The Impacts of Medicaid's Managed Long-Term Services and Supports on Health Outcomes in Medicare*

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April 3, 2026

Abstract

An aging US population has raised important questions regarding the organization, delivery, and funding of long-term services and supports (LTSS), prompting many state Medicaid programs to shift from fee-for-service to managed care models for LTSS delivery. We analyze the effects of transitioning to managed LTSS (MLTSS) on health outcomes among dual-eligible Medicare-Medicaid beneficiaries aged 65 and older in Florida and New York. Using Medicare claims data and a differences-in-differences design leveraging county-by-county MLTSS rollouts, we find that MLTSS leads to a 4.2 percent increase in hospitalizations in Florida, but no significant change in New York. Analysis of preventive care suggests that declining flu vaccination rates in Florida may have contributed to increased hospitalizations from respiratory causes. These findings highlight important differences in MLTSS effects across states and underscore the value of Medicare data for measuring health effects in the dual-eligible population.

JEL classification: H51, H75, I13, I18
Keywords: long-term services and supports; Medicaid managed care; dual-eligible population

*We thank Mark Duggan, Sherry Glied, Mary Goldstein, Sherri Rose, Jacob Wallace, and participants at the 2025 California Health Economics Conference for helpful comments. We are also extremely grateful to Mohan Ramanujan and Carla Tokman at the National Bureau of Economic Research for assistance and guidance with accessing the CMS data. Research reported in this article was supported by the National Institute on Aging of the National Institutes of Health under award number R01AG077949. Amanda Su also acknowledges support from the National Science Foundation Graduate Research Fellowship (under grant number DGE-1656518). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health or the National Science Foundation. All errors are our own.

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1 Introduction

As the US population ages, demand for assistance with basic daily living activities is increasing rapidly. Total spending on long-term services and supports—the medical and non-medical assistance that enables individuals with functional limitations to perform activities such as bathing, dressing, and eating—rose from $200 billion in 2009 to $560 billion in 2023 (Colello and Sorenson, 2025). State Medicaid agencies, which collectively finance nearly half of all LTSS spending, have sought to address these growing costs by shifting delivery from traditional fee-for-service (FFS) to managed care models. Under managed LTSS (MLTSS), private managed care plans receive fixed per-member per-month (capitated) payments from the government in exchange for arranging LTSS on behalf of enrollees (Hinton et al., 2022; Hinton and Raphael, 2025). These capitated arrangements are viewed as providing states with more predictable and possibly lower costs (Lewis et al., 2018), and allow for utilization control via provider networks, referrals, and prior authorization requirements (Salehian et al., 2022; Dobson et al., 2021; Wysocki et al., 2020). Motivated by these potential advantages, the number of states offering MLTSS has increased from eight in 2004 to 25 by the end of 2025 (Lewis et al., 2018; Dobson et al., 2021; Hodges et al., 2025).

Despite the growing adoption of MLTSS, there is limited causal evidence of its effects on patient health. This is due in part to data limitations: the poor quality of Medicaid LTSS claims data has significantly hampered researchers' ability to study the utilization of these services.[1] In this paper, we overcome this limitation by focusing on individuals who are dual-eligible for Medicare and Medicaid and use high-quality Medicare claims data to study the effects of MLTSS on patients' health.[2] For these beneficiaries, Medicaid pays for LTSS, while Medicare is the primary payer for all other healthcare services, including hospitalizations and preventive care.[3] Because these services are financed by Medicare rather than Medicaid, the outcomes we measure are not directly subject to the financial incentives embedded in MLTSS capitation arrangements, allowing us to capture changes in underlying health rather than utilization responses to MLTSS financial

[1]For example, in Medicaid data covering years 2011–2019—the period when several states transitioned to MLTSS—LTSS managed care encounter claims are largely missing. This means that it is impossible to study the effects of the transitions from FFS to MLTSS using Medicaid data over these years. We are thankful to Adrienne Sabety and Aileen Wu for investigating this issue in the Medicaid data and sharing this information with us.

[2]Individuals are dual-eligible for Medicaid and Medicare if their household income falls below their state's eligibility threshold and/or if they are eligible for Supplemental Security Income (SSI).

[3]Medicaid also pays for cost-sharing for Medicare-covered services for dual-eligible beneficiaries.

incentives.

Our analysis leverages the county-by-county transitions to Medicaid MLTSS in Florida and New York, which occurred between 2012 and 2015. We use a stacked differences-in-differences (DD) design (Cengiz et al., 2019; Deshpande and Li, 2019; Butters et al., 2022; Wing et al., 2024) in which we compare within-person changes in outcomes among beneficiaries in treated Florida and New York counties to those among beneficiaries in never-treated counties in two comparison states—Pennsylvania and California—over the same time period. Using a balanced panel of beneficiaries aged 65 and above who are continuously enrolled in full dual benefits and in traditional FFS Medicare, we find that the shift to MLTSS leads to a 0.9 percentage point (4.2 percent) increase in the likelihood of a hospitalization in the four years following the mandate in Florida, while there is no significant effect in New York. The overall hospitalization effect in Florida is driven by a 1.3 percentage point (7.2 percent) increase in hospitalizations that originated in the emergency department, and is accompanied by a 0.07 day (5.2 percent) increase in the average length of stay.[4]

We next analyze whether the effect on hospitalizations in Florida can be linked to changes in preventive care. We find that Florida's MLTSS transition leads to a 3.2 percentage point (10 percent) decline in the likelihood of an influenza (flu) vaccination. Moreover, Florida's increase in hospitalizations is concentrated among respiratory diagnoses, a plausible consequence of reduced flu vaccination rates. We do not find any significant effect on vaccinations or hospitalizations with respiratory diagnoses in New York. We mostly do not detect any significant effects on other preventive care measures, with the exception of increases in annual wellness visits in both states.

Lastly, we use a linkage between Medicare files and the Minimum Data Set (MDS) for nursing homes to examine whether changes in nursing home utilization are driving these effects. We find no significant changes in the incidence of nursing home assessments, suggesting that there is no extensive margin effect on nursing home care. We further find no evidence of switching between nursing homes nor changes in nursing home quality following the shift to MLTSS. Taken together, these results suggest that the effects of MLTSS on healthcare utilization materialize through channels occurring outside of nursing homes—that is, in home- or community-based settings.

The difference in the estimated effects of MLTSS between Florida and New York highlights

[4] The length of stay outcome is not conditional on having a hospitalization—individuals with no hospitalization are coded as zero for length of stay.

that MLTSS is not a uniform model, and its impacts depend on how states design and implement their programs. This heterogeneity may be explained by differences in payment structure: the risk adjustment models used to pay MLTSS plans differ between Florida and New York, which may translate into differences in how plans manage care for their enrollees across the two states. That payment models matter is well-established in the empirical literature on managed care (Cutler et al., 2000; Duggan, 2004; Duggan and Hayford, 2013; Kuziemko et al., 2018). Another explanation, which has received less attention in the literature, concerns how patients experience care under MLTSS. Under a FFS model, patients or their caregivers bear primary responsibility for coordinating services. MLTSS, by contrast, introduces case managers who can direct beneficiaries toward—or away from—services, including some that fall outside LTSS. The scope of this role may differ across states. For example, case managers in some states help beneficiaries schedule routine preventive services such as annual wellness visits, cancer screenings, and vaccinations (Saucier and Burwell, 2015; Pavle et al., 2019). Our finding that MLTSS reduces flu vaccination rates in Florida but not in New York is consistent with the possibility that flu vaccines are viewed as more discretionary than other forms of preventive care (Harris et al., 2009; Ernsting et al., 2012) and that case management practices differ across the two states. The accompanying increase in respiratory-related hospitalizations is consistent with extensive evidence that influenza vaccination reduces severe illness, especially among older adults (Dabestani et al., 2019).

Our paper contributes to a large body of work that compares patient outcomes between FFS and capitated managed care models in both public and private health insurance systems, mostly among relatively young and healthy patients (Cutler et al., 2000; Duggan, 2004; Howell et al., 2004; Currie and Fahr, 2005; Aizer et al., 2007; Herring and Adams, 2011; Duggan and Hayford, 2013; Brown et al., 2014; Cabral et al., 2018; Kuziemko et al., 2018; Chorniy et al., 2018; Duggan et al., 2018; Curto et al., 2019; Lee and Vabson, 2024). Three recent studies have analyzed the effects of transitions from FFS to Medicaid managed care on disabled and elderly patients, focusing on comprehensive managed care arrangements rather than LTSS specifically. Layton et al. (2022) find increased use of outpatient services and higher costs in Texas; Bogl et al. (2025) document an increase in emergency department visits and mortality in California; and Layton and Politzer

(2025) observe higher overall costs over a four-year period in national data.[5] However, these studies do not consider the effects of managed care in LTSS on healthcare utilization that is not under the same model. Two studies evaluating the effects of MLTSS specifically have reached somewhat different conclusions regarding effects on nursing home care (Bhaumik et al., 2025; Bhaumik and Grabowski, 2025). Using survey data from the Health & Retirement Study, Bhaumik et al. (2025) find no impact of MLTSS on nursing home care, hospitalizations, or the incidence of falls, though they document increases in home-based care services. Bhaumik and Grabowski (2025) use Medicare and MDS data aggregated to the state-year level and find that the adoption of MLTSS leads to a reduction in the share of dual-eligible individuals aged 65 and older who are residing in long-stay nursing homes.[6]

We build on these studies along two key dimensions. First, our analysis combines high-quality individual-level administrative Medicare data with Medicaid-driven policy variation, allowing us to detect health effects that studies relying on aggregate or survey data have limited statistical power to identify. Second, we measure treatment at the county level rather than the state level, which reduces measurement error in the analysis,[7] and allows us to uncover major differences in impacts between two states.

More broadly, our findings of increased hospitalizations and reduced flu vaccinations in Florida demonstrate that Medicaid's MLTSS can generate spillovers on the use of services covered by a different public program. A long-standing literature has examined whether changes in the organization of care delivery under one payer generate spillover effects on patients covered by other payers (Baker, 2003). Much of this work has focused on market-level channels through which changes to one payer affect provider behavior and, consequently, patients covered by all payers, including reductions in hospital costs and treatment intensity (Chernew et al., 2008; Baicker et

[5]Another recent study considers the effects of managed care in the Medicare program on hospitalizations among nursing home residents: Rahman et al. (2025) analyze the impacts of enrollment in Institutional Special Needs Plans—which are specific MA plans for individuals who are certified as requiring facility-based long-term care—and find evidence of a reduction in hospitalizations among these patients.

[6]Other analyses of Medicaid MLTSS have included a descriptive reports by Mathematica Policy Research (Libersky et al., 2018) and the Government Accountability Office (Government Accountability Office, 2020), a difference-in-differences evaluation of nursing home quality and patient composition in 3 states (Potter and Bowblis, 2021), and a pre-post evaluation of Virginia's Medicaid MLTSS transition using Medicaid data (Mellor et al., 2024). Harrison et al. (2023) study a mandatory transition to MLTSS in New York and find a reduction in nursing home use among dual-eligible beneficiaries with dementia compared to non-dual Medicare enrollees with dementia.

[7]For example, Bhaumik et al. (2025) use 2013 as Florida's year of treatment, whereas we can analyze the quarterly evolution of outcomes in Florida as different counties switched to MLTSS between August 2013 and March 2014.

al., 2013; Callison, 2016), shifts from inpatient to outpatient care (Baicker and Robbins, 2015), and changes in physician practice norms in response to payment reforms and care delivery regulations (Clemens and Gottlieb, 2017; Glied and Hong, 2018; Chen et al., 2022; Geruso and Richards, 2022; Lee, 2025). Most relevant to our analysis of spillovers from Medicaid to Medicare, studies of Affordable Care Act (ACA) Medicaid expansion on Medicare beneficiaries have reached mixed conclusions, with some finding reduced access and adverse health effects (McInerney et al., 2017) and others finding no evidence of negative spillovers (Carey et al., 2020; Barkowski et al., 2025). Our study identifies a distinct *individual-level* spillover: because dual-eligible beneficiaries are simultaneously covered by both Medicaid and Medicare, changes in how Medicaid structures LTSS coverage directly shape those same individuals' use of Medicare-financed services. This within-patient design allows us to hold constant the demographic and clinical composition of the affected population and isolate the impact of cross-payer spillovers on patient health.

2 Background

LTSS under Medicaid. Long-term services and supports encompass a broad range of services—from assistance with daily activities to occupational and physical therapy, dental care, optometry, and podiatry—that are provided in nursing homes and home- and community-based settings.[8] Medicaid pays for over 60 percent of all LTSS costs, making it the primary insurance program for these services. While state Medicaid programs have transitioned over three-quarters of all enrollees to capitated managed care plans over the past three decades (Hinton and Raphael, 2025), the shift of LTSS patients into managed care has been relatively recent (Hinton et al., 2022).

Under MLTSS, plans (which are sometimes referred to as managed care organizations, or MCOs) establish provider networks and develop coordination and gatekeeping mechanisms that aim to reduce costs and improve the efficiency of care delivery. A key feature of MLTSS plans is their use of case managers, who conduct assessments of beneficiaries' needs, help coordinate a range of services (including non-LTSS services such as vaccinations and other types of preventive care), authorize and manage benefits, and help manage transitions of care (e.g., from nursing

[8] According to most recent estimates, more than 8 million Americans use LTSS with total costs amounting to $415 billion, while an unknown (but likely even larger) number use unpaid care services provided by family members, friends, or neighbors (Chidambaram and Burns, 2024).

home to home-based services).

Florida. Florida's Medicaid program implemented its mandatory managed LTSS program for eligible beneficiaries on a staggered basis across different counties between August 2013 and March 2014. To qualify, individuals must be aged 65 or older and eligible for Medicaid (or aged 18 or older and eligible for Medicaid due to a disability) and functionally eligible based on a state assessment. Florida's MLTSS program covers nursing home care, assisted living, and home- and community-based services. Florida Medicaid's MLTSS plans receive capitation payments that account for the proportion of enrollees in home- and community-based settings relative to nursing homes. Specifically, plans are directly incentivized to facilitate the transition of enrollees to home- and community-based care (and out of nursing home care): the base capitation rate is adjusted by a transition percentage, penalizing plans for the share of nursing home enrollees until this share falls below 35 percent. Florida does not further adjust rates based on patient conditions or other demographic characteristics.

New York. New York's Medicaid program mandated enrollment in MLTSS plans (in New York, they are called managed long-term care, or MLTC, plans) on a staggered basis across different counties from September 2012 through February 2015. The mandate was specific to people who are dual-eligible for Medicaid and Medicare, aged 21 or older, and are in need of community-based LTSS for more than 120 days based on an assessment.[9] New York's MLTC plans receive a capitation payment from the state Medicaid program based on a risk-adjustment algorithm, which incorporates 26 predictor variables, including age, sex, and some selected diagnoses, including an indicator for an Alzheimer's or dementia diagnosis (Hinton et al., 2016). We present a more detailed comparison of the MLTSS programs in Florida and New York in Appendix Table C1.

Comparison states. We use beneficiaries residing in California and Pennsylvania counties that are never-treated during our study period as the comparison group when studying the effects of MLTSS transitions in both Florida and New York. As mentioned earlier, several states transitioned their Medicaid programs for LTSS to mandatory managed care programs prior to our study period

[9] An initial assessment is conducted within 30 days of referral. Then, the plans are required to conduct routine assessments every six months. Note, the mandate does not exclude nursing home residents if they qualify for community-based LTSS as well.

or concurrently, and we therefore cannot use these states in a comparison group.[10] Out of the states that remain, we chose California and Pennsylvania as two comparison states because they have similar population demographics and Medicare enrollment trends as the treatment states, and they have a large number of counties that did not experience MLTSS transitions until after the end of our analysis period (see Appendix Figure B1).[11]

Specifically, in California, 51 of 58 counties had no MLTSS mandate during our sample period; we exclude the seven that did.[12] In Pennsylvania, MLTSS implementation began in 2018, with 14 counties adopting mandates beginning in January of that year.[13] We exclude these 14 counties to avoid contaminating our comparison group within the three-year post-treatment event window used in our New York analyses, where the last MLTSS transition occurred in February 2015. Our comparison group thus consists of 51 California counties and 53 Pennsylvania counties that are never treated during the study period.

3 Data

We use administrative Medicare enrollment and FFS claims data for years 2008–2019 from the Centers for Medicare and Medicaid Services (CMS) for beneficiaries residing in California, Florida, New York, and Pennsylvania. For each individual enrolled in Medicare, we observe their demographic characteristics (age, sex, race, ethnicity), county of residence, and enrollment status. For individuals enrolled in FFS Medicare, we also observe all of their inpatient and outpatient claims. Additionally, for a random 20 percent sample of beneficiaries, we observe detailed claims submitted by non-institutional providers (e.g., physicians, laboratories, and ambulance services). Finally, we link the Medicare enrollment file to the Minimum Data Set (MDS), which contains information on nursing home assessments, to capture nursing home care utilization and quality.

[10] These states include: Arizona, Delaware, Hawaii, Illinois, Iowa, Kansas, Michigan, Minnesota, New Jersey, New Mexico, Ohio, Tennessee, Texas, and Virginia (Watts et al., 2017; Lewis et al., 2018; MACPAC, 2018).

[11] We were required by the Centers for Medicare & Medicaid Services to select our comparison states prior to receiving access to the data. Our data reuse agreement forbids us from accessing data from any states other than Florida, New York, California, and Pennsylvania.

[12] These excluded California counties are Los Angeles, Orange, Riverside, San Bernardino, San Diego, San Mateo, and Santa Clara.

[13] The Pennsylvania counties that adopted in 2018 are Allegheny, Armstrong, Beaver, Bedford, Blair, Butler, Cambria, Fayette, Greene, Indiana, Lawrence, Somerset, Washington, and Westmoreland. The remaining 53 counties adopted the mandate in 2019 or 2020.

Identifying dual-eligible beneficiaries. Only beneficiaries who are enrolled in full dual (rather than partial dual) benefits have LTSS covered by Medicaid, and are therefore affected by the transition to MLTSS. Following guidance from the CMS Research Data Assistance Center (ResDAC), we categorize a beneficiary as having full dual benefits based on their dual status code.[14] We consider a beneficiary to have full dual benefits if they have a qualifying code in at least one month in a calendar quarter.

Outcomes. Our main outcome is a binary indicator capturing whether a beneficiary had a hospitalization in a given calendar year-quarter. Additionally, we create mutually exclusive indicators for a hospitalization that did and did not originate in the emergency department (ED). We also measure the unconditional average length of an inpatient stay (in days) in every year-quarter, in which individuals without any hospitalization are assigned a zero. We further use diagnosis codes to identify hospitalizations for respiratory conditions.

For the 20% random sample of beneficiaries for whom we observe both carrier and outpatient claims, we create binary indicators for the receipt of preventive services that Medicare recommends or pays for on an annual basis (Centers for Medicare and Medicaid Services, n.d.), including influenza vaccinations, cancer screenings, and diabetes monitoring.[15] More details on exact codes used in constructing all of our outcomes are in Appendix A.

We observe nursing home assessments from the MDS, which contains assessment records for all residents of Medicaid- and Medicare-certified nursing homes regardless of payer.[16] These assessments occur upon admission, periodically, and upon discharge. We use an indicator for having any assessment record in this file to measure nursing home utilization on the extensive margin. We also use the Online Survey, Certification and Reporting (OSCAR) database to merge on indicators of nursing home quality, including information about the nursing home's staffing (measured

[14]Specifically, dual status codes of "02", "04", or "08" signal full dual status. The codes are defined as follows: "02"—QMB and full Medicaid coverage, including prescription drugs; "04"—SLMB and full Medicaid coverage, including prescription drugs; "08"—Other dual eligible (not QMB, SLMB, QWDI, or QI) with full Medicaid coverage, including prescription drugs (Centers for Medicare & Medicaid Services, 2021).

[15]Specifically, services that Medicare recommends annually include: influenza vaccinations, diabetes screenings, annual wellness visits, depression screenings, and diabetes monitoring (for diabetic patients) (Centers for Medicare and Medicaid Services, n.d.). We also consider two cancer screenings that are covered by Medicare annually: breast cancer screenings (recommended biennially) and prostate cancer screening (timing determined between patient and provider) (Centers for Medicare and Medicaid Services, n.d.).

[16]We use MDS versions 2.0 (for January 2009–September 2010) and 3.0 (for October 2010–December 2017).

through total hours per resident day), use of restraints (measured as the share of residents who are restrained), and occupancy (measured as the share of available beds that are occupied by residents) in each calendar year.[17]

4 Empirical Design

Our goal is to estimate the causal effect of MLTSS on health outcomes among dual-eligible Medicare-Medicaid beneficiaries. To do so, we leverage the staggered rollout of MLTSS mandates by county in Florida and New York. However, an important empirical challenge is that these mandates occurred over a relatively short time period in each state. As outlined in Appendix Table C2, all 67 Florida counties transitioned to MLTSS between August 2013 and March 2014, and all 62 New York counties did so between September 2012 and February 2015.

To address this challenge, we use a stacked difference-in-differences (DD) design (Cengiz et al., 2019; Deshpande and Li, 2019; Butters et al., 2022; Wing et al., 2024), which constructs separate "experiments" for each treatment cohort that compare changes in treated counties to those in never-treated counties over the same period, and stacks them together for estimation. Specifically, we define each experiment k based on the calendar year-quarter in which the MLTSS mandate went into effect. Within each experiment, the treatment group consists of all full dual beneficiaries who reside in a treated county and are aged 65 or older as of three years before the quarter of the transition to MLTSS, and the comparison group consists of all full dual beneficiaries who reside in a never-treated county and are aged 65 or older as of three years before the relevant transition quarter.[18] Since Florida counties transitioned to MLTSS over three distinct calendar year-quarters, we create three separate experiments for the Florida analysis. Analogously, since New York counties transitioned to MLTSS over nine distinct calendar year-quarters, we create nine experiments that we stack together for estimation in our analysis of New York's transition to MLTSS.

[17] The OSCAR data is obtained through (LTCFocus, 2000-2020). LTCFocus is sponsored by the National Institute on Aging (1P01AG027296) through a cooperative agreement with the Brown University School of Public Health.

[18] Put differently, we center each of our experiments relative to the year-quarter in which the MLTSS mandate being studied goes into effect.

Using our stacked dataset, we estimate the following model:

$$Y_{ictk} = \alpha + \beta MLTSS_{ctk} + \delta_{ik} + \gamma_{tk} + \zeta' X_{itk} + \varepsilon_{ictk} \tag{1}$$

for beneficiary i in county c observed in year t and in experiment k. Y_{ictk} is an outcome of interest, such as a binary indicator for whether a beneficiary experiences a hospitalization. $MLTSS_{ctk}$ is a binary indicator equal to 1 for treated counties in all years once the MLTSS mandate is in effect, and 0 otherwise. δ_{ik} are individual-by-experiment fixed effects, which account for all observable and unobservable time-invariant differences across individuals within each experiment, while γ_{tk} are experiment-by-year fixed effects, which account for any time trends in outcomes within each experiment. We include vector X_{itk} consisting of three indicators for an individual's age category (65-74, 75-84, and 85+) in each year and experiment. For many of our outcomes, we restrict our analysis to a seven-year event window that spans three years before the mandate, the year of the mandate, and three years after the mandate. We drop individuals who move counties at any point during this seven-year window,[19] and we require individuals to be continuously enrolled in full dual benefits and traditional FFS Medicare throughout the entire event window, as discussed further below. Standard errors are clustered on the county level.[20]

Our main coefficient of interest, β, captures the difference between the change in the outcome among individuals in treated counties from before to after the MLTSS mandate and the change in the outcome among those in comparison counties over the same time period within the experiment. We estimate separate regression models to study the effects of Florida and New York Medicaid's MLTSS transitions, using the same comparison group of beneficiaries residing in the 51 California counties and 53 Pennsylvania counties that are never treated during the study period.

The key identifying assumption for a causal interpretation of β in equation (1) is that, in the absence of an MLTSS mandate, outcome trends would have evolved in parallel between beneficiaries in treated and comparison counties within each experiment. While this assumption is inherently untestable, we estimate event study models that allow us to check for systematic differences

[19]Since we drop movers, we do not include county fixed effects, as they are subsumed by the individual-by-experiment fixed effects.

[20]We cluster standard errors on the county level as that is the level of variation in our analyses. Because counties can appear multiple times in our stacked DD framework, clustering at the county level will allow for dependence across groups and yield more conservative standard errors (Bertrand et al., 2004; Cameron et al., 2011; Wing et al., 2024). Results when clustering at the experiment-by-county level are similar.

in pre-treatment trends between treated and comparison groups. Specifically, for beneficiary i in county c observed in year t and in experiment k, we model outcome Y_{ictk} as:

$$Y_{ictk} = \alpha + \sum_{j=-3, j\neq -1}^{j=3} \beta_j \mathbf{1}[t - MLTSS_{ctk} = j] + \delta_{ik} + \gamma_{tk} + \zeta' X_{itk} + \varepsilon_{ictk} \tag{2}$$

The variables in equation (2) are the same as in equation (1), except that we now include indicators $\mathbf{1}[t - MLTSS_{ctk} = j]$ to capture event-time indicators for the three years before, the year of, and three years following the mandate quarter, with event-time -1 as the omitted category. This model additionally allows us to explore dynamic treatment effects over time.

As some of our outcomes are only available in a subset of our analysis years (see Appendix A for more details), the pre- and post-treatment windows and experiments used to estimate equations (1) and (2) vary somewhat across the outcomes considered.[21]

Continuous enrollment restriction. As noted above, our main analysis sample consists of individuals who are continuously enrolled in full dual benefits and FFS Medicare. This restriction is necessary because full dual benefits are required for Medicaid coverage of LTSS, and we only have FFS claims in our Medicare data. Therefore, this analysis sample allows us to: (i) focus on the population of individuals affected by MLTSS, and (ii) observe all of their healthcare utilization covered by Medicare.

The restriction to individuals who are continuously enrolled in full dual benefits is further necessary to avoid confounding our estimates with the large increase in Medicaid enrollment due to the 2014 ACA Medicaid expansion. Specifically, we require that individuals in our sample are enrolled in full dual benefits over the entire period spanning from three years before to three years after the MLTSS transition. This means that all of the individuals included in our sample were enrolled in Medicaid starting in 2012 or earlier (i.e., before the ACA expansion), as the latest MLTSS transition included in our analysis occurred in 2015 (see Appendix Table C2). Since Florida did not

[21]Specifically, for influenza vaccinations, which we only observe in 2011–2017, we only use the 2013 and 2014 MLTSS transitions and use an event window that spans from two years before to three years after the mandate. Similarly, for annual wellness visits and depression screenings, we only have data in 2011–2019, and therefore use experiments from 2013 onward and an event window that spans from two years before to three years after the mandate. Our nursing home quality measures are only available on an annual level in 2009–2017. Therefore, for these outcomes, we define experiments based on the calendar year (rather than quarter) of treatment, and only study transitions that took place in 2012, 2013, and 2014.

participate in the ACA Medicaid expansion, but all three of the other analysis states did, comparing trends in enrollment in full dual benefits between treated counties in Florida and comparison counties in California and Pennsylvania mostly reflects differences in enrollment due to the ACA expansion rather than MLTSS. By fixing our sample to individuals enrolled pre-ACA, we avoid potential bias from compositional changes in full-dual beneficiaries due to the ACA.

The restriction to beneficiaries who are continuously enrolled in traditional Medicare is important because MLTSS can cause people to switch into Medicare Advantage (MA), Medicare's privatized managed care program. This is plausible, as some plans offer consolidated Medicare and Medicaid services, so the MLTSS transition might encourage some enrollees to choose a managed care plan covering all of their healthcare. To examine this possibility, we use a broader sample of individuals who are continuously enrolled in Medicare (either traditional or MA) and full dual benefits over the event-time window, and estimate the event study model in equation (2) using as outcomes binary indicators for enrollment in FFS Medicare and MA, respectively. Appendix Figure B2 shows that in both Florida and New York, the shift to MLTSS reduces the likelihood that a Medicare full-dual beneficiary is enrolled in traditional FFS Medicare and correspondingly increases the likelihood that they opt into MA. The slight pre-trend in Florida might reflect anticipatory responses—MLTSS was announced several years before going into effect in both states, allowing beneficiaries to make these decisions preemptively.[22] Therefore, as we do not observe any MA claims and to avoid bias due to a change in the composition of individuals who remain in traditional Medicare, we require that all of the beneficiaries included in our sample stay enrolled in FFS Medicare for the entire length of the event-time window and include individual fixed effects in all of our regression models.

Summary statistics. Table 1 presents the means of selected characteristics of the individuals in our main analysis sample, measured in the year-quarter before the transition to MLTSS in each experiment. Our sample consists of 53,942 individuals in Florida, 131,855 individuals in New York, 123,505 individuals in California, and 28,916 individuals in Pennsylvania. Almost all beneficiaries (96 to 98 percent) have at least one chronic condition. The variation in other demographic charac-

[22]Florida passed House Bill 7107 in July 2011, which announced the transition to managed care for all Medicaid-covered services, including LTSS (see: https://www.flsenate.gov/Session/Bill/2011/7107). In New York, the Department of Health announced plans to transition to managed long-term care in June 2011 (see: https://www.health.ny.gov/press/releases/2011/2011-06-14_long_term_care_medicaid.htm).

teristics between the four states motivates our difference-in-differences approach with individual fixed effects that can account for baseline differences in patient profiles across states. Moreover, in a robustness check, we show that our results are similar when we use a matching algorithm to select never-treated comparison counties that are most similar to the treatment counties based on observable characteristics.

5 Results

We begin by presenting our results on the effects of MLTSS on hospitalizations, which is our main health outcome. Then, we examine preventive care to better understand the potential healthcare-related channels underlying our effects. We also explore changes in nursing home use and quality as additional mechanisms.

Hospitalizations. Figure 1 plots the event study coefficients and 95 percent confidence intervals obtained from estimating equation (2) using the hospitalization indicator as an outcome, separately for Florida (in green squares) and New York (in yellow diamonds). We print the corresponding DD coefficients, standard errors, and pre-period outcome means at the top of the graph. We find that the MLTSS transition leads to an average 0.9 percentage point increase in the probability of a hospitalization among beneficiaries in Florida, which corresponds to a 4.2 percent increase relative to the pre-period mean of 21.2 percent. This estimate is statistically significant at the one percent level. While the DD estimate is an average effect measured across the post-period, the event study coefficients suggest a dynamic treatment effect that increases over time, although the confidence intervals associated with individual event study coefficients in the post-period are overlapping. In contrast, we do not find any evidence of an effect on the probability of a hospitalization in New York.

Figure 2 reports estimated effects of MLTSS on hospitalizations that originated in the ED and average length of stay. In Florida, we observe a 1.3 percentage point (7.2 percent) increase in the likelihood of an ED-initiated hospitalization (panel a) and a 0.07 day (5.2 percent) increase in the average length of stay (panel b). As with overall hospitalizations, the event study coefficients suggest that these effects increase over time. There is no change in the likelihood of a non-ED-initiated hospitalization in Florida (Appendix Figure B3, panel a), suggesting that Florida's increase in hospitalizations is driven by conditions requiring urgent care. In New York, the DD coefficient for ED-initiated hospitalizations is positive but not statistically significant (Figure 2, panel a), while there is a significant decline in non-ED-initiated hospitalizations of 0.7 percentage points (10.7 percent) in Appendix Figure B3(b). Given that non-ED (i.e., scheduled and/or elective) hospitalizations can reflect both changes in care utilization and underlying health, it is difficult to interpret the New York result, especially as it does not translate into a significant change in overall hospitalizations.

Preventive care services and influenza vaccinations. Motivated by our hospitalization findings, we next examine whether differences in the effects on hospitalizations between Florida and New York are accompanied by differences in effects on preventive care utilization. We consider several preventive care services that are recommended on an annual basis, including influenza vaccinations, wellness visits, and certain types of cancer screenings. Figure 3 presents the DD coefficients and associated 95% confidence intervals from estimating model (1) separately for each outcome and in each state: Florida in panel (a) and New York in panel (b). The corresponding event study estimates for all outcomes are presented in Appendix Figure B4.

We find that Florida's MLTSS transition resulted in a 3.2 percentage point decline in the likelihood of receiving an influenza vaccination, corresponding to a 10 percent reduction relative to the pre-period mean of 32 percent. This estimate is statistically significant at the one percent level. We do not observe any significant effect of MLTSS on influenza vaccinations in New York. We highlight the difference in event study estimates for flu vaccinations between the two states in Figure 4.

In both states, we find no significant effects among most other preventive care services, including diabetes screenings, cancer screenings, and diabetes monitoring. We do find significant increases in the incidence of annual wellness visits of 5.7 percentage points and 2.3 percentage points in Florida and New York, respectively. In Florida, we also observe a 2.5 percentage point increase in depression screenings, which are typically conducted at the wellness visits. These increases are large in relative magnitude: compared to their pre-treatment means, wellness visits increase by 80.6 and 22 percent in Florida and New York, respectively; and depression screenings in Florida increase by 284 percent. The notably low pre-period means that generate these large relative increases likely reflect the fact that Medicare only began covering annual wellness visits and depression screenings in 2011.

Importantly, the impacts on flu vaccines and wellness visits suggest that Medicaid's transition to MLTSS generates spillover effects on healthcare utilization financed by Medicare, even though Medicare's own delivery and payment structure remained unchanged. Although we cannot directly observe the underlying mechanisms, one plausible explanation involves the case managers employed by MLTSS plans, who often help beneficiaries schedule routine preventive services including wellness visits and vaccinations (Saucier and Burwell, 2015; Pavle et al., 2019). The introduction of case managers under MLTSS may drive the observed increases in wellness visits in both states, while the decline in flu vaccinations unique to Florida may reflect differences in how case managers in the two states prioritize preventive services, with flu vaccinations treated as more discretionary (Harris et al., 2009; Ernsting et al., 2012).

Hospitalizations with respiratory diagnoses. The differential impact on flu vaccinations between Florida and New York is consistent with influenza infections and their downstream complications contributing to the increase in urgent hospitalizations in Florida (and not in New York). To assess this link further, we examine hospitalizations with a respiratory diagnosis in Figure 5. We find that Florida's transition to MLTSS leads to a 0.7 percentage point increase in the likelihood of having a hospitalization with a respiratory diagnosis, representing a 19.4 percent effect relative to the pre-period mean of 4 percent. The DD coefficient for respiratory hospitalizations in New York indicates a marginally significant 0.1 percentage point increase, and the event study graph for New York does not show any statistically significant post-treatment coefficients. On the whole, these results provide further support for the possibility that the the differential decline in flu vaccinations in Florida leads to an increase in flu-related hospitalizations.

Using matching to select the comparison group. In our main analysis, we compare changes in outcomes between individuals living in treated counties in New York and Florida and those in never-treated counties in California and Pennsylvania. While our experiment×individual fixed effects account for all time invariant differences between individuals in treatment and comparison counties, differences in observable characteristics remain (Table 1). To improve comparability, we use a nearest neighbor matching algorithm to pair each treated county with the two most similar comparison counties based on a selection of 2010 county characteristics.[23] We construct separate experiments for every treatment-comparison matched group, and then stack these experiments together for estimation.[24]

Appendix Figure B5 shows that our main results are robust to using this matched sample. Specifically, in Florida, we find a 1.1 percentage point (5.3 percent) increase in the probability of hospitalization, a 0.7 percentage point (18.2 percent) increase in the probability of a hospitalization with a respiratory diagnosis, and a 2.4 percentage point (7.7 percent) decline in the likelihood of a flu vaccination. In New York, we do not observe any significant effects on hospitalizations or hospitalizations with a respiratory diagnosis with the matched sample. We do estimate a statistically significant DD coefficient for flu vaccinations when using the matched sample in New York, but we note that it appears to only be driven by a significant negative coefficient in event-time zero that may be a continuation of a pre-trend.

Nursing home use and quality. In addition to case managers as a potential channel through which MLTSS affects patient health, another mechanism may lie in the settings where beneficiaries receive LTSS. In Florida, the MLTSS payment model explicitly incentivizes a shift out of nursing home and toward home and community-based care (HCBS). While we do not have any data allowing us to observe HCBS delivery, we can use data on nursing home assessments to explore whether changes in nursing home utilization or quality may be contributing factors.

Appendix Figure B6(a) shows that the probability of receiving any nursing home assessment—our proxy for a nursing home admission—does not change following the transition to MLTSS in Florida. While this finding is inconsistent with the financial incentives in Florida's MLTSS payment structure, it is possible that impacts on location of LTSS delivery may be delayed. We also

[23] These characteristics include the log number of Medicare beneficiaries aged 65 and older, the share of beneficiaries aged 65 and older who are enrolled in full dual benefits and in FFS Medicare, the share of female beneficiaries, the share of Hispanic beneficiaries, the share of non-Hispanic Black beneficiaries, the share of beneficiaries aged 65–74, the share of beneficiaries aged 75–84, the share of beneficiaries aged 85 and older, and the urban/rural classification of the county. We use data from the American Community Survey to obtain information on urban/rural status of each county.

[24] In this analysis, each experiment k thus represents a specific treatment-comparison set, rather than the calendar year-quarter in which the MLTSS mandate went into effect. Our matched analysis sample for Florida includes 67 experiments for the 67 counties that transitioned to MLTSS, and our matched analysis sample for New York includes 62 experiments for the 62 counties in New York. Each experiment k includes only the individuals who live in the treated county and the two matched comparison counties.

do not find any changes in the probability of a nursing home assessment in New York (panel c). Further, we do not detect any effects on the likelihood of switching nursing home facilities (panels b and d) in either state.

In Appendix Figure B7, we examine whether the shift to MLTSS changes the average quality of the nursing home in which a patient resides. For this analysis, we restrict our attention to the subset of beneficiaries who are observed to be in a nursing home throughout the seven-year event window. To measure quality, we consider three commonly used markers—hours per resident day, occupancy rate, and restraint rate—and calculate each nursing home's within-state percentile rank on each measure in 2011. By holding the relative rank fixed in the pre-period, these measures allow us to detect changes in nursing home quality due to patient reallocation rather than direct effects on nursing home operations following MLTSS. Across the three measures and in both states, we do not detect any statistically significant or economically meaningful changes in the baseline quality ranking of beneficiaries' nursing homes.

Finally, Appendix Figure B8 examines effects of MLTSS on the absolute values of the three markers in a beneficiary's current nursing home. These outcomes can be interpreted as changes in the operations of the nursing home, especially since we do not find evidence of patients selecting in or out of nursing homes based on quality. While there appears to be some indication of declines in hours per resident day in Florida and an increase in the restraint rate in New York, both of these effects appear to be continuations of pre-existing trends, and therefore cannot be reliably interpreted as causal effects of MLTSS.

Overall, these analyses suggest that the effects of MLTSS on healthcare utilization operate outside the nursing home setting, potentially through in-home or community-based care.

6 Conclusion

As state Medicaid programs increasingly shift LTSS delivery from fee-for-service to managed care, understanding the health consequences of this transition is critical, both because of the scale of spending involved (Medicaid paid more than $255 billion for LTSS in 2022, see Chidambaram and Burns, 2024) and because the effects may extend beyond the services directly covered by MLTSS plans. In this paper, we study how the shifts from FFS delivery and payment models to managed care systems in Florida and New York's Medicaid LTSS programs affect patients' health outcomes. By measuring changes in healthcare utilization financed by Medicare—whose delivery and payment structure was unchanged by the MLTSS transition—we are able to capture changes in underlying health rather than shifts in care in response to financial incentives under MLTSS.

We find that Medicaid's transition to MLTSS increases the probability of a hospitalization by 4.2 percent in the following four years in Florida, with no effect in New York. The increase in Florida is driven by hospitalizations that originated in the emergency department and hospitalizations with respiratory diagnoses. When we analyze preventive care services that are recommended on an annual basis, we find a 10 percent decline in the likelihood of receiving an influenza vaccination in Florida, with no impact on vaccinations in New York. Annual wellness visits increase in both states. We find no effects on nursing home use, switching, or quality, suggesting that these effects operate through mechanisms outside the nursing home setting. A plausible explanation involves MLTSS case managers, who often help beneficiaries schedule routine services including wellness visits and vaccinations. Differences in how case managers in the two states prioritize these services—particularly flu vaccinations, which may be viewed as more discretionary—could help explain the divergent effects.

Our findings are broadly consistent with recent evidence that transitions to Medicaid managed care can adversely impact health among vulnerable populations (Bogl et al., 2025; Layton et al., 2022). Our use of rich, individual-level administrative Medicare data builds on prior work relying on survey or aggregated data (Bhaumik et al., 2025; Bhaumik and Grabowski, 2025) and allows us to capture a broader set of health outcomes and uncover significant heterogeneity in MTLSS effects across states. This heterogeneity further underscores that managed care—and many aspects of state Medicaid programs more generally—is not a uniform intervention, consistent with growing evidence of substantial heterogeneity across Medicaid managed care plans (Geruso et al., 2023; Wallace, 2023).

Finally, our results demonstrate that the effects of MLTSS extend beyond the services directly covered by Medicaid, generating spillovers onto healthcare utilization financed by Medicare, a program whose delivery structure was unchanged by the transition. While an existing literature has documented market-level spillovers across payers operating through changes in provider behavior and practice norms, our findings point to a distinct, individual-level channel: for dual-eligible beneficiaries covered by both Medicaid and Medicare, restructuring care delivery on the Medicaid side directly affects their utilization of Medicare-financed services. This is particularly policy-relevant given that dual-eligible beneficiaries represent 17 percent of Medicare FFS enrollees (Peña et al., 2023), and reforms to either program's delivery system may have unintended consequences for the other.

While this study produces new, timely evidence on the health impacts of MLTSS, there are several important avenues for future work. First, the lack of observed effects on nursing home use and quality suggests that the transition to MLTSS in Florida and New York affects beneficiaries primarily through home- and community-based delivery. More research is needed to understand how, precisely, home- and community-based delivery changes between fee-for-service and managed care models. Second, since our sample requires individuals to be continuously enrolled in FFS Medicare, our results may not generalize to LTSS patients enrolled in MA plans. Our results may also not generalize to LTSS patients who become eligible for full-dual benefits due to the ACA Medicaid expansions.

Recent calls by the US government to reduce federal spending, including in the Medicaid program, underscore an urgent need to understand how public programs can operate efficiently and effectively.[25] This impetus, combined with the rapidly aging US population, suggests that the structure of Medicaid's coverage of long-term services and supports—for which the program paid more than $255 billion in 2022—may play an important role in these considerations.

[25]For a summary of the issues related to Medicaid funding cuts, see Urban Institute's report here: https://www.urban.org/research/publication/reducing-federal-support-medicaid-expansion-would-shift-costs-states-and.

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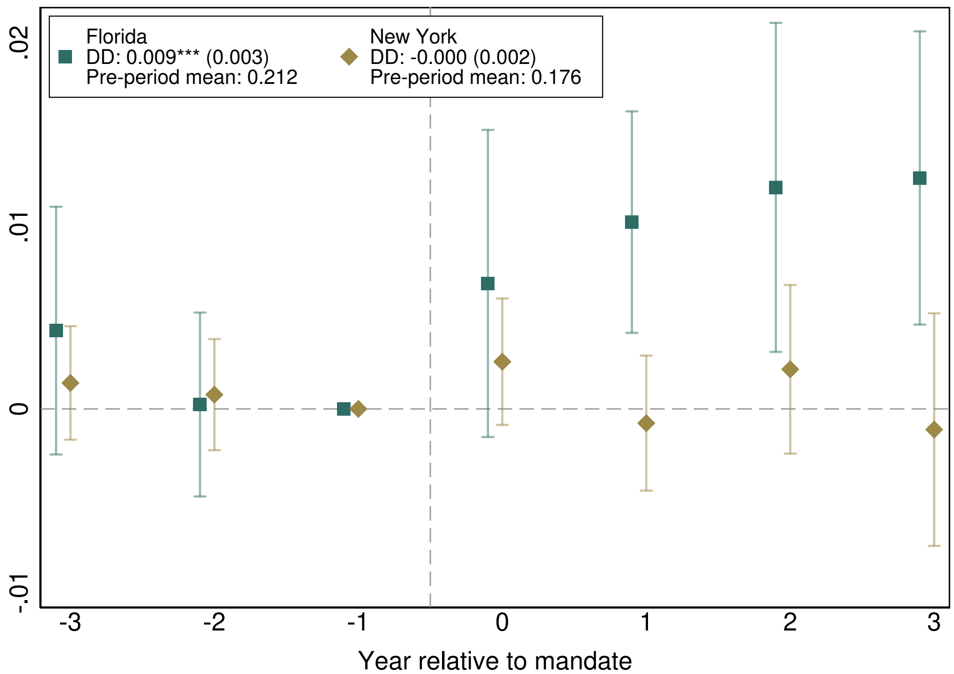
7 Figures and Tables

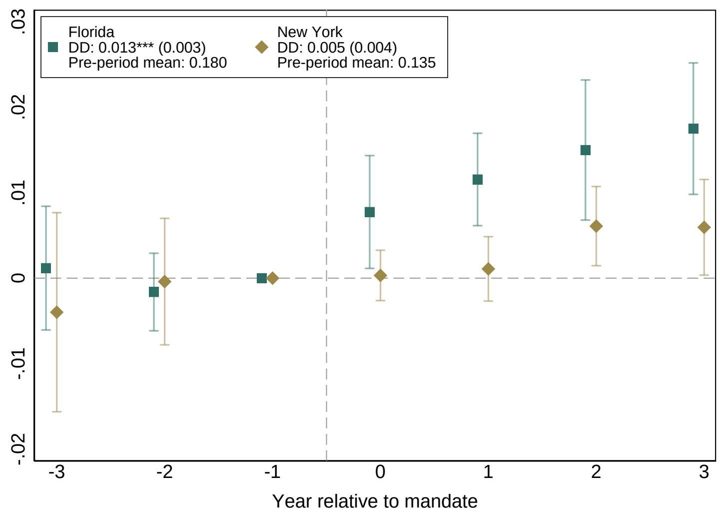
Figure 1: Event-study estimates of the impacts of MLTSS mandates on hospitalizations



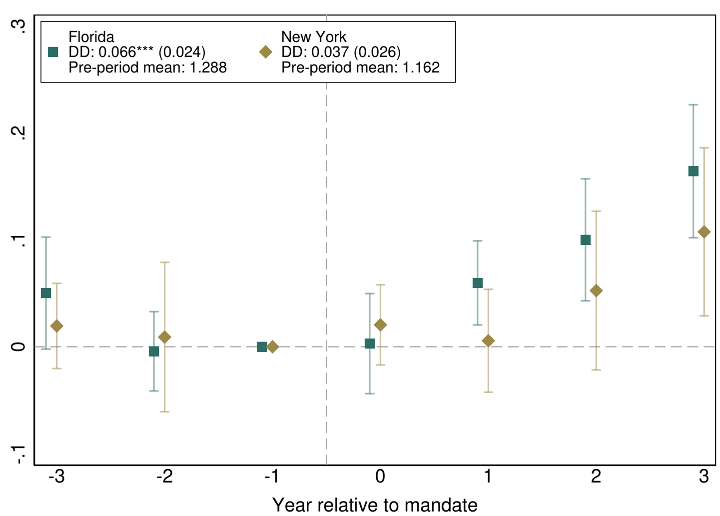
Notes: This figure presents event-study estimates and 95% confidence intervals from estimating equation (2), for Florida (in green squares) and New York (in yellow diamonds). We observe hospitalizations for the full sample. The pooled difference-in-differences estimate is reported in the top left corner, with standard errors in parentheses. Pre-period means are calculated for the treatment group.

Figure 2: Event-study estimates of the impacts of MLTSS mandates on hospitalizations that originated in the emergency department and average length of stay

(a) Hospitalizations that originated in the emergency department



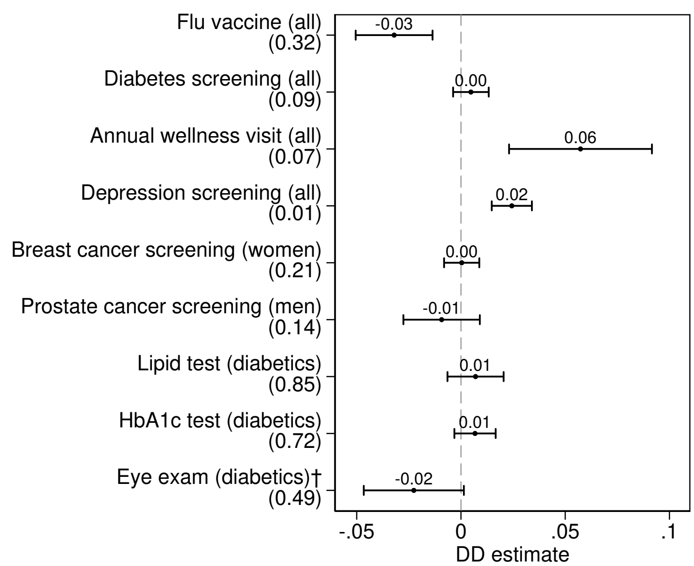
(b) Average length of stay



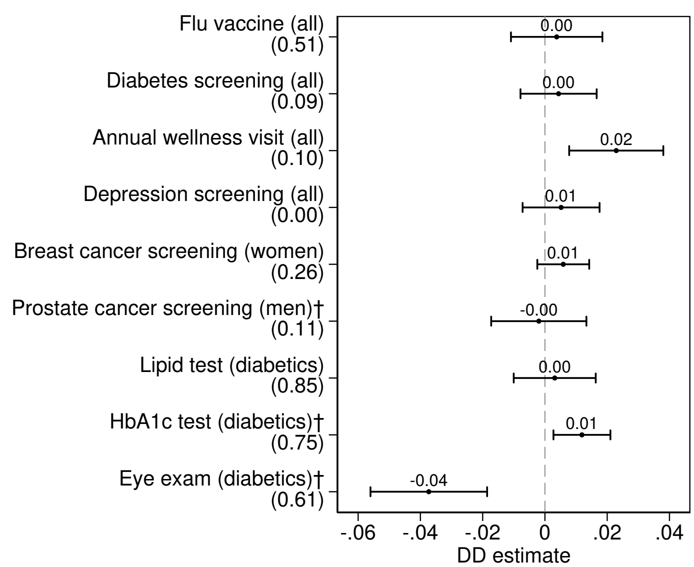
Notes: This figure presents event-study estimates and 95% confidence intervals from estimating equation (2), for Florida (in green squares) and New York (in yellow diamonds). We observe hospitalizations for the full sample. The pooled difference-in-differences estimate is reported in the top left corner, with standard errors in parentheses. Pre-period means are calculated for the treatment group.

Figure 3: Difference-in-differences estimates of the impacts of MLTSS mandates on preventive care utilization

(a) Florida

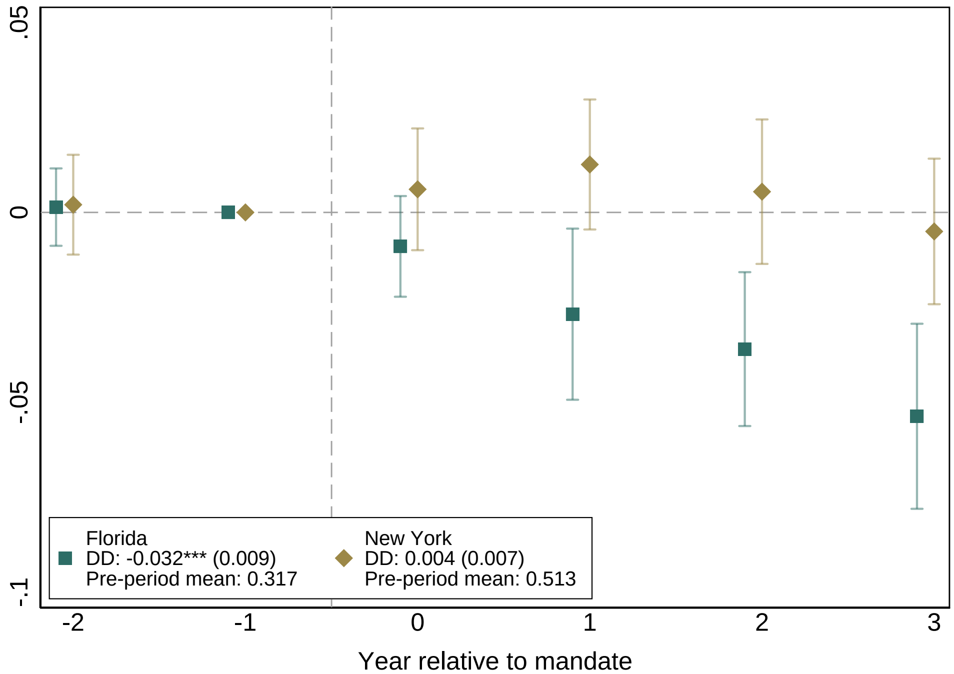


(b) New York



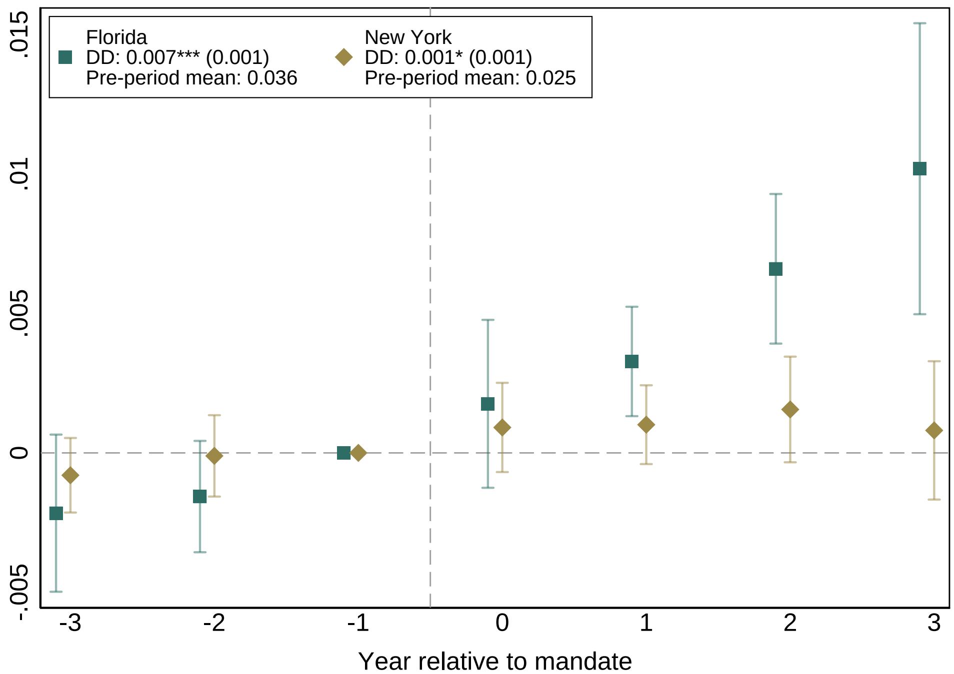
Notes: These figures plot the pooled difference-in-differences estimates and 95% confidence intervals from estimating equation (1), separately for Florida (in sub-figure a) and for New York (in sub-figure b). Each row represents a different preventative care service, with the pre-period means for the treated group reported below in parentheses. We observe preventative care utilization for a random 20% sample. † indicates that there are statistically significant pre-trends for a particular outcome.

Figure 4: Event-study estimates of the impacts of MLTSS mandates on influenza vaccinations



Notes: This figure presents event-study estimates and 95% confidence intervals from estimating equation (2), for Florida (in green squares) and New York (in yellow diamonds). We observe influenza vaccinations for a random 20% sample. The pooled difference-in-differences estimate is reported in the bottom left corner, with standard errors in parentheses. Pre-period means are calculated for the treatment group.

Figure 5: Event-study estimates of the impacts of MLTSS mandates on hospitalizations with a respiratory diagnosis



Notes: This figure presents event-study estimates and 95% confidence intervals from estimating equation (2), for Florida (in green squares) and New York (in yellow diamonds). We observe hospitalizations for the full sample. The pooled difference-in-differences estimate is reported in the top left corner, with standard errors in parentheses. Pre-period means are calculated for the treatment group.

Table 1: Mean characteristics of the analysis sample, 2008-2019

	Treated counties		Comparison counties	
	(1)	(2)	(3)	(4)
	Florida	New York	California	Pennsylvania
Percent female	73	69	63	72
Percent non-Hispanic white	43	54	43	72
Percent non-Hispanic Black	16	15	5	14
Percent Hispanic	35	9	19	3
Percent aged 65-74	37	39	43	43
Percent aged 75-84	42	42	42	38
Percent aged 85+	21	19	15	18
Percent with any chronic condition	98	98	96	97
Percent with diabetes	60	61	50	49
Observations (unique individuals)	53,942	131,855	123,505	28,916

Notes: This table presents the means of characteristics of the primary analysis sample. Each observation is a unique individual. The analysis sample includes individuals who are aged 65 or older as of three years before the transition to MLTSS, and who are continuously enrolled in fee-for-service Medicare and full dual benefits over an event window that spans from three years before the transition to MLTSS to three years after the transition. We further restrict the sample to individuals who never move counties throughout the event window. In our stacked difference-in-differences approach, individuals in the comparison group can appear multiple times. For these individuals, we report their characteristics using the first time that they appear in the data.

ONLINE APPENDIX

A More Details about Outcome Definitions

Hospitalizations that originate in the emergency department (for all beneficiaries, 100% sample) To determine whether a hospitalization originated in the emergency department, we identify inpatient claims that contain revenue center codes 0450–0459.

Hospitalizations with a respiratory diagnosis (for all beneficiaries, 100% sample). To study hospitalizations with a respiratory diagnosis, we map MS-DRG codes in the inpatient claims to Major Diagnostic Category (MDC) codes. We specifically use MS-DRG codes 163-208, which correspond to the MDC code for diseases and disorders of the respiratory system.

Influenza vaccinations (for all beneficiaries, 20% sample). To study influenza vaccinations, we use HCPCS/ CPT procedure codes G0008, Q2034-Q2039, 90653-90662, 90672-90674, 90682, 90686, and 90688 in the carrier and outpatient claims files. We also leverage a linkage to the Minimum Data Set 3.0 to identify flu vaccinations recorded in nursing home assessment records in years 2011-2017 (assessment question 0250A). Since we only observe the carrier files for a 20% random sample and since we only observe influenza vaccinations in nursing homes in years 2011-2017, our analysis of influenza vaccinations is based on the 20% random sample over years 2011–2017.

Diabetes screening (for all beneficiaries, 20% sample). To study diabetes screening utilization, we use HCPCS/ CPT procedure codes 82947, 82950, and 82951 in the carrier and outpatient claims files. Our analysis of diabetes screening is based on the 20% random sample.

Annual wellness visits (for all beneficiaries, 20% sample). To study annual wellness visits (AWV), we use HCPCS/CPT procedure codes G0438, G0439, and G0468 in the carrier and outpatient claims files. Our analysis of annual wellness visits is based on the 20% random sample. Since Medicare began covering the annual wellness visit benefit in 2011, our analysis of AWV utilization is based on years 2011–2019.

Depression screening (for all beneficiaries, 20% sample). To study depression screenings, we use HCPCS/ CPT procedure code G0444 in the carrier and outpatient claims files. Our analysis of depression screenings is based on the 20% random sample. Since Medicare began covering depression screenings in 2011, our analysis of depression screenings is based on years 2011–2019.

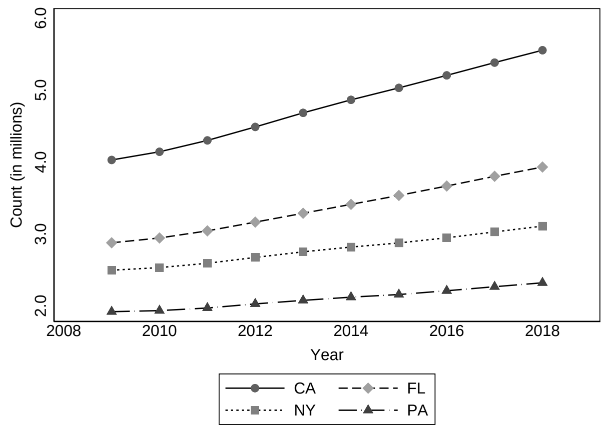
Breast cancer screening (for female beneficiaries, 20% sample). To study breast cancer screening among a subsample of women, we use HCPCS/CPT procedure codes G0202, 77057, 77067, and 77063 in the carrier and outpatient claims files. Our analysis of breast cancer screenings is based on the 20% random sample, as well as a subsample of women.

Prostate cancer screening (for male beneficiaries, 20% sample). To study prostate cancer screening among a subsample of men, we use HCPCS/CPT procedure codes G0102 and G0103 in the carrier and outpatient claims files. Our analysis of prostate cancer screenings is based on the 20% random sample, as well as a subsample of men.

Recommended diabetes monitoring services (for diabetic beneficiaries, 20% sample). We study: lipid tests, hbA1c tests, and eye exams. To identify lipid tests, we use HCPCS/CPT procedure codes 80061, 83700, 83701, 83704, 83715, 83716, 83721, 3048F, 3050F, 82465, 83718, 84478. To identify HbA1c tests, we use HCPCS/CPT procedure codes 83036, 83037, 3046F, and 3047F. To identify eye exams, we use HCPCS/CPT procedure codes 92002, 92004, 92012, 92014, 92227, 92228 and 92250. We observe these procedures in the carrier and outpatient claims files, and our analysis is based on the 20% random sample, as well as a subsample of diabetic patients. We use the date of first diabetes diagnosis in the Medicare Conditions file to determine whether beneficiaries had diabetes three years prior to the MLTSS mandate.

B Appendix Figures

Appendix Figure B1: Trends in Medicare enrollment in California, Florida, New York, and Pennsylvania, 2009–2019

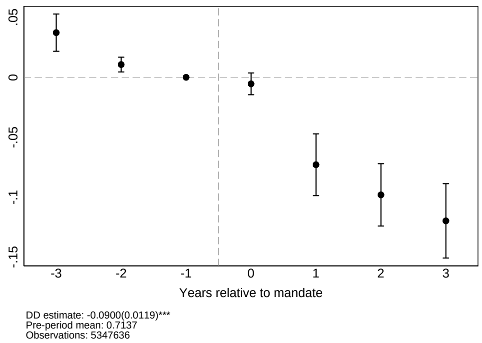


Notes: This figure presents the number of Medicare enrollees between 2009 and 2019 separately for each state (California, Florida, New York, and Pennsylvania).

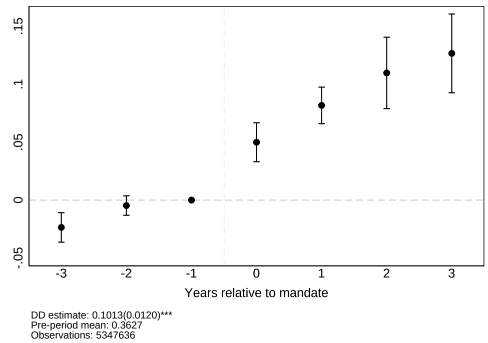
Appendix Figure B2: Event-study estimates of the impacts of MLTSS mandates on Medicare enrollment type

Florida

(a) Traditional (FFS) Medicare

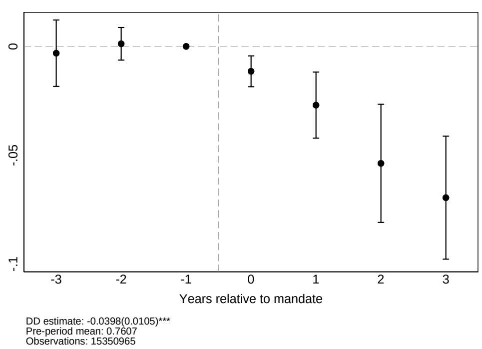


(b) Medicare Advantage

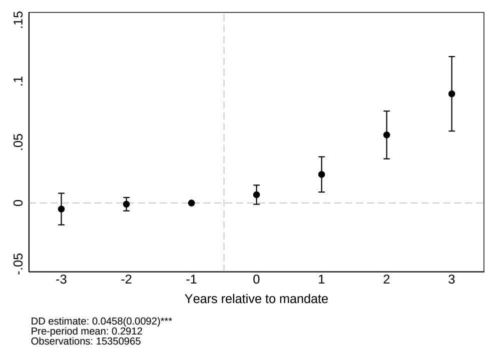


New York

(c) Traditional (FFS) Medicare



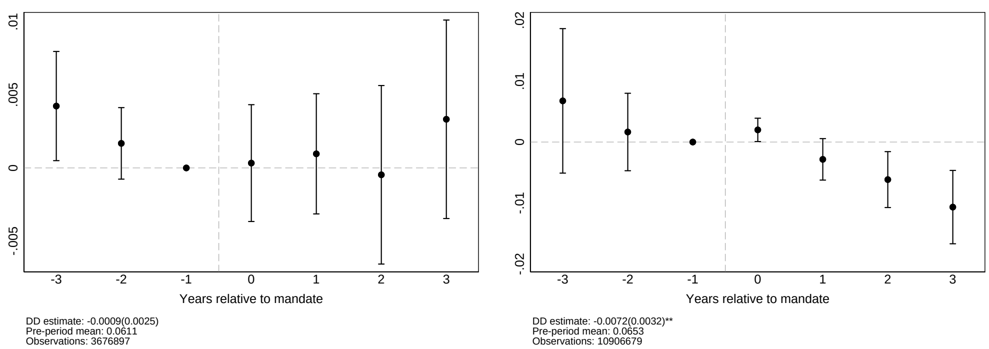
(d) Medicare Advantage



Notes: These figures plot the event-study coefficients and 95% confidence intervals from estimating equation (2). We study the impacts of the MLTSS mandates on traditional FFS Medicare and Medicare Advantage enrollment among a sample of beneficiaries who are aged 65+ at the beginning of the event window and remain continuously enrolled in Medicare and in full-dual benefits through the entire duration of the event window.

Appendix Figure B3: Event-study estimates of the impacts of MLTSS mandates on hospitalizations that did not originate in the emergency department

(a) Florida **(b)** New York

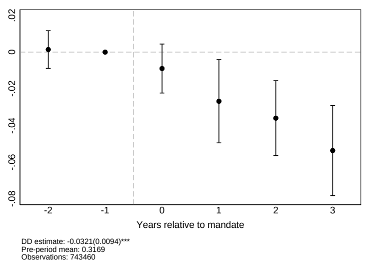


Notes: These figures plot the event-study estimates and 95% confidence intervals from estimating equation (2). We observe hospitalizations for the full sample. See notes under Table 1 for details about the analysis sample.

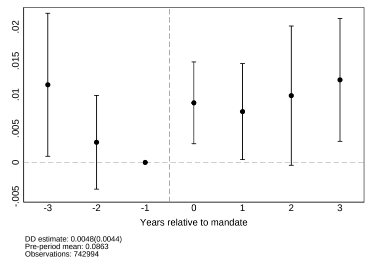
Appendix Figure B4: Event-study estimates of the impacts of MLTSS mandates on preventive care utilization

Florida

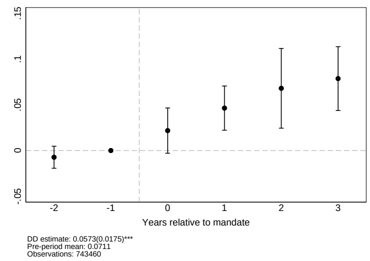
(a) Any influenza immunization



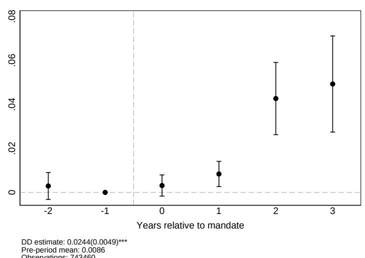
(b) Any diabetes screening



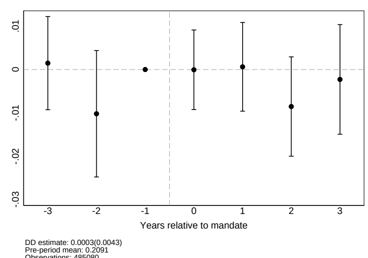
(c) Any annual wellness visit



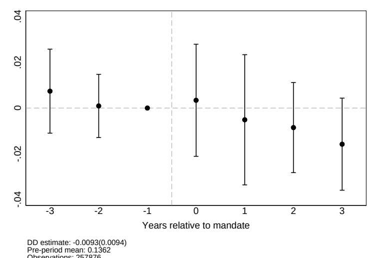
(d) Any depression screening



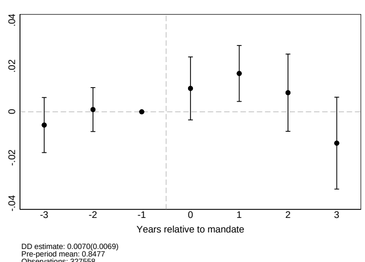
(e) Any breast cancer screening (women)



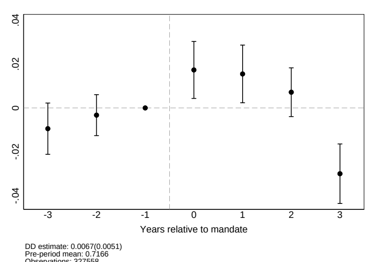
(f) Any prostate cancer screening (men)



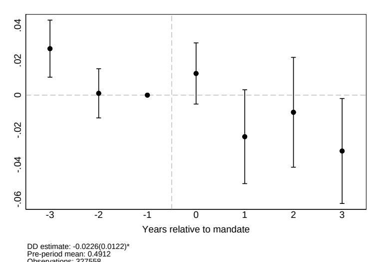
(g) Any lipid test (diabetic)



(h) Any HbA1c test (diabetic)

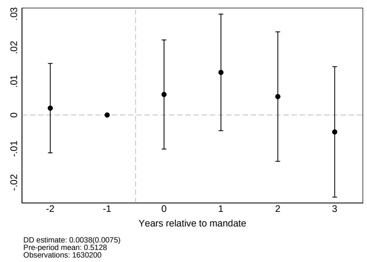


(i) Any eye exam (diabetic)

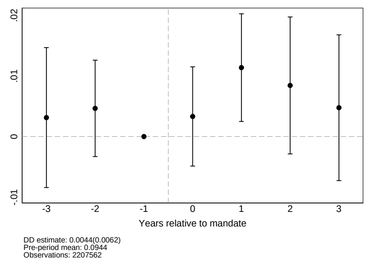


New York

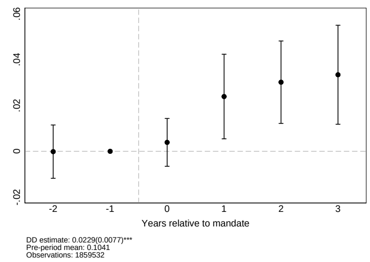
(j) Any influenza immunization



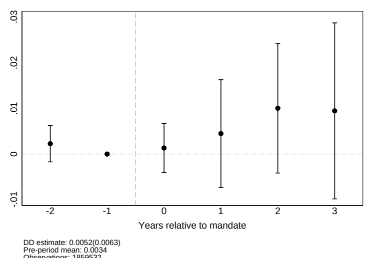
(k) Any diabetes screening



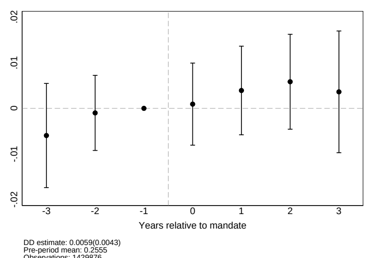
(l) Any annual wellness visit



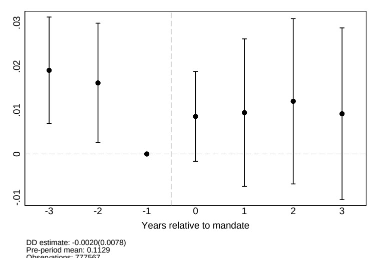
(m) Any depression screening



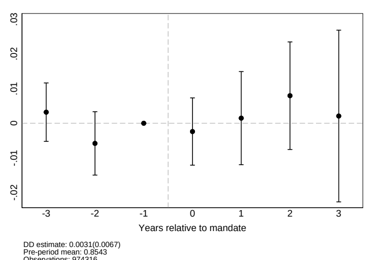
(n) Any breast cancer screening (women)



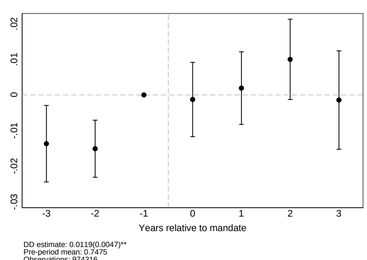
(o) Any prostate cancer screening (men)



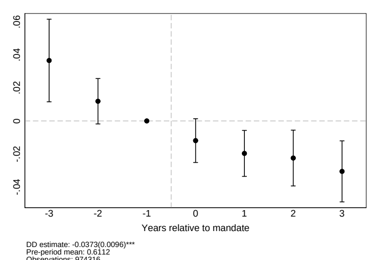
(p) Any lipid test (diabetic)



(q) Any HbA1c test (diabetic)



(r) Any eye exam (diabetic)

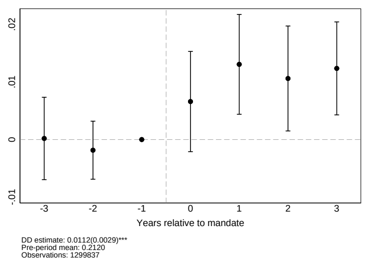


Notes: These figures plot the event-study estimates and 95% confidence intervals from estimating equation (2). We observe utilization of preventive care services for a random 20% sample of beneficiaries. See notes under Table 1 for details about the analysis sample and Appendix A for details about the preventative care measures.

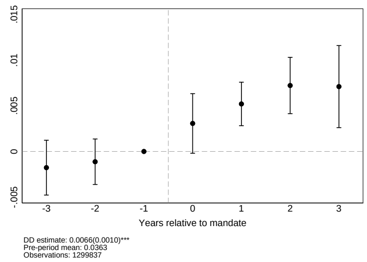
Appendix Figure B5: Event-study estimates of the impacts of MLTSS mandates on hospitalizations and influenza immunizations, nearest neighbor matched control sample

Florida

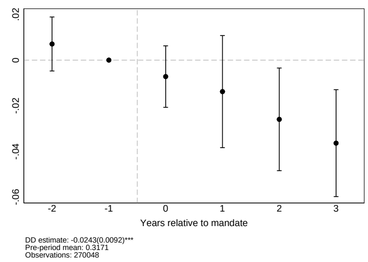
(a) Hospitalizations



(b) Hospitalizations with a respiratory diagnosis

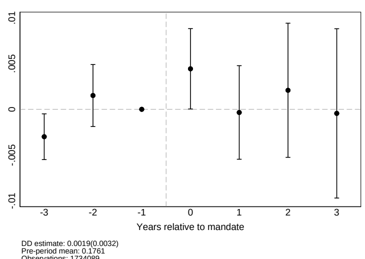


(c) Influenza vaccinations

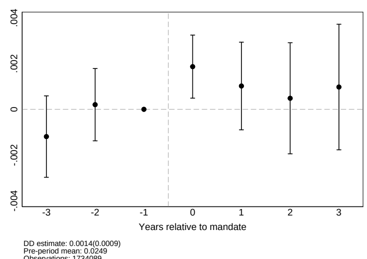


New York

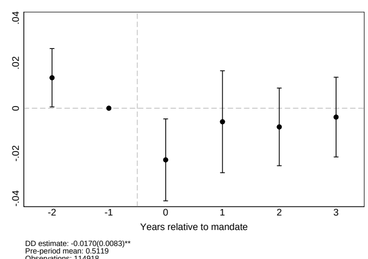
(d) Hospitalizations



(e) Hospitalizations with a respiratory diagnosis



(f) Influenza vaccinations

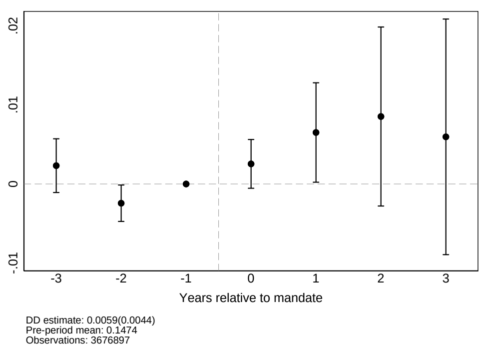


Notes: These figures plot the event-study coefficients and 95% confidence intervals from estimating equation (2). We observe hospitalizations for the full sample and influenza vaccinations for a random 20% sample of beneficiaries. See notes under Table 1 for details about the analysis sample. The analysis sample is further restricted to individuals who reside in the treated counties or nearest neighbor matched comparison counties.

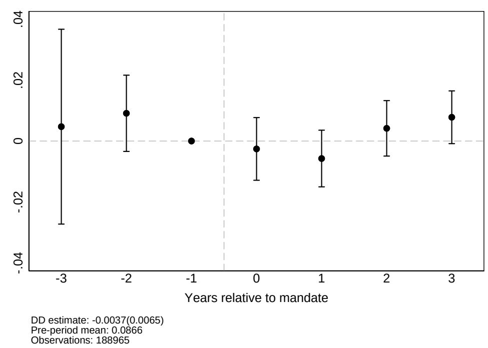
Appendix Figure B6: Event-study estimates of the impacts of MLTSS mandates on nursing home utilization

Florida

(a) Any nursing home assessment

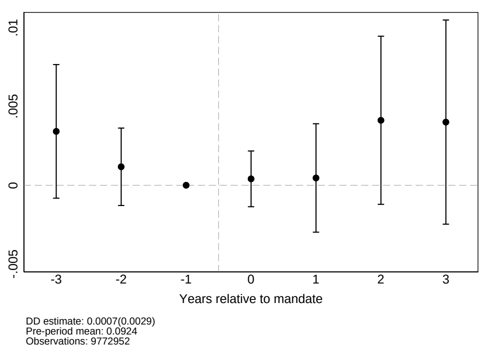


(b) Any nursing home facility change

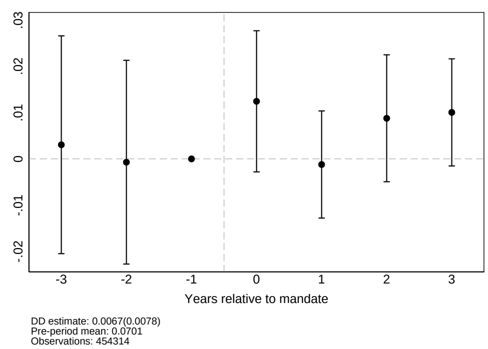


New York

(c) Any nursing home assessment



(d) Any nursing home facility change

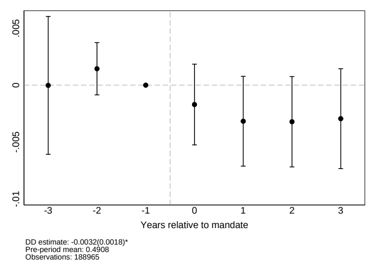


Notes: These figures plot the event-study estimates and 95% confidence intervals from estimating equation (2). We observe nursing home assessments and facility switches for individuals who appear in the MDS. We code individuals as 0 if they do not have a nursing home assessment in the MDS. See notes under Table 1 for details about the analysis sample. In our analysis of nursing home facility changes, the analysis sample is further restricted to individuals who are in a nursing home throughout the entire event window.

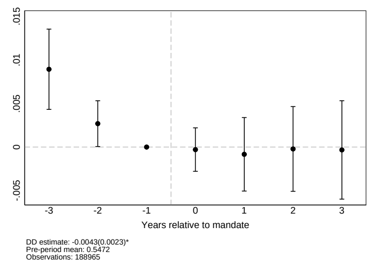
Appendix Figure B7: Event-study estimates of the impacts of MLTSS mandates on nursing home's baseline quality

Florida

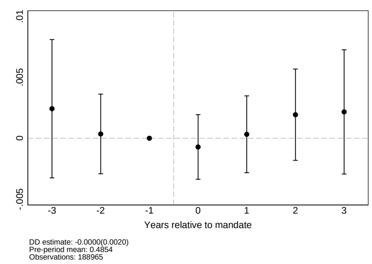
(a) Hours per resident day percentile rank



(b) Occupancy rate percentile rank

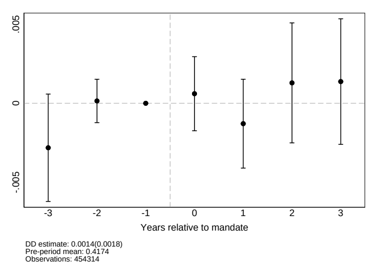


(c) Restraint rate percentile rank

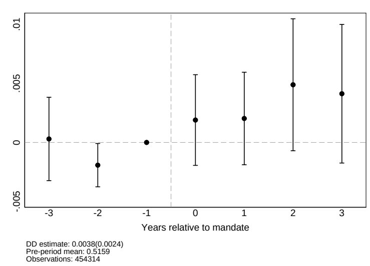


New York

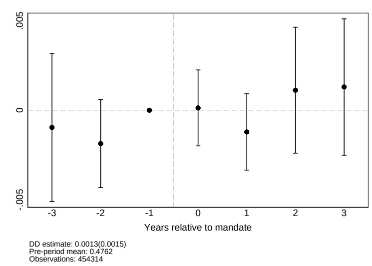
(d) Hours per resident day percentile rank



(e) Occupancy rate percentile rank



(f) Restraint rate percentile rank

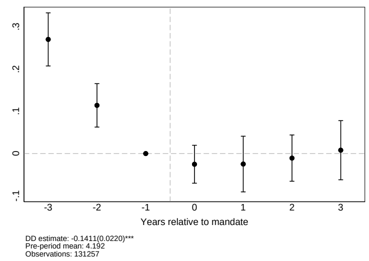


Notes: These figures plot the event-study estimates and 95% confidence intervals from estimating equation (2). Each outcome represents the current nursing home's within-state percentile rank in 2011. See notes under Table 1 for details about the analysis sample. The analysis sample is further restricted to individuals who are continuously in a nursing home throughout the entire event window.

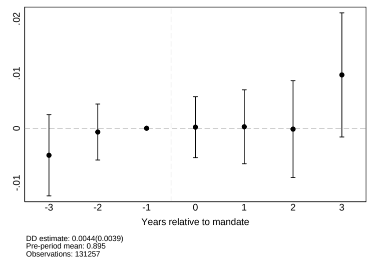
Appendix Figure B8: Event-study estimates of the impacts of MLTSS mandates on nursing home's current quality

Florida

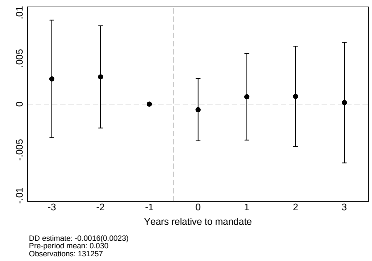
(a) Hours per resident day



(b) Occupancy rate

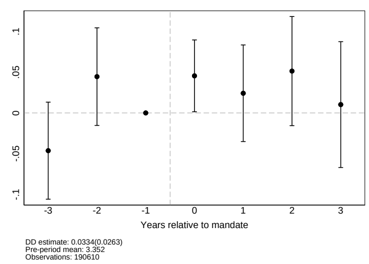


(c) Restraint rate

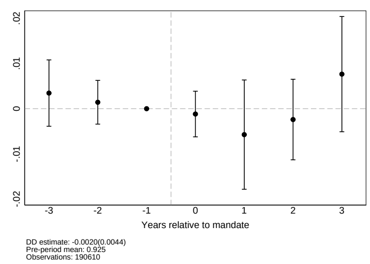


New York

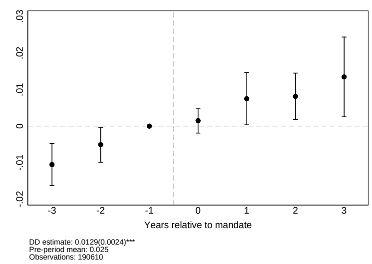
(d) Hours per resident day



(e) Occupancy rate



(f) Restraint rate



Notes: These figures plot the event-study estimates and 95% confidence intervals from estimating equation (2). Each outcome represents a measure of the current nursing home's quality. See notes under Table 1 for details about the analysis sample. The analysis sample is further restricted to individuals who are continuously in a nursing home throughout the entire event window.

C Appendix Tables

Appendix Table C1: Comparison of the MLTSS programs for dual-eligible beneficiaries in Florida and New York during the sample period

	Florida	New York
Risk adjustment	Based on population mix in nursing homes, home, and community settings	Based on an algorithm
Plan coverage†	Long-term care services only	Long-term care services only
Type of enrollment	Mandatory	Mandatory
Overall plan incentive	Capitation incentivizes cost reduction, while quality incentives encourage quality improvement	
Differential incentive by expected cost/race	A single, blended capitation rate incentivizes plans to avoid high-cost enrollees and/or to shift enrollees to lower-cost LTC settings	Incentives to risk-select enrollees when their expected costs are high relative to the regional average
Differential incentive by type of service	Incentives to reduce costs in Medicaid long-term care services	Incentives to reduce costs in Medicaid long-term care services

† Both Florida and New York also offer full-capitation plans (such as Program of All-Inclusive Care for the Elderly) that cover both Medicaid and Medicare services. Enrollment in these plans is voluntary.

Appendix Table C2: Timing of MLTSS mandates in Florida and New York

State	Month	Quarter	Counties Mandated
Florida	8/2013	2013 Q3	Brevard, Orange, Osceola, Seminole
	9/2013	2013 Q3	Charlotte, Collier, DeSoto, Glades, Hendry, Indian River, Martin Lee, Okeechobee, Palm Beach, Sarasota, St. Lucie
	11/2013	2013 Q4	Bay, Calhoun, Franklin, Gadsden, Gulf, Holmes, Jackson, Jefferson, Leon, Liberty, Madison, Taylor, Wakulla, Washington
	12/2013	2013 Q4	Broward, Miami-Dade, Monroe
	2/2014	2014 Q1	Hardee, Highlands, Hillsborough, Manatee, Pasco, Pinellas, Polk
	3/2014	2014 Q1	Alachua, Baker, Bradford, Citrus, Clay, Columbia, Dixie, Duval, Escambia, Flagler, Gilchrist, Hamilton, Hernando, Lafayette, Lake, Levy, Marion, Nassau, Okaloosa, Putnam, Santa Rosa, St. Johns, Sumpter, Suwannee, Union, Volusia, Walton
New York	9/2012	2012 Q3	Bronx, Kings, New York, Queens, Richmond
	5/2013	2013 Q2	Nassau, Suffolk, Westchester
	9/2013	2013 Q3	Rockland, Orange
	12/2013	2013 Q4	Albany, Erie, Onondaga, Monroe
	1/2014	2014 Q1	Columbia, Putnam, Sullivan, Ulster
	6/2014	2014 Q2	Cayuga, Herkimer, Oneida, Rensselaer
	7/2014	2014 Q3	Greene, Saratoga, Schenectady, Washington
	8/2014	2014 Q3	Dutchess, Montgomery, Broome, Fulton, Schoharie
	9/2014	2014 Q3	Delaware, Warren
	10/2014	2014 Q4	Niagara, Madison, Oswego
	11/2014	2014 Q4	Chenango, Cortland, Livingston, Ontario, Steuben, Tioga, Tompkins, Wayne
	12/2014	2014 Q4	Genesee, Orleans, Otsego, Wyoming
	1/2015	2015 Q1	Chautauqua, Chemung, Seneca, Schuyler, Yates, Allegany, Cattaraugus
	2/2015	2015 Q1	Clinton, Essex, Franklin, Hamilton, Jefferson, Lewis, St. Lawrence