaid Acceptance Rate	-0.02516***	-0.02518***	-0.00083+	-0.00096***
	(0.00352)	(0.00365)	(0.00043)	(0.00015)
Acceptance Rate Measure	All Medicaid	FFS Only	All Medicaid	FFS Only
Pre-Period Mean	0.031	0.031	0.002	0.002
R2	0.1	0.1	0.002	0.002
N	5839656	5839656	5839656	5839656

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each column presents results of a different regression estimated using equation 6. The outcome variable is listed in the header and we present coefficient estimates for the "post" turning 65 years old indicator, as well as an interaction between the post indicator Medicaid acceptance rates. Here the Medicaid acceptance rates are calculated as the share of providers in a given speciality-state-year that see a new Medicaid patient. This share is based on the universe of providers in the MDPPAS database and the MAX claims database. Standard errors clustered at the state-specialty level are in parentheses below the coefficient estimates. The unit of observation is a patient-specialty-month and the sample for this regression is only the "new dual" population.

Table 8: Correlation between Quality Measures and Taking Medicaid Patients

	(1)	(2)	(3)
Sum of QPP Clinical Quality Scores	-1.428***	-1.556***	-1.186***
	(0.101)	(0.108)	(0.112)
N	79715	77538	77538
Revealed Preference Measure	-0.368***	-0.154***	-0.138***
	(0.00957)	(0.00236)	(0.00246)
N	1091022	1059318	1059318
Speciality Fixed Effects	No	Yes	Yes
State Fixed Effects	No	No	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each row and column present results of a different regression. The observation counts differ by row because the top and bottom rows use two different data sources. In both rows the unit of observation is a provider, identified by their NPI (national provider identifier). The top row uses the set of providers who are in the 2017 Medicare Quality Payment Program (QPP) data and merges that with the set of providers in our Medicaid data. The outcome variable is the sum of the top 6 scores used in the QPP program and we present the coefficient on an indicator for whether or not that provider takes Medicaid using the methodology described in detail in the text.

Table 9: Intensive Margin Effects (NPI Level)

	E&M-All	E&M-OF/OP	Primary Care + Specialist
	RVU	RVU	Visits
Post	0.573	0.834***	0.003
	(0.827)	(0.165)	(0.002)
Mean Unique Physicians	2.17	1.95	1.83
R2	0.70	0.16	0.17
N	832764	692369	583738

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each row and column present results of a different regression. The outcome variable is listed in the header column and we present coefficient estimates for the "post" turning 65 years old indicator. Standard errors clustered at the patient level are in parentheses below the coefficient estimate. The unit of observation is a patient-provider-month. To be in this sample, we must have observed a patient-provider pair at least once in both the year before and the year after that patient turns 65. These coefficients are estimated using equation 7 and include patient-NPI fixed effects and calendar month fixed effects. These results are only estimated on the new-dual sample.

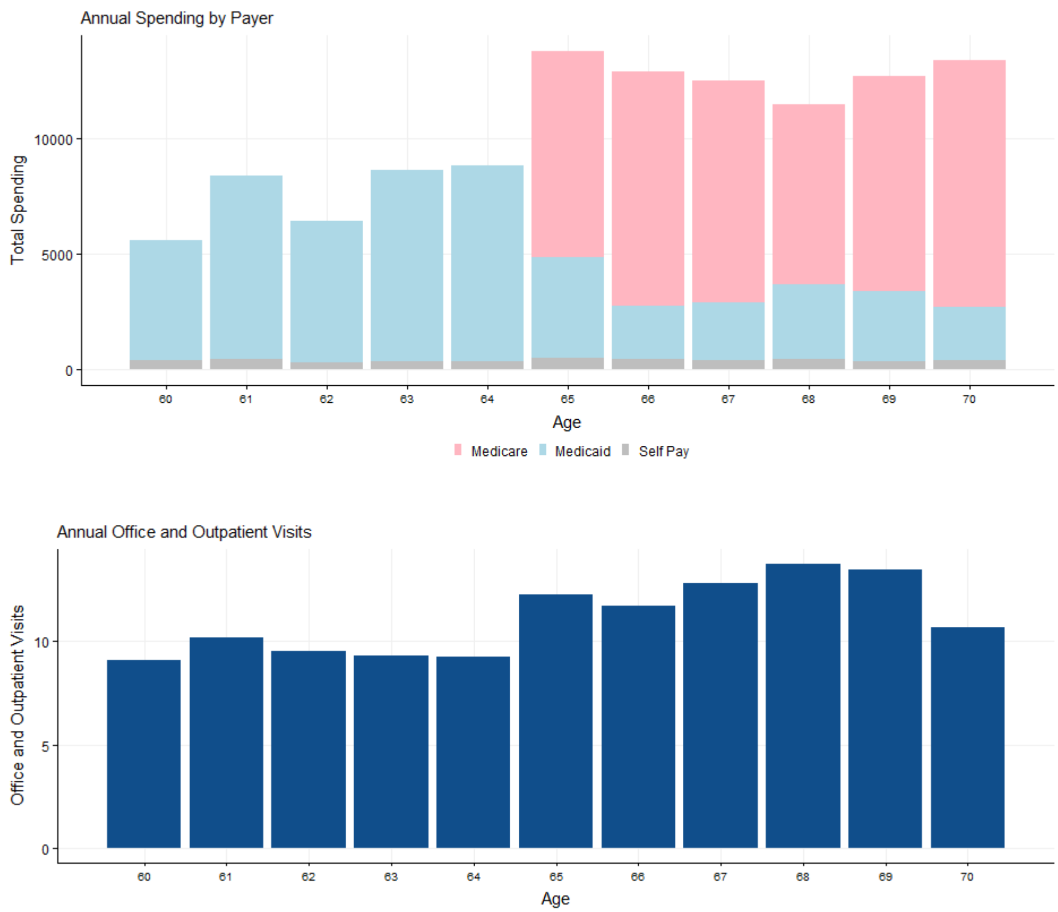
Table 10: Intensive Margin Effects (Tax-ID Level)

	Core	E&M-All	E&M-OF/OP	Primary Care + Specialist
	RVU	RVU	RVU	Visits
Post	5.94***	2.327**	2.304***	0.028***
	(0.616)	(0.844)	(0.202)	(0.002)
Mean Unique Physicians	3.56	2.06	1.84	1.7
R2	0.35	0.69	0.19	0.20
N	1803952	976022	675778	580792

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

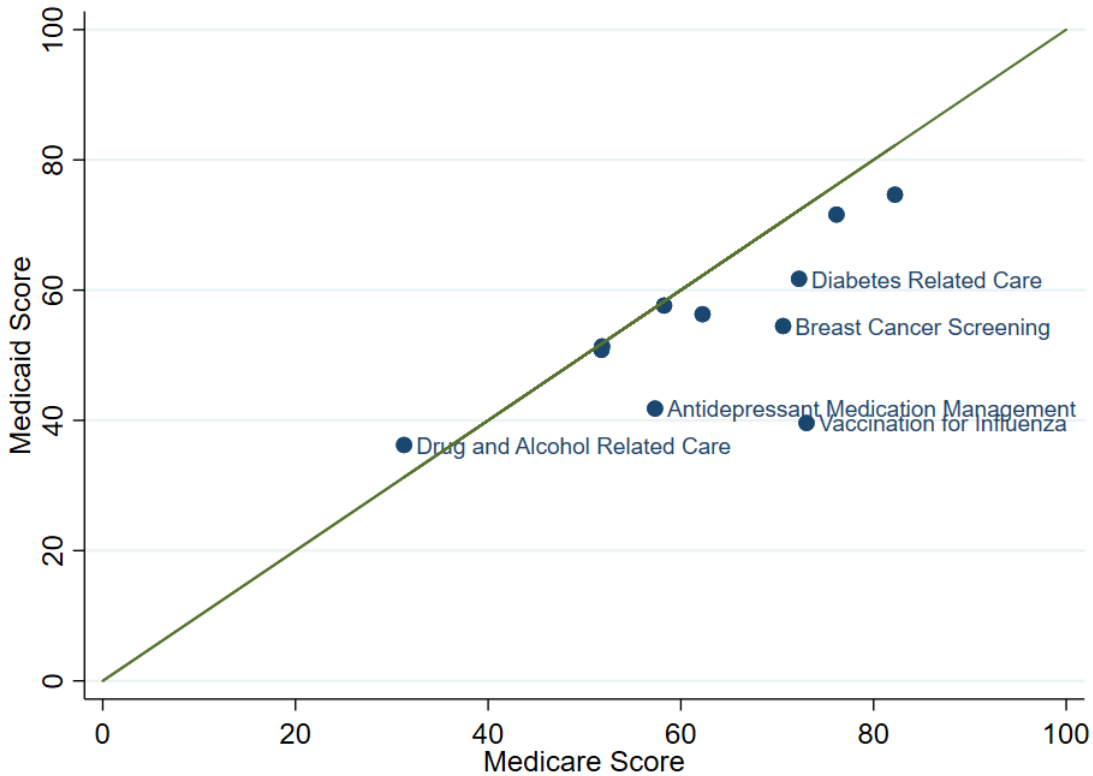
Notes: Each row and column present results of a different regression. The outcome variable is listed in the header column and we present coefficient estimates for the "post" turning 65 years old indicator. Standard errors clustered at the patient level are in parentheses below the coefficient estimate. The unit of observation is a patient-provider-month. To be in this sample, we must have observed a patient-provider pair at least once in both the year before and the year after that patient turns 65. These coefficients are estimated using equation 7 and include patient-TaxID fixed effects and calendar month fixed effects. These results are only estimated on the new-dual sample.

Figure 1: Spending by Payer Type and Number of Visits for Dual-Eligibles in the Medical Expenditure Panel Survey (MEPS)



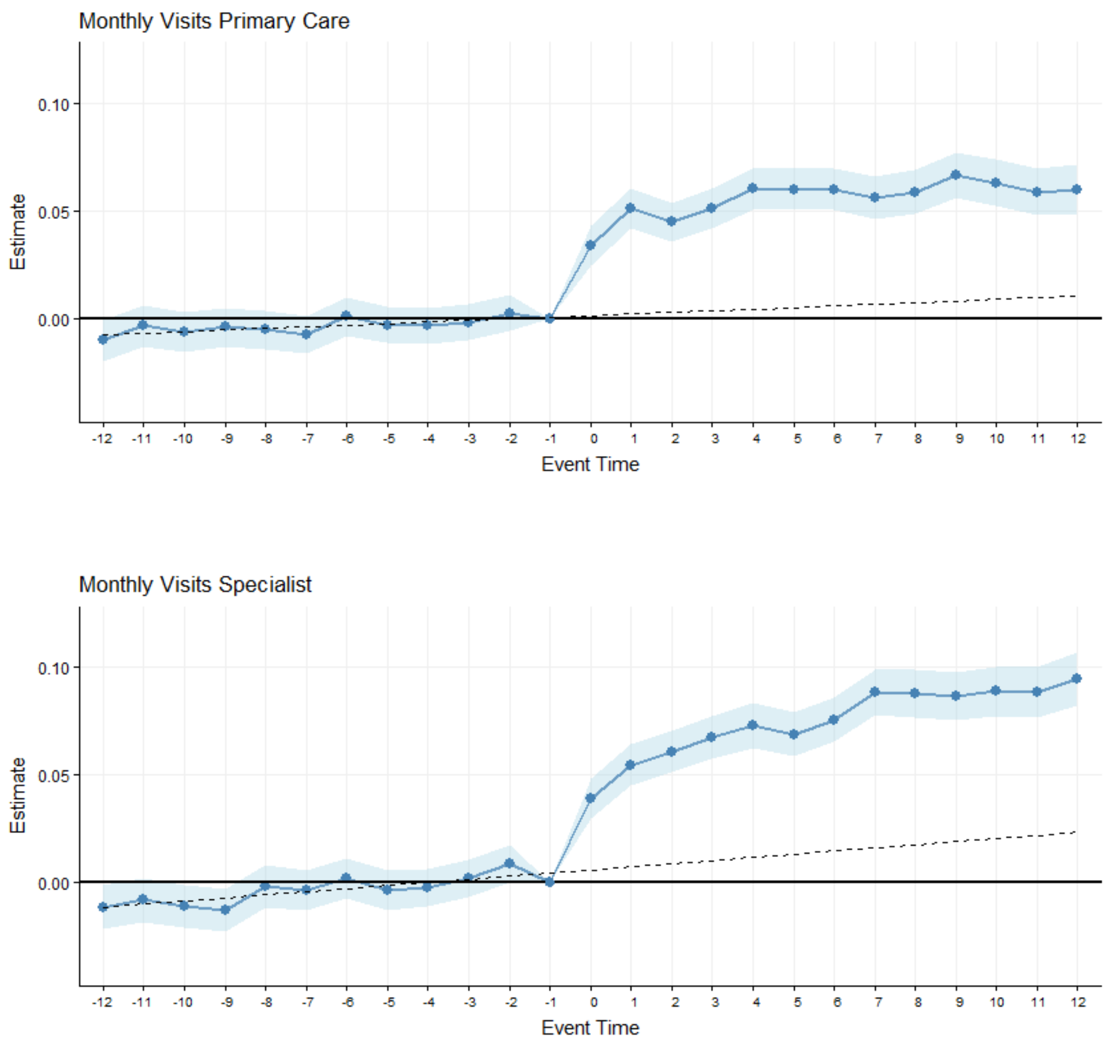
Notes: This figure presents sample means of annual spending (top) and number of office and outpatient (bottom) in the MEPS data by age. We pool years 2006-2019. The under-65 sample includes all those enrolled in Medicaid, but not Medicare or private insurance. The over-65 sample includes all those enrolled in Medicaid and Medicare, and not in private insurance.

Figure 2: Quality Measures from HEDIS



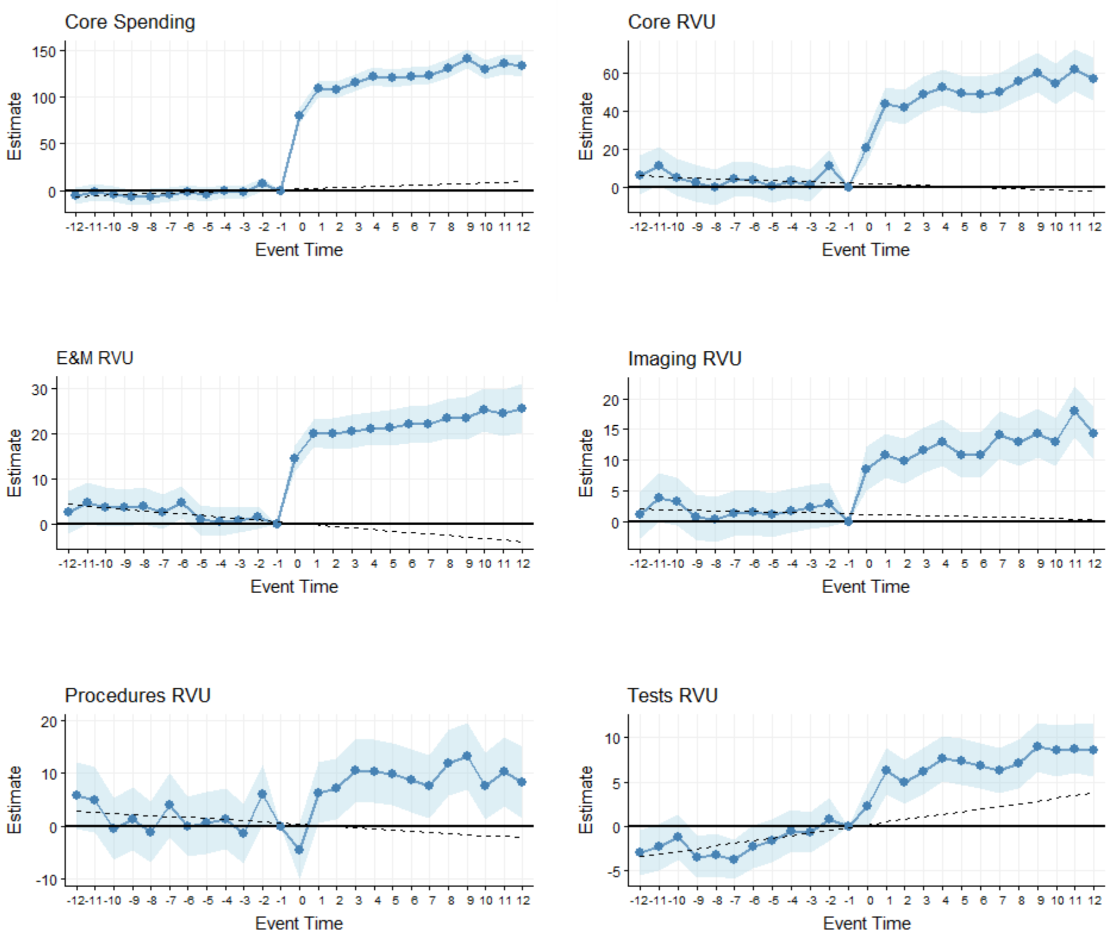
Notes: This figure presents average scores for various aggregated HEDIS measures in Medicare (x-axis) and Medicaid (y-axis). Scores range from 1-100, where 100 is the highest quality. Scores below the 45 degree line indicate Medicare performs better. We take an unweighted average across years for each measure. Then, for this figure we aggregate across similar measures (e.g. multiple measures for drug and alcohol related care) so over-sampled conditions do not receive outsize weight. The mapping from individual measure to aggregate category is shown in Figure A6.

Figure 3: Monthly Visits with Primary Care and Specialty Physicians



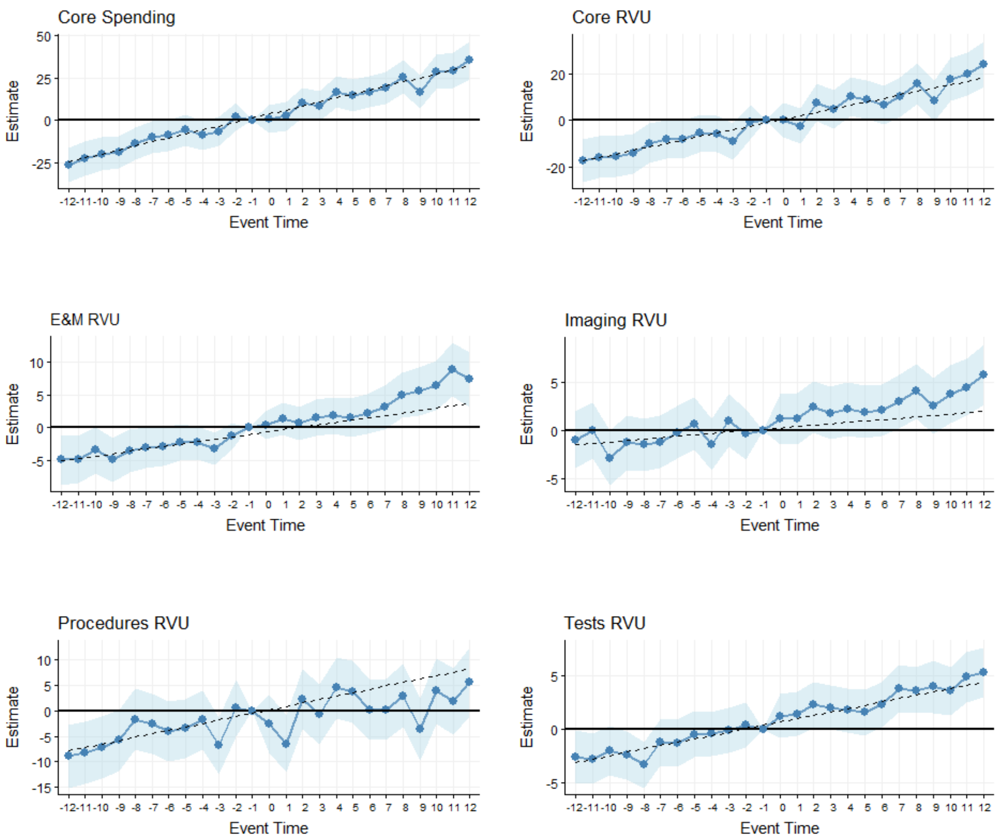
Notes: This figure presents coefficient estimates and 95% confidence intervals from our non-parametric event study described by equation 1. The unit of observation for these regressions is a patient-month. The regressions include patient fixed effects, calendar year fixed effects, and calendar month fixed effects. The blue superimposed line shows the pre-trend line which is extrapolated into the post-period. The sample for this figure is only our “new dual” treated group, those who become dual eligible at 65 years old.

Figure 4: Health-care utilization for broad measures



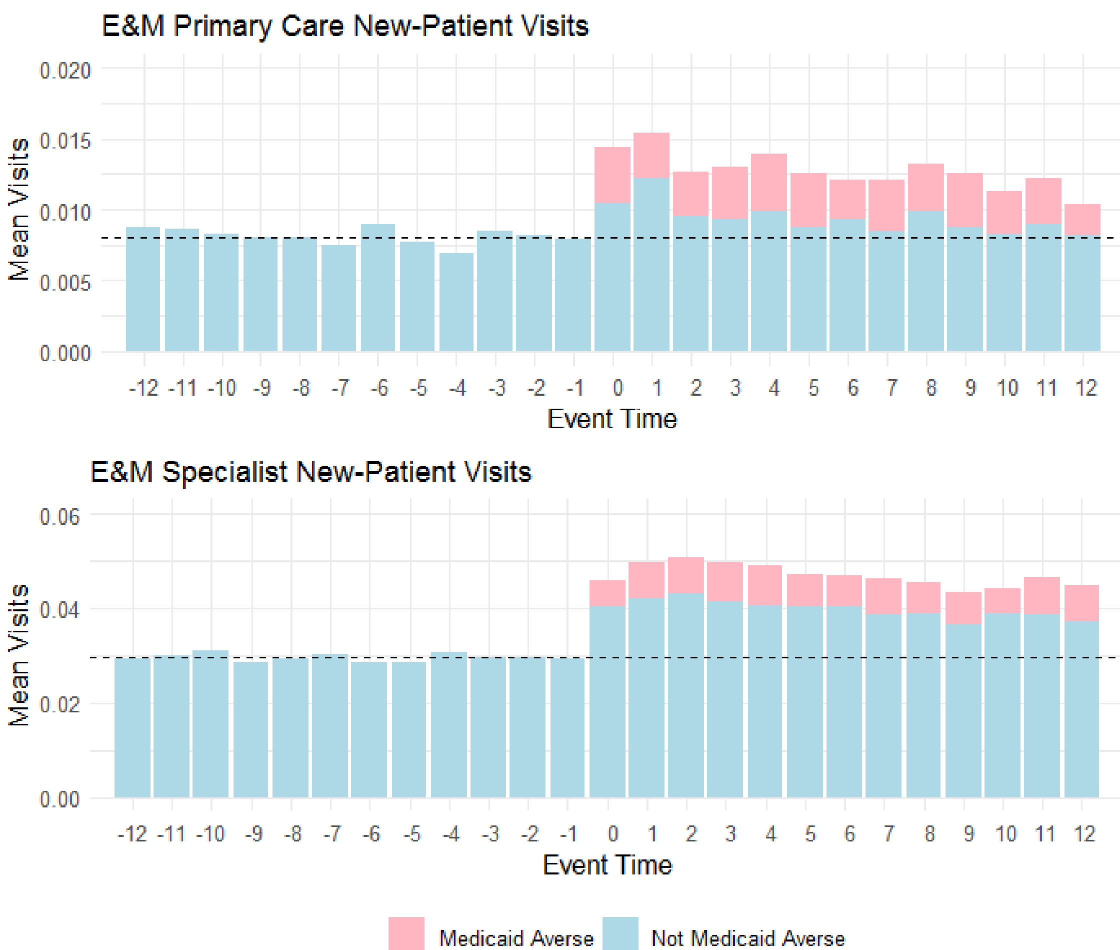
Notes: This figure presents coefficient estimates and 95% confidence intervals from our non-parametric event study described by equation 1. The unit of observation is a patient-month. The regressions include patient fixed effects, calendar year fixed effects, and calendar month fixed effects. The blue superimposed line shows the pre-trend line which is extrapolated into the post-period. The sample for this figure is only our "new dual" treated group, those who become dual eligible at 65 years old.

Figure 5: Control Group: Health-care utilization by month among the always dual population



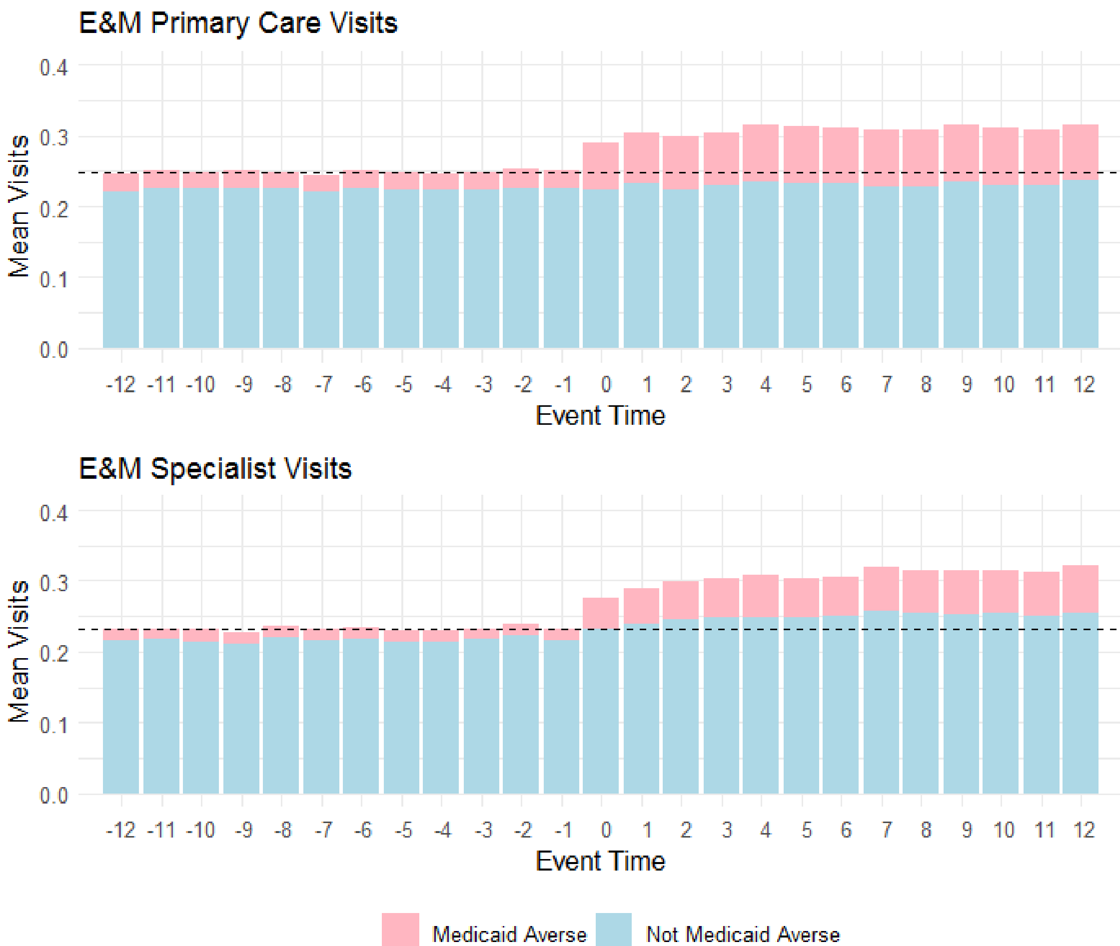
Notes: This figure is similar to figure 4, but is run only on our control group, those who are enrolled in Medicare before and after turning 65 years old. The goal of this plot is to explore whether there is a discontinuous jump in care at age 65. This figure presents coefficient estimates and 95% confidence intervals from our non-parametric event study described by equation 1. The unit of observation for these regressions is a patient-month. The regressions include patient fixed effects, calendar year fixed effects, and calendar month fixed effects. The blue superimposed line shows the pre-trend line which is extrapolated into the post-period.

Figure 6: Monthly New Patient Visits with Medicaid-Averse and Non-Medicaid-Averse Physicians



Notes: This figure presents sample means for primary care new patient visits and specialist new patient visits at the patient-month level. The pink portion of the bars represent visits to providers who do not bill Medicaid for a new patient visit in the given year (Medicaid averse), while the blue portion of the bar reflects visits at providers who see at least one new medicaid patient in the year (not Medicaid averse).

Figure 7: Monthly Visits at Medicaid-Averse and Non-Medicaid-Averse Physicians



Notes: This figure presents sample means for primary care visits and specialist visits at the patient-month level. The pink portion of the bars represent visits to providers who do not bill Medicaid for a new patient visit in the given year (Medicaid averse), while the blue portion of the bar reflects visits at providers who see at least one new medicaid patient in the year (not Medicaid averse).

Appendix

A Construction of Dual-Eligible Sample

To construct our primary sample of Medicaid enrollees who age into dual eligibility, we begin with the MAX annual summary enrollment file. We select individual beneficiaries who satisfy the following criteria: (1) the beneficiary is continuously enrolled in Medicaid fee for service and is observed in the data at both age 64 and age 65, (2) the beneficiary is not enrolled in Medicare at any time when they are under 65, (3) the beneficiary identified as a Medicaid-Medicare dual eligible after turning 65. Collectively, the group of beneficiaries who satisfy these conditions are those who we observe switching from Medicaid coverage to dual Medicaid-Medicare coverage upon turning 65. In the year that a beneficiary turns 65, we require continuous dual-eligible enrollment only for the months after initial enrollment. For full years after a beneficiary has turned 65, we require continuous dual enrollment.

Fortunately, CMS maintains a consistent set of beneficiary IDs across the Medicaid and Medicare databases. We use the set of beneficiary IDs identified in the first step to pull all claims associated with these beneficiaries from both the Medicaid MAX database and the Medicare database.

After pulling both Medicaid and Medicare claims for our main beneficiary sample, we stack these claims and harmonize variable names where necessary. For our purposes, we focus on maintaining a consistent concatenation of diagnosis codes, procedure codes, payment information, and provider information across the Medicaid and Medicare datasets. At this stage, for each beneficiary, for months prior to turning 65 we have a list of Medciaid claims, and for months after turning 65 we have a combination of Medicaid and Medicare claims.

For many dual eligibles, such as Qualified Medicare Beneficiaries (QMBs), Medicaid covers much or all of Medicare cost sharing. In this case we often observe a Medicare claim and an associated Medicaid claims, which is labelled as a Medicare-Medicaid crossover claim. We sort the data by beneficiary, day, and procedure and flag all crossover claims so that these are not double counted in our computation of payments and RVUs.

Table A1 presents the reason for eligibility in our sample. 63 percent of our sample qualifies due to their eligibility for SSI cash assistance. In addition, states could also choose to cover other populations, such as working disabled individuals whose income is too high for SSI and those with high medical expenses. Those individuals represent another 25% of the our sample of patients.

Table A1: Reasons for Eligibility for Under-65 "New Duals"

	(1) Basis of Eligibility Share of Enrollees
Blind/Disabled, SSI Cash Assistance	63
Blind/Disabled, Medically Needy	4
Blind/Disabled, Poverty	6
Other Blind/Disabled	15
Section 1115 Demonstration	7
Other	4
Observations	22500

Notes: This table presents the breakdown of the basis of eligibility for Medicaid in our sample. SSI stands for Supplemental Security Income. Observation counts are slightly higher than other tables as some individuals move states and have different reasons for eligibility across states. In these cases, this individual is counted in this table twice.

B Analysis using the Medical Expenditure Panel Survey (MEPS)

In the main text of the paper, we use MEPS data to show that average spending and utilization increase as those on Medicaid age into Medicare (Figure 1). In this section we discuss the MEPS data, and present other specifications using that data. The purpose of this section is to (1) verify that these results are valid in a different widely used dataset; (2) check robustness for some of our sample restrictions (looking at FFS Medicaid versus Managed Care); (3) provide some context for how the CMS population differs from other populations (e.g. privately insured). The MEPS also has richer individual level demographics which are not available in the claims data.

The MEPS data is a nationally representative survey of households, which gathers detailed information on health expenditures, utilization, health status, demographics, and health insurance coverage from individual households. We use MEPS data from 2006-2019.[63] Our sample consists of all 60 to 70 year olds who are either (a) under 65 and on Medicaid, but not privately insured or on Medicare or (b) 65 or older and on Medicaid and Medicare, but not privately insured. We use the terms managed care and HMO interchangeably when referring to Medicaid Managed Care. In the MEPS data, we classify individuals as having Medicaid managed care if they either were in a Medicaid HMO or a Medicaid plan with a gatekeeper.[64]

Table A2 compares the Medicaid population to the non-Medicaid population. The first column presents summary statistics for 60-70 year olds who are either privately insured or on Medicare,

[63] We start in 2006 to begin after the Medicare Modernization Act's implementation. All expenditure estimates are deflated to 2011 dollars using the PCE deflator.

[64] The gatekeeper question (which maps to the variable Medicaid Managed Care) is only asked if someone says that are not covered by an HMO.

but not on Medicaid. The second column presents summary statistics for those on Medicaid, if under-65, or dual if over-65. The third column drops those who are in Medicaid Managed Care or Medicare Advantage, which matches the CMS claims sample. The Medicaid population is considerably sicker than the non-Medicaid population. The Medicaid population (column 2) has more spending, more office and outpatient visits, worse self-reported perceived health status, and more chronic conditions than the non-Medicaid population (column 1). The fee-for-service Medicaid population (column 3) looks very similar to the entire Medicaid sample.

Table A2: Summary Statistics

	Non-Medicaid Population		All Medicaid or Dual		Medicaid or Dual Fee-for-Service	
	mean	sd	mean	sd	mean	sd
Total Spending	7,875	17,545	10,849	22,219	11,672	24,423
Office and Outpatient Spending	2,736	8,218	2,561	9,089	2,786	11,792
Office and Outpatient Visits	9.54	14.7	11	19.8	10.9	22.3
1(Female)	.532	.499	.622	.485	.615	.487
1(Asain)	.0599	.237	.0896	.286	.0795	.271
1(Black)	.176	.381	.297	.457	.316	.465
1(White)	.759	.428	.603	.489	.591	.492
1(Ever Married)	.934	.248	.839	.367	.824	.381
Family Income	71,257	62,787	25,987	31,666	25,970	33,604
Perceived Health Status	2.56	1.11	3.28	1.12	3.29	1.15
Perceived Mental Health	2.1	1	2.67	1.11	2.66	1.12
1(High Cholesterol)	.512	.5	.581	.494	.551	.498
1(Has Asthma)	.0946	.293	.157	.364	.155	.362
1(Has Diabetes)	.167	.373	.253	.435	.236	.425
BMI	27.6	8.71	28.4	9.58	28.1	10
Observations	41225		4934		1976	

Notes: This table presents sample means for various populations in the MEPS data. All individuals in this table are between 60 and 70 years old. The first column presents summary statistics for those not enrolled in Medicaid. The second column includes all individuals enrolled in Medicaid and not Medicare or private insurance (under 65) or dually enrolled in Medicaid and Medicare (over 65). The third column includes only the subset that match our CMS data sample, those not in Medicaid HMOs or Managed Care plans, and those not in Medicare Advantage, if older than 65. Perceived health status and perceived mental health are variables that range from 1-5, with 1 meaning excellent and 5 meaning poor.

Table A3 breaks out these groups in a more granular fashion, differentiating between over and under 65. It compares the FFS Medicaid population we study and to those in Medicaid HMOs (under 65) or Medicaid HMOs or Medicare Advantage (over 65). For those under 65, the FFS and HMO population look similar though the FFS population has slightly fewer office visits and lower

BMI, and is slightly less likely to have high cholesterol or diabetes, though none of these differences are statistically significant. Over 65, we again find minor differences between the FFS and HMO populations. This provides some evidence that our CMS FFS sample is not too different than the full set of Medicaid enrollees.

Table A3: Summary Statistics

	Medicaid HMO Under 65	Medicaid Fee-for-Service Under 65	Medicaid or Medicare HMO Over 65	Medicaid and Medicare FFS Over 65
	mean	mean	mean	mean
Total Spending	7,617	7,840	11,707	13,746
Office and Outpatient Spending	1,856	2,526	2,703	2,927
Office and Outpatient Visits	9.51	8.74	11.8	12
1(Female)	.631	.605	.624	.62
1(Asain)	.0972	.0605	.0959	.0897
1(Black)	.281	.301	.286	.324
1(White)	.625	.625	.605	.572
1(Ever Married)	.825	.831	.862	.82
Family Income	26,247	28,381	25,866	24,626
Perceived Health Status	3.21	3.23	3.29	3.33
Perceived Mental Health	2.63	2.63	2.69	2.68
1(High Cholesterol)	.538	.514	.634	.57
1(Has Asthma)	.148	.166	.163	.15
1(Has Diabetes)	.227	.207	.282	.252
BMI	29.4	28.3	28.1	28
Observations	1018	694	1940	1282

Notes: This table uses the MEPS data to check whether those enrolled in Medicaid fee-for-service and dual eligible enrollees in traditional Medicare have different observable characteristics than those enrolled in Medicaid managed care plans or Medicare Advantage. Column 1 includes all individuals who are between ages 60-65 who are not enrolled in Medicare or private insurance and are in enrolled in Medicaid HMO or a Medicaid Managed Care plan, as defined by the MEPS data. Column 2 includes all individuals who are between ages 60-64 who are not enrolled in Medicare or private insurance and are in enrolled in Medicaid, but not Medicaid Managed Care or a Medicaid HMO. Columns 3 and 4 include those between ages 65-70, who are enrolled in Medicaid and Medicare. Those in Medicaid HMOs or Medicare Advantage are in column 3, whereas those not in a Medicaid HMO and in traditional Medicare are in column 4.

We use an event study design to compare how various measures of costs and utilization change with age in the Medicaid population. This allows us to add controls and standard errors to the analysis we present in Figure 1, while also allowing us to work with different populations. Formally, we run an event study regression using repeated cross-sections:

$$y_{ia} = \beta_0 + \beta_1 X_i + \gamma_a + \epsilon_{ia} \tag{8}$$

y_{ia} is annual spending or the number of visits for an individual i, who is age a. X_i are individual level controls. We include two different types of controls. First, demographics such as sex, marital status, race, income, census region, and year surveyed. In some specifications, we also include self-reported health status and mental health status, though these are not in our main specification because they may be partially determined by insurance status. The coefficients of interest are age fixed effects, γ_a, which show how spending evolves. Age 64 is omitted. Standard errors are clustered at the individual level.

Table A4 presents regression results. The first column does not include controls. Someone who is 63 years old in our sample spends a (statistically insignificant) \$71 more than a 64 year old. A 65 year old spends \$4,659 more than a 64 year old. None of the under 64 fixed effects are statistically significant, while those over 65 all are both statistically and economically significant.

The second column adds demographic controls. Results are similar. The third column tests of whether our sample restrictions are important. We drop those who say they are in a Medicare HMO (Medicare Advantage) or a Medicaid HMO, as we do not observe these population in our claims sample. This cuts our sample size in half. Overall, the results are larger in magnitude, which may suggest that our results in the claims data are bigger than what we would find if we had Medicare Advantage and Medicaid Managed Care claims. The fourth column adds perceived health status and perceived mental health status. The fifth column adds BMI, which is missing after 2017, hence the reduced number of observations.

Overall, this table shows that the large increase in expenditures that we find in the CMS data is also present in the MEPS data. The result is robust in the MEPS data to various controls and sample restrictions. We find similar percentage increases in both datasets, in Table 2 we see an approximate 50% increase in expenditures, which is similar to what we find in the MEPS. However, these numbers a larger in magnitude than our main estimates for spending from Table 2 where we find an increase of about \$103 per month, or about \$1.2k per year. This is because our main estimates are limited to just core services, while the estimate in Table A4 includes all MEPS spending.

To make the set of services more comparable, Column 6 uses just outpatient and office spending, which is somewhat narrower than our core services definition.[65] Results are closer in magnitude to what we find using CMS data. Using the MEPS we find roughly an \$800 average increase in spending, while in the CMS data the increase is \$1.2k. It is worth noting that the MEPS data are noisy enough that some of the over-65 coefficients are no longer statistically significant at their smaller magnitude. As we show below, we do find statistically significant increases in office and outpatient visits, which are less noisy measures than spending, which is reassuring that the increase in office and outpatient expenditures is not solely due to noise.

[65] In the CMS data, core spending is about \$2.4k annually (Table 2), whereas office and outpatient visits are about \$2.1k annually in the MEPS.

Table A4: MEPS Regression Results - Total Expenditures

	(1) All Services	(2) All Services	(3) All Services	(4) All Services	(5) All Services	(6) Office and Outpatient
Age=60	-1642.5	-1682.3	-683.9	-1434.1	-1336.1	-518.0
	(1124.8)	(1137.3)	(2051.2)	(2065.8)	(1799.9)	(342.6)
Age=61	34.71	53.80	1511.9	1126.7	1921.3	540.8
	(1303.8)	(1311.3)	(2314.3)	(2317.0)	(1950.6)	(546.0)
Age=62	-1430.9	-1137.4	1070.0	1313.6	315.1	-91.90
	(1243.7)	(1276.5)	(2482.4)	(2471.7)	(2180.5)	(372.0)
Age=63	71.26	251.4	2795.5	2949.3	4855.6	1003.0
	(1436.7)	(1452.2)	(2742.8)	(2723.4)	(3192.8)	(931.3)
Age=65	4658.8**	4765.3**	6162.1**	5672.3*	5300.1**	497.0
	(1564.3)	(1549.7)	(2267.6)	(2228.0)	(1930.4)	(400.1)
Age=66	3797.5**	4153.4***	6500.4**	5776.2**	7090.2***	447.7
	(1249.2)	(1256.3)	(2215.0)	(2167.0)	(2015.7)	(371.1)
Age=67	3387.7*	3646.4**	5595.7*	5465.1*	5225.4***	795.5+
	(1328.1)	(1342.7)	(2205.3)	(2171.1)	(1576.3)	(466.6)
Age=68	3139.4*	3189.2*	6122.8*	5708.4*	6665.2**	1576.5*
	(1356.2)	(1368.4)	(2472.0)	(2412.4)	(2499.0)	(763.0)
Age=69	4741.8**	4769.0**	10936.8***	11042.7***	8779.0***	481.0
	(1458.2)	(1481.2)	(3006.5)	(3023.2)	(2055.3)	(364.7)
Age=70	5700.9***	5902.4***	8965.6**	9114.2**	10009.7**	901.9*
	(1592.9)	(1587.1)	(2939.7)	(2875.8)	(3099.9)	(454.2)
Observations	4934	4934	1976	1976	1398	3579
Sample	All	All	FFS	FFS	FFS	All
Demographic Controls	No	Yes	Yes	Yes	Yes	Yes
Health Controls	No	No	No	Yes	Yes	Yes
BMI control	No	No	No	No	Yes	Yes
Under-65 Sample Mean	7707	7707	7840	7840	7840	2128

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable for this table is total annual health care expenditures in the MEPS data, except for column 6 which only uses outpatient and office expenditure. The sample for columns 1,2, and 6 is all individuals under 65 enrolled in Medicaid (and not Medicare or private insurance) or on Medicaid and Medicare when over 65. Columns 3-5 drop those on Medicaid HMO or Medicare Advantage.

Table A5 presents results where the number of office and outpatient visits is the dependent variable. This provides evidence that changes in utilization are present in the MEPS data and the previous results on spending are not due to changes in prices alone. We see a similar pattern to the expenditure data, where none of the coefficients below age 64 are statistically significant, while nearly all are after 65. Using all Medicaid and Medicare patients, we see about 2-3 additional visits per year, roughly a 30% increase. Focusing on those not in HMOs, the number rises to about 4-5 additional visits per year. In percentage terms, these numbers are slightly larger in magnitude than what we find in the CMS data (roughly a 20% increase in visits).[66]

[66]For this measure, office and outpatient visits is a somewhat broader category than primary and specialist visits, so the increase in the number of visits is larger, even if the proportional increase is similar in magnitude.

Table A5: MEPS Regression Results - Office and Outpatient Visits

	(1)	(2)	(3)	(4)	(5)
Age=60	-0.0762	-0.228	0.772	0.348	-3.686
	(1.520)	(1.533)	(2.827)	(2.824)	(2.444)
Age=61	-0.107	-0.160	0.299	0.280	-1.192
	(1.177)	(1.168)	(1.975)	(1.981)	(2.405)
Age=62	-0.198	-0.0653	1.753	1.973	-0.587
	(1.186)	(1.200)	(2.038)	(2.017)	(2.596)
Age=63	-0.374	-0.364	0.552	0.748	0.241
	(1.117)	(1.116)	(1.909)	(1.933)	(2.589)
Age=65	2.390+	2.646*	4.185+	3.874+	1.472
	(1.267)	(1.276)	(2.260)	(2.271)	(2.687)
Age=66	1.805	2.232+	4.720*	4.334+	1.563
	(1.179)	(1.189)	(2.241)	(2.234)	(2.743)
Age=67	2.400+	2.758*	4.423*	4.311*	1.298
	(1.286)	(1.285)	(2.204)	(2.191)	(2.484)
Age=68	3.275*	3.480*	4.614*	4.381*	1.925
	(1.373)	(1.369)	(2.230)	(2.221)	(2.621)
Age=69	3.215*	3.505*	6.107*	6.385*	3.166
	(1.417)	(1.422)	(2.649)	(2.696)	(2.589)
Age=70	2.269+	2.802*	4.008*	4.005*	1.820
	(1.298)	(1.307)	(1.977)	(1.976)	(2.571)
Observations	4934	4934	1976	1976	1398
Sample	All	All	FFS	FFS	FFS
Demographic Controls	No	Yes	Yes	Yes	Yes
Health Controls	No	No	No	Yes	Yes
BMI control	No	No	No	No	Yes
Under-65 Sample Mean	9.196	9.196	8.736	8.736	8.736

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable for this table is annual office and outpatient visits in the MEPS data. The sample for the first two columns is all individuals under 65 enrolled in Medicaid (and not Medicare or private insurance) or on Medicaid and Medicare when over 65. Columns 3-5 drop those on Medicaid HMO or Medicare Advantage.

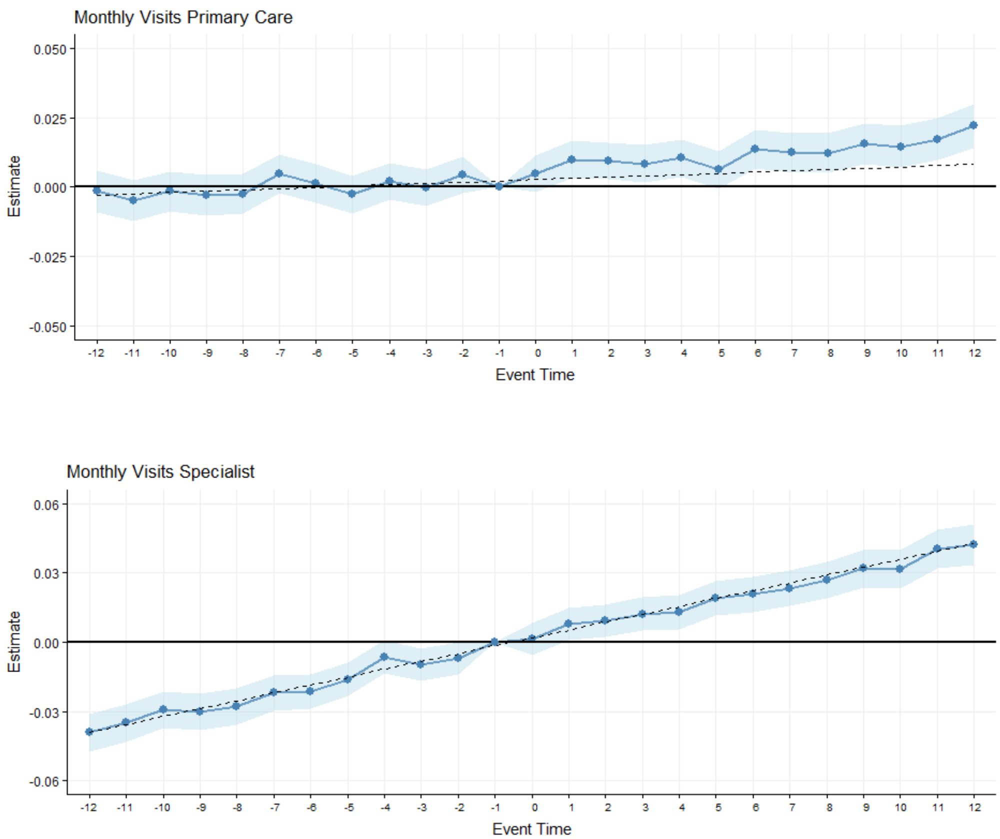
C Robustness and Placebo Checks Referenced in the Text

Table A6: Individual Measures in HEDIS Data

Measure	Disease	Medicaid	Medicare
* Poor HbA1c Control for Patients with Diabetes	Diabetes	45.6	31.1
* Risk of Continued Opioid Use	Drug and Alcohol	4.1	8.5
* Use of Opioids at High Dosage	Drug and Alcohol	6.8	6.2
* Use of Opioids from Multiple Providers - Multiple Pharmacies	Drug and Alcohol	6.4	2.8
* Use of Opioids from Multiple Providers - Multiple Prescribers	Drug and Alcohol	21	13.1
* Use of Opioids from Multiple Providers - Multiple Prescribers and Pharmacies	Drug and Alcohol	3.6	1.2
Adherence to Antipsychotic Medications for Individuals with Schizophrenia	Mental Health	59.8	91.5
Advice on Physical Activity with Older Adults	Physical Activity	48.6	48.5
Advising Smokers and Tobacco Users to Quit	Smoking	71.6	76.2
Antidepressant Medication Management for Acute Phase Treatment	Depression	49.7	64.2
Antidepressant Medication Management for Continuation Phase Treatment	Depression	33.9	50.4
Blood Pressure Control for Patients with Diabetes	Diabetes	59.7	57.2
Breast Cancer Screening Rate	Breast Cancer	54.5	70.6
Controlling High Blood Pressure	High Blood Pressure	56.3	62.2
Discussion of Physical Activity with Older Adults	Physical Activity	53	55
Engagement of AOD Treatment (Total)	Drug and Alcohol	12.2	4.4
Engagement of AOD Treatment - Alcohol Abuse or Dependence	Drug and Alcohol	10.8	4.7
Engagement of AOD Treatment - Opioid Abuse or Dependence	Drug and Alcohol	25.2	5.2
Engagement of AOD Treatment - Other Drug Abuse	Drug and Alcohol	11.5	3.3
Eye Exams for Patients with Diabetes	Diabetes	51.5	65.3
Flu Vaccinations	Flu Vaccines	39.6	73
Follow-Up Within 30 Days after ER Visit for Alcohol and Other Drug Abuse	Drug and Alcohol	19.7	13.4
Follow-Up Within 30 Days after ER Visit for Mental Illness	Mental Health	54.6	47.7
Follow-Up Within 30 Days after Hospitalization for Mental Illness	Mental Health	59.6	56.5
Follow-Up Within 7 Days after ER Visit for Alcohol and Other Drug Abuse	Drug and Alcohol	13	9
Follow-Up Within 7 Days after ER Visit for Mental Illness	Mental Health	40.2	31.8
Follow-Up Within 7 Days after Hospitalization for Mental Illness	Mental Health	40.8	36.3
HbA1c Control for Patients with Diabetes	Diabetes	46.8	63.9
HbA1c Screening for Patients with Diabetes	Diabetes	80.9	89.6
Initiation of AOD Treatment (Total)	Drug and Alcohol	42	42.7
Initiation of AOD Treatment - Alcohol Abuse or Dependence	Drug and Alcohol	42.3	39.3
Initiation of AOD Treatment - Opioid Abuse or Dependence	Drug and Alcohol	53	31.6
Initiation of AOD Treatment - Other Drug Abuse	Drug and Alcohol	42.8	31
Monitoring Nephropathy for Patients with Diabetes	Diabetes	71	79.8
Persistence of Beta-Blocker Treatment After A Heart Attack	Cardiovascular Disease	76.8	83.4
Pharmacotherapy for Opioid Use Disorder	Drug and Alcohol	30.4	34.5
Statin Therapy for Patients with Cardiovascular Disease- Received Statin Therapy	Cardiovascular Disease	76.3	80
Statin Therapy for Patients with Cardiovascular Disease- Statin Adherence 80%	Cardiovascular Disease	65	79.9
Statin Therapy for Patients with Diabetes- Received Statin Therapy	Diabetes	62.1	72.4
Statin Therapy for Patients with Diabetes- Statin Adherence 80%	Diabetes	62	78.7
Use of Bronchodilators in Management of COPD	COPD	79.3	78.4
Use of Spirometry Testing in the Assessment and Diagnosis of COPD	COPD	30.2	32.7
Use of Systemic Corticosteroids in Management of COPD	COPD	68	67.9

Notes: This figure presents average scores for various HEDIS measures. We present an unweighted average score across years for each measure. Scores range from 1-100, where 100 is the highest quality, unless the measure begins with a *. * indicates that higher scores mean worse treatment. AOD stands for Alcohol and Other Drug Abuse. The disease column indicates how we grouped categories in Figure 2.

Figure A1: Health-care utilization by month among continuously-enrolled duals



Notes: This figure is similar to Figure 3, but is run only on our control group, those who are enrolled in Medicare before and after turning 65 years old. The goal of this plot is to explore whether there is a discontinuous jump in care at age 65. This figure presents coefficient estimates and 95% confidence intervals from our non-parametric event study described by equation 1. The unit of observation for these regressions is a patient-month. The regressions include patient fixed effects, calendar year fixed effects, and calendar month fixed effects. The blue superimposed line shows the pre-trend line which is extrapolated into the post-period.

Table A7: Regression Results: Each BETOS Subcategory

	New Dual Pre-Period Sample Mean	(1) New Dual	(2) Always Dual	(3) Diff-in-Diff
Anatomic Pathology	4.11	3.248***	-0.943+	4.312***
		(0.382)	(0.564)	(0.669)
Breast	.713	0.198	0.242	-0.163
		(0.383)	(0.328)	(0.486)
Cardiography	3.17	0.976***	0.0414	0.907***
		(0.178)	(0.129)	(0.220)
Cardiovascular	5.56	1.060	0.292	0.894
		(0.901)	(0.982)	(1.275)
CT Scan	12	2.692***	0.804*	1.909**
		(0.626)	(0.371)	(0.716)
Digestive/Gastrointestinal	12	2.990**	-1.016	4.176***
		(1.012)	(0.791)	(1.250)
Eye	8.63	1.648	0.0824	1.891
		(1.132)	(0.864)	(1.405)
General Laboratory	27	-0.293	1.002*	-1.219
		(0.781)	(0.416)	(0.886)
Hematology	.547	0.780***	-0.104	0.865**
		(0.205)	(0.183)	(0.271)
Imaging - Miscellaneous	.399	0.0410	-0.0268	0.0767+
		(0.0358)	(0.0251)	(0.0436)
Magnetic Resonance	5.65	1.473**	-0.422	1.677**
		(0.507)	(0.310)	(0.584)
Calendar Time Fixed Effects		Month, Year	Month, Year	Month, Year × Treat
Person Fixed Effects		Yes	Yes	Yes
Number of Enrollees		22269	49417	71686
Person-Months		516953	1152616	1669569

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each row and column presents the coefficient estimates for the "post" turning 65 years old indicator of a different regression. The outcome variable is RVUs associated with the BETOS subcategory listed in the first column. This table and tables A8 and A9 contain all the BETOS subcategories we include in our definition of "core" services. Standard errors clustered at the patient level are in parentheses below the coefficient estimates. The unit of observation is a patient-month. The first two columns are estimated using equations 2 and 3. "New dual" refers to our treatment group, individuals whose insurance changes at 65. "Always duals" are our control group. They were dual enrolled in Medicare before and after turning 65. These regressions include patient fixed effects, calendar-month and calendar-year fixed effects, and difference out any pre-trends. The third column is a difference-in-differences specification which uses the "always duals" as the control group. The third column is estimated using equations 4 and 5, and includes patient fixed effects, calendar-month and calendar-year fixed effects, and differences out pre-trends separately for the treatment and control groups.

Table A8: Regression Results: Each BETOS Subcategory Continued

	New Dual Pre-Period Sample Mean	(1) New Dual	(2) Always Dual	(3) Diff-in-Diff
Molecular Testing	.698	0.466*	0.0298	0.438+
		(0.219)	(0.140)	(0.242)
Musculoskeletal	13	2.956**	-0.282	2.830+
		(1.094)	(1.143)	(1.555)
Neurologic	2.84	1.119*	0.0444	0.852
		(0.458)	(0.320)	(0.548)
Nuclear	6.84	2.809***	0.205	2.504**
		(0.627)	(0.501)	(0.789)
Other Organ Systems	9.51	1.288	-0.851	2.074
		(1.035)	(0.860)	(1.310)
Pulmonary	.968	0.251+	-0.0349	0.280+
		(0.137)	(0.0735)	(0.159)
Skin	6.18	1.447*	-0.390	1.609*
		(0.567)	(0.513)	(0.731)
Standard X-ray	17	2.226**	0.611	1.614
		(0.840)	(0.615)	(1.029)
Test - Miscellaneous	.636	-0.511*	0.364	-0.861*
		(0.257)	(0.392)	(0.437)
Ultrasound	9.45	3.006***	0.670*	2.341***
		(0.401)	(0.280)	(0.482)
Vascular	5.33	-0.0421	-0.496	-0.106
		(0.832)	(1.090)	(1.326)
Calendar Time Fixed Effects		Month, Year	Month, Year	Month, Year $\times$ Treat
Person Fixed Effects		Yes	Yes	Yes
Number of Enrollees		22269	49417	71686
Person-Months		516953	1152616	1669569

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each row and column presents the coefficient estimates for the "post" turning 65 years old indicator of a different regression. The outcome variable is RVUs associated with the BETOS subcategory listed in the first column. This table and tables A7 and A9 contain all the BETOS subcategories we include in our definition of "core" services. Standard errors clustered at the patient level are in parentheses below the coefficient estimates. The unit of observation is a patient-month. The first two columns are estimated using equations 2 and 3. "New dual" refers to our treatment group, individuals whose insurance changes at 65. "Always duals" are our control group. They were dual enrolled in Medicare before and after turning 65. These regressions include patient fixed effects, calendar-month and calendar-year fixed effects, and difference out any pre-trends. The third column is a difference-in-differences specification which uses the "always duals" as the control group. The third column is estimated using equations 4 and 5, and includes patient fixed effects, calendar-month and calendar-year fixed effects, and differences out pre-trends separately for the treatment and control groups.

Table A9: Regression Results: Each BETOS Subcategory: E&M Subcategories

	New Dual Pre-Period Sample Mean	(1) New Dual	(2) Always Dual	(3) Diff-in-Diff
Behavioral Health Services	46	7.790***	2.376	9.513***
		(1.998)	(1.609)	(2.597)
Care Management/Coordination	1.52	-0.157	0.0109	0.0324
		(0.213)	(0.0304)	(0.215)
Observation Care Services	2.02	-0.0733	0.0236	-0.164
		(0.270)	(0.128)	(0.291)
Office/Outpatient Services	53	16.31***	0.814	15.13***
		(0.663)	(0.497)	(0.819)
Ophthalmological Services	4.75	0.310	0.0135	0.403+
		(0.197)	(0.132)	(0.233)
Calendar Time Fixed Effects		Month, Year	Month, Year	Month, Year × Treat
Person Fixed Effects		Yes	Yes	Yes
Number of Enrollees		22269	49417	71686
Person-Months		516953	1152616	1669569

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each row and column presents the coefficient estimates for the "post" turning 65 years old indicator of a different regression. The outcome variable is RVUs associated with the BETOS subcategory listed in the first column. This table and tables A7 and A8 contain all the BETOS subcategories we include in our definition of "core" services. Standard errors clustered at the patient level are in parentheses below the coefficient estimates. The unit of observation is a patient-month. The first two columns are estimated using equations 2 and 3. "New dual" refers to our treatment group, individuals whose insurance changes at 65. "Always duals" are our control group. They were dual enrolled in Medicare before and after turning 65. These regressions include patient fixed effects, calendar-month and calendar-year fixed effects, and difference out any pre-trends. The third column is a difference-in-differences specification which uses the "always duals" as the control group. The third column is estimated using equations 4 and 5, and includes patient fixed effects, calendar-month and calendar-year fixed effects, and differences out pre-trends separately for the treatment and control groups.

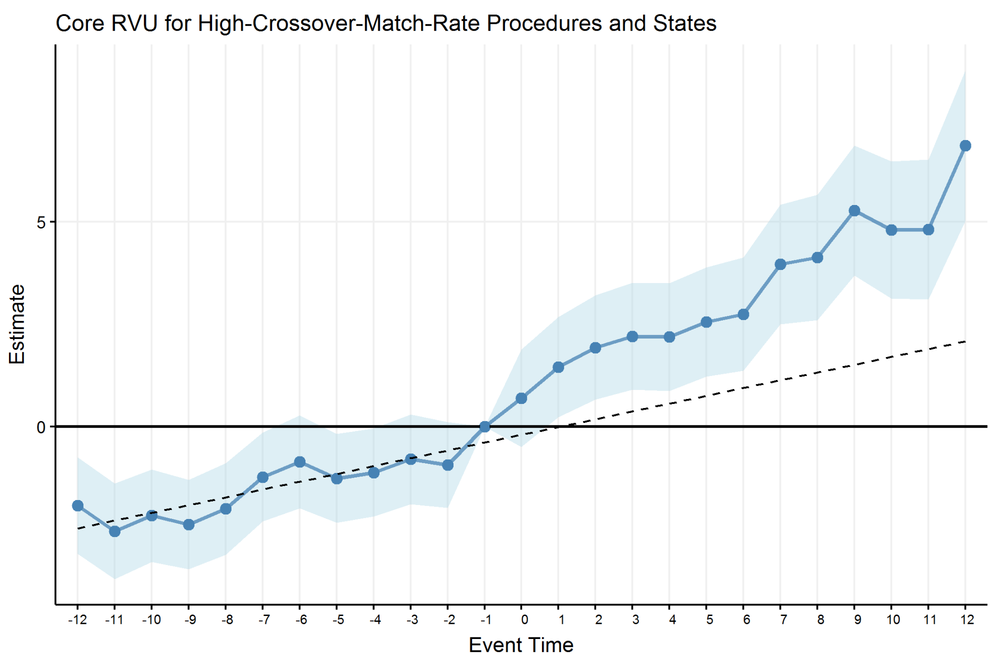
Table A10: Robustness Checks: Dropping Calendar-Month and Calendar-Year Effects, Dropping 2014 data

	(1) New Dual	(2) Diff-in-Diff	(3) New Dual	(4) Diff-in-Diff	(5) New Dual	(6) Diff-in-Diff
Core Spending	87.26***	85.29***	89.95***	83.33***	88.48***	90.23***
	(3.272)	(4.654)	(3.244)	(4.624)	(3.994)	(5.753)
Core RVUs	49.32***	48.27***	53.25***	47.02***	46.32***	46.53***
	(4.357)	(5.622)	(4.301)	(5.570)	(5.374)	(7.003)
E&M RVUs	21.95***	19.46***	23.90***	19.82***	18.58***	18.43***
	(2.074)	(2.601)	(2.076)	(2.601)	(2.543)	(3.245)
Office and Outpatient E&M RVUs	15.98***	14.69***	16.74***	14.70***	15.11***	13.14***
	(0.646)	(0.797)	(0.640)	(0.791)	(0.797)	(0.990)
Imaging RVUs	11.90***	10.09***	13.03***	10.22***	12.33***	10.85***
	(1.554)	(1.885)	(1.529)	(1.861)	(1.909)	(2.342)
Procedures RVUs	10.33***	13.25***	10.91***	11.73***	9.543**	11.52**
	(2.528)	(3.416)	(2.488)	(3.377)	(3.119)	(4.256)
Tests RVUs	5.139***	5.471***	5.419***	5.250***	5.870***	5.729**
	(1.066)	(1.386)	(1.058)	(1.379)	(1.357)	(1.748)
Primary Care Visits	0.0505***	0.0434***	0.0531***	0.0448***	0.0517***	0.0416***
	(0.00394)	(0.00483)	(0.00392)	(0.00481)	(0.00481)	(0.00600)
New Patient Visit, Primary	0.00546***	0.00492***	0.00568***	0.00508***	0.00605***	0.00418***
	(0.000686)	(0.000863)	(0.000679)	(0.000857)	(0.000822)	(0.00105)
Number of Providers, Primary	0.105***	0.0976***	0.107***	0.0993***	0.0975***	0.0909***
	(0.00542)	(0.00681)	(0.00537)	(0.00675)	(0.00659)	(0.00839)
Specialists Visits	0.0621***	0.0600***	0.0663***	0.0586***	0.0598***	0.0499***
	(0.00420)	(0.00523)	(0.00415)	(0.00519)	(0.00517)	(0.00652)
New Patient Visit, Specialist	0.0175***	0.0170***	0.0182***	0.0165***	0.0177***	0.0154***
	(0.00136)	(0.00176)	(0.00133)	(0.00174)	(0.00163)	(0.00217)
Number of Providers, Specialist	0.150***	0.154***	0.159***	0.153***	0.132***	0.151***
	(0.0124)	(0.0156)	(0.0123)	(0.0155)	(0.0155)	(0.0197)
Number of Procedure Codes	1.083***	1.182***	1.172***	1.192***	1.169***	1.259***
	(0.0810)	(0.100)	(0.0800)	(0.0993)	(0.0986)	(0.124)
Flu Vaccine RVUs	0.816***	0.636***	0.750***	0.833***	0.768***	0.627***
	(0.0227)	(0.0328)	(0.0246)	(0.0363)	(0.0220)	(0.0378)
Flu Vaccine Visits	0.0161***	0.0144***	0.0122***	0.0182***	0.0144***	0.0129***
	(0.000723)	(0.00100)	(0.000753)	(0.00109)	(0.000894)	(0.00127)
Calendar Time Fixed Effects	Month	Month × Treatment	None	None	Month	Month × Treatment
Person Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Includes 2014 Data	Yes	Yes	Yes	Yes	No	No
Number of Enrollees	22269	71686	22269	71686	14758	44705
Person-Months	516953	1669569	516953	1669569	343585	1047792

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

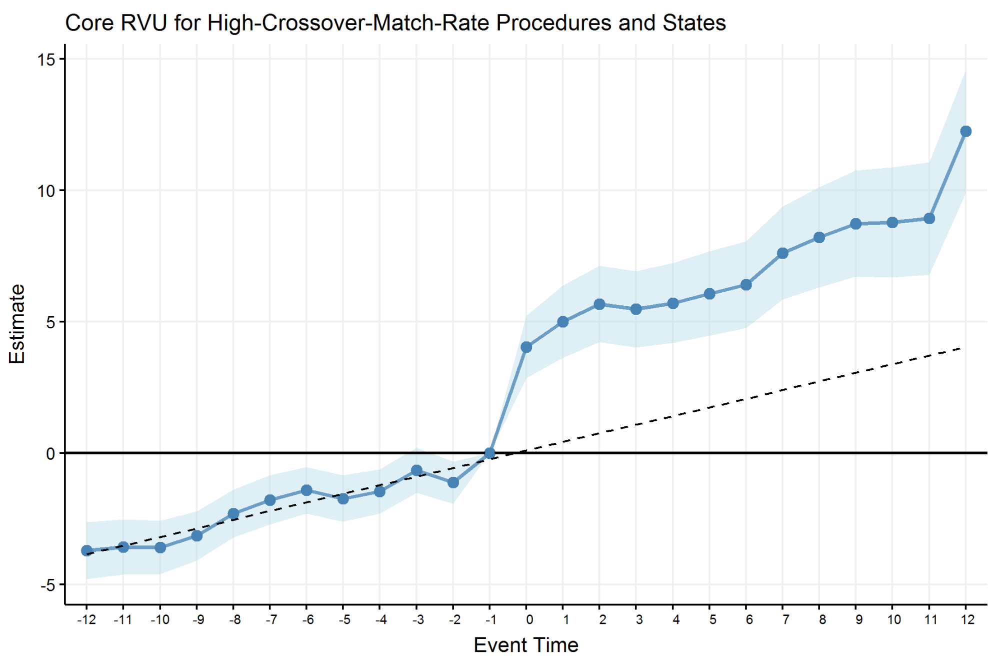
Notes: This table is similar to Table 2, except we vary the set of calendar time fixed effects, whether we include person fixed effects, and whether we include 2014 data. See the lower panel for the specification. Each row and column present results of a different regression. The outcome variable is listed in the first column and we present coefficient estimates for the "post" turning 65 years old indicator. Standard errors clustered at the patient level are in parentheses below the coefficient estimate. The unit of observation is a patient-month.

Figure A2: Robustness Checks: Event Study using only Medicaid Claims where the Crossover Match Rate is High



Notes: This figure is similar to Figure 3, but is run only on a sample of Medicaid claims from 10 states with the highest match rate for Medicare and crossover claims and only on procedures where the match rate exceeds 90%. This figure presents coefficient estimates and 95% confidence intervals from our non-parametric event study described by equation 1. The unit of observation for these regressions is a patient-month. The regressions include patient fixed effects, calendar year fixed effects, and calendar month fixed effects. The blue superimposed line shows the pre-trend line which is extrapolated into the post-period.

Figure A3: Robustness Checks: Event Study using only Medicaid Claims where the Crossover Match Rate is High



Notes: This figure is similar to Figure 3, but is run only on a sample of Medicaid claims from 5 states with the highest match rate for Medicare and crossover claims and only on procedures where the match rate exceeds 90%. This figure presents coefficient estimates and 95% confidence intervals from our non-parametric event study described by equation 1. The unit of observation for these regressions is a patient-month. The regressions include patient fixed effects, calendar year fixed effects, and calendar month fixed effects. The blue superimposed line shows the pre-trend line which is extrapolated into the post-period.

Table A11: Robustness Checks: Changing Panel Time Window and Dropping Person Fixed Effects

	(1) New Dual	(2) Diff-in-Diff	(3) New Dual	(4) Diff-in-Diff	(5) New Dual	(6) Diff-in-Diff
Core Spending	89.62***	89.08***	88.95***	95.66***	91.36***	93.75***
	(3.398)	(4.817)	(3.890)	(5.485)	(3.903)	(5.504)
Core RVUs	54.01***	53.82***	52.45***	57.69***	54.27***	55.21***
	(4.528)	(5.837)	(5.123)	(6.622)	(5.181)	(6.679)
E&M RVUs	24.18***	24.92***	21.53***	21.94***	23.76***	20.48***
	(2.164)	(2.785)	(2.357)	(3.119)	(2.489)	(3.218)
Office and Outpatient E&M RVUs	16.31***	15.13***	15.24***	15.49***	15.34***	15.44***
	(0.663)	(0.819)	(0.788)	(0.955)	(0.788)	(0.958)
Imaging RVUs	12.25***	10.12***	12.39***	12.54***	12.25***	12.15***
	(1.639)	(1.959)	(1.803)	(2.188)	(1.788)	(2.189)
Procedures RVUs	12.33***	14.07***	10.33***	14.54***	10.06***	14.38***
	(2.608)	(3.486)	(3.016)	(3.985)	(3.002)	(3.989)
Tests RVUs	5.256***	4.709**	8.200***	8.671***	8.209***	8.195***
	(1.121)	(1.447)	(1.225)	(1.615)	(1.259)	(1.626)
Primary Care Visits	0.0529***	0.0452***	0.0470***	0.0446***	0.0453***	0.0427***
	(0.00404)	(0.00496)	(0.00496)	(0.00593)	(0.00497)	(0.00596)
New Patient Visit, Primary	0.00556***	0.00492***	0.00565***	0.00502***	0.00559***	0.00493***
	(0.000723)	(0.000891)	(0.000825)	(0.00101)	(0.000812)	(0.00101)
Number of Providers, Primary	0.107***	0.100***	0.0978***	0.0974***	0.0996***	0.0944***
	(0.00564)	(0.00705)	(0.00661)	(0.00816)	(0.00663)	(0.00821)
Specialists Visits	0.0626***	0.0627***	0.0622***	0.0702***	0.0648***	0.0680***
	(0.00434)	(0.00541)	(0.00515)	(0.00631)	(0.00511)	(0.00630)
New Patient Visit, Specialist	0.0178***	0.0178***	0.0188***	0.0198***	0.0189***	0.0197***
	(0.00142)	(0.00180)	(0.00165)	(0.00208)	(0.00161)	(0.00207)
Number of Providers, Specialist	0.153***	0.153***	0.152***	0.177***	0.152***	0.176***
	(0.0129)	(0.0161)	(0.0147)	(0.0184)	(0.0148)	(0.0185)
Number of Procedure Codes	1.116***	1.279***	1.222***	1.488***	1.330***	1.363***
	(0.0841)	(0.106)	(0.0976)	(0.123)	(0.103)	(0.127)
Flu Vaccine RVUs	0.811***	0.619***	0.819***	0.644***	0.818***	0.645***
	(0.0223)	(0.0330)	(0.0340)	(0.0452)	(0.0327)	(0.0441)
Flu Vaccine Visits	0.0158***	0.0139***	0.0167***	0.0145***	0.0166***	0.0145***
	(0.000725)	(0.00101)	(0.000987)	(0.00131)	(0.000963)	(0.00130)
Panel Restriction	2 Months	2 Months	12 Months	12 Months	12 Months	12 Months
Calendar Time Fixed Effects	Month, Year	Month, Year × Treat	Month, Year	Month, Year × Treat	Month, Year	Month, Year × Treat
Person Fixed Effects	Yes	Yes	Yes	Yes	No	No
Number of Enrollees	22269	71686	15253	52636	15253	52636
Person-Months	516953	1669569	337647	1231057	337647	1231057

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table is similar to Table 2, except we vary the amount of time we require an individual to be continuously enrolled around turning 65 to remain in our sample. The baseline is 6 months. The last 2 columns also drops person fixed effects. Person fixed effects control for differences in patient composition, however, with a 12 month continuous enrollment window there is no change in the composition of patients across time as we have a fully balanced panel. See the lower panel for the specification. Each row and column present results of a different regression. The outcome variable is listed in the first column and we present coefficient estimates for the "post" turning 65 years old indicator. Standard errors clustered at the patient level are in parentheses below the coefficient estimate. The unit of observation is a patient-month.

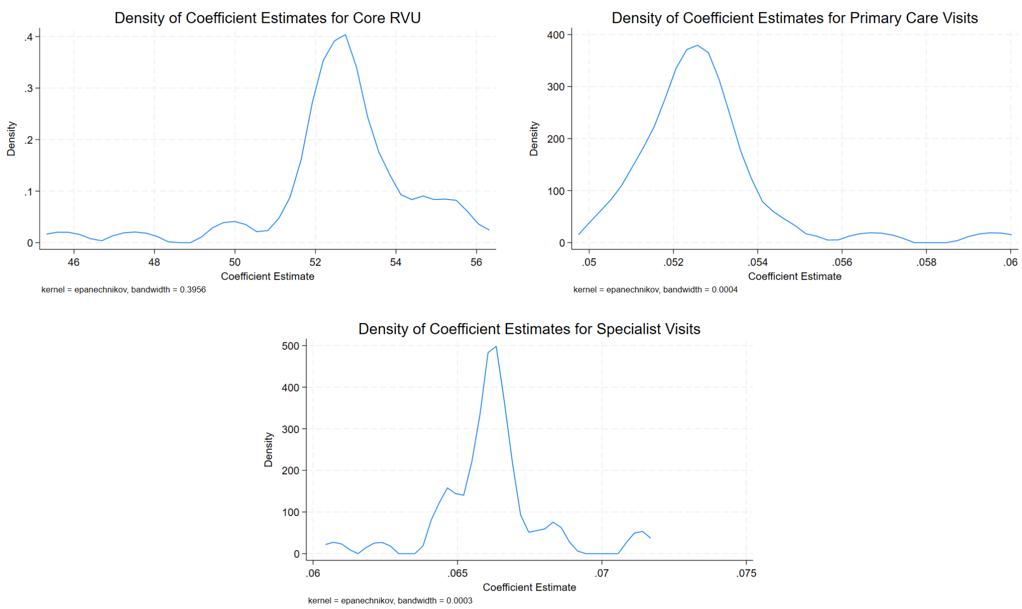
Table A12: Robustness Checks: Dropping Individuals Ever in a Nursing Home Over the Sample Period

	(1) New Dual	(2) Always Dual	(3) Diff-in-Diff
Core Spending	90.27***	4.439	89.60***
	(3.618)	(3.744)	(5.118)
Core RVUs	55.44***	3.230	55.73***
	(4.767)	(4.013)	(6.150)
E&M RVUs	22.91***	3.176+	23.62***
	(2.228)	(1.687)	(2.821)
Office and Outpatient E&M RVUs	17.93***	1.112*	16.59***
	(0.721)	(0.537)	(0.889)
Imaging RVUs	12.42***	1.823	10.43***
	(1.746)	(1.204)	(2.100)
Procedures RVUs	13.02***	-1.984	14.82***
	(2.804)	(2.623)	(3.736)
Tests RVUs	7.089***	0.215	6.857***
	(1.028)	(1.024)	(1.418)
Primary Care Visits	0.0598***	0.00861**	0.0510***
	(0.00442)	(0.00321)	(0.00543)
New Patient Visit, Primary	0.00601***	0.0000862	0.00556***
	(0.000797)	(0.000609)	(0.000980)
Number of Providers, Primary	0.0978***	0.00986*	0.0880***
	(0.00541)	(0.00435)	(0.00687)
Specialists Visits	0.0691***	0.000384	0.0696***
	(0.00470)	(0.00356)	(0.00585)
New Patient Visit, Specialist	0.0197***	0.000118	0.0198***
	(0.00153)	(0.00128)	(0.00194)
Number of Providers, Specialist	0.147***	0.00487	0.144***
	(0.0122)	(0.00978)	(0.0155)
Number of Procedure Codes	0.657***	-0.0375	0.836***
	(0.0806)	(0.0568)	(0.101)
Flu Vaccine RVUs	0.807***	0.162***	0.598***
	(0.0253)	(0.0255)	(0.0363)
Flu Vaccine Visits	0.0149***	0.000948	0.0128***
	(0.000809)	(0.000748)	(0.00110)
Calendar Time Fixed Effects	Month, Year	Month, Year	Month, Year $\times$ Treatment
Person Fixed Effects	Yes	Yes	Yes
Number of Enrollees	19133	43413	62546
Person-Months	444010	1011652	1455662

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table is similar to Table 2, except we drop individuals ever enrolled in a nursing home during our sample period. Each row and column present results of a different regression. The outcome variable is listed in the first column and we present coefficient estimates for the "post" turning 65 years old indicator. Standard errors clustered at the patient level are in parentheses below the coefficient estimate. The unit of observation is a patient-month.

Figure A4: Robustness check: Leaving one state out at a time



Notes: This figure presents the density of coefficient estimates for a "leave-one-state" out analysis. We rerun our main "new dual" regression dropping one state at a time. This figure presents the density of the coefficient estimates from that exercise.

Table A13: Robustness Checks: Results by Region

	(1) Midwest	(2) Northeast	(3) South	(4) West
Core Spending	97.30***	91.58***	77.04***	110.7***
	(6.398)	(6.168)	(5.769)	(11.40)
Core RVUs	53.99***	80.72***	31.37***	71.50***
	(8.682)	(7.095)	(8.129)	(13.85)
E&M RVUs	23.58***	38.52***	16.30***	16.66*
	(3.918)	(3.538)	(3.894)	(6.994)
Office and Outpatient E&M RVUs	15.77***	21.49***	13.48***	14.70***
	(1.261)	(1.357)	(1.017)	(2.420)
Imaging RVUs	6.875*	17.24***	9.995***	24.87***
	(3.326)	(2.148)	(2.976)	(4.982)
Procedures RVUs	15.89**	18.17***	4.610	16.13+
	(4.954)	(4.376)	(4.570)	(8.670)
Tests RVUs	7.638***	6.792***	0.472	13.84***
	(2.032)	(1.520)	(2.243)	(2.390)
Primary Care Visits	0.0466***	0.0615***	0.0603***	0.0174
	(0.00793)	(0.00743)	(0.00627)	(0.0166)
New Patient Visit, Primary	0.00612***	0.00630***	0.00486***	0.00516*
	(0.00140)	(0.00122)	(0.00127)	(0.00220)
Number of Providers, Primary	0.125***	0.146***	0.0773***	0.0687***
	(0.0100)	(0.0112)	(0.00964)	(0.0189)
Specialists Visits	0.0694***	0.0700***	0.0543***	0.0543***
	(0.00821)	(0.00846)	(0.00720)	(0.0140)
New Patient Visit, Specialist	0.0191***	0.0142***	0.0178***	0.0229***
	(0.00254)	(0.00280)	(0.00245)	(0.00440)
Number of Providers, Specialist	0.163***	0.185***	0.121***	0.179***
	(0.0237)	(0.0254)	(0.0222)	(0.0384)
Number of Procedure Codes	1.049***	1.544***	0.939***	0.944***
	(0.175)	(0.153)	(0.141)	(0.202)
Flu Vaccine RVUs	0.903***	0.788***	0.796***	0.615***
	(0.0383)	(0.0356)	(0.0237)	(0.152)
Flu Vaccine Visits	0.0199***	0.0131***	0.0156***	0.00951***
	(0.00124)	(0.00172)	(0.00111)	(0.00248)
Calendar Time Fixed Effects	Month, Year	Month, Year	Month, Year	Month, Year
Person Fixed Effects	Yes	Yes	Yes	Yes
Number of Enrollees	6558	5354	8230	2127
Person-Months	151681	125244	190686	49342

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table is similar to the "new dual" results of Table 2, except we run the regressions separately by region. Each row and column present results of a different regression. The outcome variable is listed in the first column and we present coefficient estimates for the "post" turning 65 years old indicator. Standard errors clustered at the patient level are in parentheses below the coefficient estimate. The unit of observation is a patient-month.

Table A14: Cross-state variation in acceptance rates measured with survey data

	(1) Primary Care All Visits	(2) Primary Care New-Patient Visits	(3) Specialists All Visits	(4) Specialists New-Patient Visits	(5) Total Physician Visits
Post=1	0.0350+	0.00331**	0.0359*	0.00737+	0.0709**
	(0.0184)	(0.00105)	(0.0151)	(0.00351)	(0.0220)
Post=1 × Difference in Acceptance Rates	-0.122	-0.0203	-0.277*	-0.101**	-0.399*
	(0.111)	(0.0126)	(0.116)	(0.0264)	(0.149)
Pre-Period Mean	0.260	0.008	0.243	0.031	0.503
Mean Difference in Acceptance Rates	-0.109	-0.109	-0.109	-0.109	-0.109
Person Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Enrollees	19242	19242	19242	19242	19242
Person-Months	447207	447207	447207	447207	447207

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table is similar to Table 6, but uses the difference in acceptance rates, rather than including the Medicare and Medicaid acceptance rates separately. Each column presents results of a different regression estimated using equation 6. The outcome variable is listed in the header and we present coefficient estimates for the "post" turning 65 years old indicator, as well as an interaction between the post indicator and the difference in Medicare and Medicaid acceptance rates. Medicaid and Medicare acceptance rates are derived from MACPAC (2021). Standard errors clustered at the state level are in parentheses below the coefficient estimates. The unit of observation is a patient-month and the sample for this regression is only the "new dual" population.

Table A15: Cross-state variation in acceptance rates measured with survey data

	(1) Core RVUs	(2) E&M RVUs	(3) Office/Outpatient RVUs
Post=1	-54.76	-211.2+	-68.15+
	(212.7)	(115.0)	(38.54)
Post=1 × State Medicaid Accept. Rate	-169.5	-46.98	-22.92
	(111.3)	(58.15)	(17.72)
Post=1 × State Medicare Accept. Rate	265.8	302.7+	114.5*
	(289.5)	(144.9)	(49.23)
Pre-Period Mean	253.787	102.002	52.946
Mean Medicaid Accept. Rate	0.780	0.780	0.780
Mean Medicare Accept. Rate	0.889	0.889	0.889
Person Fixed Effects	Yes	Yes	Yes
Number of Enrollees	19242	19242	19242
Person-Months	447207	447207	447207

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table is similar to Table 6, but the outcomes are RVU measures rather than visits. Each column presents results of a different regression estimated using equation 6. The outcome variable is listed in the header and we present coefficient estimates for the "post" turning 65 years old indicator, as well as an interaction between the post indicator and Medicare and Medicaid acceptance rates, derived from MACPAC (2021). Standard errors clustered at the state level are in parentheses below the coefficient estimates. The unit of observation is a patient-month and the sample for this regression is only the "new dual" population.

Table A16: Cross-state variation in the fee gap

	(1) Primary Care All Visits	(2) Primary Care New-Patient Visits	(3) Specialists All Visits	(4) Specialists New-Patient Visits	(5) Total Physician Visits
Post=1	0.0432***	0.00546***	0.0667***	0.0163***	0.110***
	(0.00880)	(0.000958)	(0.00972)	(0.00320)	(0.0125)
Post=1 × Fee Gap	0.0453	0.000862	0.000309	0.0194	0.0456
	(0.0519)	(0.00448)	(0.0498)	(0.0113)	(0.0811)
Pre-Period Mean	0.260	0.008	0.243	0.031	0.503
Mean Fee Gap	0.117	0.117	0.117	0.117	0.117
Person Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Enrollees	19242	19242	19242	19242	19242
Person-Months	447207	447207	447207	447207	447207

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each column presents results of a different regression estimated using equation 6, except we use the fee gap between Medicaid and Medicare instead of acceptance rates. The outcome variable is listed in the header and we present coefficient estimates for the "post" turning 65 years old indicator, as well as an interaction between the post indicator and the fee gap. We construct the fee gap using a regression with Medicare and Medicaid fees as the outcome, with a state-Medicaid indicator and CPT code fixed effects. Larger numbers means that Medicare pays relatively more than Medicaid. Standard errors clustered at the state level are in parentheses below the coefficient estimates. The unit of observation is a patient-month and the sample for this regression is only the "new dual" population.

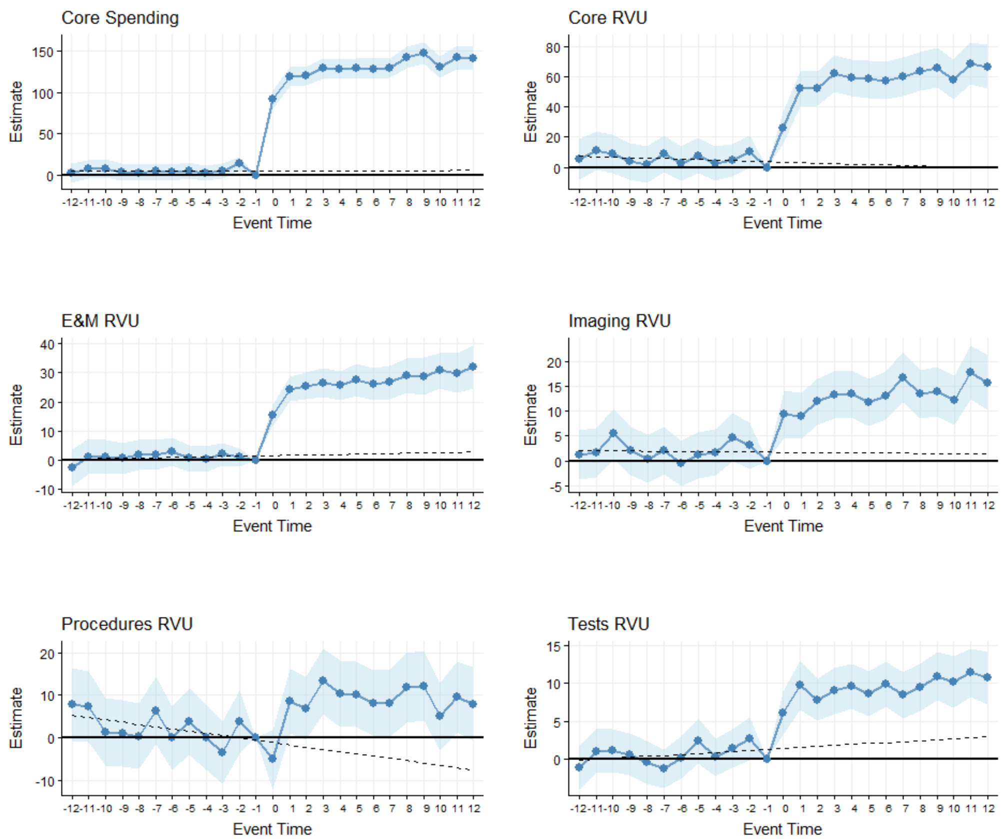
Table A17: Cross-state variation in the fee gap, dropping "lesser of" states

	(1) Primary Care All Visits	(2) Primary Care New-Patient Visits	(3) Specialists All Visits	(4) Specialists New-Patient Visits	(5) Total Physician Visits
Post=1	0.0303	0.00316+	0.0709*	0.0170*	0.101*
	(0.0179)	(0.00133)	(0.0181)	(0.00476)	(0.0257)
Post=1 $\times$ Fee Gap	0.212*	0.00429	0.0834	0.0241	0.296*
	(0.0753)	(0.00485)	(0.0919)	(0.0169)	(0.0998)
Pre-Period Mean	0.242	0.010	0.200	0.027	0.442
Mean Fee Gap	0.117	0.117	0.117	0.117	0.117
Person Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Enrollees	4101	4101	4101	4101	4101
Person-Months	94957	94957	94957	94957	94957

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

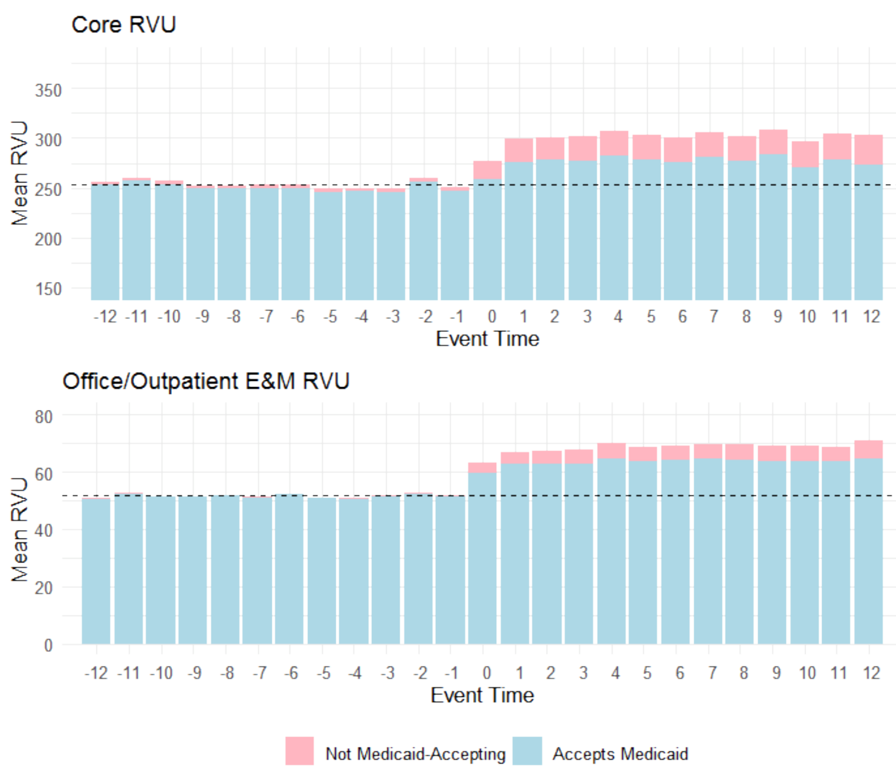
Notes: Each column presents results of a different regression estimated using equation 6, except we use the fee gap between Medicaid and Medicare instead of acceptance rates. This table is the same as Table A16, except we only keep states without "lesser-of" policies. The outcome variable is listed in the header and we present coefficient estimates for the "post" turning 65 years old indicator, as well as an interaction between the post indicator and the fee gap. We construct the fee gap using a regression with Medicare and Medicaid fees as the outcome, with a state-Medicaid indicator and CPT code fixed effects. Larger numbers means that Medicare pays relatively more than Medicaid. Standard errors clustered at the state level are in parentheses below the coefficient estimates. The unit of observation is a patient-month and the sample for this regression is only the "new dual" population.

Figure A5: Health-care utilization by month for those becoming dual-enrolled in the QMB program



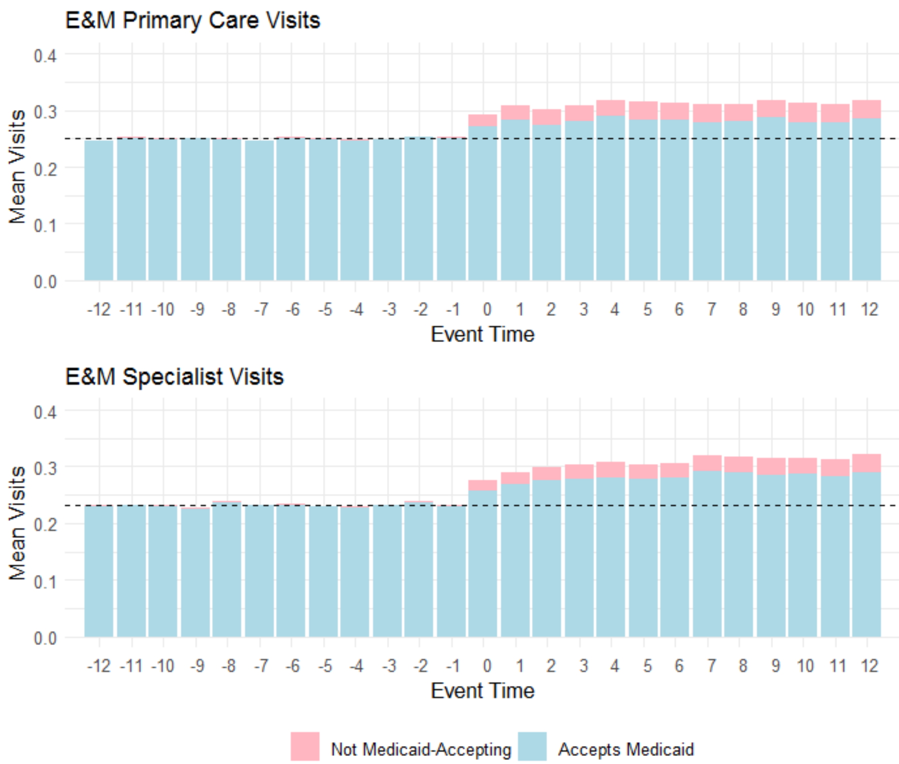
Notes: This figure is similar to Figure 4, except we only include the subset of enrollees covered under the full-benefit Qualified Medicare Beneficiary (QMB), also known as QMB Plus. This figure presents coefficient estimates and 95% confidence intervals from our non-parametric event study described by equation 1. The unit of observation for these regressions is a patient-month. The regressions include patient fixed effects, calendar year fixed effects and calendar month fixed effects. The blue superimposed line shows the pre-trend line which is extrapolated into the post-period. The sample for this figure is only our "new dual" treated group, those who become dual eligible at 65 years old.

Figure A6: Monthly Utilization by Medicaid-Accepting and Non-Medicaid-Accepting Providers



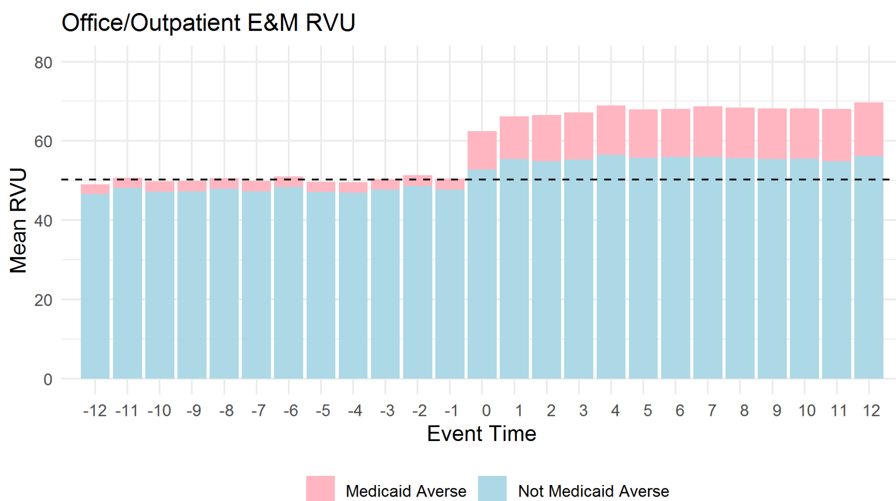
Notes: This figure presents sample means for Core RVU and Office/Outpatient E&M RVU at the patient-month level. The superimposed blue line represents the pre-period average for each variable. The blue bars represent visits or RVUs for providers who are Medicaid-accepting, while the pink bars represent visits or RVUs to providers who we define as Non-Medicaid-accepting. Non-Medicaid-accepting is defined as a provider either (1) having less than 1% of their claims being Medicaid or (2) responding as not taking Medicaid in SK&A and having less than 2% of of their claims being Medicaid. The share of Medicaid claims is computed based on a provider's combined number of Medicare and Medicaid claims.

Figure A7: Monthly Visits by Medicaid-Accepting and Non-Medicaid-Accepting Providers



Notes: This figure presents sample means for Core RVU and E&M RVU at the patient-month level. The superimposed blue line represents the pre-period average for each variable. The blue bars represent visits or RVUs for providers who are Medicaid-accepting, while the pink bars represent visits or RVUs to providers who we define as Non-Medicaid-accepting. Non-Medicaid-accepting is defined as a provider either (1) having less than 1% of their claims being Medicaid or (2) responding as not taking Medicaid in SK&A and having less than 2% of of their claims being Medicaid. The share of Medicaid claims is computed based on a provider's combined number of Medicare and Medicaid claims.

Figure A8: Office and Outpatient E&M Utilization at Medicaid-Averse and Non-Medicaid-Averse Physicians



Notes: This figure presents sample means for monthly office and outpatient E&M RVUs. The pink portion of the bars represent visits to providers who do not see a new medicaid patient in the given year (Medicaid averse), while the blue portion of the bar reflects visits at providers who see at least one new medicaid patient in the year (not Medicaid averse).

D More Details on Quality Measures

D.1 Quality Payment Program Quality Measure

Medicare's quality payment program data were collected as part of the merit-based incentive payment system which began in 2017. We use the data from 2017, which is the first year the data were collected. The data is at the provider level and contain an aggregated score as well as specific quality measures (e.g. the share of women receiving breast cancer screenings, influenza immunization rates, or screening for future fall risk). Each measure is scored out of 10 points, which corresponds to the decile for that measure.

In Table A18 we present results for the top 5 most commonly reported measures, vary the set of controls and the sample of providers used to test robustness. Column 1 has no controls. Each of the top 5 most commonly submitted measures has a coefficient between -0.2 and -0.32, suggesting that providers who take Medicaid score 0.2 to 0.3 deciles worse for that measure than providers who do not take Medicaid, on average. This effect size is consistent with the -1.43 coefficient across the top 6 scores. Column 2 adds state fixed effects. Column 3 adds specialty fixed effects. Column 4 adds years serving Medicare patients, an indicator for whether the provider practices in a health professional shortage area, and practice size. Results are very similar regardless of the set of controls used.

Finally, column 5 includes both large and small providers. For most of the analysis, we focus on small providers because there is more scope to manipulate the scores for large providers (they have more scores that will meet minimum volume requirements, and they can choose to participate individually or as a group). These results show that our results still hold for all providers. However, effect sizes are much smaller. This is because there is considerably less variation in large provider QPP scores.

D.2 Revealed-preference Quality Measure

For traditional fee-for-service Medicare patient, i, visiting physician, p, the distance, $d_{i,p}$ between the patient and physician is determined based on location of the patient's zip code and the physician's zip code. Let $f()$ be a flexible function of distance. Let the mean utility of visiting physician p be δ_p and let the idiosyncratic component of utility be denoted $\epsilon_{i,p}$, which is distributed type I extreme value. The utility of patient , i, visiting physician, p, be denoted:

$$U_{i,p} = \delta_p +^1 \cdot f(d_{i,p}) + \epsilon_{i,p} \tag{9}$$

The number of patients in the data as well of the number of physicians creates a computational challenge applying standard maximum likelihood estimation. To sidestep this issue, we simplify by aggregating over patients that reside in the same zip code area, so the only difference between patients that reside within the same zip code is the idiosyncratic error, $\epsilon_{i,p}$. Let z represent the aggregate patient zip code. We also assume an outside good market share of 5 percent, which one can think of as patients potentially not seeking care or seeking care in an emergency room. We let $S_{z,0}$ denotes the market share of the outside good where the utility has been normalized to zero, With these assumptions, the share of patients in zip code z that visit physician p may be expressed as:

$$S_{z,p} = \frac{\delta_p +^1 \cdot f(d_{z,p})}{1 + \sum_{p=1}^{AllP} \delta_p +^1 \cdot f(d_{z,p})} \tag{10}$$

We can then estimate a linear demand function using OLS by applying the insights of Berry (1994). The linear regression model is:

$$log(S_{z,p}) - log(S_{z,0}) = \delta_p +^1 \cdot f(d_{i,p}) \tag{11}$$

The estimated mean utility is then $\hat{\delta_p}$ is then our measure of quality. The revealed-preference measure of quality is intended to capture a dimension of quality that is distinct from the QPP measures. It may capture other measures of clinical quality not captured by the QPP measures, but it may also capture non-clinical aspects of quality, such as office amenities, which were found to be important in Romley and Goldman (2011).

Table A18: Correlation between Medicare Quality Payment Program Quality Measures and Taking Medicaid Patients

	(1)	(2)	(3)	(4)	(5)
Clinical Quality Measures:					
Sum of QPP Clinical Quality Scores	-1.428***	-1.556***	-1.186***	-1.230***	-0.451***
	(0.101)	(0.108)	(0.112)	(0.112)	(0.0406)
N	79715	77538	77538	77538	498742
Five Most Common Measures:					
Screening for Tobacco Use	-0.203***	-0.204***	-0.231***	-0.236***	-0.0475***
	(0.0314)	(0.0333)	(0.0349)	(0.0352)	(0.0103)
N	39920	38653	38653	38653	284164
Controlling High Blood Pressure	-0.283***	-0.337***	-0.295***	-0.288***	-0.128***
	(0.0416)	(0.0446)	(0.0436)	(0.0440)	(0.00927)
N	23373	22450	22450	22450	270872
Breast Cancer Screening	-0.246***	-0.255***	-0.423***	-0.413***	-0.0580***
	(0.0633)	(0.0690)	(0.0684)	(0.0690)	(0.00794)
N	10125	9686	9686	9686	257662
Pneumococcal Vaccination	-0.318***	-0.389***	-0.300***	-0.286***	-0.0862***
	(0.0451)	(0.0485)	(0.0519)	(0.0523)	(0.00935)
N	16761	16095	16095	16095	254882
Influenza Immunization	-0.247***	-0.290***	-0.275***	-0.288***	-0.0572***
	(0.0462)	(0.0493)	(0.0513)	(0.0516)	(0.00938)
N	18403	17641	17641	17641	242627
Sample	Small	Small	Small	Small	All
Speciality Fixed Effects	No	No	Yes	Yes	Yes
State Fixed Effects	No	Yes	Yes	Yes	Yes
Other Controls	No	No	No	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each row and column presents results of a different regression. The coefficient estimate presented is for an indicator for whether that provider sees Medicaid patients. The unit of observation is a provider, identified by their NPI (national provider identifier). The sample is all providers in the 2017 Medicare Quality Payment Program (QPP) data and merges that with the set of providers in our Medicaid and MDPPAS data. The outcome variable is listed in the first column. "Other controls" refer to years serving Medicare patients, an indicator for whether the provider practices in a health professional shortage area, and practice size.