The Consequences of (Partial) Privatization of Social Insurance for Individuals with Disabilities: Evidence from Medicaid*

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Abstract

In 2014, over 43 million individuals were enrolled in a private comprehensive Medicaid managed care plan, accounting for 61% of Medicaid enrollees. Combined state and federal payments to these private plans exceeded $160 billion. Despite the clear policy significance of the privatization of public health insurance programs like Medicaid, many of its consequences remain unknown, especially for sicker and more vulnerable populations that are simultaneously more likely to benefit from the tools of managed care employed by these private plans and more likely to be harmed by efforts of private managed care plans to deter these (typically unprofitable) individuals from enrolling by limiting their access to needed care. In this paper, we study the consequences of Medicaid privatization for Medicaid enrollees with disabilities, exploiting sharp variation in enrollment in private Medicaid managed care plans induced by the introduction of managed care mandates for SSI recipients in select counties in Texas and New York. Using contiguous counties where private Medicaid plans were not introduced as controls, we show that state spending on Medicaid benefits for SSI recipients increased by over $1300 per person, per year (about 10% of pre-privatization spending), with part of the spending increase coming from private plan payments exceeding counterfactual fee-for-service spending and part coming from increased spending on services carved out of the managed care contract. We also find that privatization decreased inpatient spending for an individual by 19% and increased spending on prescription drugs by 27%, with most of the increase in drug spending coming from drugs used to treat chronic conditions common in this population. Finally, we observe additional increases in office visits and outpatient utilization, consistent with the hypothesis that private managed care plans decrease the use of expensive inpatient care by increasing utilization of less-expensive drugs, office visits, and outpatient treatment. We conclude by analyzing the effects of privatization on various measures of the quality of care received by Medicaid enrollees with disabilities.

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1 Introduction

The question of whether private firms can provide social insurance benefits more efficiently than government is fundamental to public policy and economics. On the one hand, it is argued that competition in the private market could drive down the costs of benefit provision and improve efficiency in health care utilization; on the other hand, distortions generated by adverse selection, incomplete contracting and other market failures could lead to higher costs of benefit provision and worse health outcomes (Geruso and Layton, 2017). Nowhere is the answer to this question more controversial–and perhaps more consequential–than with respect to public health insurance programs in the United States (Gruber, 2017). In the U.S. Medicare program, beneficiaries have a choice between enrolling in the publicly managed traditional Medicare program or enrolling in a private Medicare Advantage plan. In 2017, 19 million people (33% of Medicare beneficiaries) opted for a private plan. Medicare Part D prescription drug benefits are provided entirely by the private market. The Medicaid program in most states is also comprised of public and private options, although states often do not allow groups free choice between these two options, instead making enrollment in private Medicaid Managed Care plans (MMC) mandatory. In 2014, over 43 million people (61% of Medicaid beneficiaries) were enrolled in a private comprehensive MMC plan, with $162 billion going to this program. (Centers for Medicare and Medicaid Services, 2016)

Although U.S. policymakers have increasingly favored privatization of public health insurance programs, many of privatization's consequences remain unknown. In this paper, we focus on how privatization of the Medicaid program has affected a highly vulnerable (and expensive) population: individuals with disabilities enrolled in the Supplemental Security Income (SSI) program. While previous work has studied the effects of privatization for other Medicaid populations such as mothers, children, and babies (see Sparer, 2012, for a comprehensive review), individuals with disabilities have been largely overlooked.[1] This is a critical omission in the literature: In 2014, Medicaid spending for this population amounted to almost $187 billion. That equates to 40% of total Medicaid spending, despite this population only making up about 13.5% of total Medicaid enrollment. (Kaiser Family Foundation, 2014*a*,*b*) Additionally, this population is currently the most policy relevant population with respect to question of public vs. private provision: While most states have already shifted other Medicaid populations to private MMC plans, this population has either only recently been enrolled

[1]The primary exception to this is a concurrent paper by one member of our team (Vabson, 2017).

in, is currently being transitioned to, or is currently under consideration for transition to MMC. Finally, this population is among the sickest and most vulnerable of the groups enrolled in any social insurance system, implying that changes to MMC programs that may have small effects for healthier populations could have magnified consequences for these individuals.

To study the consequences of privatization of Medicaid for individuals with disabilities, we leverage natural experiments in Texas and New York. In the mid-2000s, both states transitioned SSI beneficiaries and other Medicaid enrollees with disabilities into private MMC plans. The transition was mandatory, resulting in a rapid and dramatic increase in the portion of the disabled population enrolled in private MMC plans. Importantly, Texas and New York implemented this transition only in a subset of counties, providing a clean natural experiment that we exploit to estimate how a variety of relevant outcomes changed differentially in counties where MMC was implemented relative to contiguous counties that maintained the publicly managed traditional fee-for-service (FFS) Medicaid program. While implementation of state MMC mandates had large effects on MMC enrollment in both states, changes in MMC enrollment were much sharper in Texas than in New York, leading us to rely most heavily on the Texas experiment, using the New York experiment to buttress our Texas findings.

We find that the shift to managed care had important fiscal consequences: The transition of this population to private MMC plans in Texas caused total spending to increase by $1,344 per person, per year, or about 10% of baseline spending. This dramatic increase in spending is caused by two factors. First, both states “carved out" certain services from the MMC contracts, meaning that these services continued to be covered under the traditional FFS Medicaid program even for beneficiaries in the private program. Both states carved out prescription drug services, while Texas also carved out inpatient services. We find that implementing MMC in Texas led to an overall increase in spending on these carved-out services of $439, or about one-third of the overall effect. Second, states attempt to set their premium payments to MMC plans approximately equal to the counterfactual costs of these enrollees in the traditional FFS Medicaid program. We find that Texas set these payments too high, with this problem only becoming more magnified over time, resulting in an increase in state spending of an additional $905 per person, per year, or about two-thirds of the overall effect. Results from New York support these findings.

We then ask what benefits the state receives in return for these higher spending levels, specif-

ically in terms of care provided to program beneficiaries. We do this by analyzing the effects of privatization on healthcare utilization among individuals in this population. We find that enrolling an SSI beneficiary in a private MMC plan decreases utilization of (more-expensive) inpatient care and increases utilization of (less-expensive) outpatient care. In Texas, we find that privatization decreases (carved-out) inpatient spending per individual by 19%, with the decrease operating through both the intensive (lower probability of any inpatient admission) and extensive (lower spending conditional on having an admission) margins.[2] This decrease in inpatient spending occurs despite the carve-out of inpatient services from MMC contracts. We observe similar decreases in inpatient use in New York where inpatient services are included in the MMC contract.

These decreases in inpatient utilization are offset by increases in utilization of outpatient care and office visits in both states. Privatization led to 7.8 additional outpatient days and 1.05 additional office visits, 28% and 25% of the respective baseline levels of utilization. Here, increases occurred largely on the intensive margin, due to high baseline rates of the probability of any use.

In addition to effects of privatization on utilization of medical care, we find important effects on (carved-out) prescription drug use. Specifically, we find that enrolling an SSI beneficiary in a private MMC plan in Texas caused a 27% increase in prescription drug spending. Because drug spending remained covered by the traditional FFS Medicaid program, this effect cannot be explained by changes in unit prices for drugs. Substitution between branded and generic drugs also appears unimportant, with increases in the use of both under MMC. Instead, the drug spending effects appear driven by general increases in drug utilization. These increases appear to be driven by initiation of drug treatments used for managing chronic conditions that are prevalent in this population, particularly drugs for mental health conditions (which account for almost half of drug spending in this population) but also drugs for other chronic conditions such as diabetes, heart disease, asthma, and pain. This suggests the potential for important health effects of MMC in this high-mortality population. We identify similar increases in drug utilization in New York, again largely driven by drugs used to treat mental health conditions.

Our findings advance the literature on Medicaid privatization specifically as well as the broader literature on private vs. public provision of social insurance. In the Medicaid context, to our knowledge this is the first paper to examine Medicaid privatization among disabled beneficiaries specifi-

[2]Because inpatient spending is carved out in Texas, this result cannot be explained by differential unit prices between the public and private Medicaid programs. Instead it is likely driven by changes the in composition and quantity of care.

cally, with the exception of concurrent work by Vabson (2017). Furthermore, we provide important contributions to the literature on the fiscal cost of Medicaid privatization. Previous work has shown that transitioning other populations to MMC can either increase or decrease overall Medicaid spending in non-disabled populations (Duggan and Hayford, 2013). Our work shows that transitioning the disabled to MMC is unambiguously cost-increasing, with the increase coming both from "errors" in setting the premium payments for private MMC plans and from incomplete contracting. Our work also reinforces the result from previous research that MMC decreases utilization of inpatient care (Van Parys, 2015; Vabson, 2017). Simultaneously, we provide novel evidence that MMC offsets decreases in inpatient utilization with increases in office visits and outpatient utilization. Our result that MMC causes individuals with disabilities to initiate drug treatments used to treat chronic conditions is also novel and important. While the conventional wisdom suggests that the mission of MMC is to lower inpatient use by increasing use of high-value drugs and primary care, our results provide novel evidence that MMC plans do this in practice. However, combined with the increased fiscal cost of Medicaid under MMC, the welfare consequences remain ambiguous.

Our work also relates to the broader literature focusing on public vs. private health insurance benefits generally. Our results show similarities and differences between the consequences of privatization in Medicaid and Medicare. Our results that privatization decreases inpatient utilization and increases use of drugs for treating chronic conditions are consistent with results from studies of the Medicare Advantage program (Curto et al., 2017; Duggan, Gruber and Vabson, 2017; Starc and Town, 2015), though effect sizes differ with the effect of MMC on inpatient utilization being smaller and the effect of MMC on drug utilization being larger than effects observed in Medicare Advantage. However, the positive effects of MMC on office visits and outpatient utilization differ from what has been observed in Medicare Advantage, where work suggests that Medicare Advantage is a "blunt tool" that decreases utilization of all types of services (Curto et al., 2017). It is important that these differences be pointed out given that privatization is more common in Medicaid and the beneficiary population and program structure differ significantly along several dimensions.

Our work also contributes to the literature on incomplete contracting and offsets. While there is some evidence from the Medicare context that suggests that the use of prescription drugs can have important spillover effects on the use of other medical spending (Chandra, Gruber and McKnight, 2010; Starc and Town, 2015) and limited recent evidence of the impact of MMC drug carve-outs on

drug prices (Dranove, Ody and Starc, 2017), we are the first to document enormous increases in drug use for chronic conditions in a setting where prescription drug costs are carved out of the private managed care plan contract.

Finally, we contribute to the literature on disability insurance. Most of the literature on federal disability insurance programs, including the Social Security Disability Insurance (SSDI) program and the Supplemental Security Income (SSI) program have focused on the impact of these programs on employment, earnings, and other economic outcomes.[3] However, Medicaid spending on the SSI population was almost $187 billion in 2014, dwarfing federal expenditures for cash payments under the SSI program which amounted to $54 billion in the same year. Despite the importance of public health insurance programs for these populations and clear complementarities between the SSI and Medicaid programs (Burns and Dague, 2017), little research focuses on the experience of SSI or SSDI recipients in Medicaid and Medicare, and the effects of ongoing reforms of these public health insurance programs on these populations, especially relative to their large contribution to overall government healthcare spending. This paper adds to this extremely limited literature by studying the consequences of the most prominent reform of the public health insurance program for the disabled to occur since the formation of the Medicaid and disability programs.

We proceed by first describing the institutional background of the Texas and New York Medicaid programs in Section 2. We then describe our data in Section 3 and methods in Section 4. We present our results in Section 5. Section 6 concludes.

2 Background

Texas and New York both transitioned adults with disabilities out of their publicly managed fee-for-service Medicaid programs and into private Medicaid managed care (MMC) plans during the mid- to late-2000s. Because this transition was much sharper in Texas than in New York, we emphasize the Texas results throughout the paper, using the New York results to back up our Texas analysis. As a result, we describe the institutional background in Texas in detail here, while providing a more basic description for New York, leaving the details for the appendix.

[3] In the SSDI context, recent work includes von Wachter, Song and Manchester (2011) , Maestas, Mullen and Strand (2013), French and Song (2014), Moore (2015), Autor et al. (2015), and Gelber, Moore and Strand (2017). In the SSI context, recent work includes Neumark and Powers (2000), Duggan and Kearney (2007), Deshpande (2016*a*), and Deshpande (2016*b*).

2.1 Texas

Texas's Medicaid program is divided into ten service areas, shown in the left panel of Figure 1 (where the 10th service area is shown in white). Starting in February 2007, four of those service areas (Travis, Harris, Bexar, and Nueces) required that all Medicaid recipients over the age of 21 whose eligibility was based on receiving Supplemental Security Income (SSI) enroll in a private Medicaid managed care plan as part of the STAR+Plus program.[4] We refer to this group of individuals as "adults with disabilities" for the remainder of the paper.

Prior to February 2007, all adults with disabilities in Texas were enrolled in a traditional fee-for-service Medicaid program, under which the state directly reimbursed physicians for health care services using the state's price schedule.[5] Starting in February 2007, enrollment in STAR+Plus became mandatory for all adults with disabilities in the four affected service areas, with this group consequently shifted into a private managed care plan on February 1. Adults outside these service areas remained in the traditional fee-for-service program.

Under STAR+Plus, instead of directly reimbursing physicians for the services they provide, the state effectively outsources the provision of Medicaid coverage to private managed care plans and pays those plans a fixed monthly premium or capitation payment for each individual they enroll. The private managed care plans then contract with physicians and hospitals to provide care to their members, negotiating their own prices and building their own networks of providers. Under the STAR+Plus model, all enrollees are required to choose a primary care physician (PCP) (or are assigned one), and this PCP acts as a gatekeeper to all non-primary care medical services.

The goals of the shift from public traditional Medicaid to private Medicaid managed care plans were to (1) improve efficiency by providing insurers with strong incentives to restrain spending and (2) provide adults with disabilities (who often had unmanaged chronic conditions) with care coordination and management to help control their diseases and improve their health and quality of life. Adults with disabilities are one of the most costly groups among the Medicaid population, mak-

[4]Other groups, including Medicaid Buy-in and Community Based Alternative waiver enrollees, were also included in the STAR+Plus program. Here, we focus only on the SSI population, given that they are the largest and most policy-relevant group in STAR+Plus. Additionally, some groups were explicitly excluded from STAR+Plus, including Medicaid enrollees in institutional settings, enrollees from other waiver programs, children in foster care, and enrollees not eligible for full Medicaid benefits. Children (under 21) were not required to join STAR+Plus, but were allowed to join on a strictly voluntary basis. After reaching age 21, these individuals were required to join a managed care plan.

[5]The Harris service area is the only exception to this, as this service area transitioned the disabled to a different form of managed care (the regular STAR program) at an earlier date.

ing up just 20% of the Medicaid population in Texas but accounting for more than 50% of Medicaid spending.

The stated focus of Texas's managed care program was prevention: Access to PCP's was to become easier, all members were to have access to a 24-hour nurse line, and the managed care plans were required to contact all members and ascertain need for long-term services and supports (LTSS). Enrollees were also given access to a new benefit: annual wellness check-ups that were not previously covered by Medicaid. Adults with disabilities represented the ideal group for this type of intervention due to their high rates of chronic disease. Unlike most Medicaid populations, adults with disabilities typically have relatively long Medicaid enrollment spells, allowing managed care plans to recoup upfront investments in prevention through longer-term acute care cost reductions.

Like many state Medicaid managed care programs at the time, Texas "carved out" prescription drug services from its managed care contracts, continuing to pay for all prescriptions on a fee-for-service basis, including for beneficaries enrolled in Medicaid Managed Care. As a result, the state rather than the managed care plan served as the residual claimant on all drug spending. This carve-out implies that where drug therapies represent even weak substitutes for other therapies, managed care plans are highly incentivized to shift patients to drug therapies and away from other carved-in health care services.

A unique feature of STAR+Plus was the additional carve-out of inpatient services for adults with disabilities. This was done to retain eligibility for federal matching funds for Upper Payment Limit (UPL) supplemental payments to hospitals, which are meant to augment the traditionally low Medicaid hospital rates. Had inpatient services been carved-into Medicaid Managed Care plans, Texas's UPL supplements for these hospitals for MMC beneficiaries specifically would have no longer been eligible for federal matching. While this inpatient carve-out may have also shaped managed care plan incentives, this carve-out was unique to adults with disabilities and, unlike the drug carve-out, did not extend to other Medicaid populations in managed care. Given that adults with disabilities make up a relatively small share of all managed care enrollees in Texas, unsophisticated managed care plans may have not adopted a strategy customized for this particular population, and may have instead employed a single strategy across all populations. This could mean that the overall behavior of managed care plans remains unaffected by the presence of an inpatient carve-out for the disabled alone. Altogether, given that the inpatient carve-out is not universally applied across the Medicaid

Managed Care population, its effects on managed care plan incentives is likely to be weaker than the effect of the prescription drug carve-out.

STAR+Plus is also unique in covering various forms of behavioral and long-term care, in contrast to other states that carve-out these services from their managed care contracts. Specifically, STAR+Plus plans cover a comprehensive set of mental health services, including cognitive behavioral therapy. STAR+Plus plans also cover home health services, along with all institutional long-term care stays shorter than 4 months in duration.

Texas selects a limited number of insurers to participate in STAR+Plus through a special process. Throughout our study period, the set of participating carriers included Amerigroup, Molina, EverCare, and Superior HealthPlan.

2.2 New York

While MMC was available in New York as early as the 1990's, it was only introduced to adults with disabilities in the mid-2000's. Specifically, it became available in different counties at different times, with counties falling into three different groups in terms of timing of MMC availability and mandated enrollment: Early transition counties, mainstream transition counties, and late transition counties. The middle panel of Figure 2 shows the three groups. Early transition counties are in white, mainstream transition counties are dark shaded colors, and late transition counties are light shaded colors. Dark and light shades of the same color belong to the same rating area. Prior to MMC's introduction based on the timeline outlined below, it was unavailable to adults with disabilities altogether, even on a voluntary basis. In both early and mainstream transition counties, MMC become available to adults with disabilities in January 2007. For late transition counties, MMC was mostly unavailable to adults with disabilities until after 2010 (the end of our sample period).

Alongside the roll-out of MMC's availability to the disabled population on a voluntary basis, New York State proceeded to make enrollment in MMC mandatory for certain disabled populations. Specifically, New York rolled-out MMC enrollment requirements across counties on a staggered basis, with the first set of mandates applying to the early transition counties, and implemented in 2007-08, while mandates for mainstream transition counties were rolled out during 2008-09. Throughout this period, certain disabled populations remained ineligible for Medicaid Managed Care enrollment and were instead required to be in fee-for-service Medicaid. These included long-term nursing home res-

idents and dual-eligibles (those Medicaid recipients who were simultaneously enrolled in Medicare). New York's Medicaid Managed Care plans covered inpatient, outpatient, and laboratory services. Meanwhile, certain services remained carved-out of the states managed care contracts, including prescription drugs, mental health, and long-term care, and consequently remained covered by fee-for-service Medicaid even for beneficiaries in managed care.

3 Data

In this paper, we use several administrative datasets from CMS for the states of New York and Texas, containing information on Medicaid enrollment status, along with inpatient, ER, outpatient, and drug utilization. This data extends from 2004 through 2010. Uniquely, it allows for construction of an individual-level panel of utilization, which covers everyone in Medicaid fee-for-service as well as Medicaid Managed Care, including those switching between the two. Sample inclusion in these data also remains unconditional on utilization, in contrast to the stand-alone discharge data typically used for researching Medicaid. This data is also unique in tracking outpatient and prescription drug utilization, in contrast to past studies employing only inpatient data, allowing for a more complete picture of patient care.

Using information contained in the administrative data, we can precisely construct cohorts that are relevant to our analyses. Specifically, we restrict to New York and Texas residents enrolled in Medicaid in a given month, who qualified for the program on the basis of disability. We further restrict to those who are not simultaneously enrolled in Medicare in a given month. Finally, we restrict our main analyses to individuals over 21, given that Medicaid Managed Care enrollment always remained optional for those under 21.

3.1 Beneficiary Characteristics and Enrollment Information

To derive information on beneficiary characteristics and enrollment status, we use administrative data from the Centers for Medicare Medicaid Services (CMS), covering New York and Texas for the 2004-2010 period. The data are comprised specifically of the Medicaid Analytic eXtract (MAX) Personal Summary files for these states, which contain person-month level information on overall Medicaid and Medicare enrollment status. For those enrolled in Medicaid, these files identify whether the

individual's Medicaid coverage in a given month comes in the form of fee-for-service or Medicaid Managed Care. These files also identify the basis for each beneficiary's eligibility for Medicaid, such as through disability (via SSI) or AFDC qualification. Finally, among those in Medicaid Managed Care, the data also tracks each individual's specific plan of enrollment through standardized ID's, which can be used for linking to external plan characteristics data.

3.2 Inpatient, Outpatient, and Prescription Drug Utilization Data

We track inpatient, outpatient, and prescription drug utilization using claims-level information from CMS. This data is comprised of the MAX IP, OT, and RX files and covers all Medicaid recipients in New York and Texas over the 2004-2010 period. Notably, this data covers those in Medicaid fee-for-service as well as those in Medicaid Managed Care, and also allows us to track health care use longitudinally among those switching between these two forms of coverage. Moreover, this data allows us to get a more complete picture of each individual's health care usage than would be possible with inpatient data alone, which has been the only form of data used in most previous Medicaid studies. This is particularly valuable, given that non-inpatient care accounts for over 65% of this population's medical spending.

Given that inpatient as well as prescription drug services are carved-out of managed care contracts in Texas, these forms of care continue to be paid for on a fee-for-service basis by the state, and consequently can be fully tracked using Medicaid fee-for-service data (in New York, prescription drug services are carved-out and so can similarly be tracked in fee-for-service claims). Since these services are paid for and tracked under an identical arrangement, irrespective of whether a beneficiary is otherwise enrolled in Medicaid fee-for-service or Medicaid Managed Care, data quality will likewise remain uniform across beneficiaries and will not confound our analyses on Medicaid Managed Care's effects.

However, differential data quality could be more of a concern for outpatient care given its carved-in status, with outpatient data for Medicaid Managed Care beneficiaries originally getting tracked by the plans themselves. A specific concern is that data quality is lower for these Medicaid Managed Care claims, particularly through visit underreporting, based on the apparent incompleteness of past data turnovers (Lewin Group, 2012). These concerns are mitigated in our setting, where at the time of the transition of the disabled population into MMC, managed care had been in force for other

populations for a number of years, resulting in the disabled transition being less disruptive to the reporting of claims and encounters. Concerns are also mitigated by our finding of generally *higher* outpatient utilization under Medicaid Managed Care, since data quality issues would most plausibly produce the opposite effect, through undercounting of Medicaid Managed Care visits. This suggests that if there is a reporting issue, it would imply that our estimates of outpatient utilization increases should be seen as a lower bound. Finally, reporting concerns should be mitigated by the timing of the effects we observe. For no outcome do we observe a discontinuous drop in utilization immediately following the sharp transition to MMC in Texas, as would be the case if there were significant under-reporting.

The utilization data is rich. Inpatient data tracks the timing of each hospital visit. The data also provides visit-level information on treatment intensity and composition, including hospitalization type, length of hospital stay, set of procedures performed, and total visit costs. Using fields contained in the data, it is furthermore possible to classify hospitalizations into various relevant categories, including elective, emergency, and surgical admissions. Finally, the data specifies the name and location of the hospital visited, allowing us to link to external hospital characteristics measures and also to estimate each patient's hospital travel time. Again, as inpatient claims are carved out of MMC and always paid directly by the state, the reporting of these claims is unaffected by the transition to MMC.

The outpatient data, meanwhile, contains information on the site and date of care, along with the diagnoses and procedures associated with any given visit. Based on this information, we are able to classify outpatient care into different categories, including regular office visits, surgeries, as well as diagnostic and imaging procedures. For office visits, we are able to specifically separate out visits to primary care providers from visits to specialists. We are also able to identify outpatient care that is of a preventive nature, using an accepted classification system among insurers. In addition, the outpatient data includes information on actual cost amounts, specifically the negotiated amounts actually paid out to providers. In the outpatient data, these actual cost amounts are available for all Medicaid fee-for-service claims in New York and Texas, as well as for about 80% of all Medicaid Managed Care claims in Texas; actual amounts paid are unfortunately missing from all of New York's Medicaid Managed Care claims. For the 20% of Texas Medicaid Managed Care claims missing cost information, we are able to impute this information, based on median observed Medicaid Managed

Care rates for a given procedure.

The prescription drug data includes information on the quantity and types of drugs used, including individual drug identifiers (NDC codes), which we link to external data grouping drugs by therapeutic class. Specifically, we are able to identify the costs of a given prescription, the dates on which it was written as well as filled, and the number of days supply associated with it. Based on a drug's therapeutic class, meanwhile, we are able to identify the types of chronic conditions that it could be meant to treat. Again, because drugs are carved out of the MMC contracts in both states and always paid for directly by the states, drug claim reporting is unaffected by the transition to MMC.

3.3 Quality of Care Metrics

To measure quality of care, we consider the overall quality of hospitals used, along with visit and patient-specific information on the care delivered. First, we consider the characteristics of hospitals visited, such as their classification as major teaching centers. We also consider patient and visit-level metrics such as 30-day rates of hospital readmission. As part of this, we additionally consider rates of ambulatory-sensitive hospital admissions, which could have been prevented through better outpatient treatment as identified by an Agency for Healthcare Research and Quality (AHRQ) algorithm.

Unfortunately, the above measures serve as incomplete indicators of care quality and patient well-being. The coarseness of these measures constitutes a meaningful limitation of our study, and prevents us from drawing more sweeping conclusions around the welfare consequences of Medicaid Managed Care.

3.4 Government Expenditure Metrics

We construct beneficiary-level measures of government Medicaid expenditures based off information contained in the different CMS MAX files. First, we track government spending in the form of fee-for-service Medicaid payments, and furthermore break this spending down into specific subcategories such as long-term care, inpatient care, and prescription drugs. Texas and New York will incur spending in the form of fee-for-service payments for patients enrolled in the fee-for-service version of Medicaid. Furthermore, these states will also incur these expenditures for carved-out services, across all Medicaid beneficiaries. Separately, we also track government spending in the form of premium payments to Medicaid Managed Care plans, which are available in our data at a beneficiary-month

level.

4 Empirical Framework

4.1 Control and Treatment Counties

To study the effects of Medicaid privatization on the SSI population, we leverage the introduction of the STAR+Plus program to four of the ten Medicaid service areas in Texas (Travis, Harris, Bexar, and Nueces) starting in February 2007. As discussed in detail in Section 2, at the time of the introduction of STAR+Plus to these service areas, all eligible SSI recipients who were not also eligible for Medicare were disenrolled from Texas's traditional fee-for-service Medicaid program and enrolled in a private Medicaid Managed Care plan. SSI recipients residing in other service areas remained in the traditional fee-for-service Medicaid program throughout the study period. We thus use a difference-in-differences strategy to estimate the effects of Medicaid privatization on the SSI population.

Treatment (red) and control (blue) counties are shown in the midle panel of Figure 1. The set of treatment counties is defined as any county in the affected service areas that is contiguous to at least one county in an unaffected service area. The set of control counties is similarly defined as any county in the unaffected service areas that is contiguous to at least one county in an affected service area. Table 1 shows summary statistics for the treatment counties, the contiguous control counties, and the non-contiguous control counties. The summary statistics reveal that for most (but not all) variables, contiguous control counties are much more similar to treatment counties than non-contiguous control counties. This is especially apparent with respect to the age distribution, with 40% of disabled individuals in non-contiguous control counties being between the age of 20 and 24 while only 9-10% of individuals in treatment and contiguous control counties are in that age range. These differences are likely due to the fact that STAR+Plus was implemented in urban areas of the state, while the vast majority of Texas is sparsely populated and rural. By implementing the contiguity requirement, we restrict to relatively less-sparsely-populated control counties, and the treatment and control groups become much more comparable.

In addition to the contiguity restriction, we divide control counties into four groups, matching the four treatment service areas where STAR+Plus was implemented. These groups are illustrated in the right panel of Figure 1. We use these groups to construct a set of indicators we refer to as "service

area grouping"-by-year fixed effects. For each treatment service area, the indicator is equal to one if the individual resides in either a treatment county or a control county assigned to that service area grouping, as illustrated in the right panel of Figure 1. We include these fixed effects in all regressions to ensure that a particular treatment county is compared only to control counties that are contiguous to counties in the treatment county's service area grouping.

The left panel of Figure 3 shows the portion of SSI recipients enrolled in a private Medicaid Managed Care plan in treatment and control counties in Texas for each month between January 2004 and December 2010. STAR+Plus was introduced in the treatment counties in February 2007. It is clear that the switch from the traditional public (FFS) program to private managed care plans was swift and sharp. Effectively overnight, the portion of SSI recipients enrolled in a private managed care plan in treatment counties went from 0% to around 70%. This sharp variation in enrollment in private Medicaid is the variation we exploit to identify the effects of Medicaid privatization on SSI recipients.

Figure 3 illustrates that while take-up of MMC is sharp, it is not complete. There are several possible reasons for this. First, some groups within the SSI population were exempted from the requirement that they enroll in a private managed care plan. Unfortunately, our data does not allow us to identify these exempted groups. Second, upon enrolling for Medicaid, individuals receive retroactive coverage for any health care expenditures they may have incurred in the previous 60 days. This retroactive coverage is provided by the public FFS program, appearing in our data as enrollment in that program.

To provide additional evidence on the consequences of privatization of MMC for adults with disabilities, we exploit a similar county-level transition to private MMC plans in New York, described in Section 2.2. We define mainstream transition counties with at least one contiguous late transition county as treatment counties and late transition counties with at least one contiguous mainstream transition county as control counties. We drop the early transition counties entirely as these consist of the New York City metropolitan area, for which there is no valid control in the state. We also group counties by rating area according to the New York Health Insurance Marketplace rating areas, constructing rating area-by-year fixed effects that we include in all regressions to ensure that treatment counties are only compared to local control counties.

Figure 3 shows the portion of adults with disabilities enrolled in a private MMC plan in treatment

and control counties in NY. It is clear that the transition to MMC is much more gradual than in TX. The transition appears to occur in two stages with an early stage characterized by slow but consistent increases in take-up followed by later stage characterized by a rapid increase in MMC enrollment. These stages are indicated by the vertical red lines. Because take-up in NY is much more gradual, we emphasize the TX results throughout.

4.2 Regression Framework

Because take-up is incomplete, throughout the paper we present reduced form effects in both graphical and regression form as well as instrumental variable (IV) local average treatment effects (LATEs) specific to the population of SSI recipients who complied with the managed care enrollment mandate in regression form. For the annual reduced form results, we estimate event study difference-in-difference regressions of the following form:

$$Y_{it} = \beta_0 + \sum_{t=2004}^{2010} \beta_t Treat_{it} + \alpha_{st} + \gamma_i + \epsilon_{it} \tag{1}$$

where Y_{it} is the outcome of interest, $Treat_{it}$ is an indicator equal to one if person i is living in a treatment county in year t and zero otherwise, α_{st} represents the full set of service area grouping-by-year fixed effects illustrated in the right panel Figure 1, and ϵ_{it} represents a random error term. We also include a full set of individual fixed effects, γ_i to ensure that our estimates are not driven by differential changes in the composition of Medicaid enrollees over time in treatment vs. control counties.[6]

Our IV specification uses the county-level mandates as an instrument for enrollment in a private plan. The first stage regression is:

$$Private_{it} = \delta_0 + \delta_1 Treat_{it} \times Post_t + \alpha_{st} + \gamma_i + \eta_{it} \tag{2}$$

where $Private_{it}$ is equal to the portion of year t that person i is enrolled in a private plan, $Post_t$ is an indicator equal to 1 for any year during the post period (2007-2010), and η is a random error term.

[6]We do not include individual fixed effects in the New York analysis due to concerns about endogenous timing of switches from FFS to MMC raised by the gradual implementation of the MMC mandates observed in the right panel of Figure 3. Endogenous timing is clearly not a concern in Texas, as can be observed in the left panel of Figure 3. For New York, we estimate regressions similar to the ones described in Equation 1 but without the γ_is. This allows us to identify effects off of the (exogenous) changes in MMC market share over time rather than off of the timing of individual switches. This identification strategy mimics the one used by Geruso and Layton (2016) to study upcoding in Medicare Advantage.

Here, δ represents the portion of person-years spent in private plans during the post-mandate years in treatment counties relative to control counties. The IV regression specification is:

$$Y_{it} = \theta_0 + \theta_1 \widehat{Private}_{it} + \alpha_{st} + \gamma_i + \psi_{it} \tag{3}$$

where $\widehat{Private}_{it}$ represents the predicted values from Equation 2 and ψ_{it} is a random error term. Here, θ_1 represents the average difference in the outcome between public vs. private Medicaid for the group of Medicaid enrollees who comply with the MMC mandate.

4.3 Identification

In order for θ_1 to represent the causal effect of an individual being enrolled in a private Medicaid plan vs. the public FFS program, the following identifying assumption must be satisfied: There must be no change in the treatment counties between the pre- and post-STAR+Plus periods that is unrelated to the introduction of STAR+Plus and that does not also occur in the control counties. Because there was no other contemporaneous change in Texas' Medicaid program that affected only the treatment counties and not the controls, the main threat to identification is spurious differential trends in the outcome in the treatment vs. control counties. To ensure that differential trends do not explain our results, for all outcomes we present event study graphs that show how the difference in the outcome between the treatment and control counties changes over time, providing a visual test of whether differential pre-trends exist.

A more subtle threat to identification is the potential of effects of privatization on the composition of Medicaid enrollees. It is plausible that Medicaid privatization could affect who is enrolled in Medicaid. A Medicaid plan is incentivized to encourage healthy individuals who are eligible for Medicaid to enroll, resulting in the plan receiving a monthly premium payment while hopefully paying out little in claims. Plans are also incentivized to encourage sick individuals to drop out of the program, via selective eligibility redetermination or other means. There is some evidence that managed care plans engage in this type of selection behavior for the mainstream Medicaid population (Currie and Fahr, 2005). However, such selective enrollment/disenrollment is unlikely among individuals with disabilities because eligibility is typically determined by the Social Security Administration rather than by state Medicaid programs. Finally, privatization may affect an individual's health which can affect Medicaid enrollment. On the one hand, private Medicaid plans may improve the management

of certain chronic conditions, potentially allowing an individual receiving SSI to overcome her disability and return to work, possibly resulting in her exit from the Medicaid program. Alternatively, private plans may make it difficult for an individual to access important specialty services and ultimately lead to her death. While such significant health effects may seem implausible, it is important to note that the population of individuals receiving SSI is a very sick population.

While any effect of privatization on the composition of individuals enrolled in Medicaid is itself of interest, such shifts in composition can bias IV estimates of the effect of privatization on utilization outcomes for an individual because post-period (pre-period) utilization is unobserved for any individual who exits (enters) the Medicaid program after privatization. The inclusion of individual fixed-effects largely addresses the potential problem of differential shifts in the composition of Medicaid enrollees in treatment vs. control counties, but we also present an additional result that provides evidence that these types of differential shifts do not explain our results. Table 2 shows that there is no significant effect of MMC on the number of adults with disabilities entering or exiting Medicaid. Alongside our use of individual fixed effects, these results provide confidence that results are not driven by differential shifts in the composition of Medicaid enrollment

5 Results

5.1 Total Medicaid Spending

We start by presenting the effects of Medicaid privatization on total Medicaid spending. We define total Medicaid spending as total fee-for-service spending plus any premium payments made to private managed care plans.[7] We do not include individual fixed effects in the total Medicaid spending regressions because we want to determine the effect of implementing MMC on state spending, allowing incomplete take-up of MMC to affect the estimates. In other words, we assume that incomplete take-up of MMC is a necessary part of privatization, even with enrollment mandates. For this same reason, we discuss reduced form instead of IV results, though we provide IV results for the interested reader. Figure 4 plots annual event study coefficients for total Medicaid spending for treatment vs. control counties in Texas. During the pre-period (2004-2006), trends in Medicaid spending in treat-

[7] We subtract $600 per person per year from the premium payments to account for administrative costs which we do not observe for the public program in our data. Including administrative costs makes the effects of privatization on total Medicaid spending even larger.

ment and control counties are identical. Medicaid spending in treatment and control counties clearly diverges starting in 2007, corresponding with the introduction of STAR+Plus. The differential increase pooled across the entire post-period is equal to $1,344.24 or around 10% of average pre-period Medicaid spending in the treatment counties. These results are also presented in Table 3.[8]

Medicaid spending can be affected by privatization directly and indirectly. The direct effect is due to managed care plan premiums being set larger than it would have cost to pay for the services covered by the premium under the public fee-for-service program. The indirect effect is due to incomplete contracting: private managed care plans may affect utilization of carved-out services that remain covered by the state on a fee-for-service basis (inpatient admissions and prescription drugs in Texas). We decompose the effects of privatization on state spending in Table 3, which presents coefficients from difference-in-differences (DiD) regressions of different components of state spending. Event study graphs for these outcomes are presented in Appendix Figure A2. The direct and indirect effects of MMC on Medicaid spending can be found in columns (2) and (3) of Table 3, respectively. It is clear that privatization affected Medicaid spending on both margins. Column (2) indicates that MMC premiums were set to be about $905.28 higher than counterfactual FFS spending, while column (3) indicates that MMC caused an increase in spending on carved-out services of $438.96. This equates to about one-third of the effect of privatization on Medicaid spending coming from spending increases on carved-out services and two-thirds coming from premiums that exceeded counterfactual fee-for-service spending.

The graphical presentations of these regressions in Appendix Figure A2 reveal that the more important direct effects of privatization on total Medicaid spending start out small and increase over time. This is consistent with a story that states initially set premiums close to counterfactual fee-for-service spending but this becomes more difficult over time as the state loses access to its primary counterfactual (past fee-for-service spending trended forward). One reason for this divergence between premiums and counterfactual fee-for-service spending could be the unanticipated slow-down in health care costs that occurred around this same time. While this was a unique situation, it highlights how difficult it is for states to determine counterfactual fee-for-service spending and set MMC premiums accordingly. However, it is also important to note that even if Texas had been able to set

[8]For most spending outcomes, we present results from regressions where the outcome is log spending. Here, we present results from regressions where the outcome is spending in levels because the effects of MMC are so large that the log spending results are difficult to interpret. Log spending results are even more stark than the results reported here.

MMC premiums equal to counterfactual fee-for-service spending, the effect of privatization on total Medicaid spending would have remained positive, causing an increase in spending equal to $393.40 or 3% of baseline spending.

Results from New York provide further support for the conclusion that rolling out MMC to adults with disabilities increases total Medicaid spending. In Table A4 we show that by the end of the MMC transition in NY (2010), total Medicaid spending increased by $862.57 (the sum of the three post-period coefficients) more in treatment counties than in control counties, or about 5% of baseline spending.[9] This smaller increase in largely due to NY setting MMC premiums much closer to counterfactual FFS spending.

The clear result here is that privatization increased state spending by a non-trivial amount. However, the welfare consequences of this increase in spending remain unclear. It could be the case that the additional spending went toward services whose social value exceeded the additional cost. We now turn to the question of how privatization affected utilization of healthcare by individuals.

5.2 Healthcare Utilization

We now move away from the fiscal consequences of privatization and ask how privatization affected individuals. We start with the carved-out services (inpatient admissions and prescription drugs in TX) and then turn to the carved-in services.

5.2.1 Carved-out Services

Appendix Figure A2 showed that privatization led to a dramatic increase in spending on carved-out services. In Figures 5 and 8 we present event study coefficients from DiD regressions of log annual inpatient and prescription drug spending in Texas. In both cases, we observe similar pre-trends between treatment and control counties. In both cases, we also observe breaks in trend between 2006 and 2007, corresponding to the introduction of STAR+Plus, though in opposite directions: MMC leads to lower inpatient spending and higher drug spending. In Tables 4 and 7 we present coefficients from IV regressions for these services. These coefficients indicate that enrolling an individual in

[9] While the coefficients from the regressions using Medicaid spending in levels as the outcome are not statistically significant, the coefficients from the regressions using log Medicaid spending as the outcome are highly significant. We interpret this difference as being driven by the log-normal distribution of medical spending. While we present both specifications in Table A4, we focus our discussion on the spending levels specification to be consistent with our discussion of the Texas results.

MMC causes that individual to have a 19% reduction in inpatient spending and a 27% increase in drug spending. Note that because both of these services were paid under the public fee-for-service program both pre- and post-reform in treatment and control counties, these differential changes in spending cannot be explained by differential changes in prices (or reporting).

Results in Table 4 suggest that the inpatient spending reduction comes through both the intensive and extensive margins. Columns (3) and (4) show significant decreases in the probability of any admission and the number of admissions. These decreases both represent 8% of their respective baseline quantities. Column (2) shows a similarly significant decrease on the intensive margin, with inpatient spending conditional on having an admission dropping by 33.6%. While this could possibly be driven by a shift in the composition of inpatient admissions, this seems unlikely given that it would have to be the case that the marginal admissions prevented by MMC were the highest cost admissions. It seems much more likely that marginal admissions are low cost, making this a lower bound for the actual intensive margin effects of MMC. Column (7) of Table 4 shows that the entire decrease in admissions comes from non-surgery admissions.

While New York did not carve out inpatient services, the effects of MMC appear similar there. Appendix Table A5 presents these results. Again, MMC significantly decreased inpatient spending, and this decrease came through both the intensive and extensive margins, with reductions in length of stay and spending conditional on having an admission as well as in the number of admissions. Again, the decrease is concentrated in non-surgery admissions.

While it is clear that privatization led to a significant reduction in inpatient spending in both states, it is unclear whether the marginal spending was wasteful or beneficial for enrollees' health. It is also unclear whether the decrease in inpatient spending should be taken as a sign of improved management of patients' diseases or a decrease in access to inpatient care. We explore these questions in more detail in Section 5.3.

We now shift to the effects of privatization on drug utilization. As discussed above, Figure 8 shows rapid and significant increases in drug spending in treatment counties relative to control counties after the introduction of STAR+Plus. Appendix Table A8 shows similar, though smaller, increases in drug spending due to MMC in New York. Columns (6) and (7) of Table 7 breaks down total drug spending into spending on brand and generic drugs for Texas. It is clear that both are important, suggesting that the spending decrease is not driven by a shift from brand to generic drugs but instead

by an increase in utilization of both types drugs.

Table 7 shows that this spending increase is entirely driven by the intensive rather than the extensive margin, with no effect on the probability of having any prescription (column 2) or the effect of getting a prescription conditional on having an office visit (column 5). Total days supply (column 3) and days supply conditional on having an office visit (column 4) both see significant increases. This lack of an extensive margin result seems largely due to the fact that this is a sick population, and the vast majority (73%) of individuals in this population were already taking drugs prior to privatization. The bottom panel of Table 8 shows that MMC had important effects on the extensive margin of drug use at the level of the therapeutic class for the ten largest drug classes for this population. One way MMC can influence drug utilization is by getting individuals who have not been seeing a physician to visit a doctor for the first time, get diagnosed with a set of conditions, and receive prescriptions for drugs to treat those conditions. This does not appear to be what is going on here, given that there is no effect on the probability of any prescription but there are important effects on the probabilities of having a prescription within a given class. Instead, it appears that MMC is somehow resulting in new diagnoses and drug treatments among people who are already engaged with the healthcare system.

The top panel of Table 8 shows the effects of MMC on log total drug spending by therapeutic class, reporting regression coefficients for the ten largest classes for this population. There appear to be important effects of MMC for almost all of these classes, with 6 of the 10 classes seeing spending increases exceeding 30%. In Appendix Figure A1 and Appendix Tables A1, A2, and A3 we further drill into the three largest drug classes for this population: Central Nervous System (46.38% of all drug spending), Cardiovascular Agents (12.71%) and Hormones and Synthetic Substitutes (8.33%). For the Central Nervous System category, most of the effect is driven by an increase in the use of anti-depressants and anti-psychotics, with pain-killers (opioid and non-opioid) and Benzodiazepines also playing an important role. For the Cardiovascular Agent class, most of the effect is driven by an increase in the use of Antihyperlipidemic Agents (statins), with ACE Inhibitors and Beta Blockers also seeing significant increases in use. Finally, for the Hormones and Synthetic Substitutes category, most of the effect is driven by drugs used to treat diabetes, including Insulins and Sulfonylureas, as well as Adrenal Agents.

These results suggest that the enrollment of SSI recipients in private managed care plans caused

large increases in drug utilization with most of the increase concentrated in drugs used to treat chronic conditions that are highly prevalent among individuals with disabilities: mental illness and depression, heart disease, diabetes, and pain. Given that there was no effect of MMC on the probability that an individual has any prescription this does not seem to be driven by managed care plans getting adults with disabilities who were not previously engaging with the health care system to the doctor for the first time. Instead, this appears to be driven by individuals who were already taking drugs starting new drug treatments linked to conditions for which they had not previously been diagnosed. The initiation of these treatments is likely to improve health, given that the drugs where the largest increases were observed are unlikely to be "over-prescribed".

The increase in the use of drugs used to treat mental illness and depression (observed in both states) has another potential explanation with health consequences that are less clear. Drugs used to treat depression and other mental illnesses can act as complements to in-person psychotherapy or they can also be used to substitute for more expensive in-office psychotherapy for which the private managed care plans pay the bills. Drugs used to treat pain could also potentially be used as substitutes for more expensive in-person physical therapy, again covered by the managed care plan.[10] Below, we explore in more detail this substitutes vs. complements question.

5.2.2 Carved-in Services

We now shift our attention to the effects of privatization on the utilization of services that were included as part of the managed care contract. For these services we look at measures of utilization instead of spending because while we observe encounter records for services paid for by MMC plans, we do not consistently observe payments amounts for these services. We start by looking at the effects of MMC on office visits. These results are reported in Figure 7 and Table 6. Privatization clearly increased office visits. Column (2) shows that MMC increased the probability of any office visit in a year by 8.3 percentage points, or 13.7% of the baseline probability. Column (1) shows that MMC increased the average number of office visits in a year by 1.05, or 25% of the baseline number of visits. Columns (3) and (4) show effects of MMC aresimilar for PCP and specialist visits. Further investiga-

[10]We note that the increase in the use of painkillers was largely driven by non-opioid (analgesics) rather than opioid drugs, suggesting that Medicaid privatization is unlikely to have played much of a role in the increase in the use of opioids over the last two decades

tion shows that much of the increase is concentrated in visits to multi-specialty clinics.[11] Office visit results for New York presented in Appendix Table A7 reveal similar increases due to MMC.

The other primary category of carved-in services is outpatient services. Figure 6 and Table 5 present event study coefficient estimates and IV regression coefficients where the number of outpatient days in a year is the outcome. These results indicate that MMC had important intensive margin effects on outpatient use (columns 2 and 3) but no extensive margin effects (column 1). This is not surprising given the high baseline rate of any outpatient use in this population (83%). Column (2) indicates that MMC increases the number of days that an individual uses outpatient care by 7.8 days, or 28%. This is an enormous increase in outpatient use. Again, similar increases in outpatient use due to MMC are observed in MMC. These results are presented in Appendix Table A6.

6 Conclusion

We have provided strong evidence of the consequences of privatization for adults with disabilities enrolled in the largest social insurance program in the United States. We leveraged a unique setting that provides rare sharp quasi-experimental variation in private vs. public provision of Medicaid benefits for this group.

Our results suggest that the welfare consequences of privatization for this group are ambiguous. We find that privatization significantly increases the cost of providing Medicaid benefits to this group, but that private plans also significantly alter patterns of health care utilization, increasing utilization of office visits, outpatient utilization, and prescription drug use and decreasing utilization of expensive inpatient care. To fully understand the welfare consequences of privatization, additional research on its effects on health outcomes and the quality of care is necessary.

Our results that managed care lowers inpatient utilization while simultaneously increasing utilization of non-inpatient services is consistent with the mission of private managed care plans. However, the evidence we provide that managed care plans actually behave consistently with that mission is somewhat unique. Previous literature on public vs. private provision of Medicare benefits, for example, finds that managed care seems to be a "blunt tool" for decreasing spending, lowering utilization of nearly every type of health care service (Curto et al., 2017).

[11] Multi-specialty clinics are identified by the specialty code "70". We assigned this specialty code to the primary care category rather than the specialist category. If the assignment of this code were switched to the specialist category, most of the office visit effect would appear to be driven by specialist visits.

In the Medicaid privatization literature, our results are unique in terms of the quality and transparency of the research design and the wide range of utilization outcomes, providing unambiguous estimates of the effects of managed care on a variety of important spending and utilization outcomes for adults with disabilities, a key population of interest. Other work studying privatization of Medicaid in other populations but still using credible identification strategies is largely restricted to hospital-based outcomes due to data limitations (Van Parys, 2015). Further, the overall literature on public vs. private provision of Medicaid benefits in other populations provides results that effectively span all possible effects of privatization, from increasing access to primary care and lowering spending to killing babies with no cost savings (Sparer, 2012).

Our work raises a number of important questions. First, while privatization alters patterns of utilization in ways that are typically believed to be consistent with improvements in health (lower inpatient use, higher use of primary care and "high-value" prescription drugs), we have not been able to provide any evidence of the effects of privatization on health outcomes such as disability status, functional limitations, or mortality. Future work that links clean variation in MMC enrollment to these outcomes is critical for understanding the full impact of privatization. Second, not all private Medicaid managed care programs are created equal. There is wide variation across states and over time in the structure of these programs (Layton, Ndikumana and Shepard, 2017). Shifts in key program features, such as the carving in of drug benefits (Dranove, Ody and Starc, 2017), the carving out of behavioral health benefits (Richards and Trillo, 2017), or implementing competitive bidding schemes for managed care plan selection, could significantly alter the consequences of privatization. Future work should aim to better understand the contributions of specific program features to the effects of privatization.

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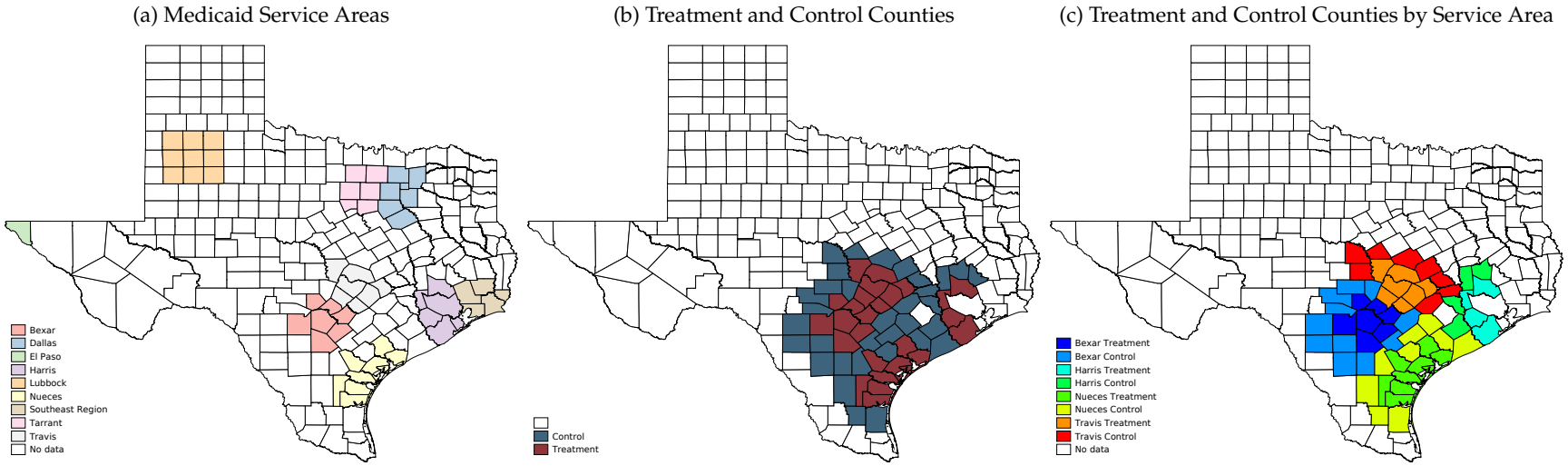
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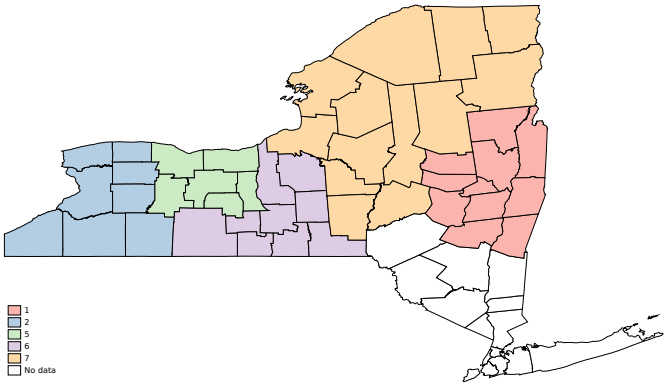
Figure 1: Texas Counties



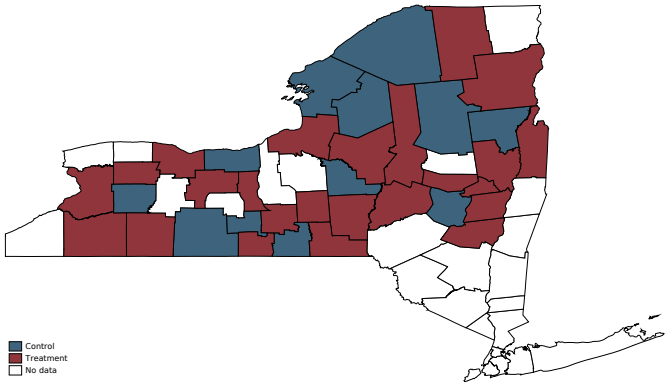
Note: Figure shows Medicaid service areas and the treatment and control counties we define based on these service areas in Texas. Panel (a) shows all nine of the Medicaid service areas designated by the Texas Health and Human Services Commission in April 2004. Panel (b) shows the Texas counties that we include in our sample as treatment and control counties. Treatment counties are counties where Medicaid Managed Care was expanded that are contiguous with at least one county where Medicaid Managed Care was not expanded. Control counties are counties where Medicaid Managed Care was not expanded that are contiguous with at least one county where Medicaid Managed Care was expanded. Panel (c) shows treatment and control counties by service area. For more details, see Section 4.1.

Figure 2: New York Counties

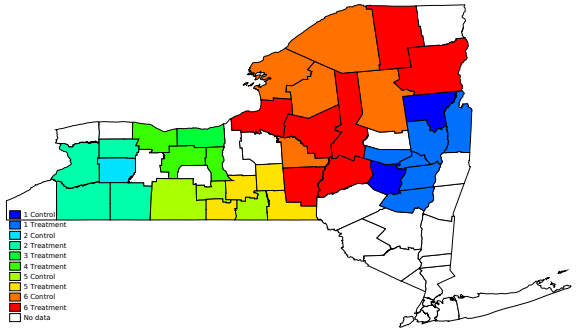
(a) Medicaid Service Areas



(b) Treatment and Control Counties

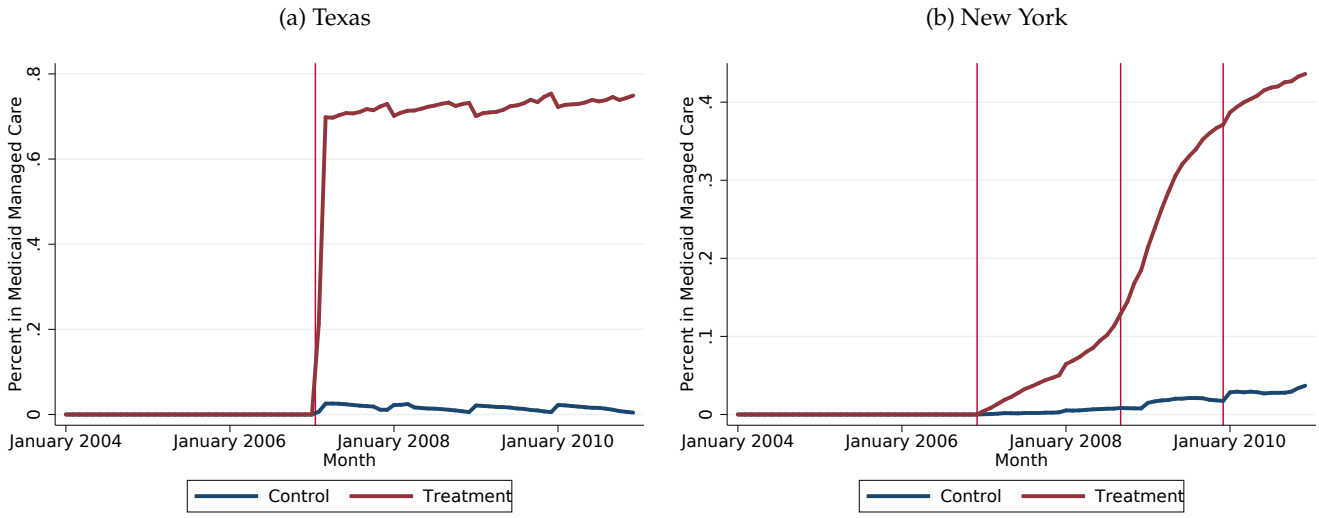


(c) Treatment and Control Counties by Service Area



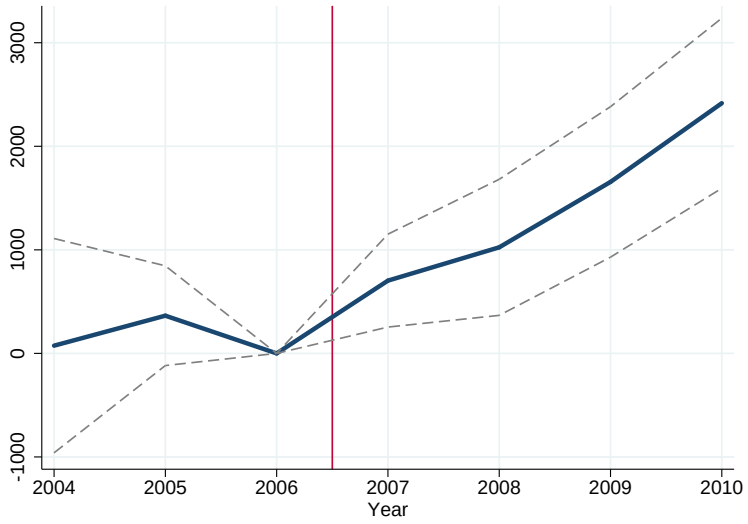
Note: Figure shows Medicaid service areas and the treatment and control counties we define based on these service areas in New York. Panel (a) shows the five geographic rating areas (defined by the Centers for Medicare & Medicaid Services) that we include in our analysis. (We exclude the other three geographic rating areas because there is no variation *within* these areas in Medicare Managed Care status.) Panel (b) shows the New York counties that we include in our sample as treatment and control counties. Treatment counties are counties where Medicaid Managed Care was expanded that are contiguous with at least one county (within their own geographic rating area) where Medicaid Managed Care was not expanded. Control counties are counties where Medicaid Managed Care was not expanded that are contiguous with at least one county (within their own geographic rating area) where Medicaid Managed Care was expanded. Panel (c) shows treatment and control counties by service area. For more details, see Section 4.1.

Figure 3: First Stage



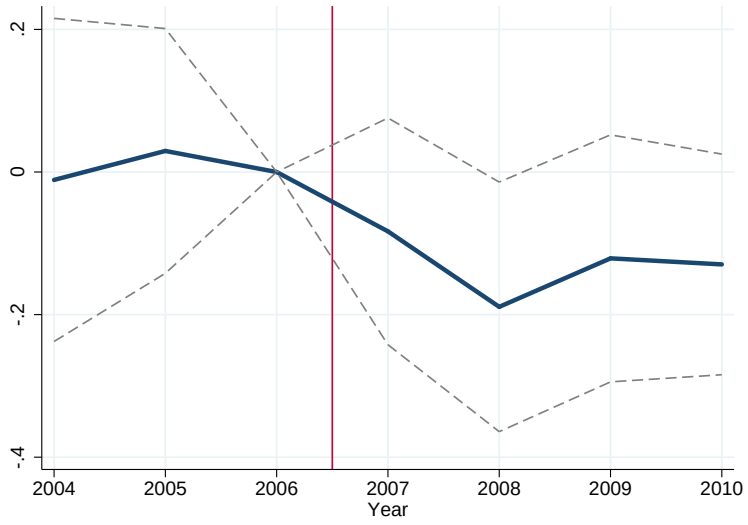
Note: Figure shows Medicaid Managed Care enrollment in treatment and control counties in Texas and New York. Panel (a) shows Medicaid Managed Care enrollment in treatment and control counties in Texas. The red vertical line between January and February 2007 corresponds to the date of the introduction of the STAR+Plus Medicaid Managed Care program in the treatment counties. Panel (b) shows Medicaid Managed Care enrollment in treatment and control counties in New York. The red vertical lines (December 2006, September 2008, and December 2009) indicate the starts of the three stages of increasing Medicaid Managed Care penetration that we define. For more details, see Section 4.1.

Figure 4: Medicaid Spending



Note: Figure shows control-treatment differences in total Medicaid spending in Texas. These difference-in-differences coefficients are from estimating equation 1. We control for service area by year fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Figure 5: Log Inpatient Spending



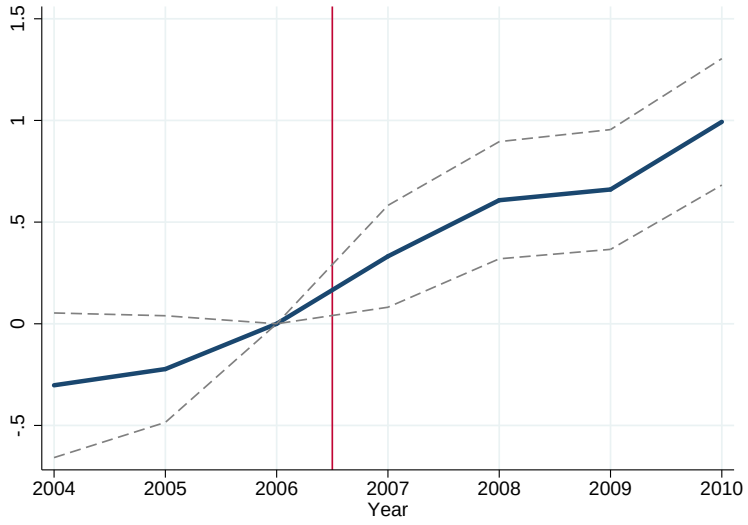
Note: Figure shows control-treatment differences in log inpatient spending in Texas. These difference-in-differences coefficients are from estimating equation 1. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Figure 6: Outpatient Days



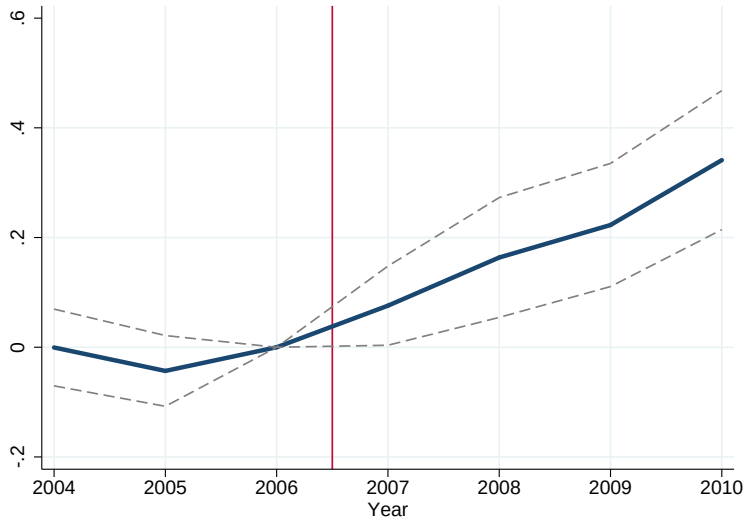
Note: Figure shows control-treatment differences in the number of outpatient days in Texas. These difference-in-differences coefficients are from estimating equation 1. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Figure 7: Number of Office Visits



Note: Figure shows control-treatment differences in the number of office visits in Texas. These difference-in-differences coefficients are from estimating equation 1. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Figure 8: Log Rx Spending



Note: Figure shows control-treatment differences in log prescription drug spending in Texas. These difference-in-differences coefficients are from estimating equation 1. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table 1: Summary statistics

	Contiguous Control	Treatment	Non-Contiguous Control
Average Total spending 2004	10,729	11,404	11,742
Average Inpatient spending 2004	2,929	3,050	2,603
Average Outpatient spending 2004	5,499	5,868	6,906
Average Rx spending 2004	2,302	2,486	2,232
Age 20 to 24	.09083	.1037	.4011
Age 25 to 29	.07696	.08478	.0507
Age 30 to 34	.0778	.08149	.0484
Age 35 to 39	.0817	.08782	.0524
Age 40 to 44	.1013	.111	.06816
Age 45 to 49	.1294	.1281	.08035
Age 50 to 54	.1415	.1362	.09267
Age 55 to 59	.1636	.1457	.1084
Age 60 to 64	.1369	.1212	.09791
Female	.5782	.5556	.5071
Male	.4218	.4444	.4929
Heart Disease	.1165	.1103	.08127
Diabetes	.06873	.06954	.04699
HIV/AIDS	.003315	.005541	.002895
Cancer	.01823	.01853	.01329
Rheumatoid Arthritis	.00884	.007052	.005853
Obesity	.02376	.0281	.018
Substance Use	.0379	.04942	.0235
Mental Illness	.05171	.06291	.03369
N recipients Jan 2004	7,401	30,510	112,833
N recipients Dec 2010	9,206	42,210	174,233
N pre-period recipient months	289,353	1,202,845	4,623,825
N post-period recipient months	405,188	1,824,141	7,333,701

Note: Table shows summary statistics for control and treatment counties in Texas. In our analysis, treatment counties are counties where Medicaid Managed Care was expanded that are contiguous with at least one county where Medicaid Managed Care was not expanded. In our analysis, control counties are counties where Medicaid Managed Care was not expanded that are contiguous with at least one county where Medicaid Managed Care was expanded. However, here we also show summary statistics for all counties in Texas where Medicaid Managed Care was not expanded. For more details, see Section 4.1.

Table 2: Medicaid Entry and Exit

	(1) Enter	(2) Exit
[ITT] Treatment $\times Post$	-0.004	-0.001
	(0.004)	(0.003)
[IV] Medicaid Managed Care	-0.026	-0.005
	(0.028)	(0.019)
Treatment	0.017**	-0.003
	(0.008)	(0.006)
Baseline Mean	.148	.101

Standard errors in parentheses

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

Note: Table shows control-treatment differences in Medicaid entry and exit in Texas. Results are from estimating equation 3. We control for service area by year fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table 3: Medicaid Spending: Texas

	(1) Medicaid Spending	(2) Medicaid Spending Covered by Premium	(3) Medicaid Spending Not Covered by Premium
[RF] Treatment $\times Post$	1,344.239***	905.275***	438.964***
	(319.636)	(295.273)	(129.800)
[IV] Portion of year in MMC	2,505.812***	1,687.534***	818.278***
	(565.990)	(519.109)	(248.800)
Treatment	1,027.558	1,043.286	-15.729
	(1,504.237)	(1,550.872)	(137.178)
Baseline Mean	12573.788	8317.143	4256.645

Standard errors in parentheses

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

Note: Table shows control-treatment differences in total Medicaid spending, Medicaid spending covered by the premium paid by the state to managed care plans and Medicaid spending not covered by the premium paid by the state to managed care plans in Texas. Results are from estimating equation 3. We control for service area by year fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table 4: Inpatient outcomes

	(1) Log Spending	(2) Log Spending Conditional	(3) Any Admissions	(4) Admissions	(5) Emergency	(6) Surgery	(7) Non-Surgery	(8) Length
[RF] Treatment $\times Post$	-0.133**	-0.248**	-0.010*	-0.019	-0.002	0.002	-0.020*	-0.035
	(0.051)	(0.120)	(0.005)	(0.014)	(0.010)	(0.007)	(0.011)	(0.138)
[IV] Portion of year in MMC	-0.190***	-0.336***	-0.015**	-0.027*	-0.003	0.002	-0.029**	-0.050
	(0.056)	(0.090)	(0.006)	(0.016)	(0.011)	(0.007)	(0.013)	(0.156)
Baseline Mean	1.695	8.955	.189	.325	.206	.133	.193	2.33

Standard errors in parentheses

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

Note: Table shows control-treatment differences in various inpatient outcomes in Texas. Results are from estimating equation 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table 5: Outpatient outcomes

	(1) Number of Outpatient Days	(2) Number of Outpatient Days Conditional	(3) Any Use
[RF] Treatment $\times Post$	5.500***	5.597***	-0.004
	(1.120)	(1.190)	(0.005)
[IV] Portion of year in MMC	7.767***	7.647***	-0.006
	(1.231)	(1.287)	(0.005)
Baseline Mean	27.844	33.506	.827

Standard errors in parentheses

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

Note: Table shows control-treatment differences in various outpatient outcomes in Texas. Results are from estimating equation 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table 6: Office visits outcomes

	(1) Number of Visits	(2) Any Visits	(3) PCP Visits	(4) Specialist Visits
[RF] Treatment $\times Post$	0.740***	0.059***	0.387***	0.352***
	(0.149)	(0.014)	(0.117)	(0.077)
[IV] Portion of year in MMC	1.045***	0.083***	0.547***	0.498***
	(0.174)	(0.017)	(0.130)	(0.095)
Baseline Mean	4.104	.606	2.893	1.211

Standard errors in parentheses

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

Note: Table shows control-treatment differences in various office visit outcomes in Texas. Results are from estimating equation 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table 7: Rx outcomes

	(1) Log Spending	(2) Any Prescriptions	(3) Total Days Supply	(4) Total Days Supply Conditional on Office Visit	(5) Any Prescriptions Conditional on Office Visit	(6) Log Spending Branded Drugs	(7) Log Spending Generic Drugs
[RF] Treatment $\times Post$	0.190***	0.006	220.814***	312.661***	0.000	0.286***	0.211***
	(0.048)	(0.005)	(27.800)	(32.151)	(0.005)	(0.054)	(0.033)
[IV] Portion of year in MMC	0.269***	0.008	311.827***	413.907***	0.000	0.404***	0.298***
	(0.052)	(0.006)	(25.752)	(26.483)	(0.006)	(0.058)	(0.038)
Baseline Mean	5.137	.734	653.376	918.115	.948	4.578	3.578

Standard errors in parentheses

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

Note: Table shows control-treatment differences in various prescription drug outcomes in Texas. Results are from estimating equation 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table 8: Therapeutic Classes

(a) Log Spending

	(1) Anti-Infective Agents	(2) Anti-neoplastic Agents	(3) Autonomic Drugs	(4) Blood Form/Coagul Agents	(5) Cardiovascular Agents	(6) Central Nervous System	(7) Gastrointestinal Drugs	(8) Hormones & Synthetic Subst	(9) Immunosuppressants	(10) Misc Therapeutic Agents
[RF] Treatment $\times Post$	0.334***	0.033**	0.365***	0.034*	0.238***	0.300***	0.317***	0.256***	0.009	0.088***
	(0.041)	(0.014)	(0.060)	(0.019)	(0.046)	(0.048)	(0.056)	(0.048)	(0.011)	(0.020)
[IV] Portion of year in MMC	0.471***	0.047***	0.515***	0.048**	0.336***	0.423***	0.448***	0.362***	0.012	0.124***
	(0.044)	(0.015)	(0.060)	(0.022)	(0.047)	(0.053)	(0.056)	(0.048)	(0.012)	(0.021)
Baseline Mean	1.774	.113	1.052	.378	1.834	3.639	1.13	1.625	.083	.221

Standard errors in parentheses

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

(b) Any Spending

	(1) Anti-Infective Agents	(2) Anti-neoplastic Agents	(3) Autonomic Drugs	(4) Blood Form/Coagul Agents	(5) Cardiovascular Agents	(6) Central Nervous System	(7) Gastrointestinal Drugs	(8) Hormones & Synthetic Subst	(9) Immunosuppressants	(10) Misc Therapeutic Agents
[RF] Treatment $\times Post$	0.059***	0.006***	0.069***	0.008**	0.025***	0.028***	0.053***	0.043***	0.001	0.020***
	(0.009)	(0.002)	(0.010)	(0.004)	(0.008)	(0.008)	(0.009)	(0.007)	(0.001)	(0.004)
[IV] Portion of year in MMC	0.084***	0.009***	0.098***	0.011***	0.036***	0.039***	0.075***	0.060***	0.002	0.028***
	(0.009)	(0.002)	(0.010)	(0.004)	(0.009)	(0.009)	(0.009)	(0.007)	(0.001)	(0.004)
Baseline Mean	.411	.02	.246	.072	.32	.61	.215	.303	.011	.046

Standard errors in parentheses

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

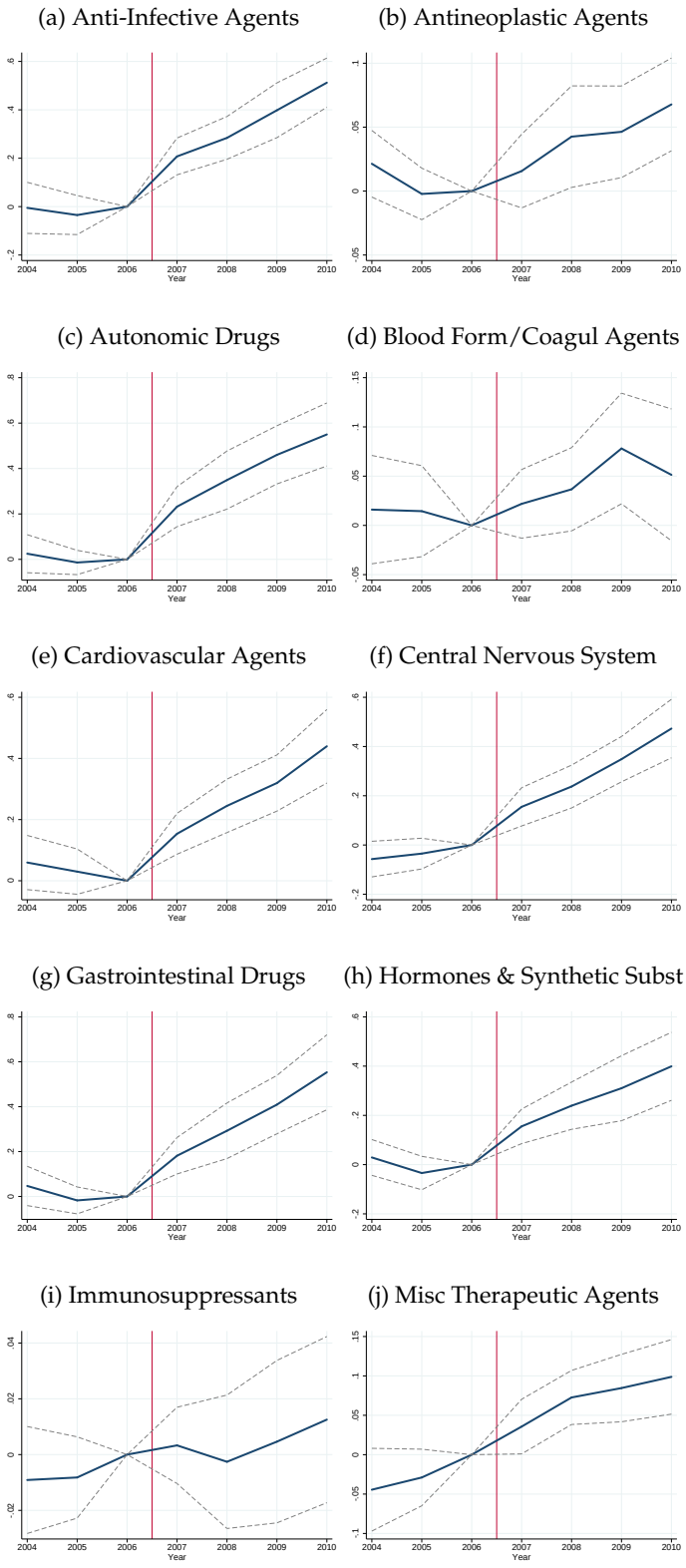
Note: Table shows control-treatment differences spending for the most common therapeutic classes in Texas. Results are from estimating equation 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Online Appendix for:

The Consequences of (Partial) Privatization of Social Insurance for Individuals with Disabilities: Evidence from Medicaid

A Additional Figures and Tables

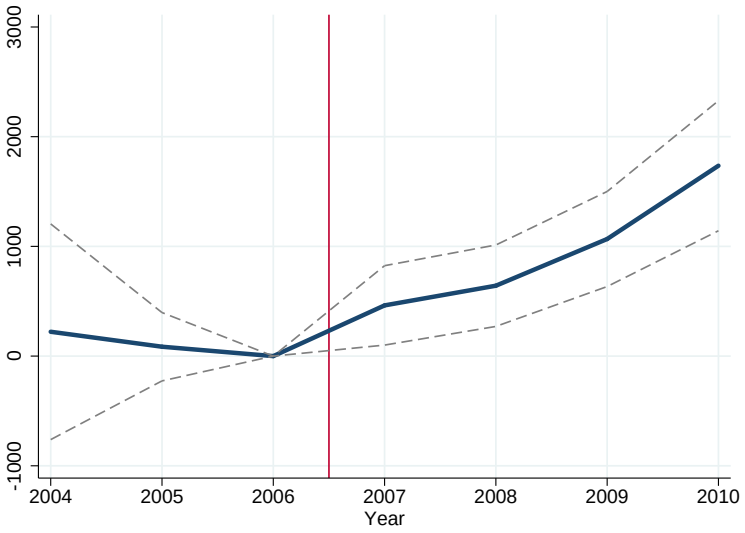
Figure A1: Rx Classes



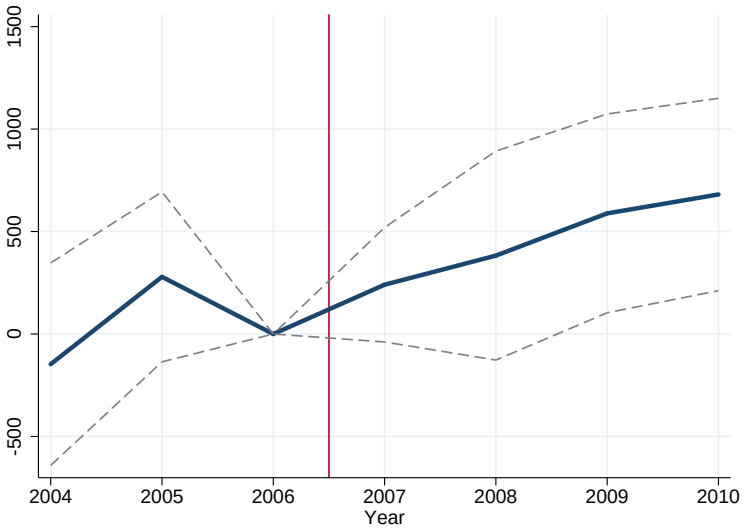
Note: Figure shows control-treatment differences in spending for the top therapeutic classes in Texas. These difference-in-differences coefficients are from estimating equation 1. We control for service area by year fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Figure A2: Medicaid Spending (Texas)

(a) Covered Spending



(b) Not Covered Spending



Note: Figure shows control-treatment differences in Medicaid spending on services covered by premiums paid by the state to MCOs and on services not covered by the premiums in Texas. These difference-in-differences coefficients are from estimating equation 1. We control for service area by year fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table A1: Central Nervous System Classes

	(1) Analg/ Antipyr, Nonstr/ Antiinflm	(2) Analg/ Antipyr, Opiate Agonists	(3) Analg/ Antipyr, NEC	(4) Anti-convulsant, Benzo-diazepine	(5) Anti-conv, Hydan-toin Deri-vative	(6) Anti-conv, Misc	(7) Psych other, Anti-depres-sants	(8) Psychother, Tranq/ Anti-psy-chotic	(9) ASH, Benzo-dia-zepines	(10) ASH, NEC
[RF] Treatment $\times Post$	0.307***	0.189***	0.124***	0.027***	0.011	0.118***	0.247***	0.219***	0.106***	0.137***
	(0.031)	(0.039)	(0.023)	(0.009)	(0.012)	(0.032)	(0.046)	(0.037)	(0.027)	(0.018)
[IV] Portion of year in MMC	0.434***	0.266***	0.175***	0.038***	0.016	0.167***	0.349***	0.309***	0.150***	0.193***
	(0.036)	(0.041)	(0.028)	(0.010)	(0.013)	(0.035)	(0.048)	(0.041)	(0.028)	(0.023)
Baseline Mean	.778	1.139	.324	.182	.177	.99	1.453	1.118	.749	.606

Standard errors in parentheses

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

Note: Table shows control-treatment differences spending for the most common subclasses of the central nervous system therapeutic class in Texas. The first row shows reduced form results from estimating equation 1 and the second row shows instrumental variables estimates from estimating 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table A2: Cardiovascular Classes

	(1) NEC	(2) ACE Inhibitors	(3) Cardiac Glycosides	(4) Anti-arrhythmic Agents	(5) Alpha-Beta Blockers	(6) Beta Blockers	(7) Calcium Channel	(8) Anti-hyperlipidemic Drugs, NEC	(9) Hypotensive Agents, NEC	(10) Vasodilating Agents, NEC
[RF] Treatment $\times Post$	0.031	0.156***	0.013**	-0.002	0.002	0.114***	0.082***	0.168***	0.039***	0.046***
	(0.031)	(0.022)	(0.006)	(0.004)	(0.004)	(0.027)	(0.017)	(0.057)	(0.011)	(0.009)
[IV] Portion of year in MMC	0.044	0.221***	0.019***	-0.002	0.002	0.160***	0.115***	0.237***	0.055***	0.065***
	(0.034)	(0.023)	(0.006)	(0.005)	(0.005)	(0.029)	(0.019)	(0.061)	(0.013)	(0.009)
Baseline Mean	.361	.509	.038	.015	.013	.427	.482	.898	.124	.102

Standard errors in parentheses

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

Note: Table shows control-treatment differences spending for the most common subclasses of the cardiovascular agents therapeutic class in Texas. The first row shows reduced form results from estimating equation 1 and the second row shows instrumental variables estimates from estimating 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table A3: Hormones Classes

	(1) Adrenals & Comb, NEC	(2) Contra-ceptive, Oral Comb, NEC	(3) Estrogens & Comb, NEC	(4) Anti-diabetic Agents, Insulins	(5) Anti-diabetic Agents, Sulfo nylureas	(6) Anti-diabetic Agents, Misc	(7) Para-thyroid Hor-mones, NEC	(8) Pituitary Hor-mones, NEC	(9) Pro-gestins, NEC	(10) Thy /Antithy, Thyroid/ Hor-mones
[RF] Treatment $\times Post$	0.244***	-0.009	0.026*	0.006	0.075***	0.084***	0.002	-0.003	0.001	0.072***
	(0.041)	(0.010)	(0.014)	(0.027)	(0.017)	(0.022)	(0.004)	(0.003)	(0.006)	(0.015)
[IV] Portion of year in MMC	0.344***	-0.013	0.037**	0.009	0.106***	0.119***	0.003	-0.004	0.002	0.102***
	(0.040)	(0.011)	(0.016)	(0.030)	(0.019)	(0.024)	(0.005)	(0.003)	(0.006)	(0.016)
Baseline Mean	.39	.112	.15	.399	.326	.58	.018	.018	.022	.245

Standard errors in parentheses

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

Note: Table shows control-treatment differences spending for the most common subclasses of the hormones and synthetic substances therapeutic class in Texas. The first row shows reduced form results from estimating equation 1 and the second row shows instrumental variables estimates from estimating 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table A4: Medicaid Spending (New York)

	(1) Medicaid Spending	(2) Log Medicaid Spending	(3) Medicaid Spending Covered by Premium	(4) Log Medicaid Spending Covered by Premium	(5) Medicaid Spending Not Covered by Premium	(6) Log Medicaid Spending Not Covered by Premium
Treatment $\times Post1$	419.458	0.064	258.083	0.095**	161.375	-0.017
	(482.251)	(0.045)	(362.971)	(0.046)	(314.764)	(0.043)
Treatment $\times Post2$	119.119	0.310***	156.284	0.341***	-37.165	0.042
	(457.508)	(0.079)	(311.186)	(0.094)	(366.911)	(0.040)
Treatment $\times Post3$	323.988	0.083**	-70.454	0.085**	394.443	0.054
	(544.591)	(0.039)	(297.509)	(0.040)	(400.411)	(0.039)
Treatment	1,575.852**	-0.295**	1,220.393*	-0.192	355.459**	-0.355***
	(709.316)	(0.123)	(664.690)	(0.120)	(153.801)	(0.117)

Standard errors in parentheses

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

Note: Table shows control-treatment differences in total Medicaid spending, Medicaid spending covered by the premium paid by the state to managed care plans and Medicaid spending not covered by the premium paid by the state to managed care plans in Texas. The first row shows reduced form results from estimating equation 1 and the second row shows instrumental variables estimates from estimating 3. We control for service area by year fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table A5: Inpatient outcomes (New York)

	(1) Log Spending	(2) Log Spending Conditional	(3) Any Admissions	(4) Admissions	(5) Surgery	(6) Non-Surgery	(7) Length
Treatment $\times Post1$	-0.079**	-0.296**	-0.003	0.003	-0.000	0.004	-0.078
	(0.037)	(0.122)	(0.003)	(0.011)	(0.005)	(0.008)	(0.123)
Treatment $\times Post2$	-0.115**	-0.545***	-0.002	0.003	0.002	0.001	0.223
	(0.054)	(0.172)	(0.007)	(0.017)	(0.005)	(0.013)	(0.162)
Treatment $\times Post3$	-0.223***	-0.374**	-0.022***	-0.063***	-0.009	-0.054***	-0.823***
	(0.052)	(0.151)	(0.008)	(0.014)	(0.006)	(0.016)	(0.149)
Treatment	0.094	0.167**	0.008	0.024	0.001	0.023	0.330
	(0.091)	(0.066)	(0.012)	(0.028)	(0.004)	(0.026)	(0.199)

Standard errors in parentheses

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

Note: Table shows control-treatment differences in various inpatient outcomes in Texas. The first row shows reduced form results from estimating equation 1 and the second row shows instrumental variables estimates from estimating 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table A6: Outpatient outcomes (New York)

	(1) Number of Outpatient Days	(2) Number of Outpatient Days Conditional	(3) Any Use
Treatment $\times Post1$	1.134	0.750	0.003
	(0.700)	(0.836)	(0.004)
Treatment $\times Post2$	2.763***	1.973**	0.002
	(0.878)	(0.766)	(0.004)
Treatment $\times Post3$	-0.721	-1.333**	0.008
	(0.503)	(0.549)	(0.005)
Treatment	1.359	3.275**	-0.037***
	(1.503)	(1.574)	(0.012)

Standard errors in parentheses

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

Note: Table shows control-treatment differences in various outpatient outcomes in Texas. The first row shows reduced form results from estimating equation 1 and the second row shows instrumental variables estimates from estimating 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table A7: Office visits outcomes (New York)

	(1) Number of Visits	(2) Any Visits
Treatment $\times Post1$	0.378**	0.039***
	(0.159)	(0.013)
Treatment $\times Post2$	0.758***	0.073***
	(0.150)	(0.018)
Treatment $\times Post3$	0.012	0.000
	(0.098)	(0.012)
Treatment	-0.820***	-0.094**
	(0.293)	(0.037)

Standard errors in parentheses

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

Note: Table shows control-treatment differences in various office visit outcomes in Texas. The first row shows reduced form results from estimating equation 1 and the second row shows instrumental variables estimates from estimating 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.

Table A8: Rx outcomes (New York)

	(1) Log Spending	(2) Any Prescriptions	(3) Total Days Supply	(4) Total Days Supply Conditional on Office Visit	(5) Any Prescriptions Conditional on Office Visit	(6) Log Spending Branded Drugs	(7) Log Spending Generic Drugs
Treatment $\times Post1$	-0.019	-0.000	-30.415*	-74.501***	-0.000	-0.025	0.011
	(0.041)	(0.004)	(15.317)	(24.839)	(0.002)	(0.051)	(0.030)
Treatment $\times Post2$	0.067*	0.008	8.970	-43.663**	-0.004	0.014	0.092*
	(0.038)	(0.005)	(11.207)	(20.935)	(0.004)	(0.041)	(0.046)
Treatment $\times Post3$	0.048	0.002	14.595	18.619	0.004	0.088**	0.011
	(0.039)	(0.006)	(11.636)	(27.579)	(0.003)	(0.042)	(0.034)
Treatment	-0.431***	-0.047***	-130.593**	-46.756	-0.008**	-0.429***	-0.397***
	(0.138)	(0.016)	(49.784)	(59.429)	(0.004)	(0.126)	(0.137)

Standard errors in parentheses

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

Note: Table shows control-treatment differences in various prescription drug outcomes in Texas. The first row shows reduced form results from estimating equation 1 and the second row shows instrumental variables estimates from estimating 3. We control for service area by year fixed effects and individual fixed effects. Standard errors are clustered at the county level. For more details, see Section 4.2.