Supplemental Appendix
The Private Provision of Public Services: Evidence from Random Assignment in Medicaid

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I Medicaid managed care in Louisiana

A. Public vs. private provision of Medicaid

In 2012, the state of Louisiana transitioned its Medicaid fee-for-service program to a mandatory Medicaid managed care (MMC) program with a blend of full-risk Medicaid manage care and a managed fee-for-service (FFS) program known as enhanced primary care case management (ePCCM). There were three full-risk MMC plans and two ePCCM plans, which we refer to as "FFS" plans.

The MMC plans received a prospective, monthly risk-adjusted capitation payment (averaging $263 per member per month) to cover a wide range of contracted services for their Medicaid enrollees. The FFS plans receive a small monthly fee (approximately $11 per member per month) to cover the costs of coordinating care and contracting directly with primary care providers (PCPs). However, services other than primary care were coordinated by the FFS plan but provided via the state's legacy FFS network and paid directly by the state. The FFS plans were technically eligible to share up 20% of savings depending on performance, but in practice both plans received less than $5 per member per month in shared savings payouts.

Payment to the full-risk and shared savings plans could be affected by plan performance on five quality measures focusing on adult access to preventive/ambulatory health services, diabetes care, chlamydia screening, and well child and adolescent visits. For the full-risk plans, the state could deduct up to 0.5% of the monthly capitation payment for each of the measures that did not meet a benchmark.

B. Auto assignment in Louisiana

Mandatory MMC was required only for specific Medicaid eligibility categories within Louisiana at the time of transition. The two major eligibility groups mandated into MMC during our study period were Low-Income Families & Children (LIFC) and Families & Children. The LIFC category provides eligibility to children and families that meet the eligibility requirements defined by the Aid to Families with Dependent Children (AFDC) state plan that was in effect since July 16th, 1996. Through different programs, the Families and Children eligibility category provides coverage to pregnant women, parents or caregivers of a child under age 19, children under age 19, or women who need treatment for cervical or breast cancer with coverage allowable for income up to 250% of the federal poverty level depending upon the specific program.

Mandatory MMC was phased in region-by-region in Louisiana. Eastern Louisiana (which contains New Orleans), the first region to use MMC, is the subject of our study. This region underwent the transition in February 2012. On December 15, 2011, enrollees in this region received written notice of the switch to MMC and were given 30 days to choose a plan. A series of outbound calls were made to enrollees to remind them to make a decision (if they had not already done so). A person was automatically allocated to one of the five active plans if a decision was not made within 30 days of the initial packet being provided.

At the time of the switch to MMC, the state's auto-assignment algorithm gave priority to three goals: Preserving existing provider relationships, keeping families together, and balancing auto-assignee across plans. Because of this, not every auto-assignment was random. For instance, enrollees with family members in a plan at the time of assignment were automatically assigned to their family members' plan (rather than at random). We remove these non-random assignments from our sample. The second goal, maintaining previous provider ties, also creates a challenge. To account for this conditional randomization (enrollees' providers did not necessarily participate in all plans), all models control for the unit of randomization, an enrollee's 2011 linked PCCM provider, and cluster standard errors at that level to allow for correlation among enrollees with the same 2011 PCCM provider.

II Data

A. Administrative data and outcomes

We use our administrative data to construct a series of outcomes including enrollee spending, utilization of medical services and drugs, healthcare quality (including avoidable hospitalizations) and plan satisfaction through a "willingness-to-stay" measure. We briefly describe the details of these outcomes below.

- **Winsorized spending outcomes**. Total annual healthcare spending is winsorized at \$25,000. For the auto-assignment population this corresponds to the 99.77^{th} percentile of spending. For consistency, when examining different components of care (inpatient, outpatient, pharmacy) or spending aggregated to shorter time intervals (monthly or quarterly) we winsorize each at the spending level defined by the 99.77^{th} percentile of that distribution. For the plan transition experiment we also winsorize total annual spending at \$25,000. This corresponds to the 98.83^{th} percentile of the spending distribution for this population, so any different aggregations of spending for this experiment are winsorized at the 98.83^{th} percentile of that distribution.
- **Annual well-child visits.** Percentage of children (3-6 years old) and adolescents (12-21 years old) who had at least 1 comprehensive well-care visit with a PCP during the measurement year.
- **Access to primary care.** This is modeled on the children and adolescents access to primary care Healthcare Effectiveness Data and Information Set (HEDIS) measure. It is the percentage of children and adolescents ages 12 months to 19 years who had a visit with a primary care practitioner (PCP). The HEDIS measure reports four separate percentages, stratified by age, which we combine into a single outcome:
  - Children ages 12 to 24 months and 25 months to 6 years who had a visit with a PCP during the measurement year.
  - Children ages 7 to 11 years and adolescents 12 to 19 years who had a visit with a PCP during the measurement year or the year prior to the measurement year.
- **Preventive care measures.** We followed the HEDIS measure sets — commonly used to evaluate health plan performance in Medicaid — to evaluate the receipt of recommended services for preventative care and acute and chronic conditions:
  - *Cervical cancer screening.* Percentage of women ages 24 to 64 who were screened for cervical cancer. Eligible population: women 24 -64 years old. Excludes women who have a history of hysterectomy with no residual cervix, cervical agenesis, or acquired absence of cervix.
  - *Chlamydia screening in women.* Percentage of women ages 16 to 24 who were identified as sexually active and who had at least one test for chlamydia. Eligible population: Women 16 to 24 years old who are identified as sexually active during the year.

- *Follow-up care for children prescribed ADHD medication.* Percentage of children newly prescribed attention-deficit/hyperactivity disorder (ADHD) medication who had at least three follow-up care visits within a 10-month period, one of which was within 30 days of when the first ADHD medication was dispensed.

- **Drug classification.** We assign each drug to an ATC-4 therapeutic class using the Anatomical Therapeutic Chemical (ATC) Classification System, which provides a way to identify drugs that are clinical substitutes (Ganapati and McKibbin, 2019; Dubois, Gandhi and Vasserman, 2019; National Library of Medicine, 2020). The ATC system classifies the active ingredients of drugs according to the organ or system on which they act as well as their therapeutic, pharmacological, and chemical properties. Drugs are classified at five different levels. We use the ATC 4^{th} level (e.g., fast-acting insulins and analogues for injection) to classify drugs into a therapeutic class. For asthma medications we exclude R03BA, glucocorticoids.

- **Behavioral and dental healthcare utilization.** We evaluate whether enrollees have any utilization of behavioral health or dental services within a year. We rely on a state-specific typology to identify claims associated with these services and create indicator variables for enrollees set to one if they have at least one claim for a particular service in a given year, and zero otherwise.

- **Avoidable emergency department use.** This measure captures emergency department (ED) utilization for low-acuity services that could be treated in another ambulatory setting (California Department of Health Care Services, Medi-Cal Division, 2012).

- **Low-value care composite** We create a monthly composite measure of low-value care, which measures if there was any instance of low-value among the following categories: head imaging for uncomplicated headaches, head imaging for syncope, simultaneous brain and sinus CT scan, thorax CT combined studies, CT scan for acute uncomplicated rhinosinusitis, abdomen CT combined studies, arthroscopic surgery for knee arthritis, EEG for headaches, imaging for non-specific low back pain, spinal injections for back pain and imaging for diagnosis of plantar fasciitis. We invert the HEDIS measure "appropriate treatment for upper respiratory tract infections" to obtain a low-value care measure of inappropriate prescribing of antibiotics for treatment of upper respiratory tract infections.

- **Imaging.** We identify healthcare claims that involve imaging using Berenson-Eggers Type of Service (BETOS) codes (Centers for Medicare and Medicaid Services, 2020).

- **Primary care and preventative composite.** We create a composite member for each enrollee, which measures the overall share of primary care and preventative outcomes that an enrollee receives. The composite averages binary outcomes across annual well-child visits, access to primary care, cervical cancer screening, chlamydia screening in women, follow-up care for children prescribed ADHD medication, behavioral utilization and dental utilization. As some measures only apply to specific populations, for each enrollee $\times$ year the denominator is the set of eligible measures for that enrollee $\times$ year.

B. Predicting enrollee health spending (i.e., risk) using enrollee baseline characteristics

To predict enrollee health status we estimate a cross-validated LASSO regression with mean annual post-assignment healthcare spending (in the 3 years after random assignment) as the outcome and use a set of demographic and baseline utilization measures as predictors. For demographics, we use enrollees' Medicaid eligibility category, ZIP code, race, five year age by gender bins, and an indicator for whether they were an "auto-assignee" or "active chooser." In addition to these predictors, we use indicators for the 700 most common baseline diagnosis codes (those obtained by enrollees at any time in the 12 months prior to assignment), baseline medical spending, and baseline pharmacy spending. The baseline spending variables are z-score normalized because they are continuous and on a different scale than the binary indicators which can lead to problems in LASSO estimation.

III Robustness and external validity

In this section we present three separate analyses to explore the robustness and external validity of the main results. First, we present plan transition estimates for a different sample which allows for plan switching after the plan transition. Second, for external validity, we re-weight the auto-assignee sample to better represent the observational Medicaid population which selected plans, and the generally older population of the plan transition experiment. Finally, we re-weight the auto-assignees to resemble a much older Medicaid expansion population to extrapolate the effects to this important population which did not exist at the time of the initial experiment.

A. Robustness of plan transition estimates

The primary plan transition sample excludes enrollees that switched between plans during the 2-year study period. We assess the robustness of our results to an alternative sample of enrollees continuously enrolled from Feb 2014 to Jan 2016 who were permitted to switch plans after the plan transition occurred in February 2015. For this alternative sample, we define the treatment assignment based on their pre-transition plan.

Figure A19 illustrates the rate of switching within this sample after the plan transition. 12 months after the plan transition most enrollees remain in the plan they were enrolled with before the transition (89.0% in the transitioned plan and 93.4% on average across the three control plans). Though the rate of switching is greater within the transitioned plan, given the overall low rate of switching among enrollees who remain in the same plan for a year before the transition, the potential impact of this exclusion in our main specification is greatly minimized.

Table A17 replicates the plan transition estimates within this sample which allows for switching and reports those estimates alongside the re-weighted estimates in Table A10 from the sample where switchers were excluded. Results between the two samples are entirely consistent, though the level of significance of some estimates changes (inpatient spending, primary care and preventative composite, and annual well-child visits).

B. Re-weighting samples

B..1 Active choosers and plan transition populations

In order to investigate external validity and facilitate a comparison of our plan transition (PT) experiment and auto-assignment (AA) experiment, in some analyses we re-weight our samples on three dimensions: Gender, age-buckets (0-5, 6-18, 18+) and 3M Clinical Risk Group (CRG), which use an enrollee's prior claims history to categorize their severity of illness.

- **Auto-assignment experiment.** In the auto-assignee experiment (presented in Section III) we examine the external validity of our estimates based on the auto-assignee sample by re-weighting the auto-assignee population to balance its characteristics with those of the active chooser population. Table A11 presents our re-weighted results.

- **Plan transition experiment.** In the plan transition natural experiment, we lead with estimates that re-weight the PT sample to balance its characteristics with those of the AA sample.

Because of strong joint support between the different samples, and the coarseness of our re-weighting cells, only 4 (0.004%) of the auto-assignee enrollees cannot be assigned a weight when re-weighting to match the characteristics of the active choosers and fewer than 0.2% of the enrollees in the PT natural experiment cannot be assigned a weight when re-weighting to match the characteristics of the auto-assignee sample.

B..2 Post-expansion Medicaid population

The main study period of this paper was prior to the Affordable Care Act's (ACA) Medicaid expansion. In this section, we describe the age distribution in more detail and discuss external validity with respect to a current Medicaid population that would include more adults.

Louisiana expanded coverage to its adult population in July 2016, after our study period. We identify the post-ACA population as all beneficiaries who are enrolled in December 2016 (the latest period post-ACA for which we have administrative enrollment data) and belong to the following eligibility groups: Families & Children, Low-Income Families & Children, or Expansion. Thus, this population includes the same eligibility categories as the auto-assignee population, with the sole addition of the ACA expansion members. As in the auto-assignee sample we limit to enrollees age 65 and younger who have no history of home-health claims.

Figure A20 shows the distribution of age and gender for this post-ACA population relative to the auto-assignee population. On average, the post-ACA population is older than the auto-assignees (20.5 years compared to 9.4 years) and the post-ACA population has a much larger share of enrollees over the age of 18 – 44.5% of the population compared with just 5% for the auto-assignees. We re-weight the auto-assigned sample on three dimensions: Sex, 3M Clinical Risk Group, and age-buckets. We bin age into 5-year intervals between 0-65 to better capture the older post-ACA population distribution.

Table A6 reproduces the results of Table 3 with the auto-assignees re-weighted to the post-ACA population. After re-weighting the average annual spending increases to $2171 annually from $1451 in the unweighted sample, a 50% overall increase, with inpatient spending having the largest percent increase due to re-weighting. However, none of the estimated effects of MMC are significant. We attribute this to lack of precision. For example, in our main analysis for total spending the 2SLS standard errors are 1.4% of the population average, allowing us to detect relatively small and precise differences. In this re-weighted analysis the 2SLS standard errors are 8.2% of the overall population average, reducing our ability to detect significant effects by nearly a factor of 6.

Ultimately, because our auto-assignee sample is young and we lack significant overlap with the age distribution of an older post-ACA expansion population, the reported estimates are too noisily estimated to draw strong conclusions.

IV Decomposition of spending reductions

A. Decomposition of pharmacy spending

Both sources of identifying variation (across Sections III and IV) showed that spending reductions were largely associated with prescription drug coverage, and Figure 3 showed that substitution from brand to generic drugs was important. But exactly how much do price, quantity, and substitution effects—in drugs and elsewhere—account for in the overall spending differences between MMC and FFS? In this section, we decompose managed care's impact on spending into four mutually-exclusive components. The first component is provider price differences, which applies to all products and services. The second and third are focused on drug spending. These are steering *within* brand or generic drugs to lower cost therapies (within narrow therapeutic classes), and steering *from* brand *to* generic drugs (also within narrow therapeutic classes). A residual captures outright quantity reductions and quantity substitutions to lower-cost procedures or drug therapies.

A..1 Decomposition of pharmacy spending framework

Our decomposition approach follows Brot-Goldberg et al. (2017). We begin by restricting to services we observe at least 5 times in both MMC and FFS in each year. We also exclude any cost associated with claim lines that are missing service codes.[1] This ensures that we are examining a consistent set of procedures and drugs for which we can measure price in both MMC and FFS. With these restrictions, we retain 86% of the spending represented in our main auto-assignee analysis sample.[2]

To explain the observed reductions in spending for enrollees assigned to managed care relative to FFS ($\Delta TS_{MMC,FFS}$), we decompose the total spending differential into price and quantity terms:

$$\Delta TS_{MMC,FFS} \equiv \Delta P_{MMC,FFS} + \Delta Q_{MMC,FFS}. \tag{A1}$$

The total spending differential, $\Delta TS_{MMC,FFS}$, is defined to be equal to our IV estimate, $\hat{\beta}^{TS}$, which is expressed in Equation 2 and reported in Table 3. $\hat{\beta}^{TS}$ is the expected spending difference in dollars between a person randomly assigned to MMC in place of FFS. The superscript TS is added to the coefficient to make explicit that the estimate corresponds to a regression in which total spending is the dependent variable.[3] The price term $\Delta P_{MMC,FFS}$ captures the extent to which spending differences are driven by MMC plans paying lower prices than FFS for the same service at the same provider or by MMC plans steering enrollees toward lower priced providers for the same services. The quantity term, $\Delta Q_{MMC,FFS}$, is the causal effect of managed care on overall quantity (i.e., price-normalized healthcare consumption), which includes outright quantity reductions and changes to the composition of services.

We start by isolating the price term, and then further decompose the quantity term. To estimate the price component, we reprice claims so that all claims that share the same service code × year have the same price. We assign these prices using estimated service code fixed effects ν_{dt} from a regression run at the claim-line level in which price is the dependent variable:

$$P_{dct} = \alpha + \nu_{dt} + \pi AssignedManagedCare_{ct} + \mu_{dct} \tag{A2}$$

P_{dct} indicates the price per unit paid[4] in year t for service code d (i.e., individual procedure codes, NDCs, RxCUIs, ATC-4 therapeutic classes) on individual claim record c in our data. The above regression is weighted by the units on each claim[5]. $AssignedManagedCare_{ct}$ indicates the relative price level of MMC to the FFS option in year t. If the data generating process underlying prices consisted of each model determining prices as a constant-multiple markup for all services relative to some

[1] Some claims are paid very small amounts, i.e. \$0.01. Our estimates are unchanged if we remove any claims that cost less than \$1.00 as these represent a very small number of claims and spending.

[2] For these analyses, we use our primary sample of 94,976 enrollees randomly assigned on February 1st 2012. We omit January 2012 as treatment starts in February and annualize the remaining 11 months. We include calendar year 2011—i.e., data from one year prior to assignment to MMC or managed FFS when all enrollees were in legacy FFS—as an additional balance check.

[3] The decomposition can be recast in terms of percentage reductions relative to FFS spending by dividing all terms by the FFS spending level: $\frac{TS_{MMC}-TS_{FFS}}{\overline{TS}_{FFS}}$. $\overline{TS}_{FFS}$ is mean total spending for enrollees *assigned* to the FFS option.

[4] For inpatient claims, each claim is assigned a single unit. For outpatient and pharmacy claims, the number of units is defined as the number of services per claim and number of days supplied per claim respectively.

[5] As a robustness check for differential reporting of units across models, we reprice claims at the claim level and use analogous regressions to the "per-unit" version. We do not see any significant differences relative to the "per-unit" version and conclude that our decomposition results are robust to differential reporting of units. Results available upon request.

common index price for each service (such as the FFS Medicaid price), then $AssignedManagedCare_{ct}$ would exactly recover that markup.

To reprice the claims, we use predicted values from this regression, assigning a common price across models for each code group. This common price is set to equal $(\alpha + \nu_{dt}) \times units_c$ — the code group fixed effect plus the constant, multiplied by the number of units in each claim c. This ensures that all per year per unit prices within each code group are identical within and across models such that the only difference between models is the number of units they administered, i.e. quantity.

Note, the difference-in-differences setting from Section IV uses the following repricing regression:

$$P_{dct} = \alpha + \nu_{dt} + \pi TransitionedPlan_{ct} + \mu_{dct} \tag{A3}$$

where $Treatment_{ct}$ is an indicator variable set to one if claim c is part of the treatment group in year t and zero otherwise. This difference is to account for the difference-in-differences variation and specification. The rest of decomposition is identical for both experiments (Plan Transition and Auto-Assignment).

After repricing all claims in our data, we regress the new price-standardized[6] version of the healthcare spending variable ($Y_{ijt}^{\overline{P}}$) using Equation 2 and recover $\hat{\beta}^{\overline{P}}$, where the superscript $\overline{P}$ indicates a regression that holds prices fixed. In this estimate of the spending difference between MMC and FFS, prices are equalized, so the total spending differences can only be attributable to differences in the number and composition of services—i.e. quantity.

Following Brot-Goldberg et al. (2017), the difference between the main estimate (without repricing), $\hat{\beta}^{TS}$, and the coefficient from the repriced regression, $\hat{\beta}^{\overline{P}}$, yields the contribution of price differences to overall spending differences. Rearranging Equation A1 and substituting gives:

$$\Delta P_{MMC,FFS} = \Delta TS_{MMC,FFS} - \Delta Q_{MMC,FFS} = \hat{\beta}^{TS} - \hat{\beta}^{\overline{P}}. \tag{A4}$$

Focusing on prescription drug utilization—which drives the overall spending effects and for which substitutes are clinically well-defined—we further decompose the quantity effect ($\hat{\beta}^{\overline{P}}$) into three mutually exclusive components. These are defined precisely below and represent (i) a drug steering effect $\Delta Q^{Steering}_{MMC,FFS}$, which captures substitutions among the brand drugs in a therapeutic class or among the generic drugs in a therapeutic class; (ii) a brand-generic drug substitution effect $\Delta Q^{Generic}_{MMC,FFS}$, which captures substitutions between brand and generic drugs within a therapeutic class; and (iii) a residual $Q^{R}_{MMC,FFS}$. This last term includes outright quantity reductions (or increases) and other substitutions unaccounted for by within-class substitutions (or substitutions away from drugs towards medical therapies). For example, this term would capture spending differences due to substitution between ACE inhibitors and beta-blockers in the treatment of high blood pressure. The four terms decompose $\Delta TS_{MMC,FFS}$ as follows:

$$\Delta TS_{MMC,FFS} = \underbrace{\Delta P_{MMC,FFS}}_{\substack{\text{Price diffs. in}\\ \text{identical products}}} + \underbrace{\Delta Q^{Steering}_{MMC,FFS}}_{\substack{\text{Steering within}\\ \text{brand/generic groups}}} + \underbrace{\Delta Q^{Generic}_{MMC,FFS}}_{\substack{\text{Substitution from}\\ \text{brands to generics}}} + \underbrace{\Delta Q^{R}_{MMC,FFS}}_{\substack{\text{Residual quantity}\\ \text{differences}}}. \tag{A5}$$

To recover the terms of this decomposition, we sequentially estimate our main IV specification (Equation 2) on alternative constructions of the dependent variable. To recover the steering compo-

[6] As in Table 3, overall enrollee-year spending is Winsorized at $25,000 whereas other spending measures are winsorized at the corresponding percentile.

nent, we assign each drug to an ATC-4 therapeutic class using the Anatomical Therapeutic Chemical (ATC) Classification System, which provides a way to identify drugs that are clinical substitutes (Ganapati and McKibbin, 2019; Dubois, Gandhi and Vasserman, 2019).[7] We then reprice all pharmacy services at the therapeutic class $\times$ brand/generic level, so that all generic drugs within an ATC-4 are assigned the same price and all brand drugs within an ATC-4 are assigned the same price. We then re-aggregate the repriced claims to construct an alternative measure of repriced enrollee-year level spending, $Y_{ijt}^{\overline{Steering}}$. We use this as the dependent variable in the Equation 2 regression to recover $\hat{\beta}^{\overline{Steering}}$, the reduction in spending due to managed care that is *not* due to steering towards substitutes within generics or brands in a therapeutic class (i.e., that is not due to shifts from high to low-cost brand or generic drugs within an ATC-4). Note that $\hat{\beta}^{\overline{Steering}}$ also zeroes-out any MMC-FFS price difference for the same product because it zeroes out MMC-FFS price differences for the *entire set* of products in the same ATC-4 $\times$ brand/generic grouping. With this estimate, we can isolate the effect of drug steering as the difference between the overall (price-normalized) quantity effect ($\hat{\beta}^{\overline{P}}$) and the estimate that additionally zeros-out the contribution of steering ($\hat{\beta}^{\overline{Steering}}$):

$$\Delta Q_{MMC,FFS}^{Steering} \equiv \hat{\beta}^{\overline{P}} - \hat{\beta}^{\overline{Steering}}. \tag{A6}$$

Reductions in pharmacy spending may also come from enrollees in managed care substituting from brand to generic drugs. This may either be for an identical molecule or a related drug within the same narrow therapeutic class. To assess this contribution, we reprice all pharmacy claims within an ATC-4 (brand and generic) to equal the average price within an ATC-4. From this we construct an alternative measure of repriced enrollee-year level spending, $Y_{ijt}^{\overline{Generic}}$. Estimating Equation 2 with this as the dependent variable recovers $\hat{\beta}^{\overline{Generic}}$, which is the reduction in spending caused by managed care that is *not* due to price differences for the same product, drug substitutions within brand/generic groups in a therapeutic class, or brand-generic substitutions within a therapeutic class. Subtracting this from $\hat{\beta}^{\overline{Steering}}$ (which zeroes-out price differences price differences for the same product, drug substitutions within brand/generic groups in a therapeutic class, *but not* brand-generic substitutions within a therapeutic class) isolates the effect of brand-generic substitution:

$$\Delta Q_{MMC,FFS}^{Generic} \equiv \hat{\beta}^{\overline{Steering}} - \hat{\beta}^{\overline{Generic}}. \tag{A7}$$

Finally, the $\hat{\beta}^{\overline{Generic}}$ coefficient—considered alone—measures the final term of the quantity decomposition, $\Delta Q_{MMC,FFS}^{R}$. This is a residual that captures both outright quantity reductions and quantity substitutions between services.

A..2 Decomposition of pharmacy spending results

Table A14 presents the decomposition results for the auto-assignee experiment and sample. The overall effects to be decomposed are similar to the instrumental variable results on overall spending in the first row of Table 3, except that we generate results separately for each year from 2011 to 2014, estimating Equation 2 over sub-samples defined by year to document how the effects of managed care evolve over time.[8] Recall that the carve-in of prescription drugs occurred in November 2012. Hence,

[7]The ATC system classifies the active ingredients of drugs according to the organ or system on which they act as well as their therapeutic, pharmacological, and chemical properties. Drugs are classified at five different levels. We use the ATC 4th level (e.g., fast-acting insulins and analogues for injection) to classify drugs into a therapeutic class.

[8]Results for t_0–t_2 (i.e., 2012-2014) use the instrumental variables approach in Table 3. Because 2011 (i.e., t_{-1}) is a pre-assignment period, estimates for that year are based on estimating a reduced form version of Equation 2, comparing the outcomes for enrollees *eventually assigned* to MMC versus FFS, but who have not yet been assigned or enrolled.

the first full year that MMC plans managed prescription drugs was 2013 (t_1). We present results for the year prior to assignment (i.e., t_{-1}) to illustrate that enrollees assigned to managed care did not have lower healthcare spending prior to assignment. To facilitate interpretation of magnitudes, results in Table A14 are scaled as percentage changes by dividing the estimates from Equations A4 through A7 by the mean FFS spending in the indicated category (total, medical, or pharmacy).

The first column presents differences in total healthcare spending (in percentage terms) between managed care and the FFS option that are consistent with analyses presented in Figure **??** and Table 3. After prescription drugs were carved into managed care we find that the MMC plans generated substantial reductions in total healthcare spending, ranging from about 7.49 to 8.52% over 2013–2014. Managed care generated a smaller reduction of 4.8% in spending in 2012 (t_0) when managed care plans were only responsible for prescription drugs for two months of that year. Consistent with evidence in Section A., we observe large reductions in pharmacy spending after carve-in and modest reductions in medical spending throughout the post-assignment period.

The second column, $\Delta P_{MMC,FFS}$, examines the role of prices paid to providers. The effect of provider prices on total healthcare spending (medical and pharmacy together in *Panel A*) is fairly small for each year of the post-assignment period, ranging from -0.67% in t_2 to -2.62% in t_1. The effect of drug steering within sets of generic or brand substitutes ($\Delta Q^{Steering}_{MMC,FFS}$) is also modest, at most -2.44% of pharmacy spending in t_2. By comparison, the contribution of steering away from brands towards generics in the fourth column ($\Delta Q^{Generic}_{MMC,FFS}$), demonstrates that one of the main reasons for the reduction in pharmacy spending in managed care was quantity substitutions to generics within narrow therapeutic classes. In the period after pharmacy was carved into managed care, there were large quantity substitution effects for drugs, ranging from -8.61% in t_1 to -11.22% in t_2 of pharmacy spending, about half of the overall pharmacy effect (-25.48%).[9] The final column ($\Delta Q^{R}_{MMC,FFS}$) is the residual; it captures both outright quantity reductions and quantity substitutions to lower-cost drugs in different therapeutic classes and to other procedures.

Figure A12 summarizes the decomposition in Table A14 and adds the analogous results decomposing estimates from the plan transition identification strategy. The results are qualitatively similar between the two distinct identification strategies and samples: Spending reductions are driven primarily by quantity substitutions and outright reductions, rather than price, and, are concentrated in pharmacy spending. Figure A12 demonstrates that, within pharmacy, spending reductions by therapeutic class were strikingly similar across the two different identification strategies.

B. Decomposition of components of care

Similar to the pharmacy decomposition, we provide two formal decompositions of managed care's impact on spending. The first decomposition, shown in Table 5, decomposes the overall effect into price and quantity components. A second decomposition, shown in Table A13, decomposes the overall effect into network and provider components.

B..1 Price-quantity decomposition framework

For each component of care, S, we decompose the spending differential between managed care and FFS into a price and quantity term:

[9] These effects—which comprise the largest component of the decomposition—capture shifts in utilization to generic drugs via two channels: (1) shifts from brand drugs to chemically identical generic drugs within narrow therapeutic classes (e.g., the statin Zocor to its generic equivalent simvastatin); and (2) shifts from brand drugs to chemically-distinct generic drugs within the same narrow therapeutic class (e.g., Zocor to rosuvastatin, which is the generic equivalent of Crestor).

$$\Delta TS^{S}_{MMC,FFS} \equiv \Delta P^{S}_{MMC,FFS} + \Delta Q^{S}_{MMC,FFS}. \tag{A8}$$

The spending differential for each component of care, $\Delta TS^{S}_{MMC,FFS}$, is defined to be equal to our IV estimate, $\hat{\beta}^{S}$, which is expressed in Equation 2. The price term $\Delta P^{S}_{MMC,FFS}$ captures the extent to which spending differences are driven by MMC plans paying lower prices than FFS for the same service at the same provider or by MMC plans steering enrollees toward lower priced providers for the same services. Claims are assigned prices using the same methodology for the decomposition of pharmacy spending (Equation A2)[10]. After repricing claims, we regress the new price-standardized version of the spending variable using Equation 2 and recover $\hat{\beta}^{\overline{PS}}$, where the superscript $\overline{P}$ indicates a regression that holds prices fixed. The difference between the main estimate for each component (without repricing), $\hat{\beta}^{S}$, and the coefficient from the repriced regression, $\hat{\beta}^{\overline{PS}}$, yields the contribution of price differences to overall spending differences.

$$\Delta P^{S}_{MMC,FFS} = \hat{\beta}^{S} - \hat{\beta}^{\overline{PS}}. \tag{A9}$$

The quantity term, which is equivalent to the residual after estimating the price channel, is defined by the coefficient from the price standardized regression,

$$\Delta Q^{S}_{MMC,FFS} = \hat{\beta}^{\overline{PS}}. \tag{A10}$$

B..2 Network-Provider decomposition framework

For each component of care, S, we decompose the spending differential between managed care and FFS into a network term, a provider term, and a residual term

$$\Delta TS^{S}_{MMC,FFS} \equiv \Delta N^{S}_{MMC,FFS} + \Delta D^{S}_{MMC,FFS} + \Delta R^{S}_{MMC,FFS}. \tag{A11}$$

The network term, $\Delta N^{S}_{MMC,FFS}$, captures the extent to which differences in the network of contracted primary care providers result in differences in spending (e.g., constraining cost by having a narrower set of allowed providers). $\Delta D^{S}_{MMC,FFS}$ is a provider term, which measures whether steering to particular providers (responsible for the plurality of an enrollee's care), who may have particular treatment patterns (e.g., referrals or quantity and types of services rendered) results in spending differences. The final term is a residual term, to make the decomposition exact.

To isolate the network component, we use equation 2 with the addition of a linear adjustment for the primary care network breadth in the ZIP code in which the enrollee resides. From this regression we obtain $\hat{\beta}^{\overline{NS}}$ where the superscript $\overline{N}$ indicates a regression adjustment for network breadth. The difference between the main estimate for each component, $\hat{\beta}^{S}$, and the coefficient from the network adjusted regression, $\hat{\beta}^{\overline{NS}}$, yields the contribution of network to overall spending differences.

$$\Delta N^{S}_{MMC,FFS} = \hat{\beta}^{S} - \hat{\beta}^{\overline{NS}}. \tag{A12}$$

[10] For inpatient claims we group services by the Diagnosis Related Group (DRG) and for non-inpatient medical claims we use the HCPCs or CPT code on each claim line.

To identify the provider component, we add fixed effects for the individual NPI responsible for the plurality of an enrollee's care and re-estimate equation 2 to obtain $\hat{\beta}^{\overline{D}S}$ where the superscript $\overline{D}$ indicates a regression that includes an adjustment for the enrollee's primary doctor. The provider component is calculated as

$$\Delta D^{S}_{MMC,FFS} = \hat{\beta}^{S} - \hat{\beta}^{\overline{D}S}. \tag{A13}$$

The residual term accounts for price and quantity effects beyond those captured by the network and provider terms and any interactions between network and provider effects that aren't accounted for independently. This term makes the decomposition exact,

$$\Delta R^{S}_{MMC,FFS} = \hat{\beta}^{\overline{D}S} + \hat{\beta}^{\overline{N}S} - \hat{\beta}^{S}. \tag{A14}$$

B..3 Construction of primary care provider network breadth

To measure the breadth of a plan's primary care provider network in each ZIP code, we take into account the number of in-network primary care providers for the plan, where those providers are located, and what the distribution of patient preferences over those (and other) providers looks like (Centers for Medicare and Medicaid Services, 2018). To do this, we build on the pioneering work of Ericson and Starc (2015*a*) and Wallace (2023). A key insight in these papers is that enrollee preferences over providers lead to patient flows which, when observed in the data, allow researchers to recover enrollee preferences and use them to model provider demand. Another insight of these papers is that simple models of provider network breadth based on realized patient flows yield very similar measures of network breadth to more complex methods that estimate provider demand systems and recover measures of provider network breath (Wallace, 2023). In light of this insight, we opt for the simpler approach in this paper and construct a measure of primary care provider network breadth at the plan-by-year-by-ZIP code level as the fraction of primary care visits—with primary care visits defined as visits involving primary care providers (i.e., internal medicine, family medicine, pediatrics, obstetrics and gynecology, or general practice physicians)—for enrollees living in a given ZIP code covered by each plan's network. We pool healthcare claims for the period (01/2012 to 12/2014) to construct this measure. Intuitively, the measure varies across plans and ZIP codes based on systematic differences in where enrollees in different ZIP codes seek primary care and which providers are in network for each plan.

B..4 Provider attribution used in network-provider decomposition

We allow enrollees to be attributed to a different provider each year. To satisfy joint-support requirements, we restrict to the set of providers that have at least 5 enrollees attributed to them in both the MMC and FFS models during the the post period (35 months from Feb 2012 to Dec 2014). We attribute each enrollee to their modal provider (each year) based on the number of claims they have with each provider. If two or more modal providers exist, we keep the first provider in our data. If an *enrollee* $\times$ *year* observation does not have a mode (i.e., enrollee i has no claims in year t), we forward and then backward fill within enrollee.[11] We are able to attribute 97.1% of auto-assigned enrollees to one or multiple providers in the post period. For enrollees with no claims during the post period—and hence no attributed providers—we create a unique fixed effect for the group and include them in our regressions.

[11] Our findings are not sensitive to the imputation method used. Results available upon request.

In order to verify that attribution to a current provider is not a function of treatment itself, we estimate the following reduced form model:

$$HasProvider_i = \alpha + \pi AssignedManagedCare_i + \phi_i^p + \mu_i \tag{A15}$$

where $HasProvider_i$ is an indicator variable set to one if enrollee i was attributed to a provider; $AssignedManagedCare_i$ is an indicator variable set to one if the auto-assignment algorithm assigned enrollee i to a full-risk, managed care plan at the time of the program transition in February 2012 and zero otherwise; and ϕ_i^p are fixed effects for each enrollee's provider prior to assignment. In results available upon request, we find that the coefficient on $\hat{\pi}$ is not statistically significant, and small relative to its mean. This suggests that the likelihood we are able to attribute an enrollee to a provider is not correlated with whether they were assigned to managed care or FFS.

C. Decomposition standard errors

We obtain standard errors for each component of the decomposition using a bootstrap resampling method. The data has 167 units of randomization so we cluster resample 167 units of randomization with replacement for each of the replicates. Within each replicate, we re-estimate all regressions to obtain the price, quantity, network, provider and residual terms. We define the standard error as the standard deviation of this bootstrap distribution from the replicates. The number of replicates is indicated in table notes where bootstrapped standard errors are provided.

V Denials matching strategy

The nature of pharmacy denials differs from medical denials in that pharmacy denials are subject to real-time adjudication, i.e., if a claim is denied, the enrollee does not receive the prescribed drug and the claim is usually resolved instantaneously. This means that there is real scope for plans to use denials as utilization management tools.

To dig into this potential mechanism, we create a matching strategy that allows us to trace the path of care, from the initial claim that was denied until a final paid claim, if it exists. Starting with a denied claim in the the three month period following the carve-in of pharmacy benefits (we "wash-out" November 2012 as it is the transition month) – this is the same study period as for Panel B of Figure 6 – we match it to a paid claim, if it exists, using the enrollee's ID, the drug NDC, and the claims' dates. Claims are matched for up to 7 days after their denial.[12]. In cases where enrollees have multiple paid claims within 7 days of a denial, the match gives precedence in the following order: (1) same NDC; (2) same ATC-4; (3) same ATC-3; (4) same ATC-2; (5) same ATC-1. That is, we preferentially match denials to paid claims which are for the most similar drug.

Using this matching strategy, we can categorise claims as the following:

1. Administrative denials: denied claims that result in a paid claim within 7 days that have the same NDC. Panel B in Figure A16 further conditions by imposing units to differ between the denied and paid claim.

2. Substitution denials: these are denied claims that result in a paid claim within 7 days that have a different NDC. No restriction is applied for the units. Panel C in Figure A16 uses these.

3. Walk-away denials: these are denied claims for which we were not able to find a paid matching claim.

[12] Because of this, paid claims can be found in the month following the end of the study period, a period for which we still have complete pharmacy data.

The number of denials in each category varies as a function of the time elapsed between denied and paid claims. This variation is due to the limitations of our matching strategy: we can not say with certainty if a particular paid claim is indeed a result of the denied claim or if the paid claim just happens to have matched but for a completely different healthcare episode. However, our results are similar when limiting the time elapsed to the same day. It is also the case that most of these subsequent paid claims are at the same pharmacy.

VI Medical offsets due to pharmacy utilization management

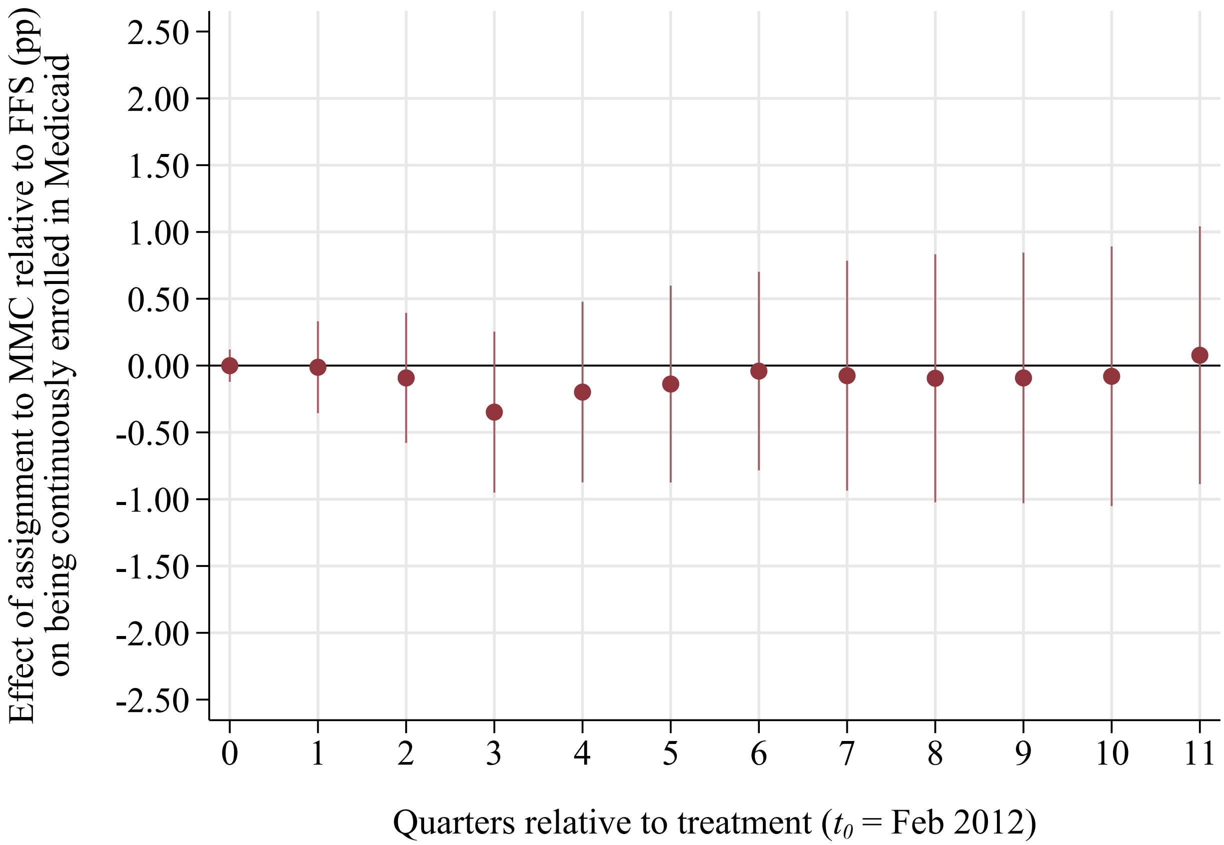
Starc and Town (2019) "find substantial medical care offsets in MA-PD [Medicare Advantage Prescription Drug] plans: a $1 increase in prescription drug spending reduces non-drug expenditure by approximately 27 cents," so it is possible that the smaller medical spending reductions we find in this paper are the result of a much larger medical reduction which is partially offset by pharmacy utilization management. In this section, we incorporate offsets estimated by Starc and Town to determine what level of (counterfactual) medical spending effects might have been observed if there had not been a large reduction in pharmacy spending.

It is important to caveat that this analysis relies on two main assumptions: (1) that we can transport the results across the different populations, and (2) that the mechanisms by which reductions occur are similar in both settings. Regarding (1), Starc and Town study an older Medicare population with heavy prescription drug utilization (76.87 years old and 1,302 days supply annually), while we study a younger Medicaid population with relatively low prescription drug utilization (9.36 years old and 119 days supply annually). It is possible that the offsets generated across these populations are different given the differing compositions of medical services and drug utilization across the two populations. Regarding (2), the 27% offset in Starc and Town is calculated through an offset of $0.59 per day supply (with an average prescription cost of $2.20 per day in their setting). In our context the main mechanism by which managed care reduces pharmacy spending is through substitutions to generic equivalents, not outright quantity reductions. Given this, we translate between their parameters and ours according to reductions in quantity. In particular, we apply their offset of $0.59 per day supply to the reduction in days supply that we calculate as a causal effect of MMC enrollment.

We calculate the effect of managed care on annual days supply for all drugs and separately for the potentially high-value drug classes using our main 2SLS specification including estimates subset to the two years post pharmacy carve-in (this is to ensure we do not understate managed care effects by including 2012 when pharmacy was only carved-in during the last quarter). As Starc and Town estimate an offset of $0.59 per day supply (their Section 4.3.3), we multiply these effects by the offset of $0.59 per day supply to calculate the amount by which our spending results are diminished given this offset. Table A16 shows that managed care has a statistically insignificant negative effect on overall days supply (-3.48 days annually; std. err. = 2.45) when compared to FFS which corresponds to an expected increase in medical costs of $2.05. This offset is extremely small; by incorporating it we would estimate MMC's true medical effect (absent pharmacy offsets) to be -$18.72, 12.3% larger than we currently report, and still statistically insignificant and small relative to the annual level of non-pharmacy spending ($1053). Similarly, using estimates only after pharmacy is carved in we would estimate a $2.21 offset, such that MMC's true medical effect would be -$12.41. This estimate is 22% larger than we currently report, but is still statistically insignificant and extremely small relative to the annual level of spending.

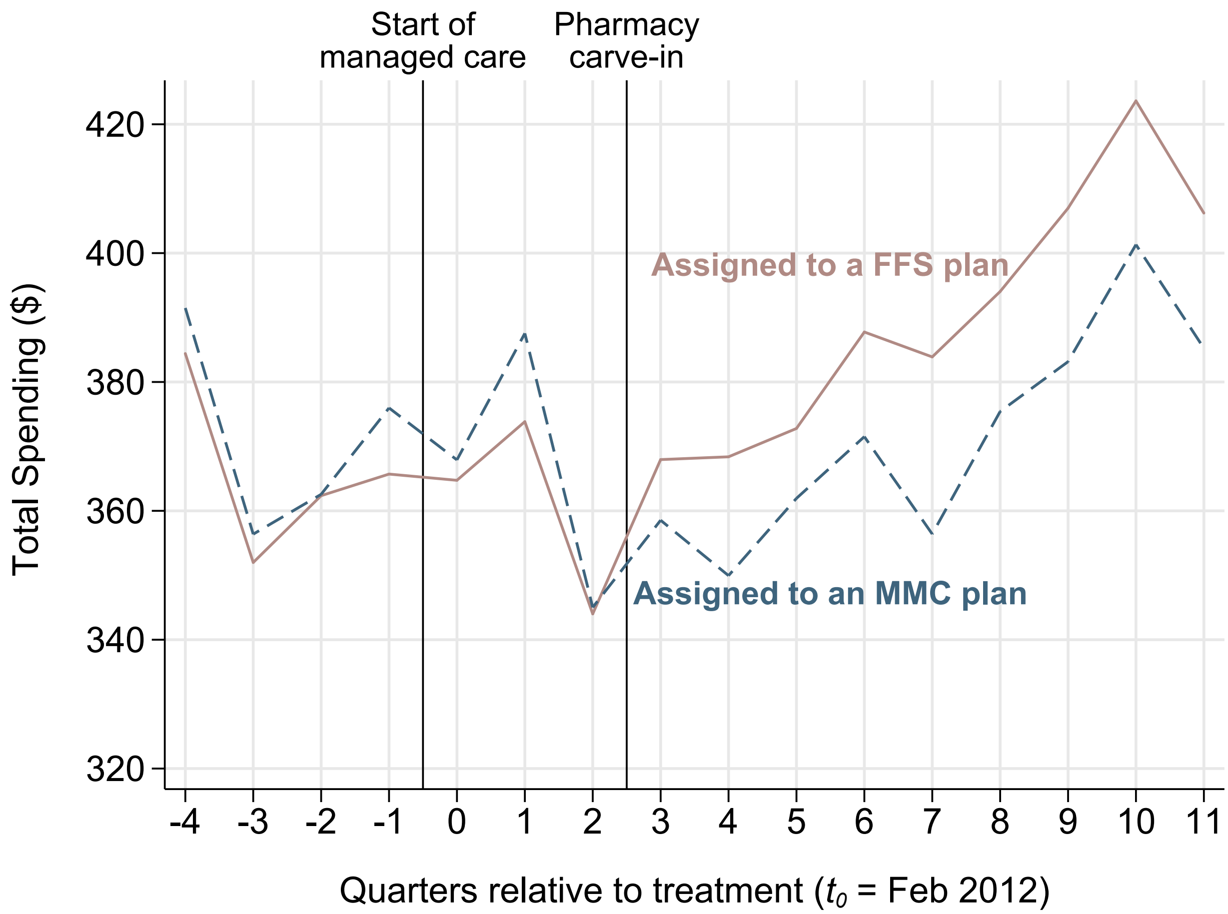
VII Additional Figures and Tables

Appendix Figure A1: Assignment to Medicaid managed care vs. FFS did not lead to differential attrition from the Medicaid program



Note: Figure reports on the probability of continued enrollment in Medicaid—in MMC or in FFS—as a function of the coverage model of assignment (i.e., MMC vs. FFS). The sample is restricted to 141,223 enrollees auto-assigned to plans in February 2012. We impose the same sample restrictions as for our primary sample (described in Section F.), with the exception of our continuous enrollment restriction, which is not imposed here (hence the larger number of unique enrollees relative to our primary sample). Attrition out of the Medicaid program would imply attrition out of our sample. The figure displays quarterly regression coefficients of the impact of assignment to MMC (relative to FFS) on the probability of continued enrollment in Medicaid. The dependent variables are indicators set to 1 for enrollee-month observations as long as the enrollee is still enrolled in Medicaid, and 0 for all months following an exit from Medicaid, even if the enrollee churns back into the program. Time, in quarters relative to assignment, is along the horizontal axis. Standard errors clustered on the unit of randomization (i.e., recipient's prior provider). 95% confidence intervals reported.

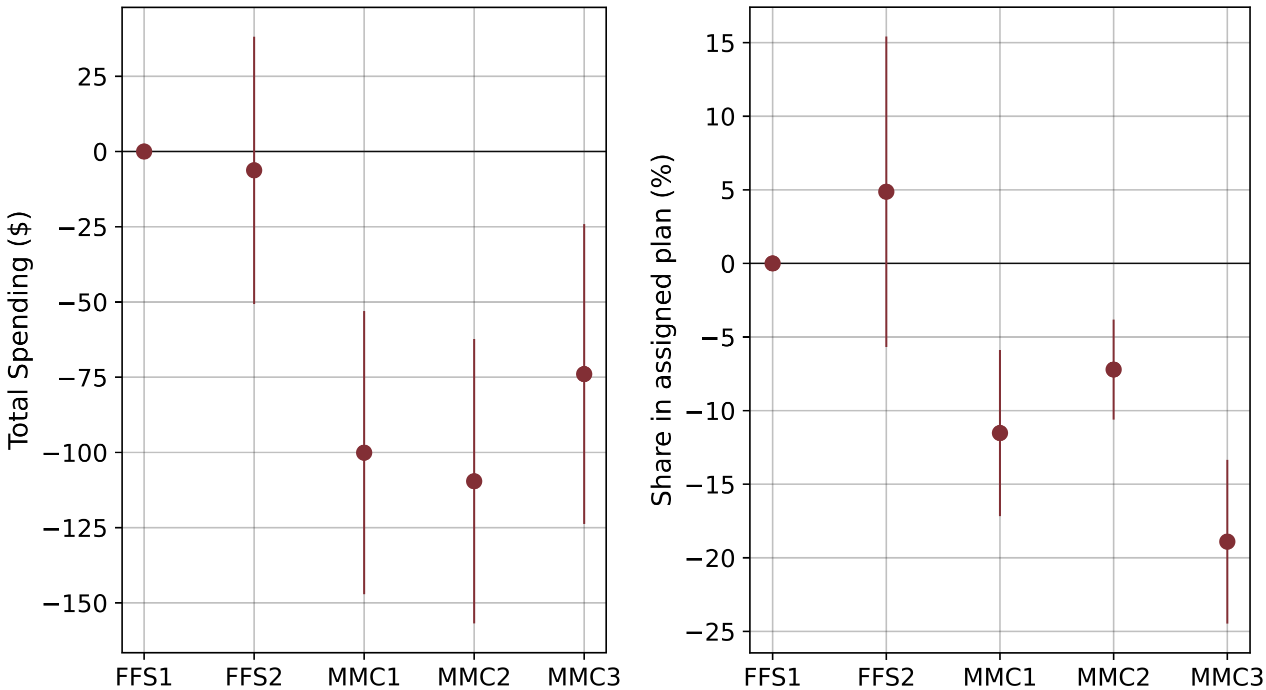
Appendix Figure A2: Time series plot of raw spending levels for enrollees assigned to MMC and FFS



Note: Figure presents quarterly enrollee spending, adjusted for prior provider and calendar quarters, for a 4-year period spanning 11 months prior to, and three years after, assignment to managed care for a balanced panel of 85,668 enrollees. Observations are at the assigned model $\times$ month level. Time, in months, is along the horizontal axis. The leftmost vertical line indicates the start of managed care (the beginning of the treatment period); the rightmost vertical line indicates when pharmacy is carved into Medicaid managed care. The figure shows that spending levels were similar between the groups prior to the assignment to managed care but diverged sharply after pharmacy was carved in to MCO responsibility. Plotted means are residualized on the unit of randomization (i.e., recipient's prior provider), and calendar quarters to adjust for seasonality..

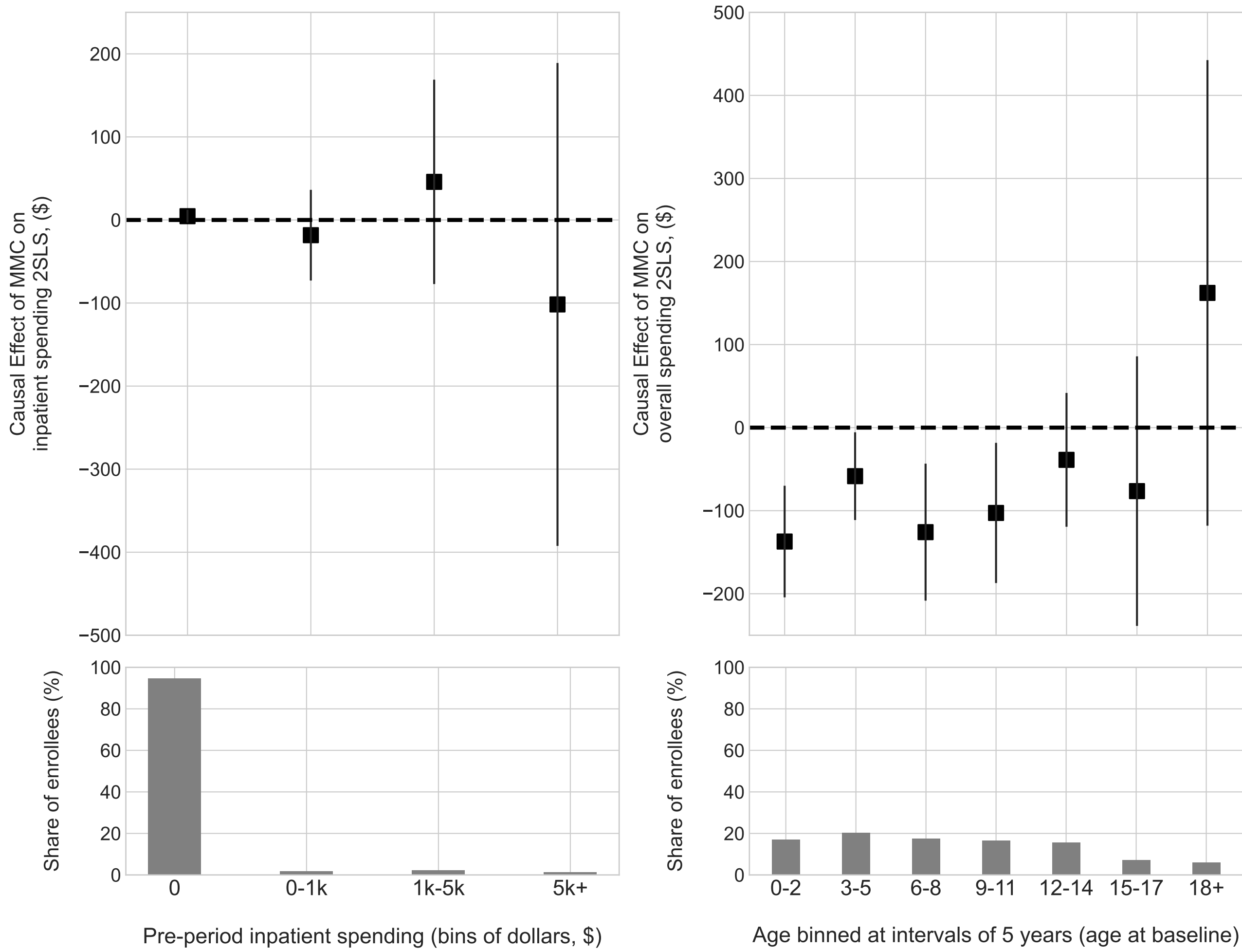
Appendix Figure A3: Individual plan effects on healthcare spending and enrollee satisfaction

Panel A. Plan effects on total spending *Panel B.* Plan effects on enrollee satisfaction



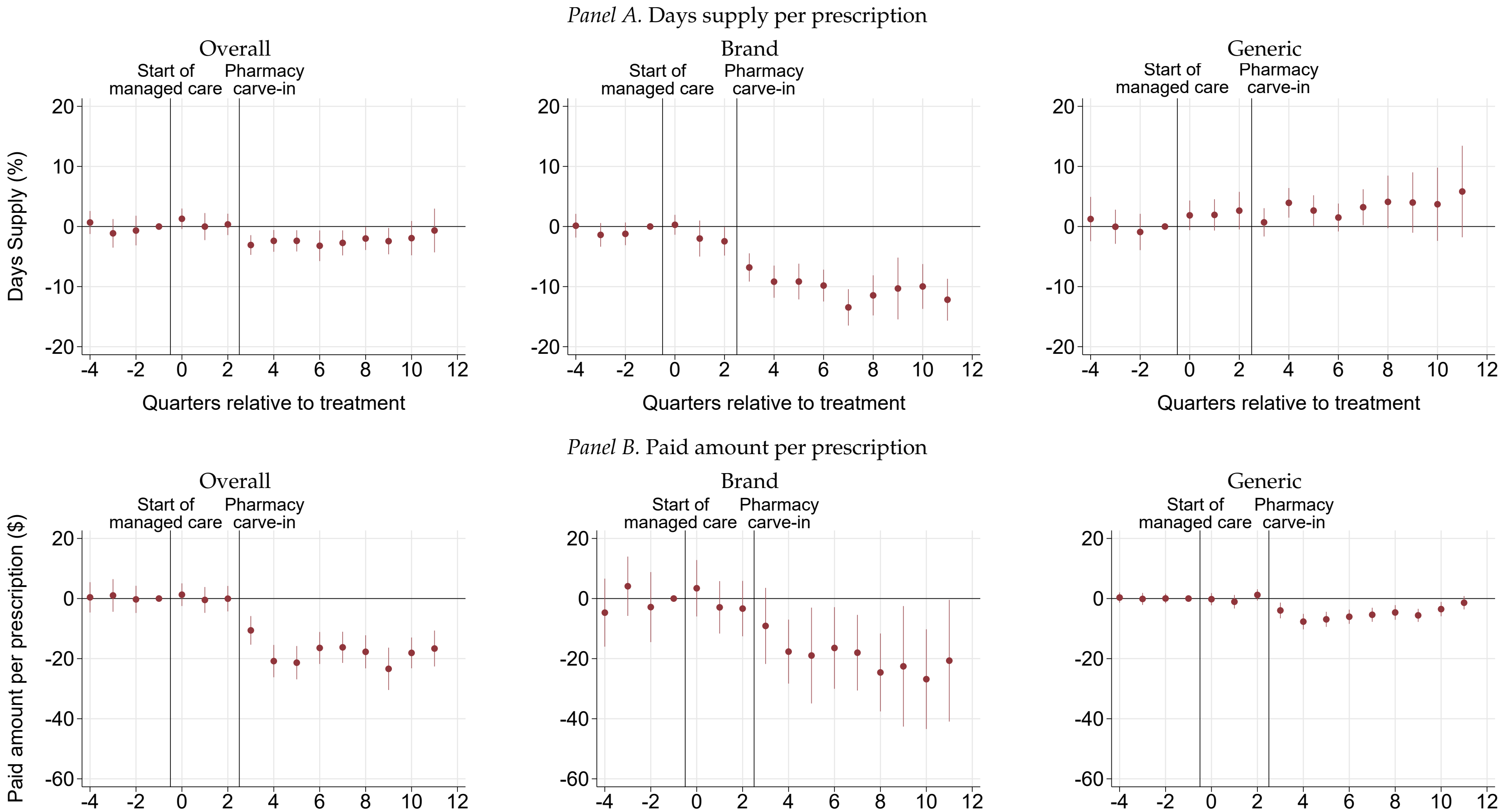
Note: Figure presents individual plan effects and associate 95% confidence intervals for total annual health care spending (left) and consumer satisfaction (right) estimated from the auto-assigned sample. Observations are at the enrollee $\times$ year level: $N = 284,928$ for auto-assignees. Number of auto-assignees: 94,976. Spending effects are estimated using the IV-specification using the randomly assigned plan as an instrument for a member's actual plan. Satisfaction effects are estimated using a reduced form specification using only an enrollee's assigned plan. In a setting with multiple treatments and strata fixed effects, the estimated plan effects may not be convex averages of their heterogeneous treatment effects (Goldsmith-Pinkham, Hull and Kolesár, 2024). To improve precision when estimating individual plan effects we include the following enrollee characteristics which are determined at baseline (the year prior to randomization): sex, race, indicators for age coarsened to 5-year increments and baseline health status measured through clinical risk groups. Total annual spending is winsorized at $25,000. All regressions adjust for the unit of randomization (i.e., recipient's prior provider). Standard errors clustered on the unit of randomization (i.e., recipient's prior provider).

Appendix Figure A4: 2SLS spending results stratified by inpatient utilization and age



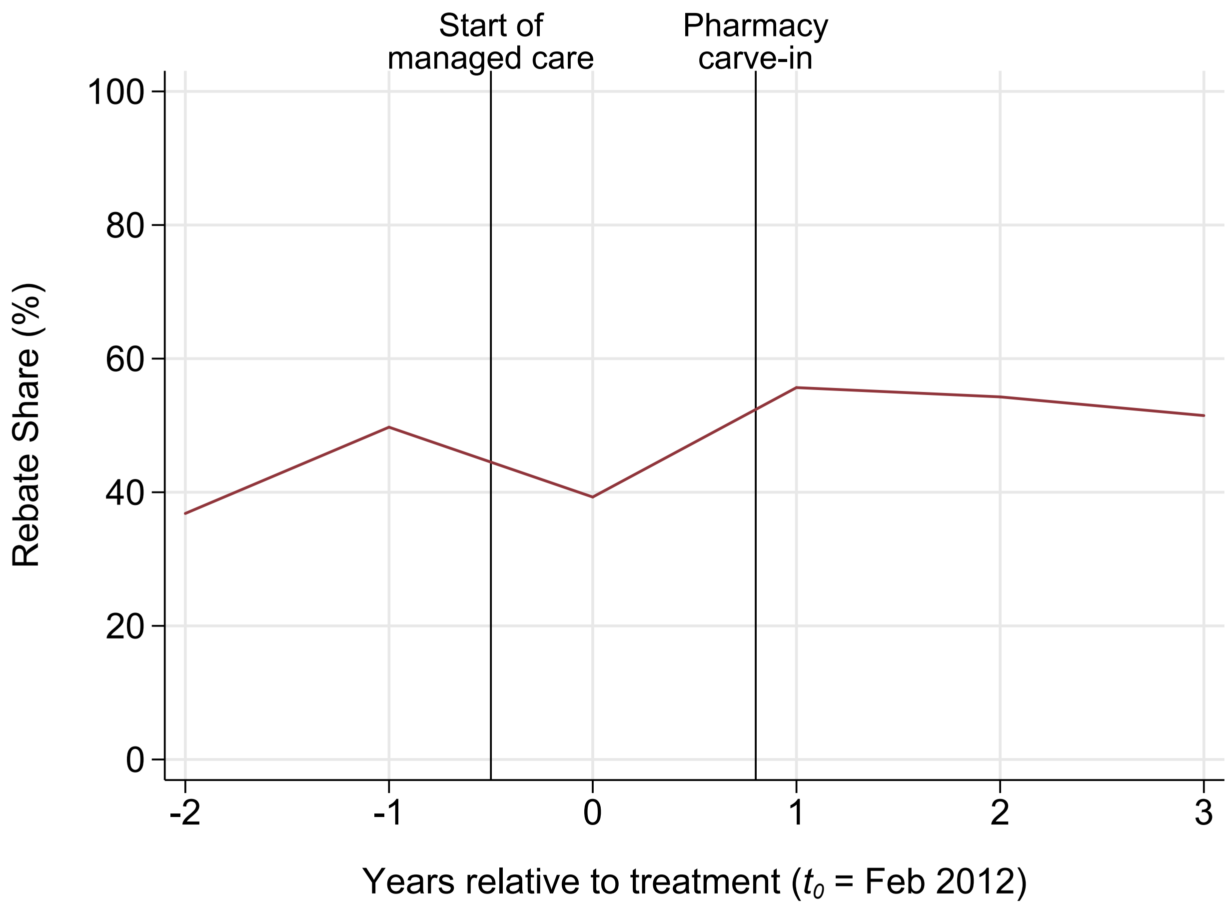
Note: Figure presents two coefficient plots of the causal effects of MMC, and associate 95% confidence intervals, on inpatient spending (left-hand side) and total spending (right-hand side). The left-hand groups the auto-assignee population by baseline inpatient spending. The right-hand side groups by age. IV regression coefficients for each group in both panels are estimated separately and correspond to Equation 2, where the regressor of interest, an indicator for enrollment in managed care, is instrumented with assignment to managed care. Only post-assignment observations are included (February 2012 to December 2014). Observations are at the enrollee $\times$ year level: $N = 284,928$ for auto-assignees. Number of auto-assignees: 94,976. All regressions adjust for the unit of randomization (i.e., recipient's prior provider). Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details). Standard errors clustered on the unit of randomization (i.e., recipient's prior provider).

Appendix Figure A5: Main result: impact of assignment to managed care on pharmacy spending and quantity



Note: Figure presents difference-in-differences event studies comparing pharmacy outcomes across assignees to MMC and FFS. Panel titles indicate the dependent variable. Panel B expresses percent change relative to the pre-period. Observations are at the assigned model × quarter level. Time, in quarters, is along the horizontal axis. The leftmost vertical line indicates the start of managed care (the beginning of the treatment period); the rightmost vertical line indicates when pharmacy is carved into Medicaid managed care. Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details). Standard errors clustered on the unit of randomization (i.e., recipient's prior provider). 95% confidence intervals reported.

Appendix Figure A6: Rebates share

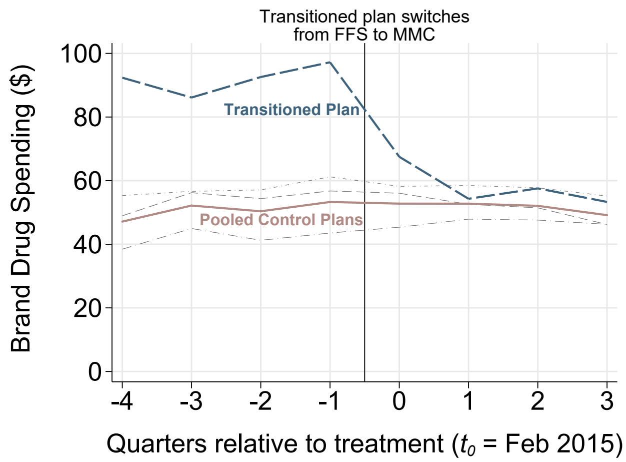


Note: Figure presents a time series of the share of point-of-sale drug spending that is returned in rebates (vertical axis) for the study state, Louisiana, over the study period. The numerator is constructed from the Medicaid Financial Management Reports, while the denominator is constructed from the Medicaid State Drug Utilization Data. Construction of the measure follows the same steps as in (Dranove, Ody and Starc, 2021). Observations are annual. The left vertical line indicates the start of managed care (the beginning of the treatment period); the right vertical line indicates when pharmacy is carved into Medicaid managed care. The figure shows that rebates do not decline after the pharmacy carve-in, which could have otherwise offset the lower spending resulting from the drug carve-in shown in Figure 2.

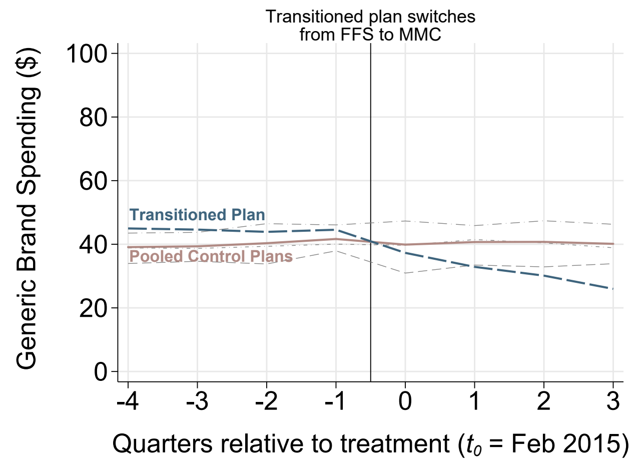
Appendix Figure A7: Plan transition time series

Panel A. Spending reductions

Brand Drug Spending

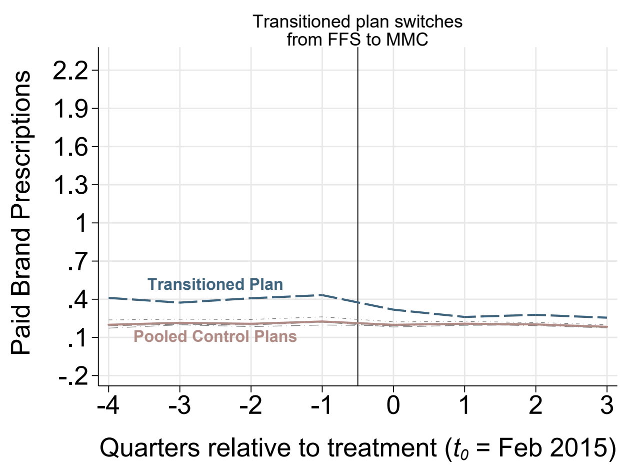


Generic Drug Spending

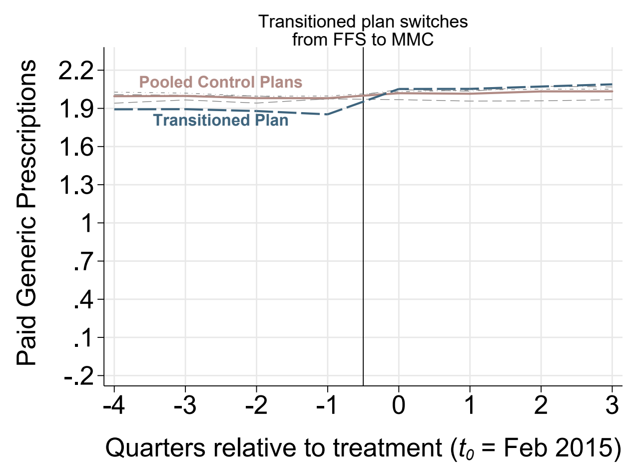


Panel B. Quantity reductions

Brand Drug Paid Prescriptions

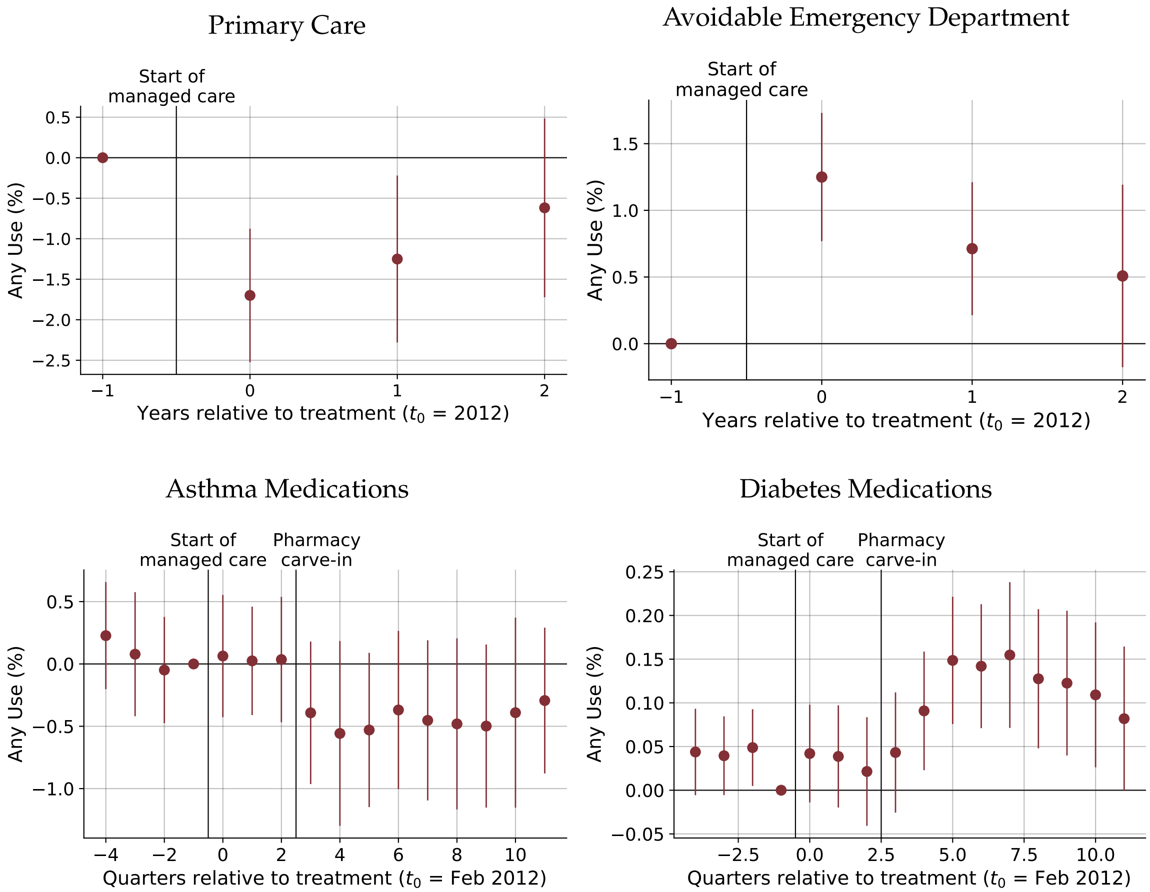


Generic Drug Paid Prescriptions



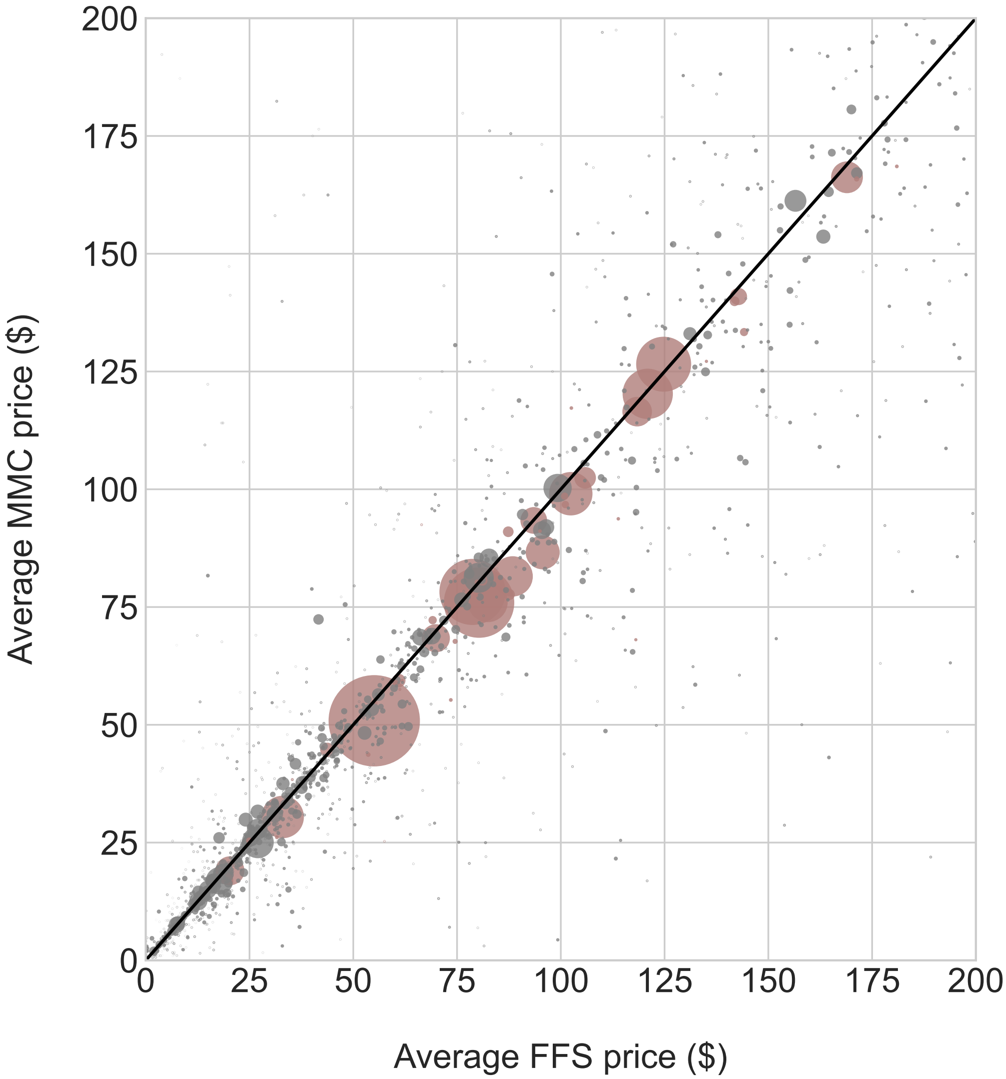
Note: Figure plots means of spending over time by plan. Individual plans contributing to the pooled control plan are shown as dashed grey lines. The vertical line indicates when the treatment plan transitioned from FFS to become a full-risk managed care plan. The plans that were already full-risk managed care plans did not experience a change at that time. This event date (February 2015) is three years after the date of the auto-assignment natural experiment used in Figures 1, 2, 3, and 4. The sample is a balanced panel of 497,057 beneficiaries. Plotted means are residualized on calendar quarters to adjust for seasonality. Observations are reweighted such that the Plan Transition sample matches the distribution of the auto-assignee sample used in the first identification strategy on health status-by-gender-by-age bins (see Supplemental Appendix Section B. for additional details).

Appendix Figure A8: Impact of assignment to managed care on utilization



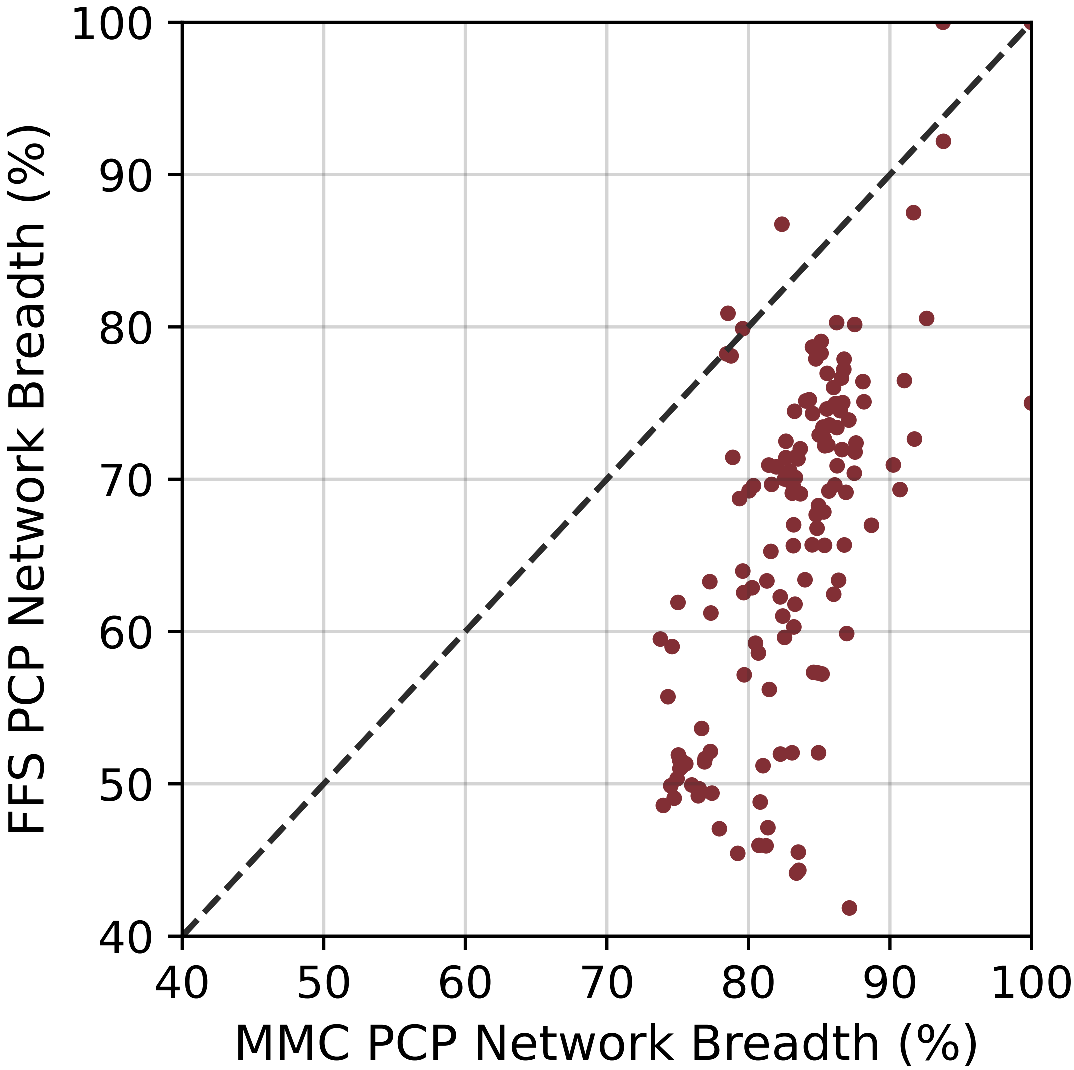
Note: Figure presents difference-in-differences event studies comparing indicators of any utilization across assignees to MMC and FFS for different types of utilization. Utilization is measured per time period (annually for the top row, quarterly for the bottom row). Estimates are based on a balanced panel of 85,668 continuously-enrolled recipients for the 47 month (February 2011–December 2014) period depicted. Time, in quarters or years, is along the horizontal axis. The leftmost vertical line indicates the start of managed care (the beginning of the treatment period); the rightmost vertical line indicates when pharmacy is carved into Medicaid managed care. The figure shows the (null) effects of assignment to managed care prior to the treatment period. Standard errors clustered on the unit of randomization (i.e., recipient's prior provider). 95% confidence intervals reported.

Appendix Figure A9: Scatter plot of average prices for individual services in MMC and FFS



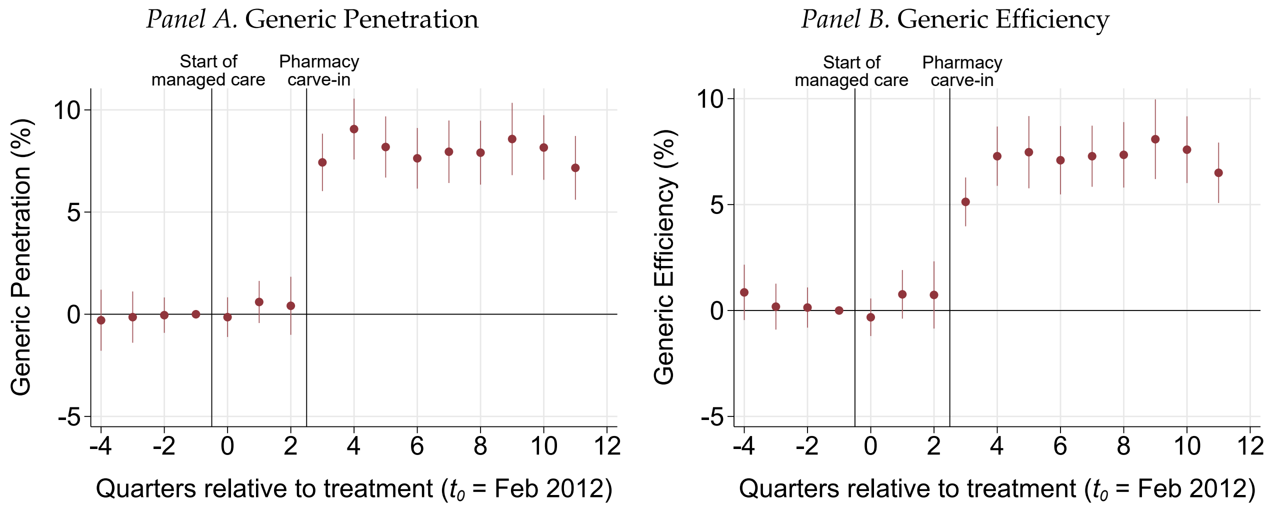
Note: Figure presents the average price for an individual service (defined by a unique Current Procedural Terminology (CPT) or Healthcare Common Procedure Coding System (HCPCS) code) in MMC and FFS. This figure presents evidence that the reduction in outpatient spending is partly driven by a reduction in prices for the same outpatient services with an overall reduction in prices of 3.06% in MMC, relative to FFS. This reduction is primarily driven by Evaluation and Management codes in red (CPT codes between 99201-99499, HCSPS codes T1015) with a reduction in MMC prices of 4.34%. Scatter plot includes 90.37% of overall outpatient spending (MMC and FFS) used in the mechanisms analysis (See Section V for additional details). For additional details on the composition of the reduction in prices, see Table A12.

Appendix Figure A10: Comparison of MMC and FFS primary care network breadth



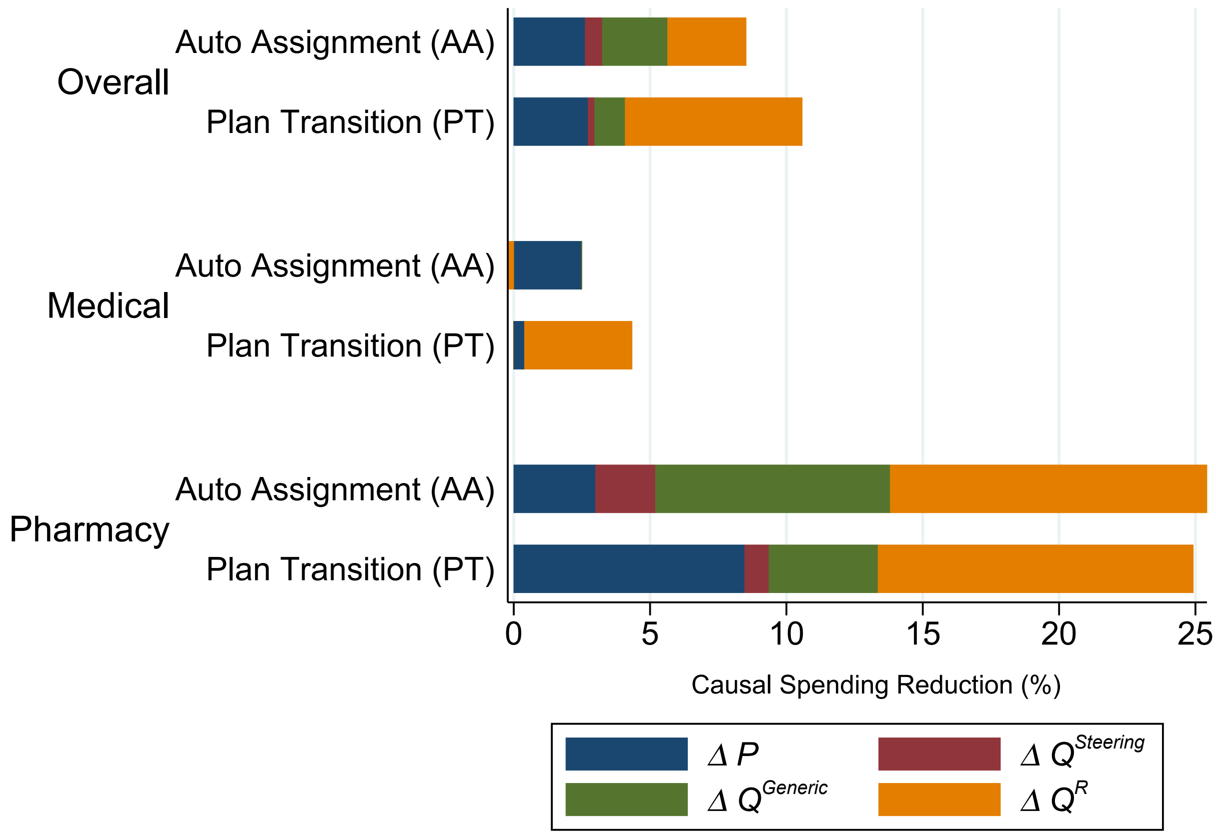
Note: Figure shows the primary care network breadth of FFS and MMC plans. We restrict to primary care as the FFS plans were only responsible for creating a primary care network, and thus have no other provider types within their stated networks. Each point represents a specific ZIP code within the first region of Louisiana to transition to Medicaid (the region of the main auto-assignment experiment). For each ZIP code, network breadth is calculated by identifying the physicians responsible for care of enrollees who reside in that ZIP code and determining what percentage of those claims are covered by PCPs listed in each plan's network. We create a single average over the 2 FFS plans and the 3 MMC plans to summarize the average breadth for each payment system. In nearly every ZIP code, the MMC primary care network is broader than the FFS primary care network.

Appendix Figure A11: Impact of assignment to MMC vs. FFS on generic usage



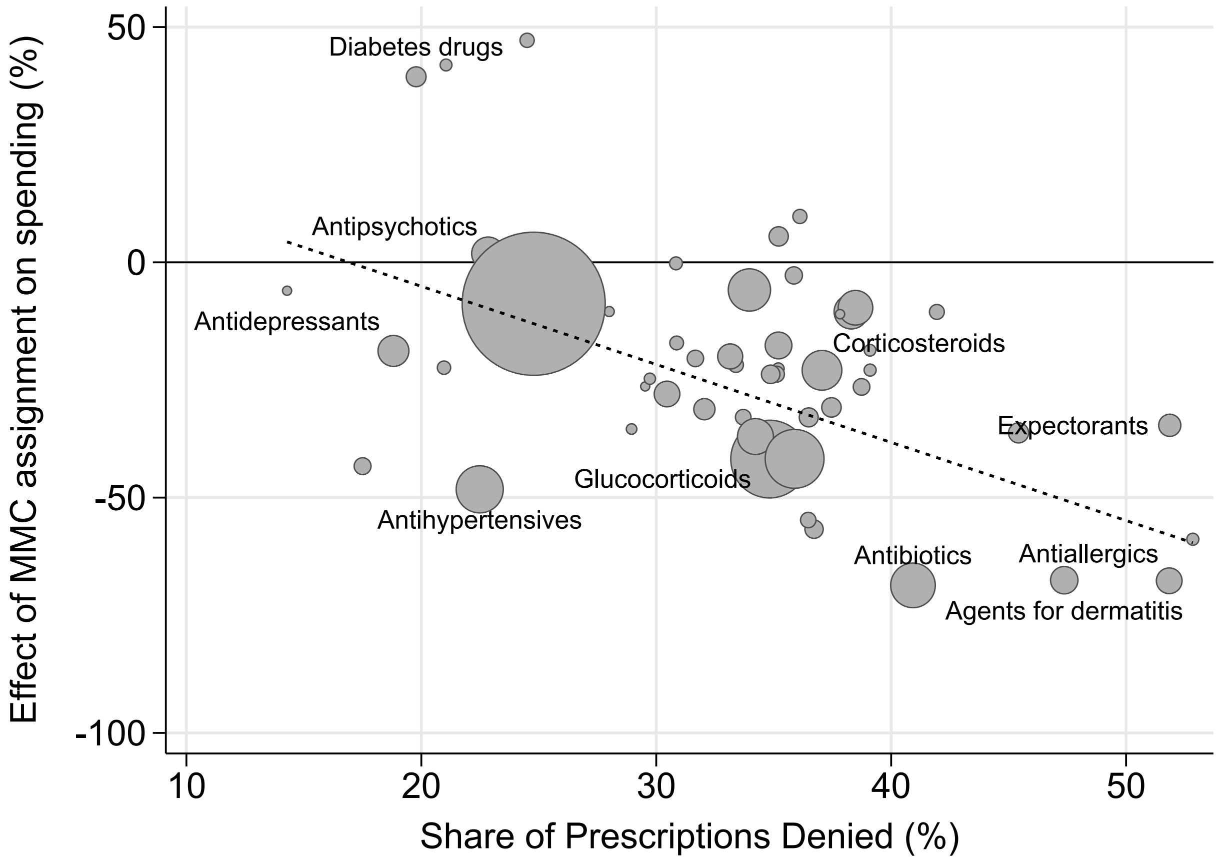
Note: Figure presents difference-in-differences event studies comparing the usage of generic drugs (Panel A) and the efficiency of this usage (Panel B) across assignees to MMC and FFS. Estimates are based on a balanced panel of 85,668 continuously-enrolled recipients for the 47 month (February 2011–December 2014) period depicted. Time, in quarters, is along the horizontal axis. The leftmost vertical line indicates the start of managed care (the beginning of the treatment period); the rightmost vertical line indicates when pharmacy is carved into Medicaid managed care. Generic penetration is the share of generic drugs among all drugs used in an enrollee-quarter. Generic efficiency is the share of drug claims that are "efficient", i.e., a pharmacy claim is said to be generic efficient if there exists a generic counterpart to the drug used, and this generic is used. Generic penetration and efficiency rise substantially and statistically significantly following the pharmacy carve-in, consistent with enrollees randomly assigned to MMC plans increasing their use of generic drugs relative to brand drugs after the carve-in of prescription drugs to managed care plan responsibility. Standard errors clustered on the unit of randomization (i.e., recipient's prior provider). 95% confidence intervals reported.

Appendix Figure A12: Decomposition of spending by type of spending and sample in t_1



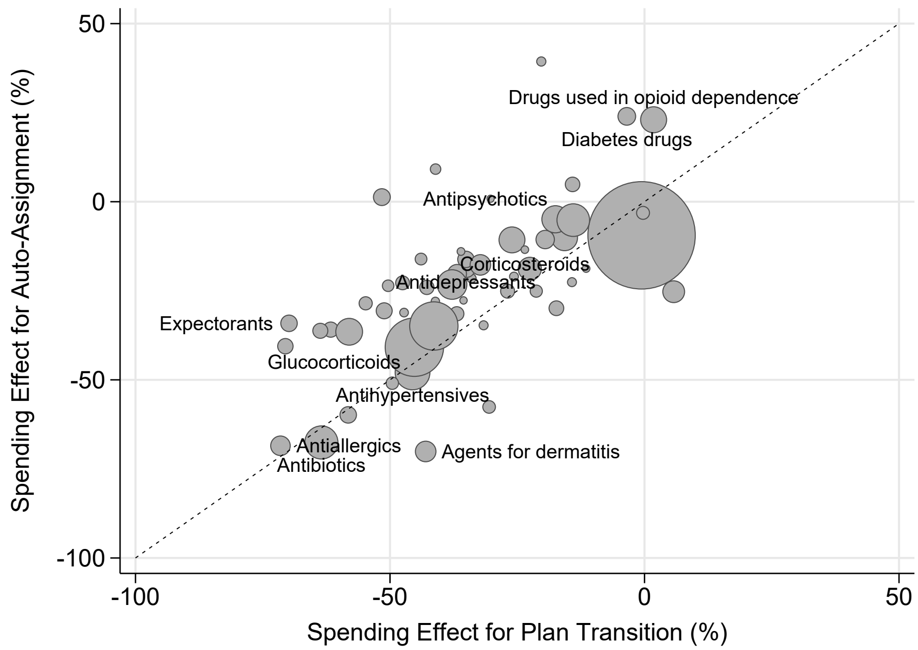
Note: This figure presents the decomposition results for $t_1 = 2013$ for the Auto-Assignment (AA) experiment and $t_1 = 2015$ the Plan Transition (PT) experiment. Additional details are available in Appendix IV. Observations are reweighted such that the Plan Transition sample matches the distribution of the auto-assignee sample used in the first identification strategy on health status-by-gender-by-age bins (see Supplemental Appendix Section B. for additional details).

Appendix Figure A13: Dose-response for ATC-4 therapeutic classes for kids



Note: Figure presents evidence restricted to children (aged 0 to 19 excluded) that pharmacy denials are a key mechanism driving the managed care spending effects. The figure compares managed care spending effects by ATC-4 therapeutic drug class (vertical axis – i.e., Anatomical Therapeutic Chemical (ATC) Classification, level 4) to the share of claims denied by managed care plans (horizontal axis). The estimates are based on the auto-assignment experiment and sample, but restricted to children. To measure the managed care claims denial rate, we restrict to the first quarter 1 month after the pharmacy carve-in to capture the peak visible in Panel A of Figure 6. The negative slope indicates that managed care plans generated larger spending reductions in drug classes where they managed utilization more aggressively via denials.

Appendix Figure A14: Generalizability: similar estimates from two identification strategies

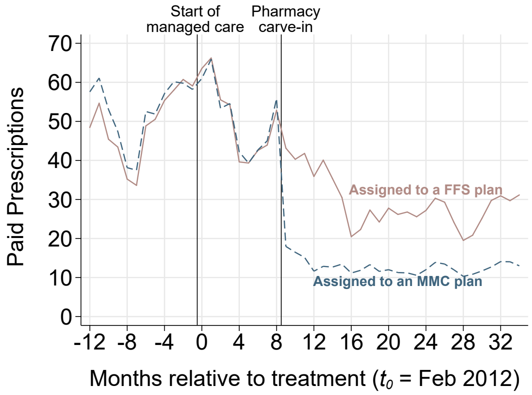


Note: Figure compares spending reductions for various ATC-4 therapeutic classes of drugs (i.e., Anatomical Therapeutic Chemical Classification, level 4) across two identification strategies. Results from the auto-assignment (AA) quasi-experiment are plotted along the vertical axis, and results from the plan transition (PT) quasi-experiment are plotted along the horizontal axis. A 45 degree line is plotted for ease of comparison. Observations are reweighted such that the the Plan Transition sample matches the distribution of the auto-assignee sample used in the first identification strategy on health status-by-gender-by-age bins (see Supplemental Appendix Section B. for additional details).

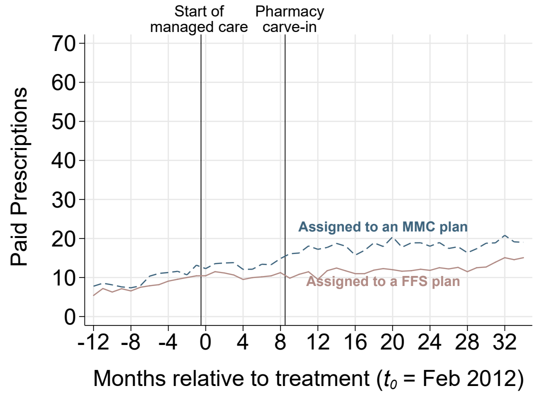
Appendix Figure A15: Denials at the individual drug level

Panel A. Quantity reductions concentrated in drugs targeted by utilization management

Drugs in top decile of denials

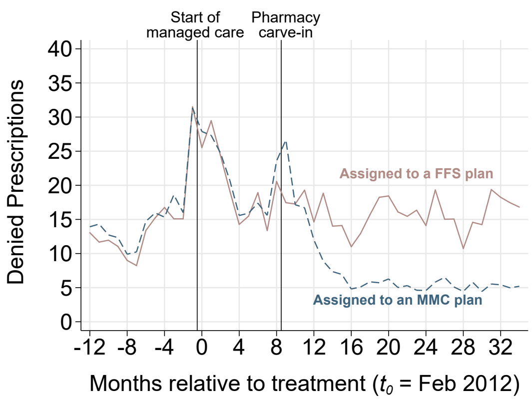


Drugs in bottom decile of denials

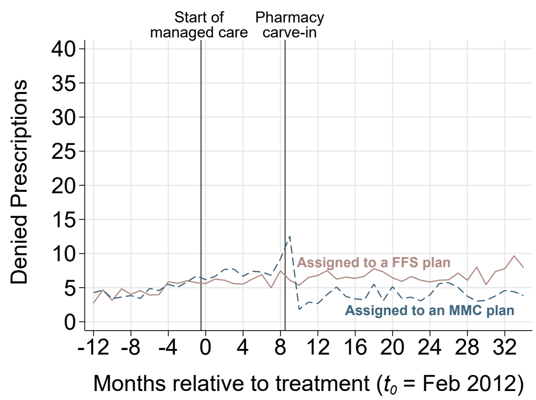


Panel B. Denied pharmacy claims first rise and then fall

Drugs in top decile of denials



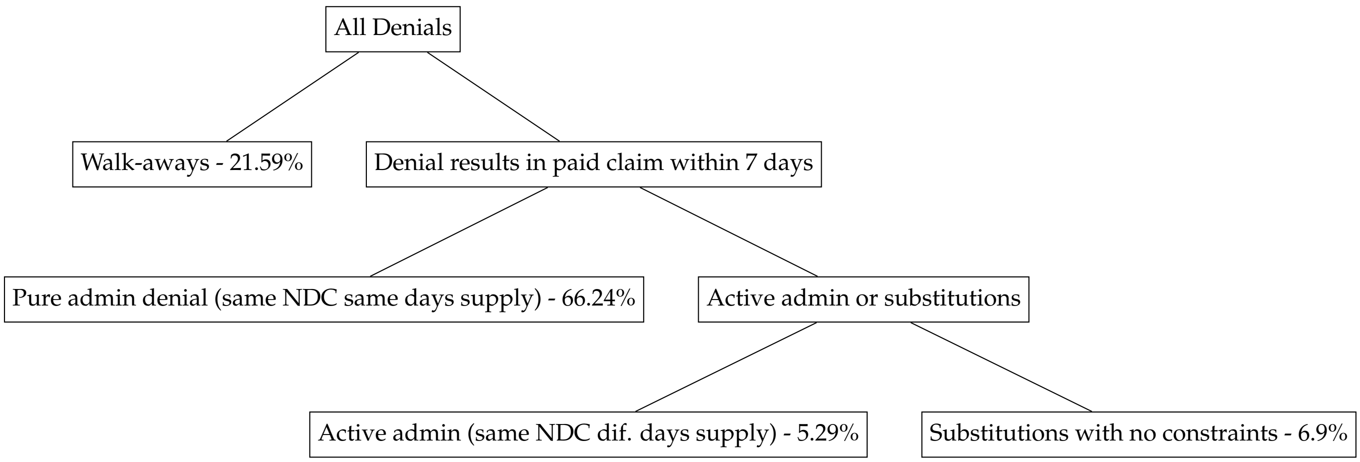
Drugs in bottom decile of denials



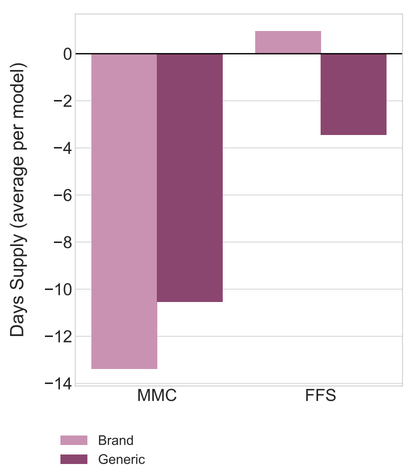
Note: Figure presents four time series plots of the number of paid and denied claims respectively for the most (left) and least (right) denied drugs, by decile. Individual drugs are identified by a unique 11-digit National Drug Code (NDC). Observations are at the assigned model $\times$ month level. Time, in months, is along the horizontal axis. The leftmost vertical line indicates the start of managed care (the beginning of the treatment period); the rightmost vertical line indicates when pharmacy is carved into Medicaid managed care.. Plotted means are residualized on the unit of randomization (i.e., recipient's prior provider).

Appendix Figure A16: Denial analysis: fewer units and substitutions

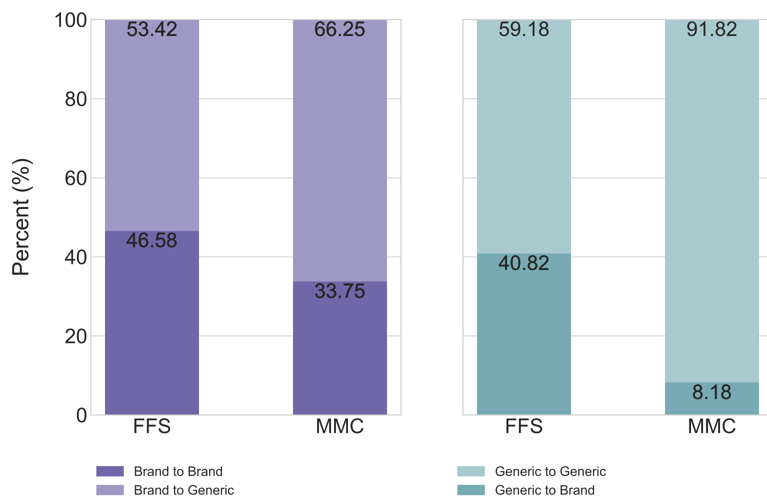
Panel A. Decomposing MMC denials - Conditions and shares



Panel B. MMC reduces days supplied per script

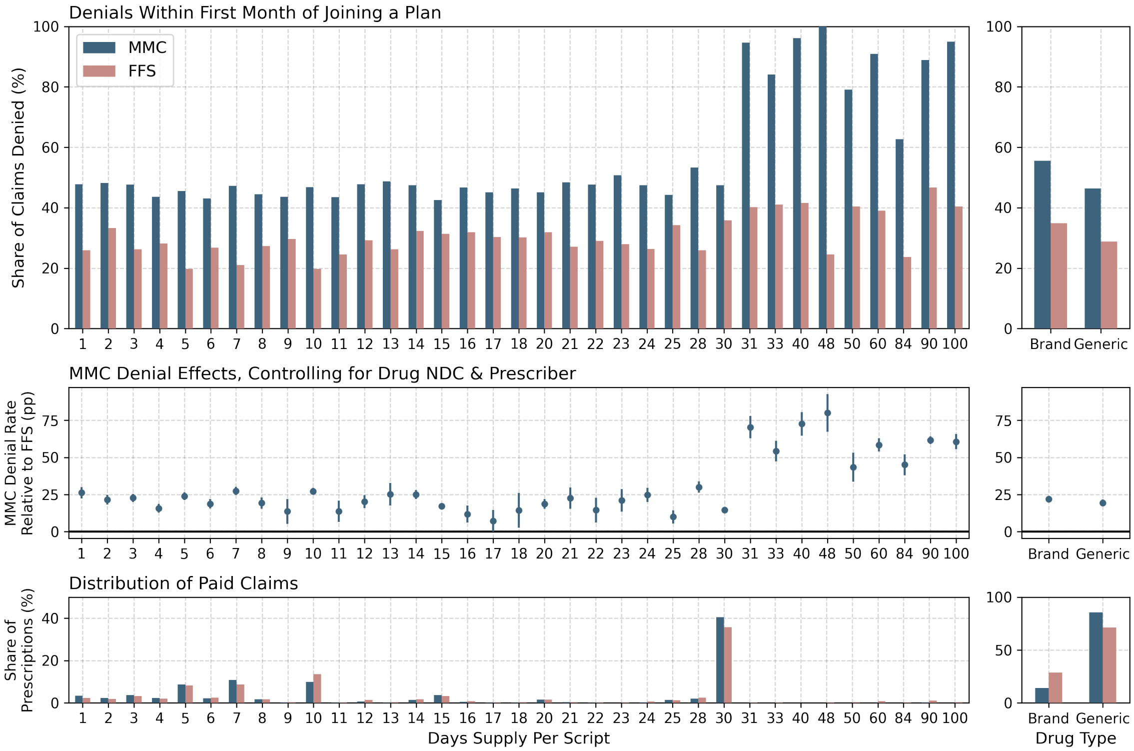


Panel C. MMC substitutes brands for generics and restricts generics to brand substitutions



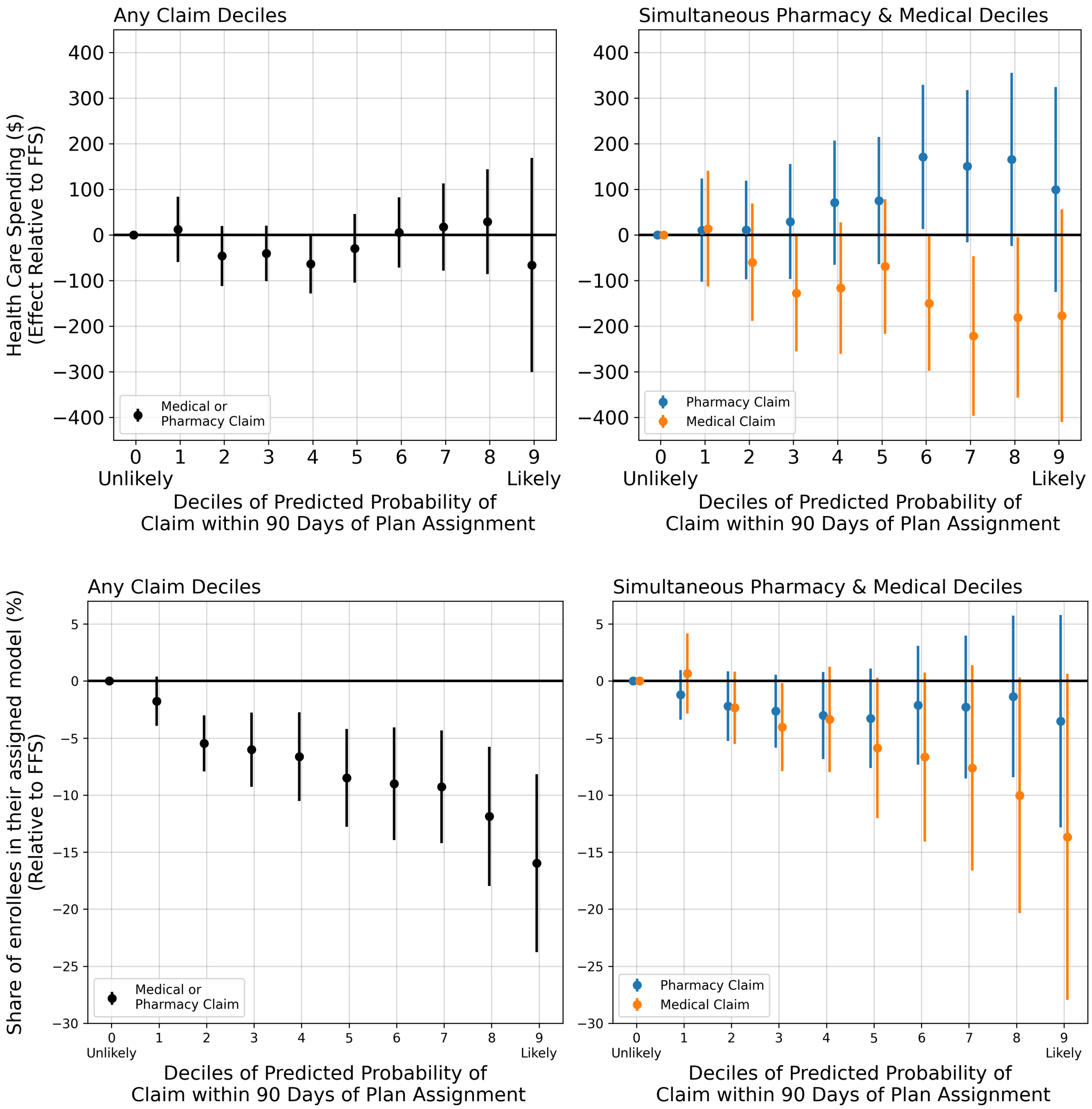
Note: These results use a matching strategy where a denial is matched to a subsequently paid claim within 7 days, if this paid claim exists. The period studied is identical to that of the dose-response Figure 6 (See Appendix V for additional details). Panel B conditions on a denial resulting in a subsequent paid claim with same NDC claim within 7 days. Panel C conditions on a denial resulting in a subsequent paid claim with different NDC. Note that the stacked barplots add up to 100, but the levels are different, especially between MMC and FFS, and between generic and brand drugs.

Appendix Figure A17: Pharmacy denials within the first month



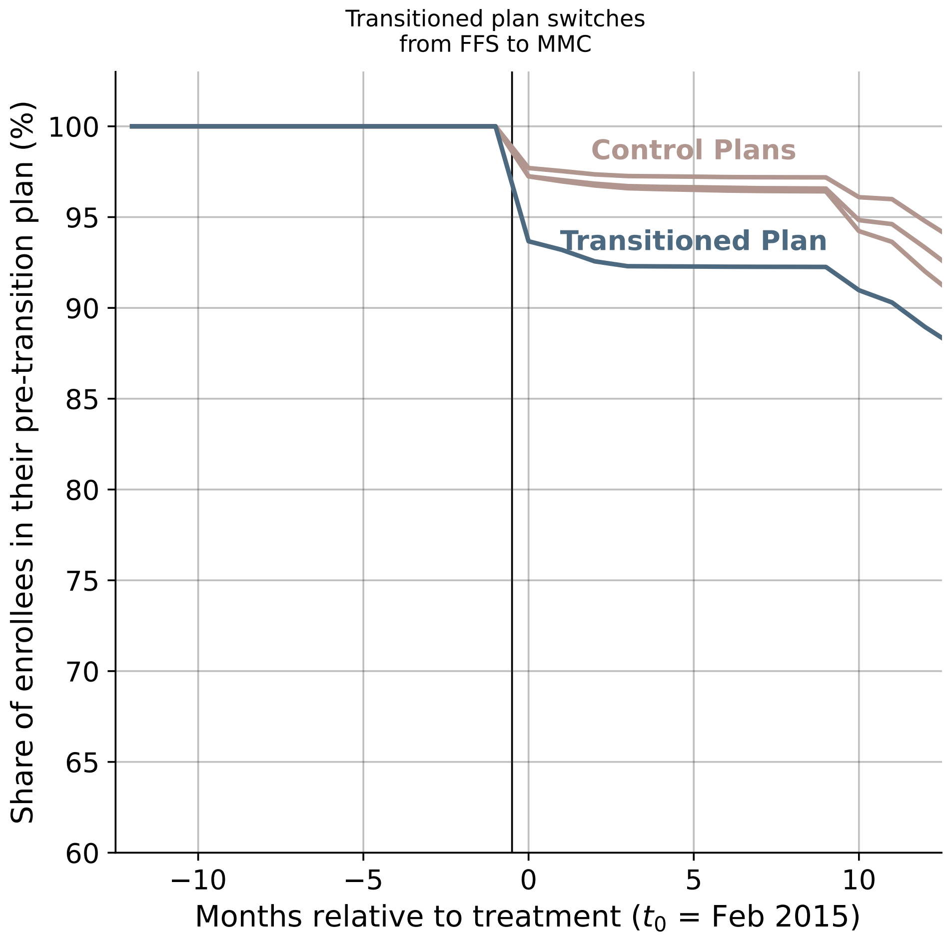
Note: Figure shows denial rates within the first month of joining for MMC and FFS stratified by characteristics of the prescriptions (days supply in the left column, branded versus generic in the right column). The sample uses the cohorts of new to Medicaid enrollees identified in Figure 9. Because pharmacy benefits were not carved-in until Nov 2012, we only consider MMC cohorts which joined beginning in Nov 2012. The first row shows raw levels of denial rates stratified by prescription characteristics for MMC and FFS. The second row provides estimates of the denial rate in MMC relative to FFS with adjustments for the specific drug and prescribing provider, which may contribute to differences in the raw-denial rates. Standard errors are clustered at the cohort level. The last row shows the distribution of paid claims by the prescription characteristic to illustrate compositional differences between MMC and FFS in fulfilled scripts.

Appendix Figure A18: MMC spending and switching effects by decile of predicted utilization post-assignment



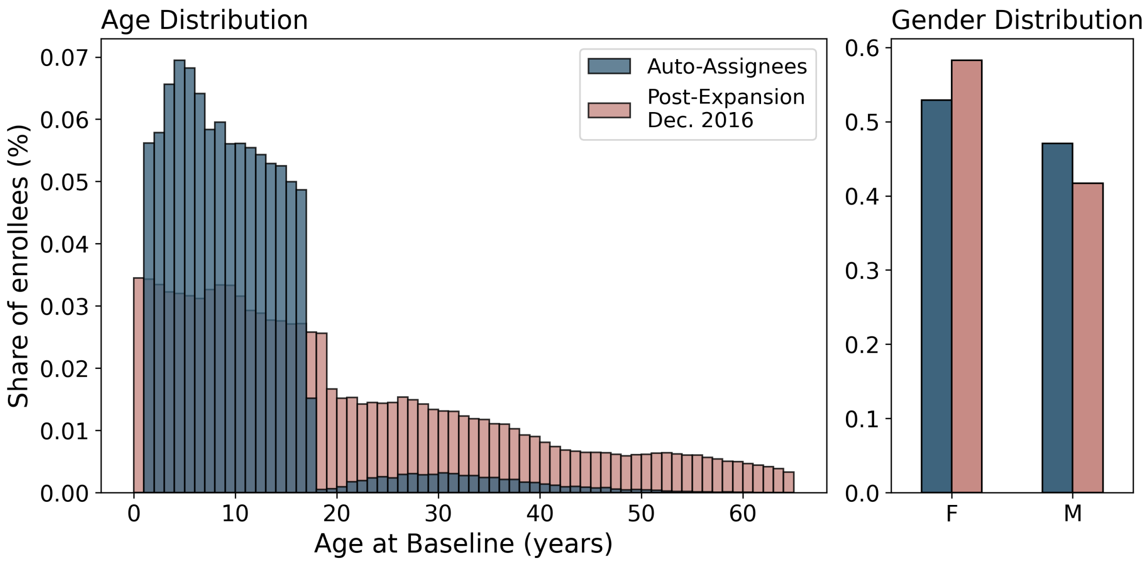
Note: Figure presents spending and switching effects of MMC relative to FFS stratified by the predicted probability of utilization post assignment. Effects are measured relative to the MMC effect within the lowest decile of predicted post-assignment utilization. Predictions are based on a logistic regression with a L1 regularization using baseline demographic characteristics and binary indicators for the 450 most common diagnoses and individual NDCs utilized in the year prior to assignment as predictors with a binary outcome indicating whether a member had any care in the 90 days immediately following random assignment. We fit three separate models where the outcome is (1) any medical or pharmacy utilization, (2) any medical utilization, and (3) any pharmacy utilization. We find large heterogeneity in switching with respect to predicted utilization, while there is no significant heterogeneity in spending. When controlling for both predicted medical and pharmacy spending concurrently, we find that the heterogeneity is predominantly driven by predicted medical utilization 90 days post-assignment, which is expected as pharmacy is not carved into MMC contracts until November 2012.

Appendix Figure A19: Enrollee switching surrounding the 2015 plan transition



Note: Figure presents the share of enrollees who remain in their pre-transition plan after one of the plans (transitioned plan) switches from FFS to MMC in January 2015. We consider a balanced panel of enrollees who are enrolled in Medicaid for 24 months (12 months pre- and post-transition) and who are consistently enrolled in the same plan for 12 months prior to the plan transition. The control plans remain MMC throughout the entire 24 months.

Appendix Figure A20: Demographic comparison of auto-assignees to post-expansion Louisiana Medicaid



Note: Figure shows the distribution of age and gender within the auto-assigned sample used in the main study and the post-expansion population within the same state. For auto-assignees, age is calculated as of Dec 2012. The post-expansion population is comprised of the same eligibility categories with the addition of the expansion eligibility group and takes all individuals enrolled in December 2016 (expansion occurred on June 1, 2016). In both samples we remove individuals who are aged > 65. Because age is calculated at the end of the first study year and individuals needed to be already enrolled in Medicaid to be auto-assigned, there are no enrollees aged 0 in the auto-assignee sample.

Appendix Table A1: Summary statistics for "auto-assignee" population

	Overall		Auto-Assignees		Active Choosers	
	$\overline{Y}$	Std Dev	$\overline{Y}$	Std Dev	$\overline{Y}$	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Enrollee characteristics						
Age at baseline	9.07	7.39	9.36	7.49	8.44	7.13
Female (%)	52.79	49.92	52.92	49.92	52.51	49.94
Panel B. enrollee spending, annually ($)						
Total	1,565.65	2,497.55	1,451.35	2,427.61	1,818.35	2,628.03
Medical	1,110.01	1,825.78	1,052.74	1,815.46	1,236.61	1,842.09
Inpatient	97.32	749.95	97.48	747.79	96.96	754.69
Outpatient	639.63	849.07	590.29	820.12	748.70	900.26
Pharmacy	436.44	1,024.41	381.45	948.76	557.99	1,165.33
Brand Drug	265.12	816.94	229.30	757.06	344.31	930.94
Generic Drug	168.14	370.10	149.63	345.53	209.05	416.45
Panel C. Any annual utilization of high- or potentially high-value care (%)						
Annual Well-Child Visits	52.65	49.93	49.34	50.00	60.19	48.95
Access to Primary Care	83.46	37.15	80.46	39.65	90.12	29.84
Chlamydia Screening	58.69	49.24	59.67	49.06	56.19	49.62
Cervical Cancer Screening	68.93	46.28	67.19	46.96	74.11	43.81
Follow-up after ADHD Prescription	53.07	49.91	51.17	49.99	57.10	49.51
Behavioral	7.64	26.56	7.40	26.18	8.16	27.38
Dental	59.01	49.18	55.18	49.73	67.48	46.84
Asthma Medication	16.44	37.06	14.87	35.58	19.91	39.93
Diabetes Medication	0.61	7.80	0.58	7.56	0.69	8.29
Panel D. Any annual utilization of low- or potentially low-value care (%)						
Any Low-Value Care Composite	0.95	9.72	0.92	9.57	1.02	10.05
Avoidable Emergency Department	8.20	27.44	8.43	27.78	7.71	26.68
Imaging	24.23	42.85	23.33	42.29	26.21	43.98

Notes: Table reports summary statistics on enrollee demographics, utilization, and spending. The sample consists of a balanced panel of Medicaid enrollees that were in Medicaid from February 2012 and remained until at least December 2014. Observations are at the enrollee $\times$ year level: $N = 413,811$ enrollee-years. Additional details on the utilization and spending measures is available in Section I. Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details). Components of spending do not sum up to "Total" due to winsorization.

Appendix Table A2: First stage regression of plan enrollment on assigned plan

	Coefficient (1)	Standard Error (2)	F-Statistic (3)
Full 3-year study period	0.76	0.03	678
Last 2 years (post pharmacy carve-in)	0.75	0.03	635

Notes: Table presents the first stage coefficient for enrollment in Medicaid managed care against assignment to Medicaid managed care. Regressions are adjusted for the unit of randomization. Standard errors clustered on the unit of randomization (i.e., recipient's prior provider).

Appendix Table A3: Imbalance among active choosers

	Mean	Coef. on Managed Care Enrollment	p-value
	(1)	(2)	(3)
Panel A. Enrollee characteristics			
Age at baseline	8.44	0.27	0.04
Female (%)	52.51	1.49	0.00
Panel B. Enrollee health conditions			
Asthma	7.61	−0.11	0.79
Serious Mental Illness	3.15	0.15	0.51
Diabetes	0.81	0.06	0.59
Pregnancy	0.98	0.32	0.02
Cardiovascular Conditions	1.35	−0.08	0.53
Panel C. Enrollee spending, annually ($)			
Total	201.84	−0.05	1.00
Medical	148.60	1.49	0.89
Pharmacy	53.24	−1.53	0.41
Panel D. Any annual utilization of high- or potentially high-value care (%)			
Annual Well-Child Visits	28.71	−1.52	0.00
Access to Primary Care	80.31	−2.07	0.01
Chlamydia Screening	0.64	0.23	0.01
Asthma Medication	3.69	0.07	0.62
Diabetes Medication	0.27	0.05	0.18
Panel E. Any annual utilization of low- and potentially low-value care (%)			
Any Low-Value Care Composite	0.90	0.08	0.31
Avoidable Emergency Department Visits	5.63	0.38	0.15
Imaging	26.89	0.00	1.00
Joint Test			0.03
N		42,961	

Notes: Table presents the results of a test for balance of predetermined characteristics among enrollees who made an active plan choice. Each row corresponds to a separate regression. The characteristics tested for balance include recipient demographics and *pre-assignment* utilization and diagnoses. To construct column 2, each baseline characteristic is regressed on an indicator for assignment to managed care with controls for, and clustering on, the unit of randomization (i.e., recipient's prior provider). Self-sorter characteristics were *highly imbalanced*, consistent with selection on observables into managed care. The estimates are based on a balanced panel of 42,961 continuously-enrolled recipients that made an active plan choice to MMC or FFS in February 2012 and remained in Medicaid until, at least, December 2015. The joint test reports the p-value of the F statistic that all baseline characteristics are jointly zero from a regression of MMC assignment status on baseline characteristics. The p-value on the joint test is calculated using randomization inference where treatment labels within each unit of randomization are randomly permuted 1000 times.

Appendix Table A4: Robustness: IV estimates of the effect of managed care using raw, unwinsorized, spending outcomes

	Auto-Assignee Sample				Full Sample
	$\overline{Y}$	RF	2SLS	2SLS-Post Pharmacy Carve-in	OLS
	(1)	(2)	(3)	(4)	(5)
Total Spending	1,516	−56	−74	−95	−285
		(26)	(34)	(37)	(30)
Panel A. Spending by components of care ($)					
Inpatient Spending	137	−12	−15	−18	−25
		(19)	(24)	(24)	(22)
Outpatient Spending	607	−9	−12	−5	−81
		(7)	(9)	(11)	(9)
Pharmacy Spending	409	−37	−49	−74	−165
		(13)	(17)	(19)	(17)
Panel B. Spending by enrollee characteristics ($)					
Female	1,564	−77	−99	−118	−259
		(41)	(54)	(59)	(34)
Male	1,463	−36	−47	−71	−312
		(31)	(41)	(48)	(50)
Black	1,343	−67	−86	−107	−187
		(45)	(58)	(61)	(39)
White	1,891	−22	−31	−54	−399
		(37)	(52)	(68)	(63)
Panel C. Spending by quartiles of predicted health care spending ($)					
0-25%	696	−45	−52	−65	−108
		(18)	(21)	(33)	(21)
26-50%	959	−45	−58	−100	−106
		(21)	(26)	(33)	(20)
51-75%	1,376	−67	−91	−95	−153
		(29)	(41)	(50)	(32)
76-100%	3,035	−106	−155	−174	−358
		(101)	(148)	(158)	(93)

Notes: Table presents sample means, and OLS and IV regression coefficients corresponding to Equation 2 using raw, unwinsorized spending as the dependent variable. Each cell in columns (2) through (4) corresponds to a separate regression, displaying the coefficient on an indicator for assignment to or enrollment in managed care. In Panel A, the variables listed indicate the dependent variable in the regression. In Panels B and C, the dependent variable is total spending, and the variables listed specify the subsample the regressing restricts to. The sample consists of auto-assignees for columns (1) through (3) and adds the active-choosers to the sample for column (4). Only post-assignment observations are included (February 2012 to December 2014). Observations are at the enrollee-year level: $N = 284,928$ for auto-assignees and $N = 413,811$ overall. Number of auto-assignees: 94,976. Number of active-choosers: 42,961. All regressions control for provider prior to the auto-assignment period. Standard errors clustered on the unit of randomization (i.e., recipient's prior provider).

Appendix Table A5: IV estimates of the effect of managed care on spending for children, aged 0-18

	Auto-Assignee Sample			Full Sample
	$\overline{Y}$	RF	2SLS	OLS
	(1)	(2)	(3)	(4)
Total Spending	1,335	−73	−96	−266
		(11)	(15)	(22)
Panel A. Spending by components of care ($)				
Inpatient Spending	100	2	3	−20
		(9)	(12)	(21)
Outpatient Spending	548	−19	−25	−84
		(5)	(6)	(8)
Pharmacy Spending	345	−54	−71	−162
		(7)	(8)	(15)
Panel B. Spending by enrollee characteristics ($)				
Female	1,264	−80	−104	−232
		(15)	(21)	(22)
Male	1,406	−67	−88	−297
		(17)	(22)	(27)
Black	1,170	−62	−79	−190
		(14)	(18)	(22)
White	1,656	−62	−88	−320
		(25)	(34)	(29)
Panel C. Spending by quartiles of predicted health care spending ($)				
0-25%	672	−39	−45	−98
		(13)	(15)	(15)
26-50%	929	−34	−44	−111
		(16)	(20)	(12)
51-75%	1,295	−93	−128	−112
		(21)	(30)	(24)
76-100%	2,625	−167	−248	−277
		(37)	(53)	(36)

Notes: Table presents results of estimating Equation 2. Each cell in columns (2) through (4) corresponds to a separate regression, displaying the coefficient on an indicator for assignment to or enrollment in managed care. In Panel A, the variables listed indicate the dependent variable in the regression. In Panels B and C, the dependent variable is total spending, and the variables listed specify the subsample the regression restricts to. The sample consists of children (aged less than 19) with columns (1) through (3) containing the sample mean and regression results for the auto-assignees and column (4) containing OLS estimates based on the full sample. Only post-assignment observations are included (February 2012 to December 2014). Observations are at the enrollee-year level: $N = 263,640$ for auto-assignees and $N = 384,915$ overall. There were 87,880 unique auto-assignees and 40,425 unique active choosers. All regressions control for provider prior to the auto-assignment period. Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details). Standard errors clustered on the unit of randomization (i.e., recipient's prior provider).

Appendix Table A6: IV estimates of the effect of managed care on spending, reweighted to resemble the post-ACA Medicaid population

	Auto-Assignee Sample			
	$\overline{Y}$	RF	2SLS	2SLS-Post
	(1)	(2)	(3)	(4)
Total Spending	2,171	98	127	135
		(112)	(144)	(178)
Panel A. Spending by components of care ($)				
Inpatient Spending	231	15	19	14
		(23)	(29)	(37)
Outpatient Spending	848	50	65	84
		(39)	(50)	(61)
Pharmacy Spending	666	−2	−2	−26
		(47)	(61)	(72)
Panel B. Spending by enrollee characteristics ($)				
Female	2,369	14	18	34
		(82)	(106)	(128)
Male	1,885	182	237	219
		(255)	(331)	(377)
Black	1,773	12	15	1
		(83)	(105)	(138)
White	2,954	214	291	349
		(274)	(369)	(430)
Panel C. Spending by quartiles of predicted enrollee health spending ($)				
0-25%	717	−36	−41	−36
		(50)	(58)	(86)
26-50%	1,037	55	69	98
		(106)	(133)	(200)
51-75%	1,520	27	36	65
		(59)	(77)	(81)
76-100%	3,819	115	161	169
		(232)	(324)	(394)

Notes: Table presents results of Equation 2 after re-weighting the "auto-assignee" sample to match the measured health status, gender, and age of the post-ACA Medicaid population (See Appendix Section B..2). Each row corresponds to a separate regression. In Panel A, the variables listed indicate the dependent variable in the regression. In Panels B and C, the dependent variable is total spending, and the variables listed specify the subsample the regression restricts to. The sample consists of auto-assignees for columns (1) through (3) and adds the active-choosers to the sample for column (4). Only post-assignment observations are included (February 2012 to December 2014). Observations are at the enrollee-year level: $N = 284,928$ for auto-assignees and $N = 413,811$ overall. Number of auto-assignees: 94,976. Number of active-choosers: 42,961. All regressions control for provider prior to the auto-assignment period. Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details). Components of spending do not sum up to "Total" due to winsorization. Standard errors clustered on the unit of randomization (i.e., recipient's prior provider).

Appendix Table A7: Impacts on quality and consumer satisfaction for children, aged 0-18

	Auto-Assignee Sample				Full Sample
	$\overline{Y}$ (1)	RF (2)	2SLS (3)	N (4)	OLS (5)
Panel A. Any primary care access and preventive care in year (%)					
Primary Care and Preventative Composite	48.90	−0.69	−0.91	263,640	−3.43
		(0.28)	(0.38)		(0.42)
Annual Well-Child Visits	49.91	−0.46	−0.60	163,330	−3.88
		(0.72)	(0.95)		(1.15)
Access to Primary Care	80.54	−1.60	−2.10	261,245	−4.75
		(0.56)	(0.73)		(0.68)
Chlamydia Screening	55.23	1.34	1.76	7,011	−0.94
		(1.50)	(1.97)		(1.30)
Follow-up care after ADHD Prescription	51.17	1.23	1.77	3,864	−1.38
		(2.22)	(3.22)		(1.70)
Behavioral	7.12	−0.44	−0.58	263,640	−1.57
		(0.19)	(0.24)		(0.23)
Dental	58.71	−0.08	−0.11	263,640	−3.77
		(0.53)	(0.69)		(0.70)
Panel B. Any potentially high-value care drug classes in a year (%)					
Asthma Medication	15.15	−0.72	−0.94	263,640	−2.63
		(0.26)	(0.34)		(0.42)
Diabetes Medication	0.26	0.05	0.07	263,640	0.00
		(0.03)	(0.04)		(0.03)
Panel C. Any potentially low-value care in a year (%)					
Any Low-Value Care Composite	0.65	−0.05	−0.06	263,640	−0.10
		(0.05)	(0.06)		(0.03)
Avoidable Emergency Department	7.67	0.92	1.20	263,640	0.90
		(0.20)	(0.29)		(0.14)
Imaging	21.06	−0.15	−0.20	263,640	−1.91
		(0.29)	(0.38)		(0.28)
Panel D. Consumer satisfaction (relative to FFS)					
Share of enrollees in their assigned model (%)	96.28	−14.12			
		(3.56)			

Notes: Table presents sample means, and OLS and IV regression coefficients corresponding to Equation 2, where the regressor of interest, an indicator for enrollment in managed care, is in some specifications instrumented with assignment to managed care. Each row corresponds to a separate regression, with the dependent variable listed in the row label (left). The sample size, listed in column (4), differs across rows because only a subset of the sample would be clinically eligible or "at risk" for certain outcomes. The sample consists of auto-assignee children (aged less than 19) for columns (1) through (4) and adds the active-choosers to the sample for column (5). Only post-assignment observations are included (February 2012 to December 2014). Standard errors clustered on the unit of randomization (i.e., recipient's prior provider).

Appendix Table A8: Summary statistics for the plan transition experiment (pre-period)

	Overall		Pooled Control		Transitioned Plan	
	$\overline{Y}$	Std Dev	$\overline{Y}$	Std Dev	$\overline{Y}$	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Enrollee characteristics						
Female (%)	52.92	49.91	52.92	49.92	52.92	49.92
Age at baseline	10.92	9.23	11.07	9.40	10.67	8.93
Panel B. enrollee spending, annually ($)						
Total	1,584.09	2,745.78	1,510.87	2,683.35	1,702.53	2,839.87
Medical	1,179.09	2,053.76	1,173.16	2,069.63	1,188.68	2,027.78
Inpatient	90.30	613.46	92.56	617.74	86.65	606.46
Outpatient	650.30	880.59	638.11	876.24	670.01	887.22
Pharmacy	370.82	935.98	305.09	829.97	477.13	1,077.32
Brand Drug	204.90	729.19	145.95	626.48	300.24	861.53
Generic Drug	158.06	336.34	151.81	337.77	168.17	333.78
Panel C. Any annual utilization of high- or potentially high-value care (%)						
Annual Well-Child Visits	50.73	49.99	49.97	50.00	51.97	49.96
Access to Primary Care	80.52	39.61	79.85	40.11	81.60	38.75
Chlamydia Screening	54.02	49.84	53.60	49.87	54.67	49.78
Cervical Cancer Screening	57.89	49.37	56.66	49.56	60.02	48.99
Follow-up after ADHD Prescription	52.34	49.95	53.07	49.91	51.12	50.00
Behavioral	7.98	27.10	7.92	27.01	8.08	27.25
Dental	50.76	49.99	48.94	49.99	53.71	49.86
Asthma Medication	15.68	36.36	14.85	35.56	17.03	37.59
Diabetes Medication	0.61	7.77	0.60	7.74	0.62	7.82
Panel D. Any annual utilization of low- or potentially low-value care (%)						
Any Low-Value Care Composite	1.10	10.43	1.10	10.44	1.09	10.40
Avoidable Emergency Department	10.85	31.10	11.36	31.74	10.01	30.01
Imaging	25.41	43.54	24.86	43.22	26.32	44.03

Notes: Table reports summary statistics on enrollee demographics, utilization, and spending. The sample consists of a balanced panel of Medicaid enrollees that were in Medicaid continuously between February 2014-2016 and did not switch plans. Observations are at the enrollee $\times$ year level: $N = 497,057$ enrollees. Observations are reweighted such that the sample matches the distribution of the auto-assignee sample used in the first identification on health status-by-gender-by-age bins (see Supplemental Appendix Section B. for additional details). Total annual spending is winsorized at $25,000. All other subcomponents are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details). Components of spending do not sum up to “Total” due to winsorization.

Appendix Table A9: Comparing auto-assignee and plan transition samples

	Auto-Assignees		Plan Transition	
	$\overline{Y}$	Std Dev	$\overline{Y}$	Std Dev
	(1)	(2)	(3)	(4)
Panel A. Enrollee characteristics				
Female (%)	52.92	49.91	52.92	49.92
Age at baseline	9.36	7.49	10.67	8.93
Panel B. enrollee spending, annually ($)				
Total	1,451.35	2,427.61	1,702.53	2,839.87
Medical	1,052.74	1,815.46	1,188.68	2,027.78
Inpatient	97.48	747.79	86.65	606.46
Outpatient	590.29	820.12	670.01	887.22
Pharmacy	381.45	948.76	477.13	1,077.32
Brand Drug	229.30	757.06	300.24	861.53
Generic Drug	149.63	345.53	168.17	333.78
Panel C. Any annual utilization of high- or potentially high-value care (%)				
Annual Well-Child Visits	49.34	50.00	51.97	49.96
Access to Primary Care	80.46	39.65	81.60	38.75
Chlamydia Screening	59.67	49.06	54.67	49.78
Cervical Cancer Screening	67.19	46.96	60.02	48.99
Follow-up after ADHD Prescription	51.17	49.99	51.12	50.00
Behavioral	7.40	26.18	8.08	27.25
Dental	55.18	49.73	53.71	49.86
Asthma Medication	14.87	35.58	17.03	37.59
Diabetes Medication	0.58	7.56	0.62	7.82
Panel D. Any annual utilization of low- or potentially low-value care (%)				
Any Low-Value Care Composite	0.92	9.57	1.09	10.40
Avoidable Emergency Department	8.43	27.78	10.01	30.01
Imaging	23.33	42.29	26.32	44.03

Notes: Table reports summary statistics on enrollee demographics, utilization, and spending for both the auto-assignee and plan transition samples. The auto-assignee sample consists of a balanced panel of Medicaid enrollees that were randomly auto-assigned to Medicaid managed care or FFS in February 2012 and remained in Medicaid until at least December 2014. Observations are at the enrollee $\times$ year level: $N = 284,928$ enrollee-years. The plan transition sample consists of a balanced panel of Medicaid enrollees that were in the Medicaid plan that transitioned in February 2015, from February 2014 and remained until at least February 2016. Observations are at the enrollee $\times$ year level: $N = 189,900$ enrollees. Observations are reweighted such that the sample matches the distribution of the auto-assignee sample used in the first identification on health status-by-gender-by-age bins (see Supplemental Appendix Section B. for additional details). Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details). Components of spending do not sum up to "Total" due to winsorization.

Appendix Table A10: Yearly differences in spending and utilization of potentially high- or low-value care for plan transition experiment

	$\overline{Y}_{i_1,t_0}$ (1)	OLS (2)	OLS (3)	N (4)
Panel A. Spending by components of care, annually ($)				
Total Spending	1,702.53	−292.25	−204.39	993,990
		(15.60)	(10.52)	
Inpatient Spending	86.65	−11.19	−6.55	993,990
		(3.33)	(2.38)	
Outpatient Spending	670.01	−54.42	−27.17	993,990
		(4.54)	(3.45)	
Pharmacy Spending	477.13	−191.64	−144.91	993,990
		(5.22)	(3.47)	
Panel B. Any primary care access and preventive care in year (%)				
Primary Care and Preventative Composite	48.10	−0.33	−0.61	993,990
		(0.10)	(0.11)	
Annual Well-Child Visits	51.97	−1.10	−1.30	508,723
		(0.29)	(0.29)	
Access to Primary Care	81.60	−0.58	−0.60	975,918
		(0.16)	(0.17)	
Chlamydia Screening	54.67	0.34	0.02	43,065
		(1.01)	(1.05)	
Cervical Cancer Screening	60.02	0.01	0.09	101,236
		(0.68)	(0.73)	
Follow-up care after ADHD Prescription	51.12	1.41	0.72	13,121
		(1.77)	(1.78)	
Behavioral	8.08	−0.84	−0.82	993,990
		(0.12)	(0.12)	
Dental	53.71	0.38	−0.11	993,990
		(0.21)	(0.22)	
Panel C. Any potentially high-value care drug classes in a year (%)				
Asthma Medication	17.03	−1.03	−0.76	993,990
		(0.16)	(0.15)	
Diabetes Medication	0.62	−0.07	−0.02	993,990
		(0.06)	(0.03)	
Panel D. Any potentially low-value care in a year (%)				
Any Low-Value Care Composite	1.09	0.07	0.09	993,990
		(0.05)	(0.04)	
Avoidable Emergency Department	9.85	0.38	0.52	971,339
		(0.14)	(0.13)	
Imaging	26.32	−0.39	0.19	993,990
		(0.19)	(0.18)	
Re-weighted	Yes	No	Yes	

Notes: Observations are at the enrollee × year level pooled over two years: $N = 994,114$. N reported in (4) is for the re-weighted OLS regression and does not match the number of enrollee × year observations due to lack of joint support for <0.2% of enrollees. Observations are reweighted such that the sample matches the distribution of the auto-assignee sample used in the first identification strategy on health status-by-gender-by-age bins (see Supplemental Appendix Section B. for additional details). Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details). Components of spending do not sum up to "Total" due to winsorization. Robust standard errors reported in parentheses.

Appendix Table A11: External validity: IV estimates of the effect of managed care on spending with sample re-weighted to match the characteristics of Medicaid enrollees that made active choices

	Auto-Assignee Sample			Full Sample
	$\overline{Y}$	RF	2SLS	OLS
	(1)	(2)	(3)	(4)
Total Spending	1,558	−71	−94	−266
		(15)	(20)	(22)
Panel A. Spending by components of care ($)				
Inpatient Spending	103	2	3	0
		(4)	(6)	(3)
Outpatient Spending	626	−16	−21	−82
		(5)	(7)	(8)
Pharmacy Spending	419	−60	−79	−166
		(8)	(10)	(14)
Panel B. Spending by enrollee characteristics ($)				
Female	1,547	−79	−103	−237
		(20)	(27)	(23)
Male	1,570	−68	−91	−297
		(21)	(27)	(27)
Black	1,374	−64	−82	−186
		(19)	(25)	(23)
White	1,936	−57	−81	−329
		(28)	(40)	(30)
Panel C. Spending by quartiles of predicted health care spending ($)				
0-25%	739	−41	−48	−100
		(15)	(18)	(15)
26-50%	996	−38	−48	−107
		(19)	(25)	(13)
51-75%	1,397	−102	−140	−115
		(24)	(35)	(22)
76-100%	2,956	−130	−191	−263
		(46)	(67)	(40)

Notes: Table presents results of Equation 2 after re-weighting the "auto-assignee" sample to match the measured health status, gender, and age of the active chooser sample. Each cell in columns (2) through (4) corresponds to a separate regression, displaying the coefficient on an indicator for assignment to or enrollment in managed care. In Panel A, the variables listed indicate the dependent variable in the regression. In Panels B and C, the dependent variable is total spending, and the variables listed specify the subsample the regression restricts to. Columns (1) through (3) contain the sample mean and regression results for the auto-assignee sample and column (4) contains OLS estimates based on the full sample, including active choosers. Only post-assignment observations are included (February 2012 to December 2014). Observations are at the enrollee-year level: $N = 284,928$ for auto-assignees and $N = 413,811$ overall. Number of auto-assignees: 94,976. Number of active-choosers: 42,961. Observations are reweighted such that the auto-assignee sample matches the distribution of the active chooser sample on health status-by-gender-by-age bins (see Supplemental Appendix Section B. for additional details). All regressions adjust for provider prior to the auto-assignment period. Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details). Components of spending do not sum up to "Total" due to winsorization. Standard errors clustered on the unit of randomization (i.e., recipient's prior provider).

Appendix Table A12: Price summary statistics of main CPT and HCPCS procedures

CPT/HCPCS Category	Code	Code Description	Share of MMC claims (%)	Share of FFS claims (%)	Mean spend per claim in MMC ($)	Mean spend per claim in FFS ($)	Difference in mean spend ($)	Perc. Difference in mean spend (%)
			(1)	(2)	(3)	(4)	(5)	(6)
E&M	99213	Established patient office visit, 20-29 minutes	11.3	12.0	50.85	55.05	−4.20	−7.62
E&M	99283	Emergency department visit for the evaluation and management of a patient (low level)	5.2	4.3	78.21	78.72	−0.51	−0.65
E&M	99214	Established patient office visit, 30-39 minutes	4.4	4.8	75.94	80.31	−4.37	−5.44
E&M	99212	Established patient office visit, 10-19 minutes	3.7	4.1	30.43	32.99	−2.55	−7.74
E&M	T1015	Clinic visit/encounter, all-inclusive	3.1	1.9	126.60	124.80	1.77	1.42
-	-	Unspecified Services	3.0	2.7	25.06	27.00	−1.94	−7.17
Medicine	90471	Immunization administration	2.7	3.0	16.90	17.78	−0.88	−4.95
E&M	99211	Established patient office visit, time not accounted for	2.6	3.0	19.01	20.29	−1.28	−6.31
E&M	99284	Emergency department visit for the evaluation and management of a patient (moderate level)	2.0	1.6	120.30	120.90	−0.69	−0.57
Medicine	99173	Screening test of visual acuity	1.8	2.2	1.96	1.93	0.03	1.66
Pathology and Laboratory	87880	Strep a assay w/optic	1.8	1.7	12.57	12.68	−0.11	−0.85
Medicine	92551	Audiologic screening test	1.7	2.2	7.57	7.49	0.08	1.10
E&M	99282	Emergency department visit for the evaluation and management of a patient (straightforward level)	1.5	1.4	99.05	102.40	−3.35	−3.27
Pathology and Laboratory	85025	Complete CBC (Complete blood count) w/auto diff wbc	1.5	1.7	7.82	7.72	0.10	1.25
Other	V2020	Frames, purchases	1.5	1.4	15.04	14.97	0.07	0.44
Medicine	90472	Immunization administration	1.4	1.5	18.36	18.72	−0.36	−1.94
Radiology	71020	Radiologic examination, chest, two views, frontal and lateral	1.2	1.1	27.84	26.87	0.97	3.59
E&M	99392	Established patient, periodic comprehensive preventive medicine (age 1-4 years)	1.2	1.4	76.01	82.41	−6.41	−7.77
E&M	99393	Established patient, periodic comprehensive preventive medicine (age 5-11 years)	1.1	1.4	81.51	88.40	−6.89	−7.80
Pathology and Laboratory	81025	Urine pregnancy test	1.0	0.7	6.20	6.28	−0.08	−1.23
E&M	99203	New patient office visit, 30-44 minutes	0.9	0.8	68.38	69.89	−1.51	−2.17
Pathology and Laboratory	87804	Influenza assay w/optic	0.9	0.7	14.08	14.02	0.06	0.42
Other	V2103	Spherocylinder, single vision, plano to plus or minus 4.00d sphere, .12 to 2.00d cylinder, per lens	0.7	0.8	16.97	16.50	0.46	2.80
Medicine	92014	Ophthalmological services for established patient	0.7	0.8	81.21	80.22	0.99	1.23
E&M	99394	Established patient, periodic comprehensive preventive medicine (age 12-17 years)	0.7	0.9	86.61	95.63	−9.03	−9.44
Pathology and Laboratory	80053	Comprehensive metabolic panel	0.7	0.6	11.98	11.54	0.44	3.80
Overall Weighted Average (with unspecified services)			100.0	100.0	45.52	46.96	−1.44	−3.06
Weighted Average for non-E&M			56.2	56.8	31.16	31.42	−0.26	−0.84
Weighted Average for E&M			40.9	40.5	67.07	70.12	−3.05	−4.34
Weighted Average for Laboratory			18.1	15.7	11.67	11.27	0.40	3.55
Weighted Average for Radiology			7.3	6.6	56.90	56.57	0.34	0.60
Weighted Average for Surgery			2.8	2.6	144.50	149.40	−4.88	−3.27

Notes: This table presents summary statistics for the top 20 CPT and HCPCS codes (out of 2724 codes with at least 1 claim and $1 of spend in both MMC and FFS simultaneously) used in the mechanisms analysis (See Section V for additional details). The table is sorted by share of MMC claims, column (1). The bottom rows present weighted averages (weighted by the number of FFS claims over the analysis period) overall, and separtely with and without Evaluation and Management codes (CPT codes between 99201-99499, HCSPS codes T1015), Laboratory codes (CPT codes between 80047-89398), Radiology codes (CPT codes between 70010-79999) and Surgery codes (CPT codes between 10021-69990).

Appendix Table A13: Mechanisms: broader primary care networks tend to increase managed care spending

	Main Effect		Decomposition		
	$\overline{Y}$	2SLS	Network	Provider	Residual
	(1)	(2)	(3)	(4)	(5)
Panel A. Spending by components of care ($)					
Total Spending	1,451.4	−81.5	34.7	14.8	−131.0
		(17.5)	(6.2)	(10.5)	(16.1)
Inpatient Spending	98.6	3.1	1.8	5.5	−4.1
		(5.1)	(2.3)	(2.1)	(5.2)
Outpatient Spending	590.2	−18.6	7.0	0.9	−26.5
		(6.6)	(2.5)	(3.9)	(6.9)
Pharmacy Spending	380.2	−68.7	12.9	−4.8	−76.8
		(8.9)	(3.1)	(3.6)	(10.0)
Panel B. Pharmacy spending by type of drug ($)					
Brand Drug Spending	228.1	−65.8	7.1	−2.2	−70.7
		(7.5)	(2.3)	(2.5)	(8.8)
Generic Drug Spending	149.3	−3.5	5.9	−2.6	−6.8
		(3.6)	(1.2)	(1.3)	(3.6)

Notes: Table presents sample means and IV regression coefficients corresponding to Equation 2, where the regressor of interest, an indicator for enrollment in managed care, is instrumented with assignment to managed care. Column 1 lists means of dependent variables and Column 2 lists the overall effect reported in the main paper. Each cell in columns 3–5 corresponds to a separate regression, with the dependent variable listed in the row label. The network component, (3), adds a linear adjustment for primary care network breadth at the ZIP level and subtracts that estimate from the main estimate in (2). The provider component, (4), adjusts for an enrollee's attributed primary care provider, and subtracts that estimate from the main estimate in (2). By definition, the residual component, (5), is the remainder so that the decomposition is exact, and equals the overall effect. The sample consists of auto-assignees. Specifications that include parametric controls for provider network breadth may not recover a well-behaved LATE (Blandhol et al., 2022). Only post-assignment observations are included (February 2012 to December 2014). Observations are at the enrollee-year level: $N = 284,716$. Total annual spending is winsorized at $25,000. Standard errors clustered on the unit of randomization (i.e., recipient's prior provider). Standard errors are obtained using 1000 cluster bootstrapped replicates and shown below estimates in parentheses (See Appendix C.).

Appendix Table A14: Decomposition of spending reductions caused by managed care

	Total Effect	Components			
	Overall Change	Change in Prices	Sub. to Cheaper Generics/Brands	Sub. from Brands to Generics	Residual
	$\Delta TS_{MMC,FFS}$	$\Delta P_{MMC,FFS}$	$\Delta Q^{Steering}_{MMC,FFS}$	$\Delta Q^{Generic}_{MMC,FFS}$	$\Delta Q^{R}_{MMC,FFS}$
	(1)	(2)	(3)	(4)	(5)
Panel A: Total Spending					
t_{-1}	0.85	0.22	0.11	0.02	0.51
	(1.26)	(0.37)	(0.08)	(0.11)	(1.17)
t_0	−4.80	−1.53	−0.27	0.00	−3.00
	(1.16)	(0.41)	(0.15)	(0.14)	(1.15)
t_1	−8.52	−2.62	−0.63	−2.39	−2.88
	(1.51)	(0.47)	(0.17)	(0.26)	(1.45)
t_2	−7.49	−0.67	−0.72	−3.13	−2.97
	(1.53)	(0.32)	(0.17)	(0.27)	(1.50)
Panel B: Medical Spending					
t_{-1}	1.61	0.04			1.57
	(1.27)	(0.44)			(1.21)
t_0	−3.67	−1.92			−1.75
	(1.34)	(0.58)			(1.42)
t_1	−2.28	−2.48			0.22
	(1.75)	(0.48)			(1.63)
t_2	−0.61	−0.23			−0.35
	(1.71)	(0.34)			(1.68)
Panel C: Pharmacy Spending					
t_{-1}	−1.19	0.29	0.44	0.05	−1.97
	(1.92)	(0.48)	(0.30)	(0.36)	(1.82)
t_0	−7.11	−0.71	−0.76	−0.15	−5.49
	(2.09)	(0.62)	(0.42)	(0.44)	(2.20)
t_1	−25.42	−3.00	−2.19	−8.61	−11.61
	(2.83)	(0.77)	(0.61)	(0.94)	(2.35)
t_2	−25.53	−1.49	−2.44	−11.22	−10.38
	(2.73)	(0.77)	(0.60)	(0.95)	(2.29)

Notes: Table presents a mutually exclusive and collectively exhaustive decomposition of the spending reduction due to assignment to managed care into four effects: (column 2) a price inflation index ΔP, (column 3) drug steering effect within an ATC-4 therapeutic class - brand/generic cell $\Delta Q^{Steering}$, (column 4) a brand-generic drug steering effect within ATC-4 therapeutic classes $\Delta Q^{Generic}$, and (column 5) a quantity effect ΔQ^{R} which captures steering across ATC-4 therapeutic classes (brand-brand or brand-generic) and outright quantity effects. Numbers presented are percent changes relative to FFS spending. Additional details are available in Appendix A.. Standard errors are shown below estimates in parentheses and are obtained using 400 cluster bootstrapped replicates (See Appendix C.). Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details).

Appendix Table A15: Utilization management summary statistics of main ATC-4 therapeutic classes

ATC4	Description	ATC2	Share of Managed FFS Spending (%)	Denial rate in MMC (%)	Decomposition of spending effect				
					Overall Change	Change in Prices	Sub. to Cheaper Generics	Sub. from Brands to Generics	Residual
					$\Delta TS_{MMC,FFS}$	$\Delta P_{MMC,FFS}$	$\Delta Q^{Steering}_{MMC,FFS}$	$\Delta Q^{Generic}_{MMC,FFS}$	$\Delta Q^{R}_{MMC,FFS}$
			(1)	(2)	(3)	(4)	(5)	(6)	(7)
A10AD	Diabetes drugs	A10	0.8	22	36.0	26.0	−0.4	0.0	10.0
N07BC	Drugs used in opioid dependence	N07	1.7	25	32.0	16.0	6.9	0.8	8.7
N03AX	Other Antiepileptics	N03	0.8	19	10.0	3.2	−1.3	0.9	7.2
N05AX	Antipsychotics	N05	1.8	23	−6.1	−1.4	1.8	−7.1	0.7
R03CC	Selective Beta-2-Adrenoreceptor Agonists	R03	2.7	33	−6.5	−6.1	−0.7	−0.3	0.6
J01FF	Lincosamides	J01	0.5	34	−6.7	9.6	−16.0	0.1	−0.2
L02AB	Progestogens	L02	0.5	42	−9.1	−12.0	−0.3	−0.1	3.4
N06BA	Centrally acting sympathomimetics	N06	29	25	−11.0	3.0	−1.5	−9.9	−2.6
J05AH	Neuraminidase Inhibitors	J05	1.7	38	−11.0	−3.6	0.3	0.0	−7.9
J01CA	Penicillins With Extended Spectrum	J01	1.7	38	−12.0	−9.5	0.3	0.0	−2.9
S01AA	Antibiotics	S01	1.1	35	−13.0	−7.0	0.1	−2.2	−3.8
S01EA	Sympathomimetics In Glaucoma Therapy	S01	1.3	19	−22.0	−19.0	−20.0	20.0	−2.7
N02BE	Anilides	N02	0.6	27	−23.0	−35.0	−10.0	−0.6	22.0
R06AE	Piperazine Derivatives	R06	0.9	33	−24.0	−12.0	−0.6	−0.6	−11.0
R03AC	Selective Beta-2-Adrenoreceptor Agonists	R03	1.2	29	−25.0	5.7	2.2	0.0	−33.0
S01BA	Corticosteroids	S01	2.2	37	−27.0	−25.0	0.5	0.0	−2.4
R06AX	Other Antihistamines For Systemic Use	R06	0.5	34	−29.0	−29.0	−3.8	−2.5	5.8
N05AH	Diazepines, Oxazepines, Thiazepines And Oxepines	N05	0.7	25	−30.0	2.9	16.0	−44.0	−4.8
A04AA	Serotonin (5Ht3) Antagonists	A04	0.4	38	−30.0	−34.0	1.2	0.0	2.5
P03AC	Pyrethrines, Incl. Synthetic Compounds	P03	0.5	37	−33.0	−21.0	1.1	0.0	−13.0
N06AX	Antidepressants	N06	0.7	20	−33.0	−7.8	−2.7	−18.0	−4.6
R03DC	Leukotriene Receptor Antagonists	R03	0.6	32	−34.0	−3.3	−2.2	−0.8	−28.0
G03AC	Progestogens	G03	0.6	19	−35.0	4.0	−21.0	−5.0	−13.0
S02BA	Corticosteroids	S02	0.5	36	−37.0	−27.0	5.8	0.0	−16.0
J01AA	Tetracyclines	J01	0.5	30	−38.0	−11.0	−3.1	−0.1	−24.0
R05CA	Expectorants	R05	0.7	51	−40.0	0.2	0.0	−0.8	−39.0
S01AE	Fluoroquinolones	S01	0.6	44	−41.0	2.5	1.4	−0.9	−44.0
S01AD	Antivirals	S01	0.6	38	−42.0	4.0	−17.0	−8.9	−21.0
S03BA	Corticosteroids	S03	1.8	34	−42.0	−3.4	−4.8	−16.0	−19.0
A02BC	Proton Pump Inhibitors	A02	0.5	28	−44.0	−6.2	1.4	−46.0	7.7
R03BA	Glucocorticoids	R03	8.5	35	−45.0	3.3	2.2	−38.0	−12.0
	All other NDCs		5.9	33	−45.0	−2.9	0.1	−1.1	−41.0
C02AC	Antihypertensives	C02	3	23	−56.0	3.7	−0.8	−37.0	−22.0
B03AD	Iron In Combination With Folic Acid	B03	0.7	33	−63.0	−4.0	0.9	−27.0	−33.0
J01DD	Antibiotics (from dose-response figure)	J01	2.7	41	−78.0	−3.1	−27.0	−0.1	−49.0
D11AH	Agents for dermatitis	D11	1.1	47	−79.0	−1.7	−13.0	−0.2	−64.0
S01GX	Antiallergics	S01	1	52	−82.0	−1.5	−0.8	−26.0	−53.0

Notes: Table presents summary statistics for the top ATC-4 therapeutic classes (i.e., Anatomical Therapeutic Chemical (ATC) Classification, level 4) used in the dose-response analysis, i.e. ATC-4s that have at least 0.15% of overall pharmacy spending and claims, excluding ATC-4s that have FFS enrollee per-year spending less than $1. Column (1) presents data for 2013-2014. Column (2) presents average denial rates for the quarter one month after the pharmacy carve-in in November 2012. The decomposition in columns (3) - (7) uses the same claims data as for the decomposition exercise in Appendix A. but combines result from 2013 and 2014. The table is sorted by the overall percentage change, column (3). Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details).

Appendix Table A16: IV effects of managed care on drug utilization

	Auto-Assignee Sample		
	$\overline{Y}$ (1)	2SLS (2)	2SLS-Post (3)
Panel A. Annual medical cost and drug utilization			
Medical Cost ($)	1,053	-16.7	-10.2
		(13.3)	(16.2)
Total Days Supply	114.29	–3.48	–3.75
		(2.45)	(2.78)
Panel B. Annual days supply for potentially high-value drug classes			
Total High-Value Days Supply	10.71	–0.79	–1.02
		(0.41)	(0.46)
Asthma Medications	9.42	–1.13	–1.39
		(0.37)	(0.43)
Diabetes Medications	1.29	0.34	0.37
		(0.18)	(0.20)

Notes: Table presents sample means and IV regression coefficients corresponding to Equation 2 using days supply as the dependent variable, where the regressor of interest, an indicator for enrollment in managed care, is instrumented with assignment to managed care. Each cell in columns (2) & (3) corresponds to a separate IV regression. Panel B looks at the effect for specific potentially high-value drug classes. The sample consists of auto-assignees and column (3) includes only post-carve-in observations (January 2013 to December 2014). Observations are at the enrollee × year level. All regressions adjust for the unit of randomization (i.e., recipeint's prior provider). Standard errors clustered on the unit of randomization (i.e., recipient's prior provider).

Appendix Table A17: Sensitivity of plan transition results to allowing for plan switching

	No Plan Switching		Allows Plan Switching	
	$\overline{Y}_{i_1,t_0}$	OLS	$\overline{Y}_{i_1,t_0}$	OLS
	(1)	(2)	(3)	(4)
Panel A. Spending by components of care, annually ($)				
Total Spending	1,702.53	−204.39	1,716.67	−198.65
		(10.52)		(10.10)
Inpatient Spending	86.65	−6.55	86.36	−5.54
		(2.38)		(2.25)
Outpatient Spending	670.01	−27.17	674.62	−25.11
		(3.45)		(3.32)
Pharmacy Spending	477.13	−144.91	481.72	−141.90
		(3.47)		(3.34)
Panel B. Any primary care access and preventive care in year (%)				
Primary Care and Preventative Composite	48.10	−0.33	48.30	−0.59
		(0.10)		(0.11)
Annual Well-Child Visits	51.97	−1.30	51.74	−0.86
		(0.29)		(0.28)
Access to Primary Care	81.60	−0.60	82.02	−0.71
		(0.17)		(0.17)
Chlamydia Screening	54.67	0.02	54.52	−0.18
		(1.05)		(1.00)
Cervical Cancer Screening	60.02	0.09	60.57	−0.30
		(0.73)		(0.69)
Follow-up care after ADHD Prescription	51.12	0.72	51.49	0.68
		(1.78)		(1.71)
Behavioral	8.08	−0.82	8.18	−0.83
		(0.12)		(0.11)
Dental	53.71	−0.11	53.99	0.09
		(0.22)		(0.21)
Panel C. Any potentially high-value care drug classes in a year (%)				
Asthma Medication	17.03	−0.76	17.09	−0.77
		(0.15)		(0.15)
Diabetes Medication	0.62	−0.02	0.61	−0.02
		(0.03)		(0.03)
Panel D. Any potentially low-value care in a year (%)				
Any Low-Value Care Composite	1.09	0.09	1.11	0.09
		(0.04)		(0.04)
Avoidable Emergency Department	9.85	0.52	9.84	0.49
		(0.13)		(0.13)
Imaging	26.32	0.19	26.49	0.04
		(0.18)		(0.18)
Re-weighted	Yes	Yes	Yes	Yes

Notes: No Plan Switching requires that enrollees remain in the same plan for the 24-month sample period, while Allows Plan Switching only requires enrollees to remain in the same plan for the 12-month period prior the the plan transition. No Plan Switching repeats the results of Table A10 for ease of comparison. Observations are reweighted such that the sample matches the distribution of the auto-assignee sample used in the first identification strategy on health status-by-gender-by-age bins (see Supplemental Appendix Section B. for additional details). Total annual spending is winsorized at $25,000. All other sub-components are winsorized at the same percentile of their distribution (see Supplemental Appendix Section II for additional details). Components of spending do not sum up to "Total" due to winsorization. Robust standard errors reported in parentheses.