Journal of Health Economics 63 (2019) 64–80

Contents lists available at ScienceDirect

Journal of Health Economics

journal homepage: www.elsevier.com/locate/econbase

# The Effect of Health Insurance on Prescription Drug Use Among Low-Income Adults:Evidence from Recent Medicaid Expansions

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ARTICLE INFO

*Article history:*
Received 7 January 2017
Received in revised form 11 October 2018
Accepted 4 November 2018
Available online 6 November 2018

*Keywords:*
Health insurance
Medicaid
Prescription drugs
Affordable Care Act

ABSTRACT

This study examines how subsidized coverage affects prescription drug utilization among low-income non-elderly adults. Using the Affordable Care Act's Medicaid expansions as a source of variation and a national, all-payer pharmacy transactions database, we find that within the first 15 months of new health insurance availability, aggregate Medicaid-paid prescriptions increased 19 percent, amounting to nearly 9 new prescriptions a year, per new enrollee. We find no evidence of reductions in uninsured or privately-insured prescriptions, suggesting that new coverage did not simply substitute for other payment sources. The largest increases occurred for medications treating conditions such as diabetes and heart disease, suggesting greater price elasticity for chronic medications. Generics increased more than brand-name drugs; and utilization increased less in expansion states with higher Medicaid drug copayments. Overall, these findings suggest that prescription drug demand among low-income populations exhibits substantial price sensitivity, and insurance expansion can increase medication treatment for chronic conditions.



## INTRODUCTION

Prescription drugs represent one of the fastest-growing areas of healthcare spending (Martin et al., 2016) but because of the effective role medications play in treatment of a vast array of health conditions and because public programs are a large source of payment for medications, demand responsiveness to price changes is subject to intense study (Carrera et al., 2018) and to policy attention regulating price increases (The Brookings Institution, 2017; The Council of Economic Advisers, 2018). Numerous studies have examined the effects of health insurance coverage on drug utilization among the elderly, particularly around the creation of the Medicare Part D program (Duggan and Scott Morton, 2010; Einav et al., 2018; Einav et al., 2015; Huh and Reif, 2017; Ketcham and Simon, 2008; Lichtenberg and Sun, 2007; Zimmer, 2015). However, much less is known about the effects of health insurance on prescription drug use among low-income adults, despite unprecedented changes in their coverage rates through the 2014 ACA expansions. The existing small literature on low-income adults typically rests on single-state studies (Baicker et al., 2017; Chandra et al., 2014), or data that only examines one payer type (Wen et al., 2016).

The passage of the Affordable Care Act (ACA) in 2010 and the subsequent Supreme Court ruling making Medicaid expansion optional provide a valuable opportunity for studying the responsiveness of low-income individuals to reduced costs of obtaining prescription drugs. We leverage this natural experiment to examine behavioral responses to price reductions across drug classes, for Medicaid-paid as well as total use. In addition, we examine whether the responses varied by the size of Medicaid copays used within expansion states. We find that low-income populations are fairly price sensitive in their demand for prescription drugs, increasing Medicaid prescriptions in aggregate by 19 percent due to Medicaid expansion. An analogous assessment of enrollment indicates that the expansion led to a 17 percent increase in Medicaid coverage, which – combined with our point estimate for drugs – indicates that expansion led to 9 additional prescription fills per year per newly enrolled individual. Unlike some other forms of healthcare such as inpatient hospitalizations where insurance expansion mostly changes the form of payment but not total utilization because hospitals act as "insurers of last resort" (Baicker et al., 2013; Freedman et al., 2017; Garthwaite et al., 2018; Nikpay et al., 2015), we find no evidence of crowd out of either cash pay or private insurance in the case of prescription drugs.

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https://doi.org/10.1016/j.jhealeco.2018.11.002
0167-6296/

An extensive literature using experimental and quasi-experimental research designs for mostly older adults establishes that the demand for prescription drugs is responsive to out-of-pocket prices; (Chandra et al., 2010; Goldman et al., 2007; Newhouse, 1993). While some papers explicitly calculate elasticity estimates because their study design and data allow it (e.g. Dunn (2016) and Einav et al. (2018) finds approximately -0.2 price elasticity of demand for prescription drugs on average, Einav et al. (2015) finds estimates in the range -0.3 to-0.5, and Goldman et al's 2007 review of the literature finds estimates in the range of -0.2 to -0.6), other papers only present percent changes in drug utilization as a result of insurance expansions (e.g. Alpert (2016), Baicker et al. (2017), Kaestner and Khan (2012)). Papers that examine low-income populations are limited because variation through Medicaid insurance expansions change two prices at once: the price of the physician visit that enables the prescription, as well as the price of the medication itself. Information on out of pocket prices paid by low income uninsured or Medicaid insured is also generally lacking in large-scale data sources. Nevertheless, Medicaid coverage is an extreme version of price variation from which we can examine responsiveness among the relatively understudied low-income non-elderly adult population. In all 50 states, Medicaid covers most major categories of medical intervention, including pharmacological therapy. Thus far, 31 states have implemented the ACA Medicaid expansion option (Kaiser, 2018), extending coverage to non-elderly adults under 138% of the federal poverty level.

The extent to which expanded Medicaid coverage induces greater use of prescription drugs in low-income populations is an economically meaningful question for understanding the overall efficiency of insurance design, as drug coverage has been shown to produce positive spillovers to other forms of healthcare (e.g. Ayyagari et al. (2017), Borrescio-Higa (2015), Chandra et al. (2010)). Non-elderly adults without health insurance are four times more likely than their insured counterparts to report foregoing needed prescription drugs due to cost, and most of the remaining uninsured are non-elderly adults (National Center for Health Statistics. Health, United States, 2016). Utilization of prescription medications can provide indirect evidence of how insurance expansions affect access to providers, because prescriptions can only be obtained through consultation with a medical practitioner with prescriptive authority. In turn, studying the effect of insurance coverage on prescription utilization may also be important for understanding future changes in health outcomes (e.g. Huh and Reif (2017)). Studying this form of health care also contributes to the literature on how different forms of care respond to insurance coverage; notably, ACA Medicaid expansion did not lead to overall increases in inpatient hospital care but did substantially diminish uncompensated hospital care because of increases in Medicaid reimbursed care (Freedman et al., 2017).

Why should the focus of the prior literature on elderly populations be viewed as a limitation of the literature? There are several reasons why the ACA Medicaid-eligible younger population may not respond in the same way as the well-studied elderly population affected by Medicare Part D. Common health conditions and available therapies are likely to be different at younger ages (Wong et al., 2012). The low-income non-elderly adult populations may have had differential access to charity care absent insurance (Finkelstein et al., 2018; Mahoney, 2015). Another key difference is that the population gaining Part D coverage in 2006 was already insured for other types of care beforehand – Medicare Part D added prescription drug benefits to otherwise comprehensive coverage. The response may differ when a population is gaining access to subsidized pharmaceuticals at the same time as insurance for provider visits, as happens under Medicaid expansion. Opposing complementarity and substitutability between provider visits and medications imply that the net effect of coverage on prescription drug utilization in the case of the ACA is theoretically ambiguous, and in any event likely differs from the experience in Medicare Part D.

The Oregon Health Insurance Experiment (OHIE) represents the only other recent study setting we are aware of in which researchers assesses changes in prescription drug utilization among low-income non-elderly adults gaining health insurance. Evidence from Oregon showed that acquiring Medicaid led to significant increases in the likelihood of using medication (Finkelstein et al., 2012). However, the subsidized public health insurance in the OHIE did not include any cost-sharing for prescription drugs. In contrast, of the 28 states that expanded Medicaid under the ACA within our study period, 20 states have prescription drug co-pays for the expansion population (Kaiser Family Foundation Report, 2015). This variation allows us to investigate price responsiveness for drugs among Medicaid beneficiaries on the intensive margin as well, which is an economically important consideration as states increasingly propose more cost-sharing for this population (Kaiser Family Foundation Issue Brief, 2017).

More broadly, using national data, we extend the scope of previous research to provide the first natural-experimental evidence on how subsidized public health insurance coverage impacts prescription utilization on the Medicaid population, estimating aggregate effects on any use as well as direct effects on Medicaid paid prescriptions and potential “crowd out” on prescriptions paid through other means. Taking advantage of a rich claims-based data source, we also assess the relative effects of insurance coverage on utilization across therapeutic classes and drug types (generic or branded), adding rich detail to our understanding of demand for pharmaceuticals among low-income adults.

Our work also fits into the broader emerging literature on the effects of the Affordable Care Act itself. Multiple studies have found that uninsurance rates have declined substantially since early 2014 (Courtemanche et al., 2017; Frean et al., 2017; Kaestner et al., 2017; Sommers et al., 2015); others have found improvements in self-reported access to primary care and prescription medications, particularly in Medicaid-expansion states (Simon et al., 2017; Sommers et al., 2016b; Sommers et al., 2015). Although changes in insurance coverage resulting from the ACA Medicaid expansions have already received substantial attention from researchers and policy makers, far less is known about its impact on the use of specific types of medical services including prescription drugs. Economically, there may be different effects on prescription drugs than other forms of care such as inpatient hospitalizations because of the existence of policy that enables hospital access for low income populations prior to the ACA (charity care and uncompensated care availability, and EMTALA); such sources of access did not typically exist for prescription medications.

Our study design focuses on the 2014 state Medicaid expansions under the ACA to examine the impact of expanded coverage on prescription drug use. We employ a difference-in-difference approach similar to that used in recent studies assessing the impact of this same source of insurance variation on hospital care and sources of payment (Dranove et al., 2016; Meinhofer and Witman, 2018; Nikpay et al., 2015; Nikpay et al., 2016), and other policy based difference-in-difference studies of the impact of health insurance expansion on coverage, access to care, and labor market outcomes (Courtemanche et al., 2017; Decker and Lipton, 2015; Dillender, 2015; Frean et al., 2017; Kaestner et al., 2017; Maestas et al., 2014; Wagner, 2016). We assess aggregate effects on overall Medicaid pharmaceutical utilization rates, examine usage patterns across specific therapeutic classes by whether they are more likely to be used for chronic or acute conditions, and branded vs. generic drugs, and test for heterogeneity of effects in areas of the country that have high rates of baseline uninsurance. We also assess whether effects differ by geographical concentration of racial/ethnic minority populations, which help assess whether expansion may have reduced race and ethnic disparities in access to medications. We explore the differential effect of Medicaid drug cost-sharing across expansion states in order to assess price sensitivity along the intensive margin. Our research also examines whether public coverage expansion simply substitutes away from utilization under uninsured or private payment sources. This helps in gauging the extent of new drug use, as opposed to a simple substitution of payment source; the issue of Medicaid 'crowd out' of private insurance has been a substantial concern in prior literature in insurance (e.g. Cutler and Gruber (1996)) but little work explores whether new insurance replaces uncompensated health care by the uninsured differently by type of healthcare.

Our key findings are as follows. We find a significant increase in prescription drug utilization in response to insurance expansions aimed at low-income adults. Medicaid prescriptions increased by 19 percent in states that expanded program eligibility in the first 15 months following the 2014 policy change, relative to states that did not adopt Medicaid expansion. An analogous assessment of Medicaid enrollment indicates a 17% increase in Medicaid coverage after expansion, and combined with our prescription point estimate, this indicates that the expansion of coverage led to 9 additional prescriptions annually per newly eligible beneficiary. Moreover, we observe heterogeneity in utilization by therapeutic category, with a general pattern of larger increases for maintenance drugs used for chronic conditions and smaller increases for acute condition medications. The largest increase of 24 percent occurred among drugs associated with treating diabetes; the next largest were a 22 percent increase for birth control, and a 21 percent increase for drugs associated with cardiovascular disease. Increases in respiratory/allergy medications and antibiotics were significantly smaller.

We observe no significant effect of Medicaid expansion on Medicare prescriptions, privately insured prescription utilization, or on uninsured prescriptions paid by cash or assistance programs. These coefficients are not statistically significant and are small in magnitude, suggesting a lack of substantial crowd out of private or self-pay prescriptions following Medicaid expansion. In other words, the increased Medicaid drug utilization appears to represent a net increase in utilization among low-income adults.

We find evidence that the rise in Medicaid prescriptions was driven by a relative increase in generic drug usage that was nearly twice as large as that for branded drugs, which suggests that the Medicaid expansions steered patients towards lower-cost prescription drugs and may have therefore helped control program costs. This has important implications for states concerned with the budget implications of drug spending in the Medicaid program, as well as for the efficiency of health insurance expansions. This pattern of utilization also matters for the pharmaceutical industry's assessments of the impacts of ACA policies on future revenues.

Unlike the Oregon Medicaid expansion studied in the past, most of the states that expanded Medicaid in our study required some cost-sharing for prescription drugs. Our results reveal smaller increases in utilization in expansion states imposing higher cost-sharing for prescription drugs, than in expansion states with low or no cost-sharing. We use these estimates to derive an implied price elasticity of -0.06, in the case of medications for respiratory illnesses, which is the only therapeutic class where we detect a statistically significant effect in the continuous copay specification. While this estimate is smaller than the -0.13 found by Chandra et al. (2014) in their regression discontinuity study of demand elasticities for prescription medications among low-income non-elderly adults with subsidized public insurance in Massachusetts, it is closer to the estimate of -0.098 for those with chronic illnesses in their analysis sample. Our use of aggregate data and weighted-average statewide copay likely introduces measurement error, which would presumably bias our estimated elasticity towards zero; we treat this analysis only as suggestive that our results on price sensitivity from Medicaid expansions extend to the intensive margin as well.

To further investigate the robustness of our results and to understand the heterogeneity of responses, we test whether estimates are larger in areas we would expect the insurance expansions to have had more substantial reach. Consistent with theory, we find that within expansion states increases in prescription drug utilization were larger in geographical areas with higher baseline uninsured rates in 2013, where the ACA likely produced the largest coverage changes. We also document suggestive evidence that increases in Medicaid prescriptions were greater in markets with higher pre-2014 rates of minority (Hispanic and black) populations, indicating that Medicaid expansion under the ACA may have diminished ethnic/racial disparities in access to medications. Our findings are robust to various alternative specifications, comparison of pre-policy trends and event study specifications, as well as placebo testing, suggesting the results can be causally attributed to the impact of expanded public health insurance to low-income populations.

## 1. BACKGROUND

Despite multiple studies demonstrating that declines in out-of-pocket (OOP) spending leads to higher use of pharmaceuticals among older Americans, the previous literature does not provide much direct evidence from which to draw inferences about the non-elderly adult population, particularly lower-income adults targeted for insurance expansion under the ACA. The ACA provides additional federal financing to states for extending Medicaid coverage to non-elderly adults earning less than 138 percent of the federal poverty level (FPL). The expansion decision was later delegated by the Supreme Court to states, and as of January 1, 2018, 32 states plus Washington DC had implemented the ACA Medicaid expansion, while the remaining 18 states had not (Kaiser Family Foundation, 2018). Medicaid is a means-tested health insurance program for low-income populations that is jointly administered by the federal and state governments. Since the creation of the Medicaid program in 1965, states have had broad discretion over a range of eligibility rules, program benefits, and provider reimbursement, subject to compliance with federal minimum standards. As a result, there has long been considerable variation in Medicaid eligibility standards and program generosity across states. Even though prescription drug coverage was a state option, all states covered pharmacological treatments prior to the ACA; following the ACA's Medicaid expansion, new enrollees must be offered so-called "benchmark" benefits, including prescription drug coverage.

Thus, the ACA's Medicaid expansion offers a unique large-scale policy experiment through which the effects of price subsidies on healthcare utilization of low-income adults, including use of prescription drugs, can be studied. Only a few prior studies estimate the impact of Medicaid on prescribed medications. The OHIE found that in the first year, Medicaid coverage increased the likelihood of using prescription medications by 15 percent among previously-uninsured low-income adults (Finkelstein et al., 2012). Using a difference-in-difference study design, Sommers et al. (2016a) estimated a 10 percentage-point reduction in low-income adults reporting skipping prescribed medication in Kentucky and Arkansas following Medicaid expansions under the ACA, relative to non-expansion Texas. Two brief national studies have explored the pharmaceutical utilization implications of the ACA Medicaid expansions. Mulcahy et al. (2016) used prescription transaction data to follow a sample of non-elderly adults who reported any prescription drug use during January 2012. They find that adults who gained Medicaid in 2014 increased their prescription drug use by 79 percent. However, their sample was limited to those already using medications, nearly two-thirds of whom reported chronic health conditions such as diabetes, asthma and breast cancer. Thus, their study population had a much higher prevalence of chronic disease than the overall population, such as adults newly eligible for coverage through the ACA Medicaid expansions (Decker et al., 2014). More importantly, their sampling design did not allow them to consider the effects on those who did not use prescription medications prior to the expansions. The second study, by Wen and colleagues (2016), examines aggregate Medicaid medication use as reported in the CMS State Drug Utilization Database (SDUD) through 2014. They find a significant increase in the number of prescriptions following expansion. Notably, none of these studies examine ACA variation as an opportunity to learn about price responsiveness in total, netting effects across payer types other than Medicaid, or heterogeneity in effects by therapeutic class, state cost-sharing requirements or pursued study designs that used sub-state geography, placebo tests or event studies to explore robustness and heterogeneity of results.

The existing literature from outside the ACA context suggests that higher consumer cost-sharing decreases utilization of medical services. Several studies have estimated the responsiveness of demand for prescription medications to out-of-pocket costs, with one meta-analysis across all payer types and populations finding that for each 10 percent increase in out-of-pocket costs, total drug spending fell by 2-6 percent (Goldman et al., 2007). To the best of our knowledge, low-income non-elderly adult population-specific elasticities have not been assessed at the national level. Chandra et al. (2014) examine the elasticity of different types of medical spending to cost-sharing among low-income non-elderly adult beneficiaries within the subsidized public health insurance in Massachusetts through a regression discontinuity design. Using discontinuous changes in patient cost-sharing around the 100 and 200 percent FPL income thresholds, they estimate a price elasticity of expenditure on prescription drugs to be -0.23, with a lower price elasticity (-0.098) for those with chronic diseases. Chandra's study is closer to the Medicare Part D context as cost sharing changes within a program that already provided comprehensive medical care, such as for physician visits. Studying healthcare demand among low-income populations is important because it is affected by institutional availability of partial implicit insurance for the low-income uninsured (Finkelstein et al., 2018; Finkelstein et al., 2017). We add to this literature by exploring this question in a national setting, in the context of a large-scale public insurance expansion, and by providing an analysis of therapeutic class-specific price elasticities by taking advantage of our rich data source.

## 2. CONCEPTUAL FRAMEWORK

The economic question we set out to answer is how does gaining insurance through Medicaid affect the use of prescription medications? Our identification strategy uses plausibly exogenous variation in likelihood of insurance coverage due to state Medicaid expansion decisions. Our conceptual model can be explained at the individual-level and follows the large literature in economics that studies the effect of insurance on healthcare use: we hypothesize that individuals whose out of pocket costs are reduced due to insurance coverage will respond by increasing use of prescription medications. While recent literature has developed the concept of demand for healthcare and value of insurance depending on availability of alternative forms of implicit insurance (Finkelstein et al., 2018; Finkelstein et al., 2017), there has been less attention paid to how the implicit insurance varies across types of care. Our emphasis on prescription medications differs from studying the effect of insurance on use of other forms of healthcare among low-income adults because of the differential availability of charity care across types of healthcare services. Our emphasis also differs from studies of prescription drug usage in other populations (for example, in the elderly) because of differences in average levels of health status, and because of the larger price reduction caused by Medicaid policy (which changed payment for both the drugs and for the physician visit at which these drugs may be prescribed, whereas Medicare Part D only changed the former).

While we use the Medicaid DD as our identification, we note that in all states, there is also increased awareness and marketing of health insurance because of other components of the ACA that were nationwide, such as the marketplace subsidies. Thus, if we look at prescription drug consumption of those in Medicaid expanding states, post expansion, relative to individuals in other states and years, we can construct a DD estimate of the effect of the incremental insurance eligibility due to the state Medicaid expansion decision. The validity of this study design does not require that the control group be unaffected by national effects of the ACA, as residents of all states likely experienced some degree of a "welcome mat" effect (Frean et al., 2017; Hamersma et al., 2018; Hudson and Moriya, 2017). As long as the treatment group experienced an additional dose of insurance eligibility in the states with Medicaid expansion, and as long as other assumptions underlying the method such as parallel pre-policy trends are met, the DD study design allows us to learn about prescription drug responses to insurance. However, it is not possible for us to estimate this model at the individual level and obtain precise elasticity estimates given available data: data sets like the Medical Expenditure Panel Survey (MEPS) contain very small sample sizes of individuals who would be in the treatment group.[1] After presenting our empirical model we explain how our data and specification follows from the individual model.

The individual model described above can be specified as follows.

$$Y_{ist} = \alpha + \beta Post_t \times Expansion_s + \theta Post_t + \pi Expansion_s + e_{ist} \qquad (1)$$

where $Y_{ist}$ is the number of prescriptions per year $t$ per person $i$ in state $s$ that are paid by Medicaid, or alternatively, paid by private sources, or total prescriptions. As our identifying variation occurs at the state by year level, we could aggregate our individual-level data to the state by year level, which yields the following model:

$$Y_{st} = \alpha + \beta Post_t \times Expansion_s + \theta Post_t + \pi Expansion_s + e_{st} \qquad (2)$$

where in equation [1], $\beta$ tells us how much greater is usage expansion states, post expansion, whereas in equation [2] $\beta$ captures the total change in annual prescriptions among individuals in that state. To enable the estimate in equation [2] to correspond to the same interpretation as $\beta$ in equation [1], we divide the left hand side in equation [2] by the number of people in that state and year, and estimate models using the natural log form given the typical skewness of prescription count data. Thus, the purpose of our final equation will be to obtain a parameter estimate $\beta$ that is akin to what we get when we use individual level data, but can be estimated with aggregate data. Our estimation strategy follows recent economics literature assessing the causal impact of insurance expansions on health care usage including Decker and Lipton (2015), Meinhofer and Witman (2018) and Wagner (2016).

[1] In 2015, the national sample size of individuals aged 19-64 who are below poverty line (100% FPL) is about 3,662 in the MEPS Household Component (author's calculations from the MEPS NET query tool at https://meps.ahrq.gov/mepsweb/data_stats/meps_query.jsp). While the relevant sample who would be affected by policy are those below the poverty line, we illustrate the model above with all individuals because of lack of data on income in our prescription data.

## 3. DATA

The database we use in this study provides a combined view of U.S. pharmaceutical distribution sales for virtually all U.S. retail brick-and-mortar and mail-order pharmacy prescription activity, including large pharmacy chains, independent pharmacies and pharmacy benefit managers (PBMs). In our empirical specifications we use data that are aggregated to the level at which variation occurs (for example, state/year-quarter/therapeutic class/payer type). The underlying microdata contains claim-level information from slightly more than 80% of all U.S. retail prescriptions and 60% of all U.S. mail order prescriptions, including more than 40,000 retail pharmacies. The data are then projected to the national level using weights to adjust for any systematic differences in the sample composition. There were no changes to the reporting frame during the years of our sample (i.e. no substantial changes in which pharmacies contributed data each year, although every year some pharmacies will move in and out of the sample); the analysis weights provided in the database are adjusted to produce nationally and sub-nationally reflective totals. Together these data files offer a rich set of information on drug claims, including the month of each transaction, the core-based statistical area (CBSA) of the pharmacy or facility, Uniform System of Classification (USC) product code for the drug, a quantity measure of package size, and payment type (including commercial plans, Medicare, cash, assistance programs, and Medicaid). The Medicaid category includes both fee-for-service Medicaid and Medicaid managed-care claims and covers all fifty states and DC. The cash and assistance programs category reflects purchases that were not covered by the other listed insurance programs and include those who are uninsured.

We obtained prescription counts aggregated by unit of geography (both state level and Core Based Statistical Areas (CBSA) level),[2] time (quarterly, from Q1 2013 through Q1 2015), drug class (total, as well as by 9 therapeutic classes), and payer type.

Key advantages of this dataset include its large and nationally-representative scope – far larger a database than any of the standard surveys that examine healthcare utilization. This feature of our data enables us to conduct state and sub-state analyses; information not only on Medicaid-covered prescriptions but also all other major payer types including uninsured patients; quarterly-level information, rather than just annual data, which bolsters our identification strategy; and information on therapeutic categories and other drug characteristics such as brand-name or generic status. Other rich data sources such as the MEPS Household Component have limited sample sizes in comparison and lack the geographic detail of our claims data. Meanwhile, other administrative data sources on drug spending – such as the State Drug Utilization Database (SDUD) collected by the federal government - lack information on non-Medicaid sources of payment and lack sub-state data.

Our data set also has important disadvantages. One is that it does not have out of pocket prices or individual level identifiers that would allow us to estimate elasticity of demand directly. Another is that it does not contain the patient-level information on demographic and socioeconomic characteristics that would allow us to estimate specifications separately by age, gender, income, or other important subgroupings of individuals who may differ in their demand for drugs or response to coverage. To control for changes in the economic climate that may independently affect state Medicaid rolls, we control for unemployment rates; we merge the pharmaceutical data with state and CBSA-level unemployment rates from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS).[3] We also incorporate information on uninsurance rates and racial/ethnic composition of the local markets using estimates produced by the Census Bureau.[4] The resulting dataset is a balanced panel of 51 states (including Washington, DC) observed for a total of 9 quarters (459 = 51*9 total cells), and a balanced panel of 781 CBSAs that do not cross state lines (we drop 143 that do) for a total of 7,029 ( = 781*9) cells.

## 4. EMPIRICAL FRAMEWORK

Our main empirical strategy uses a state-level difference-in-difference model to compare pharmaceutical utilization in all expansion states to that in non-expansion states (first difference) before and after the expansions (second difference). In a specification check, we drop from our expansion group the five states (DC, DE, MA, NY and VT) that had large expansions of public coverage to nonelderly adults prior to 2014. Appendix Table A1 provides a detailed categorization of states into expansion and non-expansion groups.

We use prescription data aggregated to the state and CBSA level, by year/quarter/therapeutic class and by each individual payer type. We are able to estimate the effects corresponding to an individual-level regression by aggregating data to the geographical area by quarter level.

$$Y_{st} = \alpha + \beta Post_t \times Expansion_s + \partial UE_{st} + \tau_t + \vartheta_s + e_{st} \quad (3)$$

Because the state population sizes are relatively fixed over time during our study period and population essentially nets out in the semi-log form and is included in the state fixed effects, this is akin to estimating models with total quantity of prescriptions as the outcome. The dependent variable in our main models is thus the logged total prescriptions in the state, with $s$ indexing state and $t$ indexing each quarter in the data, respectively. Our main outcome of interest is medication utilization under Medicaid, defined as the total number of Medicaid prescription drugs dispensed (new and refills, all therapeutic classes) where Medicaid (including both fee-for-service and managed care) is recorded as the payer. We also examine total prescriptions dispensed for other payer categories. Our data are aggregated, by quarter, to state and CBSA levels. Later, we also show estimates for models where the dependent variable is the total enrollment in Medicaid to translate our results into increases of Medicaid use by the newly insured specifically; it also helps to more transparently show the mechanism behind the results. The identifying variation in our main analysis comes from cross-state differences in expansion decisions.

The difference-in-difference coefficient, β, measures the change in Medicaid scripts in expansion states net of the change in non-expansion states. While most states implemented the Medicaid eligibility changes beginning January 2014, Indiana, Michigan, New Hampshire and Pennsylvania expanded later in 2014 or 2015. To account for this staggered implementation timeline, the difference-in-difference interaction term, $Post_t xExpansion_s$, indicates whether

[2] We use Core Based Statistical Area (CBSA) as our market definition because this is the smallest geographic unit available to us. CBSAs are geographic aggregations produced by the US Office of Management and Budget (OMB); they consist of groupings of geographic areas with a population of at least 10,000 and associated with an urban core. These areas are clusters of adjacent counties with social and economic integration. Approximately 94 percent of the total US population lives within CBSAs. An example of a CBSA is Mobile, Alabama.

[3] To obtain the unemployment rate in a CBSA, we take the average of the unemployment rates for all the counties within a CBSA. County-level unemployment rates come from BLS LAUS, and the listings of counties within CBSAs come from the Mable Geographic Correspondence Engine (http://mcdc.missouri.edu/websas/geocorr12.html).

[4] We obtain county-level 2013 uninsured rates for non-elderly adults at or below 138 percent FPL from the Census Bureau's Small Area Health Insurance Estimates (SAHIE) program, and racial/ethnic composition data from the Area Health Resource Files (AHRF).

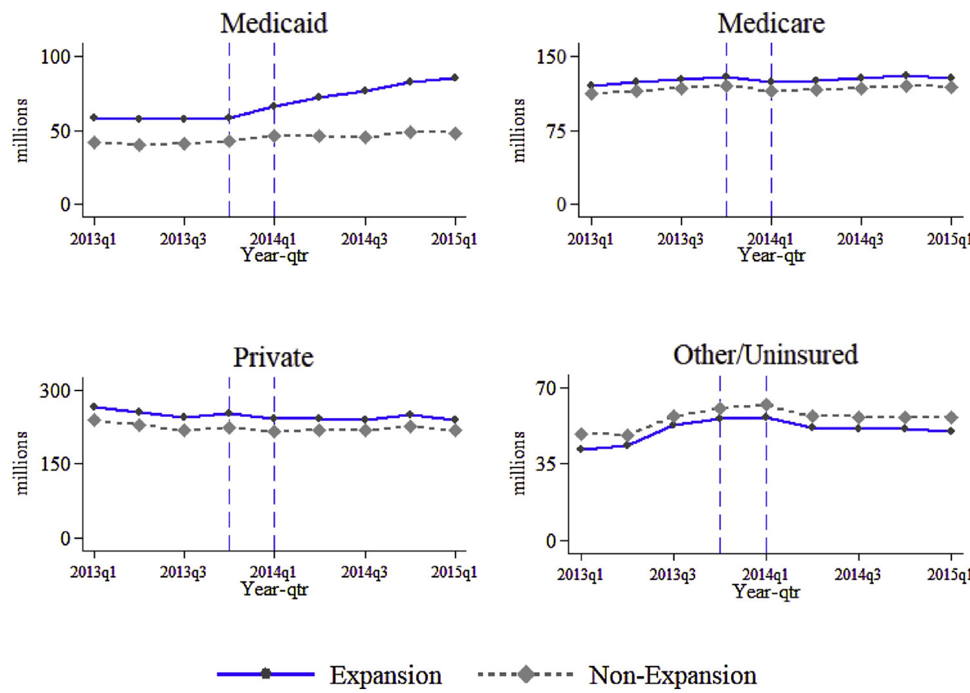


**Fig. 1.** Unadjusted Trends in Total Prescriptions Filled by Payer, 2013Q1-2015Q1.
Notes:
1. Each graph has a different y-axis scale. "Other/Uninsured" includes cash transactions and assistance programs.
2. January 2014 expansion states include: AR, AZ, CA, CO, CT, DC, DE, HI, IL, IA, IL, KY, MA, MD, MN, NV, NY, NJ, NM, ND, OH, OR, RI, VT, WA, WV. IN, MI, NH, PA are excluded from this list and from this analysis as they expanded after January 2014 (but are included in the regressions with time-varying expansion definitions).
3. Non-expansion states include: AL, AK, FL, GA, ID, KS, LA, ME, MI, MO, MT, NE, NC, OK, SC, SD, TN, TX, UT, VA, WI, WY.
4. The first vertical line is drawn at 4th quarter of 2013, and the second vertical line is drawn at the 1st quarter of 2014, thus the area in between the two lines indicates the transition into the 2014 ACA Medicaid expansion.

a state has expanded Medicaid at time $t$. The model includes state fixed effects to account for time-invariant state-specific differences in prescription drug use and time dummies for each quarter and year in the data to capture national time trends. We use state quarterly unemployment rates (*UE*) to control for changes in economic conditions that may independently influence drug utilization patterns.[5] The model is estimated using ordinary least squares, and throughout we report standard errors clustered at the state level to account for correlated error terms across states over time (Bertrand et al., 2004).

Identification in the difference-in-differences model is based on the assumption of parallel trends – that absent the 2014 Medicaid expansion, trends in outcomes would not have differed significantly across expansion and non-expansion states. While this assumption is not directly testable, we compare trends in Medicaid prescriptions across the treatment and comparison states prior to the policy change; this comparison offers support for our identifying approach. Because we have a limited number of quarters of data prior to the policy change, we also examine Medicare prescription counts as a placebo test; again, the results (presented below) support our identification strategy.

## 5. RESULTS

### 5.1. Descriptive Trends

In Fig. 1, we plot unadjusted time trends for total prescriptions paid at the state level by Medicaid, Medicare, private insurance plans, or through cash and assistance programs available to the uninsured during the study period; we plot these trends separately for the expansion and non-expansion states. The blue and grey lines represent ACA Medicaid-expansion states and non-expansion states, respectively.[6] The first vertical line in red denotes the beginning of the ACA's first open enrollment period in the fourth quarter of 2013; the second denotes the implementation of the ACA Medicaid expansions in the first quarter of 2014.

Fig. 1 demonstrates that prior to the expansions in early 2014, Medicaid prescriptions followed similar trends across the two groups of states. There is a clear divergence in trends after the first quarter of 2014, when the expansion states experience a very noticeable increase in Medicaid within 6 months of the policy change, relative to the non-expansion states. The remaining panels in Fig. 1 display trends in pharmaceuticals that were paid by Medicare, private insurance, and were uninsured (cash and assistance programs). These panels demonstrate that trends in aggregate prescriptions did not differ appreciably across the two groups of states for the non-Medicaid payment categories.

### 5.2. Effect on Medicaid Prescription Drug Utilization

Table 1 displays results from our main difference-in-differences analysis of equation (1) and unadjusted sample means of the dependent variable. The dependent variable is the natural logarithm of aggregate Medicaid prescriptions. The pattern in the

[5] We also estimate our models without including the unemployment rate as a covariate and find they do not materially alter our results.

[6] Four states (i.e., IN, MI, NH and PA) are omitted from the graphs because they expanded after January 2014. They are, however, included in the regressions that allow for more flexibility in specifying the Medicaid expansion date. The graphs do not change in any meaningful manner when these states are included in the expansion category.

**Table 1**
Effect of ACA Medicaid Expansions on Medicaid Prescription Utilization.

| Dependent variable: Ln (total Medicaid prescriptions) | (1) All States | (2) Excl. DC, DE, MA, NY, VT |
|---|---|---|
| Post x Expansion | 0.19*** | 0.23*** |
| | (0.06) | (0.06) |
| Year and quarter fixed effects | Y | Y |
| State fixed effects | Y | Y |
| Observations | 459 | 414 |
| *Dependent variable means* | | |
| Expansion, Before | 14.14 | 14.16 |
| Non-expansion, Before | 13.90 | 13.90 |
| Expansion, After | 14.42 | 14.47 |
| Non-expansion, After | 14.00 | 14.00 |

Notes:
1. Difference-in-differences (DD) estimates are based on aggregated state-quarter data covering 2013Q1 to 2015Q1. The pre-expansion period includes 2013Q1-2013Q4, while 2014Q1-2015Q1 represents the post-expansion period. All models include state fixed effects, fixed effects for each quarter in the data, and state quarterly unemployment rate. Robust standard errors clustered by state reported in parentheses. * Significant at the 10-percent level. ** Significant at the 5-percent level. *** Significant at the 1-percent level.
2. In column (1), specification includes all states being categorized into expansion vs non-expansion states.
a. Expansion states: AR, AZ, CA, CO, CT, DE, DC, HI, IL, IN, IA, IL, KY, MD, MA, MI, MN, NV, NH, NJ, NM, NY, ND, OH, OR, PA, RI, VT, WA, WV.
b. Non-expansion states: AL, AK, FL, GA, ID, KS, LA, ME, MI, MO, MT, NE, NC, OK, SC, SD, TN, TX, UT, VA, WI, WY.
3. For the analysis corresponding to column (2), DC, DE, MA, NY, and VT were dropped from the sample; the analysis is otherwise the same as in the first column.

first panel of Fig. 1 is reflected in the difference-in-difference estimate for Medicaid prescriptions in column (1) of Table 1. The estimate demonstrates that Medicaid expansions in 2014 led to sizable and statistically significant increases in Medicaid prescription drug use. The coefficient represents a 19 percent increase in Medicaid prescription utilization relative to non-expansion states for all therapeutic classes. Column (2) demonstrates that the estimate increases to 23 percent when we drop the five states that provided publicly subsidized coverage to adults at or below 100 percent of the FPL prior to 2014 (the District of Columbia, Delaware, Massachusetts, New York, and Vermont).

### 5.3. *Effect on Aggregate Prescription Drug Utilization by Payment Source*

One mechanism through which Medicaid prescriptions may increase following expansions is private insurance crowd out. Indeed, much attention in health economics has been devoted to this question (Cutler and Gruber, 1996; Gruber and Simon, 2008). Another possibility is that increased Medicaid drug claims simply reflects a substitution of Medicaid coverage for drug claims that were previously purchased in cash by uninsured patients. To explore these mechanisms, we investigate the impact of the expansions on prescriptions from private insurance, as well as cash and other assistance programs available to the uninsured. This analysis allows us to consider whether Medicaid prescriptions increased simply through a substitution of payment source or due to a net increase in utilization.

Table 2 below contains these results for other payer sources. Changes in cash/assistance programs (likely representing uninsured individuals) had a statistically insignificant and small point estimate of -0.02 in column (1). Similarly, in the case of private insurance, the statistically insignificant estimated coefficient in column (2) was -0.01. Thus, the point estimates for privately insured and uninsured prescriptions are negative but statistically indistinguishable from zero indicating little to no crowd-out of prescription drug use from payment sources other than Medicaid. This suggests that in the aggregate, the policy impact on use of Medicaid prescription drugs primarily reflects new prescriptions rather than simply a shift in payer-mix from cash to insurance or from private insurance to public insurance.

As a falsification test, we next consider changes in Medicare prescription utilization. We hypothesize that extended Medicaid eligibility for the non-elderly adult population under the ACA is unlikely to affect prescription drug use in the Medicare program. Consistent with our hypothesis, the result from this analysis, which we report in column (3) of Table 2, show that there is little evidence that Medicare is affected. The dependent variable is the natural logarithm of uninsured, privately insured, or Medicare prescriptions. In Appendix Table A2, we present event history estimates for aggregate prescriptions paid by non-Medicaid sources. Taken together, these regression estimates indicate that prescriptions from non-Medicaid payment sources did not respond significantly to the policy expanding public health insurance.

### 5.4. *Heterogeneity in Medicaid Prescription Utilization by Drug Class*

We next study whether specific therapeutic classes were differentially affected by the expansion. Prescription medications that treat acute medical conditions may respond differently to coverage expansion than maintenance drugs associated with chronic illnesses, but prior literature has not examined this among low-income populations. It is possible that demand for some short-term medications (e.g. allergy relief) would be more elastic, if those medications are viewed as more discretionary and less critical for health than those associated with chronic illnesses (e.g. diabetes or heart disease). Alternatively, some acute medications may treat condi-

**Table 2**
Effect on Aggregate Prescription Drug Use by Payer.

| Dependent variable: Ln (total prescriptions) | (1) Other/Uninsured | (2) Commercial | (3) Medicare | (4) Medicaid |
|---|---|---|---|---|
| Post x Expansion | -0.02 | -0.01 | 0.004 | 0.19*** |
| | (0.02) | (0.01) | (0.012) | (0.06) |
| Year and quarter fixed effects | Y | Y | Y | Y |
| State fixed effects | Y | Y | Y | Y |
| Observations | 459 | 459 | 459 | 459 |
| *Dependent variable means* | | | | |
| Expansion, Before | 14.03 | 15.72 | 14.98 | 14.14 |
| Non-expansion, Before | 14.18 | 15.65 | 14.92 | 13.90 |
| Expansion, After | 14.10 | 15.67 | 15.01 | 14.42 |
| Non-expansion, After | 14.27 | 15.61 | 14.95 | 14.00 |

Notes: Each coefficient comes from a separate difference-in-difference regression. Analyses are based on aggregated state-quarter prescription data by payer type, and include all states. Data covers the period 2013Q1 to 2015Q1. All models include state fixed effects, fixed effects for each quarter in the data, and unemployment rate. Robust standard errors clustered by state are reported in parentheses. * Significant at the 10-percent level. ** Significant at the 5-percent level. *** Significant at the 1-percent level.

**Table 3**
Heterogeneity by Drug Class.

| Dependent variable: Ln (total Medicaid prescriptions) | | | |
|---|---|---|---|
| Drug Class | (1)<br>DD coefficient | (2)<br>Is the effect statistically different from the effect on the remaining classes? | (3)<br>Share among all Medicaid prescriptions |
| All classes | 0.19***<br>(0.06) | | |
| Antibiotics | 0.17***<br>(0.06) | § | 0.101 |
| Birth Control | 0.22***<br>(0.06) | | 0.019 |
| Cardiovascular medications | 0.21***<br>(0.07) | | 0.140 |
| Diabetes medications | 0.24***<br>(0.06) | # | 0.037 |
| GI medications | 0.17***<br>(0.05) | # | 0.066 |
| HIV/ Hepatitis | 0.15**<br>(0.07) | | 0.011 |
| Mental health medications | 0.19***<br>(0.07) | | 0.149 |
| Respiratory and Allergy medications | 0.15***<br>(0.05) | # | 0.118 |
| Other | 0.19***<br>(0.05) | | 0.359 |

Notes: Each coefficient is from a separate difference-in-difference regression. Regressions are based on aggregated state-quarter Medicaid prescription data covering 2013Q1 to 2015Q1 by therapeutic class. The pre-expansion period includes 2013Q1-2013Q4, while 2014Q1-2015Q1 represents the post-expansion period. All models include state fixed effects, fixed effects for each quarter in the data, and unemployment rate. Robust standard errors clustered by state are reported in parentheses. This analysis includes all states.
*Significant at the 10-percent level. ** Significant at the 5-percent level. *** Significant at the 1-percent level.
# Significant at the 5-percent level. § Significant at the 10 percent level.

tions requiring immediate treatment (e.g. antibiotics for infection) and might therefore be less price sensitive and less responsive to changes in coverage. Another reason to examine heterogeneity across therapeutic classes is that the newly insured population's healthcare needs may differ from those of the nation as a whole; in particular, chronic conditions are likely to be more common among low-income individuals qualifying for Medicaid than among those with private insurance (Decker et al., 2014).

Table 3 describes the impact on utilization of a range of medication classes. Our results indicate that there were statistically significant increases in utilization across all therapeutic classes, but relatively larger effects for certain classes, particularly those relevant to common chronic medical conditions. Diabetes medications increased 24 percent; accounting for the largest growth among all therapeutic classes. This effect was statistically different from the mean effect on all the remaining classes. The use of cardiovascular medications (those for high blood pressure, high cholesterol and heart disease) increased by 21 percent, while the use of contraceptives increased by 22 percent. Meanwhile, the use of respiratory/allergy medications, antibiotics, and gastrointestinal medications, which are more commonly taken for shorter-term conditions than the other therapeutic classes, increased less than overall drug spending, with growth rates ranging from 15 to 17 percent.

The larger increases in use of medications for chronic conditions such as diabetes detected in our data accord with recent research that finds diagnoses of chronic health conditions to have increased among low-income adults in states that have broadened Medicaid eligibility under the ACA and that hospitalizations for diabetes have decreased (Freedman et al., 2017). Overall, this pattern of results suggests that health insurance expansion was particularly effective at increasing prescription drug utilization for common and potentially costly chronic medical conditions. Our results also indicate that even though state Medicaid family planning waivers existed prior to the ACA expansions, the recent expansions in coverage lead to meaningful effect on access to contraceptive treatments.

In recent years, high prices of life-saving hepatitis C and HIV medications have fueled debate about the role of public policy in providing access to costly but effective pharmacological treatments for vulnerable populations. Our finding of a more modest effect for HIV and Hepatitis C medications is likely due to two factors. First, the existence of federally funded programs such as the Ryan White HIV/AIDS Program (RWP) and the AIDS Drug Assistance Program (ADAP) already facilitated the use of these medications for many patients prior to the expansion of Medicaid in 2014. Second, growth in use of Hepatitis C medications may have been attenuated by limited access in several state Medicaid programs (such as Indiana and Washington) due to cost concerns (New York Times, 2015; Pear, 2015).

### 5.5. *Price Responsiveness of Medicaid Prescription Drug Utilization*

Our work thus far studies the effect of coverage expansions on prescription drug utilization, capturing the full effect of health insurance, which could operate through reductions in the cost of seeing a prescribing clinician as well as paying for the prescription drug itself. Since expansion states differ in the amount of cost-sharing required for prescription drugs, spatial variation in drug copayments provides us an opportunity to better understand the price elasticity of demand for medications among low-income adults, albeit with limited data on price changes.

We match our data with state level Medicaid drug copayments specific to the expansion population from the Kaiser Family Foundation (Kaiser Family Foundation Report, 2015). As of January 2015, of the 28 states that extended Medicaid eligibility under the ACA guidelines, 12 states used \$0 copay for generics, 7 states have a \$1 generic copay, and the remaining have average copayments between \$1.50 and \$4. Brand-name drug copayments track generic

**Table 4**
Effect on Medicaid Prescription Utilization, by state copayment.

| Dependent variable: Ln (total Medicaid prescriptions) | | |
|---|---|---|
| | (1) Low | (2) High |
| Post x Expansion | 0.22*** | 0.17** |
| | (0.07) | (0.07) |
| Range of copayments | $0 | $0.3-$4.4 |
| Observations | 288 | 369 |

Notes: Each coefficient is from a separate difference-in-difference regression. Regressions are based on aggregated state-quarter Medicaid prescription data covering 2013Q1 to 2015Q1. The pre-expansion period includes 2013Q1-2013Q4, while 2014Q1-2015Q1 represents the post-expansion period. We stratify expansion states by median copay rates; "Low" indicates those expansion states below the median and "High" indicates those above the median. In both columns, all non-expansion states are included in the control group. All models include state fixed effects, fixed effects for each quarter in the data, and unemployment rate. Robust standard errors clustered by state are reported in parentheses.
*Significant at the 10-percent level. ** Significant at the 5-percent level. *** Significant at the 1-percent level.

copayments closely, with $0 being the copay in 9 of these states, and varying between $1-$6 in the rest.[7]

We conducted two analyses to assess the effects of copays on prescriptive drug utilization after health insurance expansions to low-income adults. First, we split expansion states into those with copays above and below the median,[8] and estimated two difference-in-difference models akin to equation (1): one model compares high-copay expansion states to all non-expansion states, and the other compares low-copay expansion states to all non-expansion states.

Table 4 reports the results of this exercise. As expected, the policy impact on prescription drug utilization was larger in expansion states with low cost-sharing requirements than high cost-sharing. These results show that increased Medicaid drug utilization was 22 percent in states with lower copays and 17 percent in states with higher copays, both compared to non-expansion states. The coefficients are both statistically significant, providing evidence consistent with basic consumer theory. However, the two estimates are not statistically significantly different from each other, thus we interpret this evidence as suggestive rather than definitive regarding a response to cost-sharing

We next explore the effect of prescription drug copays on aggregate Medicaid prescriptions and provide a parameterized estimate of the price elasticity related to Medicaid copays through the following specification:

$$\begin{aligned} Y_{st} &= \alpha_0 + \alpha_1 Post_t \times Expansion_s \times Wtd\,Copay_s \\ &+ \alpha_2 Post_t \times Wtd\,Copay_s + \alpha_3 Post_t \times Expansion_s \\ &+ \alpha_4 Expansion_s \times Wtd\,Copay_s + \partial\, UE_{cst} + \tau_t + \vartheta_s + \varepsilon_{st} \end{aligned} \quad (4)$$

In the above equation, $Wtd\,Copay_s$ represents a weighted average of Medicaid generic and brand-name drug copayments in each expansion state, with the state's respective pre-period share of total prescriptions that are generic vs brand name used as weights.[9] Here, the effect of consumer cost-sharing is identified by $\alpha_1$, which allows us to isolate differential policy impact by state drug copayments. The terms $Expansion_s$, $Wtd\,Copay_s$, and $Expansion_s \times Wtd\,Copay_s$ are perfectly collinear with state fixed effects; hence these terms all drop out of the equation.

Table 5 displays results from the estimation of the above equation. The point estimate of -0.039 in column (1) indicates that the increase in post-expansion utilization was 3.9 percent lower for each added dollar in Medicaid copays per prescription (compared to a mean weighted cost-sharing of $1.24 in expansion states), though this estimate was not statistically significant.

Next, we test for heterogeneous response of utilization to copayments by therapeutic class. Theoretically, cost-sharing may differently affect drug use across therapeutic classes due to factors such as the availability of alternative over-the-counter (OTC) treatments and severity of the medical condition.

The results in columns (2) through (9) of Table 5 suggest that utilization in the remaining therapeutic classes appears to respond negatively to greater cost-sharing as expected, with price responsiveness varying appreciably across the classes, though the key $Post_t x\, Expansion_s x\, Wtd\,Copay_s$ interaction term was not statistically significant for most drug classes. We did detect a statistically significant point estimate for respiratory medications in column (8) which indicates that each $1 increase in the average drug copayment was associated with a 5 percent relative decline in use of medications for respiratory illnesses and allergies after Medicaid expansion (compared to an overall increase of 19.2 percent in utilization for expansion states with $0 copays, indicated in the 2nd row of the table). In contrast to these drug classes, demand for potentially life-saving medications such as cardiovascular and HIV/Hepatitis C drugs were the least price-responsive.[10] Overall, this pattern is consistent with prior research showing that medications used to treat acute symptomatic conditions such as asthma are relatively more price-sensitive than chronic treatments for cardiovascular conditions (Goldman et al., 2004; Landsman et al., 2005).

Overall, taking the point estimate from column (1) in Table 5, we calculate that each $1 increase in cost-sharing (amounting to an 81 percent increase from the mean copay of $1.24) is associated with a 3.9 percent relative decline in utilization, yielding a price elasticity of roughly -0.05. Using this approach, the copay elasticity for allergy and respiratory medications is -0.06 and is statistically significant. This degree of price elasticity is similar in direction but substantially smaller the -0.13 found by Chandra et al. (2014) for prescription medications among low-income non-elderly adults with subsidized public insurance in Massachusetts. It is worth noting that their elasticity estimate is based on variation in copayments at income thresholds alone. In contrast, we study the effect of higher copayments along with contemporaneous policy-induced gains in insurance coverage, which may bring into treatment a population with relatively inelastic pent-up demand for healthcare services. Perhaps unsurprisingly, Chandra et al. (2014) find that patients with chronic illnesses such as hypertension, high cholesterol, diabetes, asthma, arthritis or gastritis in their analysis sample, are less price sensitive, with an elasticity estimate of -0.098, which is much closer to our price elasticity estimate of -0.06. Our estimated elasticity could presumably be biased downward as aggregate data and weighted-average statewide copay likely introduces some measurement error. Notably, while we find price elasticities to be higher for respiratory and allergy medications and lowest for cardiovascular, diabetes, and other serious illness, this is largely the opposite

[7] In cases where the dollar amount of cost-sharing is reported as a range, we use the midpoint of the range.

[8] We used a weighted average of the generic and brand-name drug copay facing new enrollees in each expansion state, using the state's respective pre-period share of total prescriptions that are generic vs brand name as the weights. This is similar to the approach used by Chandra et al. (2014) for computing weighted copayments.

[9] In 2013, the average OOP cost per prescription for a low income non-elderly adult was $78.40 (authors' calculations from the MEPS NET query tool at https://meps.ahrq.gov/mepsweb/data_stats/meps_query.jsp). We assign copayments for non-expansion states a value of $78.40. The estimates presented in Table 6 are robust to the choice of alternative cost-sharing amounts such as $20 or $100.

[10] Note that under federal rules, state Medicaid programs must provide prescription birth control without cost-sharing. Hence, we exclude contraceptives from this analysis.

**Table 5**
Effect of Drug Copayments on Medicaid Prescription Utilization.

| Dependent variable: Ln (total Medicaid prescriptions) | | | | | |
|---|---|---|---|---|---|
| | (1) All classes | (2) Antibiotics | (3) Cardiovascular | (4) Diabetes | |
| Post x Expansion x Copay | -0.039 | -0.047 | -0.022 | -0.031 | |
| | (0.029) | (0.029) | (0.042) | (0.038) | |
| Post x Expansion | 0.190*** | 0.21*** | 0.154* | 0.189*** | |
| | (0.063) | (0.065) | (0.079) | (0.069) | |
| Post x Copay | -0.0004 | -0.0002 | -0.001 | -0.001 | |
| | (0.001) | (0.001) | (0.001) | (0.001) | |
| | (5) GI Meds | (6) HIV/Hepatitis | (7) Psychotherapeutic | (8) Respiratory | (9) Other |
| Post x Expansion x Copay | -0.039 | -0.014 | -0.037 | -0.050* | -0.037 |
| | (0.025) | (0.039) | (0.029) | (0.026) | (0.028) |
| Post x Expansion | 0.192*** | 0.174* | 0.189*** | 0.189*** | 0.199*** |
| | (0.057) | (0.101) | (0.064) | (0.064) | (0.062) |
| Post x Copay | -0.0001 | -0.001 | -0.001 | -0.001 | -0.0001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |

Notes: Regression estimates are based on aggregated state-quarter data covering 2013Q1 to 2015Q1. The pre-expansion period includes 2013Q1-2013Q4, while 2014Q1-2015Q1 represents the post-expansion period. All models include state fixed effects, fixed effects for each quarter in the data, and state quarterly unemployment rate. Robust standard errors clustered by state reported in parentheses. * Significant at the 10-percent level. ** Significant at the 5-percent level. *** Significant at the 1-percent level.

pattern as what we detected in Table 3, where we found that overall coverage gains from Medicaid expansion led to the largest increases in utilization for the latter conditions. One way to reconcile this apparent contradiction is that Table 3 reflects both the reduction in out-of-pocket price for medications and the reduction in cost for seeing a physician. It is likely that better access to clinicians - and thus higher rates of diagnosis and subsequent treatment of chronic conditions like diabetes - is just as important in increasing medication use as the reduction in drug-related out-of-pocket costs. This pattern again points to the value in assessing the economic effects of a comprehensive coverage expansion like Medicaid, distinct from just adding drug coverage to existing insurance as in the case of Medicare Part D.

### 5.6. *Differentiating Between Brand-Name and Generic Drug Utilization*

Several facts suggest that we should expect the use of generic medications in Medicaid to rise compared to brand-name drugs. First, patent expirations of several branded prescription drugs such as atorvastatin (Lipitor) (Jackevicius et al., 2012) and the SSRI-class of antidepressants (Huskamp et al., 2008) in recent years have increased the number of prominent generics in the market (Frank, 2007). Second, in response to budgetary constraints, many state Medicaid programs use several policy levers for utilization management – such as higher copayments for brand-name drugs, mandatory generic substitution, and lower reimbursements to pharmacies for brand-names relative to generic – that encourage utilization of generic medications (Simon et al., 2009). A recent study finds that there was a significant increase in Medicaid prescriptions following the ACA Medicaid expansions, with no detectable increase in the program's drug spending (Wen et al., 2016), which supports the notion that most new prescriptions were likely low-cost. These features of the policy environment may impact utilization of medications in ways that can potentially improve health and manage program spending growth.

In Table 6, we decompose total Medicaid prescriptions filled into brand-name, generic and other (includes prescription products recorded as medical supplies and bulk chemicals) components. To obtain estimates of the impact of the 2014 Medicaid expansions on composition of Medicaid prescriptions, we estimate equation (1) for each group using data aggregated to the CBSA level.[11] While Medicaid prescriptions increased significantly in all three categories, the magnitude of the impact was the largest for generic drugs. Generic drug claims in Medicaid increased by 24 percent, compared to 17 percent for branded drugs. At baseline, generic drugs represented nearly 79 percent of Medicaid claims in our sample, "other" less than 1 percent, and brand-name drugs the remaining 21 percent, based on total prescription counts in 2013. Taken together, this provides suggestive evidence that the Medicaid expansions steered beneficiaries towards lower-cost prescription drugs, which may help control program costs.

**Table 6**
Effect of ACA Medicaid Expansions on Medicaid Prescription Utilization, by Product Type.

| Dependent variable: Ln (total Medicaid prescriptions) | | | |
|---|---|---|---|
| | (1) Brand | (2) Generic | (3) Other |
| Post x Expansion | 0.17*** | 0.24*** | 0.21** |
| | (0.05) | (0.06) | (0.08) |
| Year and quarter fixed effects | Y | Y | Y |
| State fixed effects | Y | Y | Y |
| Observations | 441 | 441 | 441 |
| *Dependent variable means* | | | |
| Expansion, Before | 11.83 | 13.24 | 6.75 |
| Non-expansion, Before | 11.87 | 13.24 | 6.68 |
| Expansion, After | 12.01 | 13.55 | 7.05 |
| Non-expansion, After | 11.92 | 13.35 | 6.84 |

Notes: Each coefficient comes from a separate difference-in-difference regression. Analyses are based on aggregated state-quarter prescription data by payer type and include all states. Data covers the period 2013Q1 to 2015Q1; and only CBSA parts of the state are represented here. All models include state fixed effects, fixed effects for each quarter in the data, and unemployment rate. Robust standard errors clustered by state are reported in parentheses. * Significant at the 10-percent level. ** Significant at the 5-percent level. *** Significant at the 1-percent level.

[11] For this analysis, we use CBSA-aggregates, as product information on brand/generic status is only available in our database at the sub-state level. One concern in examining this specification is whether CBSAs in the sample differ in ways that introduce bias in our estimates. We re-estimate our baseline difference-in-difference model (equation 1) using this sample, comparing CBSAs in expansion states to a group of comparison CBSAs in non-expansion states. The results from this analysis are displayed in Appendix Table A5. These estimates are closely comparable in magnitude, direction and precision, confirming our findings from the main specification.

**Table 7**
Testing for Differential Pre-Expansion Trends in Medicaid Prescription Drug Utilization.

| Dependent variable: Ln (total Medicaid prescriptions) | | | |
|---|---|---|---|
| | (1) Pre-treatment trend test | (2) Event study | (3) Event study |
| Expansion x Trend (2014 Q1-Q4) | -0.03 | | |
| | (0.02) | | |
| Expansion x 2013Q2 | | 0.01 | 0.01 |
| | | (0.02) | (0.02) |
| Expansion x 2013Q3 | | -0.02 | -0.02 |
| | | (0.04) | (0.04) |
| Expansion x 2013Q4 | | -0.07 | -0.07 |
| | | (0.06) | (0.06) |
| Expansion x 2014Q1 | | -0.01 | -0.01 |
| | | (0.05) | (0.05) |
| Expansion x 2014Q2 | | 0.10* | 0.10* |
| | | (0.06) | (0.06) |
| Expansion x 2014Q3 | | 0.18*** | 0.18*** |
| | | (0.05) | (0.05) |
| Expansion x 2014Q4 | | 0.18*** | 0.18*** |
| | | (0.06) | (0.06) |
| Expansion x 2015Q1 | | 0.22*** | 0.22*** |
| | | (0.07) | (0.07) |
| Includes *Expansion x linear time trend* | Y | N | Y |
| Observations | 204 | 459 | 459 |

Notes: Analysis is based on aggregated state-quarter Medicaid prescription data. Estimate in column (1) uses data covering 2013Q1-2013Q4 and only includes separate time trends for expansion vs non-expansion states, while those in columns (2) and (3) use data from 2013Q1 to 2015Q1 and an event study approach. All models include state fixed effects, fixed effects for each quarter in the data, and unemployment rate. Robust standard errors clustered by state are reported in parentheses. * Significant at the 10-percent level. ** Significant at the 5-percent level. *** Significant at the 1-percent level.

### 5.7. Robustness Checks

To investigate the basis of support for the natural-experimental study design, we examine whether there were differential pre-trends in Medicaid prescription drug utilization across states based on treatment status. We do this by using four quarters of data from 2013Q1-2013Q4 and the following empirical specification:

$$Y_{st} = \alpha + \gamma Trend_t + \delta Expansion_s \times Trend_t + \partial UE_{st} + \tau_t + \vartheta_s + \varepsilon_{st} \quad (5)$$

In the above equation, *Trend* stands for a quarterly linear time trend, $Expansion_s$ indicates the states that expanded after 2014 Q1, and the interaction term $Expansion_s \times Trend_t$ identifies differential trends between expansion and non-expansion states during the pre-expansion period. Also included in the regression are the trend main term, the unemployment rate, and state and month-by-year fixed effects.

To further evaluate the parallel trends assumption, we use an event study approach by interacting the expansion dummy with each year-quarter in the data from 2013-2015. For the parallel trends assumption to be valid, we expect the interaction terms in 2013 to be statistically indistinguishable from 0. The point estimates in column (1) of Table 7 are indeed quite small in magnitude (and not statistically significant) relative to the difference-in-difference estimate in Table 2, indicating that no significant differential trends appear in the pre-expansion period that would otherwise threaten our identification strategy. Column (2) displays the event history estimates. Consistent with the graphical results, we find no evidence of differential trends across the states that expanded and those that did not, prior to the policy change. Starting with 2014 Q2, the estimates are positive and statistically significant as we would expect given the timing of state expansion decisions. The estimates are higher in magnitude every consecutive quarter, which implies that the impact of coverage has amplified over time, consistent with other recent evidence on the ACA's Medicaid expansion. This dynamic pattern in the data also mirrors the staggered timeline of state expansion decisions. In every successive quarter after the first six months of the policy change, the effect on aggregate Medicaid prescriptions exceeds the mean effect of 19 percent (shown in Table 2). The evolution of the ACA's impact on prescription drug utilization during this 15-month period suggests some longer-term effects on coverage, access, and utilization occur through diffusion of information about policy changes, as well as potential lags in obtaining care after acquiring coverage.

We test the sensitivity of our results to the addition of group-specific linear time trends. These results are presented in column (3) of Table 7. This specification addresses the possibility that expansion and non-expansion states may follow different, unobserved time trends correlated with Medicaid expansion decisions. We detect no difference in the estimates in column (3) compared to the baseline model, emphasizing that underlying group-specific trends are not responsible for the observed effect on Medicaid prescriptions.

### 5.8. Effect on Total Medicaid Enrollment

As discussed in Section 2, the claims data alone do not allow us to directly assess the proposed mechanism of Medicaid coverage gains as the cause for the increase in prescription drug utilization. In this section, we estimate the change in Medicaid enrollment due to the ACA expansion, to better understand the relationship between coverage changes and prescription drug utilization changes. To do so, we estimate the specification in Eq. (3) with the log of total Medicaid enrollment (including CHIP) and as the dependent variable.

These results are presented in Table 8 and indicate that there is a statistically significant 17% increase in total Medicaid enrollment (column 1). The coefficient increases slightly to 18% (column 2) when states with pre-ACA Medicaid eligibility for childless adults are excluded. Briefly, this analysis shows that there is a much larger increase in enrollment in the expansion states relative to the increase in non-expansion states, and that the magnitude is quite similar to the 19% increase in Medicaid prescription volume that we observe. We can also use these enrollment changes to derive a per-person effect size of our prescription drug estimates, which we present in Section 6. Thus, this helps illustrate our argument that our empirical analysis is the aggregate level version corresponding to the individual level conceptual model of behavior.

### 5.9. Heterogeneous Effects at the Market Level

The analysis with aggregated state data presented so far indicates that Medicaid prescription drug utilization increased significantly in response to the ACA Medicaid expansions. We next expand on this reduced-form analysis to probe whether these results are concentrated in geographical areas with higher treatment intensity. Geographic variation in factors that affect demand for healthcare services, such as rates of insurance coverage, level of income, and demographic characteristics of the population that pre-dates policy change, may affect prescription drug utilization differently across markets. Here we consider two key pre-expansion characteristics – uninsurance rate and share of minority population – to test whether the observed effects on utilization are concentrated among particular markets.

First, we examine the dose-response relationship between prescriptions paid by Medicaid and reductions in uninsurance that occurred after 2014. Using data aggregated to the CBSA level, we explore whether the effects of Medicaid expansion on prescription drugs is larger in CBSAs with higher pre-reform uninsurance levels (where we expect larger gains in coverage), relative both to CBSAs with lower baseline (2013) uninsurance in expansion states and

**Table 8**
Effect of ACA Medicaid Expansions on Medicaid Enrollment 2013Q1 to 2015Q1.

| Dependent variable: Ln (total Medicaid enrollment) | (1) All States | (2) Excl. DC, DE, MA, NY, VT |
|---|---|---|
| Post x Expansion | 0.17*** | 0.18*** |
| | (0.02) | (0.03) |
| Year and quarter fixed effects | Y | Y |
| State fixed effects | Y | Y |
| Observations | 455 | 410 |
| *Dependent variable means* | | |
| Expansion, Before | 13.49 | 13.54 |
| Non-expansion, Before | 13.28 | 13.28 |
| Expansion, After | 13.71 | 13.78 |
| Non-expansion, After | 13.3 | 13.3 |

Notes:
1. Difference-in-differences (DD) estimates are based on aggregated state-quarter enrollment (all ages) covering 2013Q1 to 2015Q1, using equation [3]. The pre-expansion period includes 2013Q1-2013Q4, while 2014Q1-2015Q1 represents the post-expansion period. All models include state fixed effects, fixed effects for each quarter in the data, and state quarterly unemployment rate. Robust standard errors clustered by state reported in parentheses. * Significant at the 10-percent level. ** Significant at the 5-percent level. *** Significant at the 1-percent level.
2. In column (1), specification includes all states being categorized into expansion vs non-expansion states.
a. Expansion states: AR, AZ, CA, CO, CT, DE, DC, HI, IL, IN, IA, IL, KY, MD, MA, MI, MN, NV, NH, NJ, NM, NY, ND, OH, OR, PA, RI, VT, WA, WV.
b. Non-expansion states: AL, AK, FL, GA, ID, KS, LA, ME, MI, MO, MT, NE, NC, OK, SC, SD, TN, TX, UT, VA, WI, WY.
3. For the analyses corresponding to column (2), DC, DE, MA, NY, and VT were dropped from the sample; the analysis is otherwise the same as in the first column.
4. Data sources:
a. Post-ACA (January 2014-March 2015) data come from Kaiser Family Foundation's Total Monthly Medicaid & CHIP Enrollment files
Download link: https://www.kff.org/health-reform/state-indicator/total-monthly-medicaid-and-chip enrollment/?currentTimeframe=40&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D).
b. Total 2013 Medicaid & CHIP enrollment data are obtained from KFF and are available from Q2-Q4 (at the quarterly level). Because 2013Q1 data are unavailable, for all analyses, 2013Q2 enrollment totals are also used for 2013Q1.
Download links: https://www.kff.org/report-section/medicaid-enrollment-june-2013-data-snapshot-appendix-a-table-a-1-total-medicaid-enrollment-by-state/ http://files.kff.org/attachment/Issue-Brief-Two-Year-Trends-in-Medicaid-and-CHIP Enrollment-Data (Appendix B; average July- September 2013 enrollment) https://www.kff.org/report-section/medicaid-enrollment-snapshot-december-2013-tables/ Post-ACA missing values were imputed from CMS MACPAC Medicaid enrollment data: https://data.medicaid.gov/Enrollment/State-Medicaid-and-CHIP-Applications-Eligibility-D/n5ce-jxme/data.

to CBSAs with higher baseline uninsurance rates in non-expansion states. The estimating equation is specified below:

$$Y_{cst} = \alpha_1 Post_t \times Expansion_s \times Pct\ Uninsured\ 2013_c + \alpha_2 Post_t \times Pct\ Uninsured\ 2013_c + \alpha_3 Post_t \times Expansion_{st} + \alpha_4 Expansion_s \times Pct\ Uninsured\ 2013_c + \partial UE_{cst} + \tau_t + \vartheta_{cs} + \varepsilon_{cst} \quad (6)$$

The main coefficient of interest in the above equation is $\alpha_1$, which represents the differential change in Medicaid prescription use in CBSAs with high 2013 uninsurance rates compared to those with low rates in expansion states, with non-expansion states as the difference-in-difference control group. We expect that there would be a greater increase in Medicaid prescription drugs in CBSAs where the baseline fraction of uninsured population was larger (i.e., $\alpha_1$ >0). The coefficient of interest in this regression appears in panel A of Table 9, along with summary statistics of 2013 uninsurance rates. The point estimate in column (1) indicates that a 10 percentage point increase in exposure to the expansions was associated with a 0.01 percent increase in Medicaid utilization. This implies that, on average, areas with 2013 uninsurance rate of 33.7 percent, experienced a 0.03 percent increase in Medicaid prescription drug utilization, due to the policy change. Column (2) displays results from a model which excludes states that partially

**Table 9**
Effect of the ACA Medicaid Expansions on Medicaid Prescriptions, Triple Difference (CBSA-level Analysis).

| Dependent variable: Ln (total Medicaid prescriptions) | (1) All States | (2) Excl. DC, DE, MA, NY, VT |
|---|---|---|
| *Panel A* | | |
| Post x Expansion x Pct Uninsured 2013 | 0.010*** | 0.011*** |
| | (0.002) | (0.002) |
| Post x Expansion | -0.045 | -0.080 |
| | (0.064) | (0.071) |
| Post x Pct Uninsured 2013 | 0.003** | 0.002** |
| | (0.001) | (0.001) |
| *Median 2013 pct uninsured* | 33.7 | 34.4 |
| *Standard deviation of 2013 pct uninsured* | 9.5 | 8.9 |
| *Panel B* | | |
| Post x Expansion x Pct Minority 2013 | 0.003** | 0.003** |
| | (0.001) | (0.001) |
| Post x Expansion | 0.188*** | 0.199*** |
| | (0.022) | (0.023) |
| Post x Pct Minority 2013 | 0.002*** | 0.002*** |
| | (0.001) | (0.0005) |
| *Median 2013 pct minority* | 12.6 | 12.9 |
| *Standard deviation of 2013 pct minority* | 19.1 | 19.4 |
| Observations | 7,029 | 6,714 |

Notes:
1. Analysis is based on aggregated CBSA-quarter Medicaid prescription data from 2013Q1 to 2015Q1. All models include CBSA fixed effects, fixed effects for each quarter in the data, and unemployment rate. Robust standard errors clustered by CBSA are reported in parentheses. * Significant at the 10-percent level. ** Significant at the 5-percent level. *** Significant at the 1-percent level.
2. In column (1), estimates are based on all states being categorized into expansion vs non-expansion states.
a. Expansion states: AR, AZ, CA, CO, CT, DE, DC, HI, IL, IN, IA, IL, KY, MD, MA, MI, MN, NV, NH, NJ, NM, NY, ND, OH, OR, PA, RI, VT, WA, WV.
b. Non-expansion states: AL, AK, FL, GA, ID, KS, LA, ME, MI, MO, MT, NE, NC, OK, SC, SD, TN, TX, UT, VA, WI, WY.
3. For the analysis corresponding to column (2), the early expansion states of DC, DE, MA, NY, and VT were dropped from the sample.

expanded Medicaid to low-income non-elderly adults before 2014. The close correspondence of these estimates with those in column (1) demonstrate that our main results are not sensitive to this exclusion.

The ACA Medicaid expansions are also expected to reduce absolute differences in insurance coverage related to race and ethnicity. Using the American Community Survey, Nikpay et al. (2016) document that in 2014, the largest declines in uninsurance occurred among Hispanics (7.1 percentage points) and blacks (5.1 percentage points), relative to whites (3 percentage points). We exploit geographic variation in racial composition to examine whether the impact on Medicaid prescriptions was comparatively larger in areas with greater Hispanic and black populations. The estimating equation is:

$$Y_{cst} = \alpha_1 Post_t \times Expansion_s \times Pct\ Minority\ 2013_c + \alpha_2 Post_t \times Pct\ Minority\ 2013_c + \alpha_3 Post_t \times Expansion_s + \alpha_4 Expansion_s \times Pct\ Minority\ 2013_c + \partial UE_{cst} + \tau_t + \vartheta_{cs} + \varepsilon_{cst} \quad (7)$$

We report this result in panel B. The coefficient on the interaction term $Post_t xPct\ Minority\ 2013_c xExpansion_s$ of 0.003 indicates that the effect of the Medicaid expansion on Medicaid prescription drug utilization was significantly higher in areas of expansion states with a greater share of Hispanic and Black populations, indicating that the Medicaid expansions reduced racial disparities in access to medications.

Appendix Tables A3 and A4 present results from a specification where we replace the post-2014 indicator with a dummy for each quarter to investigate pre-policy trends for these heterogeneity analyses in an event history framework. Appendix Table A3 shows small and statistically insignificant coefficients for the time periods before Medicaid expansion, which is reassuring. The post expansion effects appear strongest in the 3rd quarter of 2014, although statistically significant and positive effects also appear later in column 2. The results of Appendix Tables A4 & A5 are less convincing; although most coefficients are statistically insignificant in this table, they are all positive and larger in magnitude after the expansion.

The results from Table 9 and Appendix Tables A3, A4 together are suggestive that the growth in utilization of Medicaid prescription medications was more pronounced in geographical areas where the "bite" of expansions was larger because baseline uninsurance were higher, and in areas where minority populations were more concentrated. While the results from the event history specification in Appendix Table A4 are broadly consistent with the results from the triple-difference approach in Table 9 for baseline uninsurance rates, the corresponding story for is not as strong for the percent minority analyses.

## 6. DISCUSSION

This paper provides rich and nuanced evidence on the effects of health insurance coverage for low-income adults on patterns of prescription drug use. Using a national administrative dataset of prescription drug utilization, together with an identification strategy that has been used to look at other healthcare outcomes, we find that non-elderly adult Medicaid prescriptions per capita increased by 19 percent following the ACA Medicaid expansion. When restricting the set of expansion states to the ones without any Medicaid eligibility changes for non-elderly adults pre-dating 2014, we detect a larger effect on Medicaid utilization (23 percent). This pattern is consistent with the likelihood that states with larger potential gains in coverage after Medicaid expansion experienced larger increases in prescription drug use.

We next consider a back-of-the-envelope calculation to gauge the implications of our findings for the use of prescription medications among the newly enrolled population in the extensive margin. The DD estimate of 19 percent in Table 1 (column 1) translates to an increase of 262,831 Medicaid prescriptions over a baseline average of 1.38 million Medicaid prescriptions in all expansion states in 2013. This is an estimate of the average Medicaid expansion-induced increase in prescription fills per quarter in expansion states relative to non-expansion states.[12] In order to back out how many prescription fills this represents per newly enrolled beneficiary, we divide this 1.38 million by an estimate of the number of individuals who gained Medicaid coverage through the ACA expansion. In Table 8 (column 1), we estimate a 17% increase in ACA Medicaid enrollment as a result of the expansion, which corresponds to an increase of approximately 122,767 beneficiaries per state from the baseline average of 722,159 Medicaid enrollees in expansion states prior to 2014.[13] Therefore, the "treatment on the treated" estimate of the effect of Medicaid expansion on prescription drug use equates to 2.14 ( = 262,831/122,767) Medicaid prescriptions per enrollee per quarter or nearly 9 prescription fills per enrollee per year. In a related context, a recent study examining the 2014 policy change, Mulcahy et al. (2016) find that previously uninsured adults who gained Medicaid had 13.3 more prescription fills in 2014 compared to 2013. This was higher (17.8 more prescriptions) for those with chronic conditions, and lower (10.9 additional fills) among the healthier Medicaid enrollees in their sample (aged 20-61). Our results imply a similar order of magnitude as their healthier-population estimate.

Our sub-group analysis by drug-class suggests that the increase in utilization was higher for medications used in treating chronic conditions such as diabetes and cardiovascular disease, and for psychotherapeutic medications. Given that lack of appropriate management of chronic diseases through medications is one of the plausible mechanisms for coverage affecting long-term health (Tamblyn et al., 2001), and that survey-based analyses of the Medicaid expansion have shown increased rates of care for chronic conditions, these findings are encouraging in terms of their significance for potentially improving health outcomes Conversely, we find that copays within Medicaid expansion states had a smaller effect on dissuading drug utilization for serious illness like heart disease and HIV, with larger effects on utilization of contraception and allergy/respiratory medications. However, our overall estimates indicate fairly inelastic demand for drugs in this population as a whole, at least at the very small copay levels typically used in Medicaid (average weighted copay of $1.24 per prescription). Whether substantially larger copays would lead to larger proportional changes is not clear and is an important subject for future research, as states experiment with more cost-sharing in Medicaid, including approaches such as health savings accounts.

This study is not without qualifications. The claims dataset does not observe individuals longitudinally, so it cannot capture the effect of the expansions on those who were previously uninsured. However, in additional analysis using pre-expansion uninsurance rates at the sub-state level, we provide evidence on the effect of change in insurance coverage on utilization. The lack of individual-level data also precludes us from estimating directly the per-person changes in utilization, though our back-of-the-envelope calculations indicate that our estimates correspond to a little more than two additional monthly prescription fills per newly enrolled Medicaid beneficiary.

This study contributes to the literature on the economics of health insurance coverage, using variation provided by the large recent expansions as part of the ACA. Our findings also provide important new evidence to the literature on Medicaid expansions' effects on the healthcare safety net and improvements in access to and utilization in states that expanded Medicaid. Care management through pharmaceuticals may potentially reduce the use of more resource-intensive medical care such as emergency department visits or other non-drug medical spending (Goldman et al., 2007; Lavetti and Simon, 2016; Roebuck et al., 2015; Stuart et al., 2009). In part, reflecting previous research findings, the ACA classifies prescription drugs as one of the ten categories of "essential health benefits" that all commercial private insurance plans must provide. Future research should consider whether this policy-induced boost in prescription drug utilization is reflected in subsequent health impacts and downstream effects on use of other types of medical care.

Appendix Tables A3 and A4 present results from a specification where we replace the post-2014 indicator with a dummy for each quarter to investigate pre-policy trends for these heterogeneity analyses in an event history framework. Appendix Table A3 shows small and statistically insignificant coefficients for the time periods before Medicaid expansion, which is reassuring. The post expansion effects appear strongest in the 3rd quarter of 2014, although

[12] This estimate is expected to be smaller than the total realized increase in prescriptions under Medicaid from 2013 to 2014, as this estimate does not capture the "welcome mat" effect. Fortunately, other work on the ACA does not indicate any new policy emphasis on prescription drug utilization or systematic cost-control efforts that were unique to expansion states during this period (nor would we expect any, since the ACA Medicaid expansion was fully funded by the federal government during our study period).

[13] The average logarithms of Medicaid prescriptions and enrollment in expansion states are 14.14 (column (1) of Table 1) and 13.49 (column (1) of Table 8). The corresponding geometric mean Medicaid prescriptions and enrollment computed from the sample are 1.38 million and 722,159 respectively.

statistically significant and positive effects also appear later in column 2. The results of Appendix Tables A4 & A5 are less convincing; although most coefficients are statistically insignificant in this table, they are all positive and larger in magnitude after the expansion.

## Acknowledgements

We are grateful to seminar participants at the Fall 2015 and 2016 Association for Public Policy Analysis and Management (APPAM) conference, 2016 American Society of Health Economists conference, Indiana University and Vanderbilt University for helpful comments. Dr. Sommers' work on this project was supported by grant number K02HS021291 from the Agency for Healthcare Research and Quality (AHRQ). The views presented here are those of the authors and do not represent AHRQ.

## Appendix A

**Table A1**
Categorization of State Expansion Status.

| 2014 Expansion States without substantial prior Medicaid expansion | Expansion States with Substantial prior Medicaid expansion | Non-Expansion States (Control group) |
|---|---|---|
| Arkansas[1,2] | Delaware[11] | Alabama |
| Arizona[3] | District of Columbia[7] | Alaska |
| California[4,7] | Massachusetts[12] | Florida |
| Colorado[5] | New York[13] | Georgia |
| Connecticut | Vermont[14] | Idaho |
| Hawaii[9] | | Kansas |
| Illinois | | Louisiana[1] |
| Indiana[1] | | Maine |
| Iowa[6] | | Mississippi |
| Kentucky | | Missouri |
| Maryland | | Montana[1] |
| Michigan[1] | | Nebraska |
| Minnesota[7] | | North Carolina |
| Nevada | | Oklahoma |
| New Hampshire[1] | | South Carolina |
| New Jersey[7] | | South Dakota |
| New Mexico | | Tennessee |
| North Dakota | | Texas |
| Ohio | | Utah |
| Oregon[8] | | Virginia |
| Pennsylvania[1] | | Wisconsin[10] |
| Rhode Island | | Wyoming |
| Washington[7] | | |
| West Virginia | | |

*Notes:* This table shows the state classification for Medicaid eligibility used in this paper. These are mutually exclusive lists of states. We first examine states in the first two columns together, as expansion states. Later specifications separate expansion states into those with and without substantial pre-2014 Medicaid expansions. Source: Reproduced from Table A1 of (Simon et al., 2017).

[1] The Medicaid expansion became effective in January 2014 for all expansion states as of this writing, except for the following: Alaska (September 2015), Indiana (February 2015), Louisiana (July 2016), Michigan (April 2014), Montana (January 2016), New Hampshire (August 2014), and Pennsylvania (January 2015). Since this table records only expansion status as of January 2014, some of the states that later expanded Medicaid appear in the control group column. However, our regressions categorize those states that expanded after January 2014 but before March 2015 as expansion states only in the quarters after the expansion was implemented. The remaining notes to this Table explain the categorization of expansion states into columns 1 or 2.

[2] Arkansas operated a limited-benefit premium-assistance program for childless adults who worked for small, uninsured employers (ARHealthNetworks waiver) (Kaiser Family Foundation Report, 2016) prior to the ACA.

[3] Since 2000, Arizona offered Medicaid-equivalent benefits to childless adults with income below 100 percent FPL through a Section 1115 waiver program. However, the state closed the program to new enrollees in July 2011 and consequently experienced a significant expansion for childless adults in 2014.

[4] Although California expanded Medicaid for childless adults to some degree as part of the state's 1115 "Bridge to Reform" waiver, this was not available in all counties and was not full Medi-Cal benefits (http://kff.org/health-reform/fact-sheet/the-california-health-care-landscape/).

[5] Colorado had only very limited eligibility before 2014. Adults with income up to 10 percent FPL were eligible for Medicaid as of May 2012, and enrollment was capped to 10,000 adults.

[6] Under the IowaCare program, childless adults with income below 200 percent FPL were eligible for public health insurance since 2005. However, IowaCare provided limited services in a limited network, and so low-income adults in Iowa effectively underwent substantial expansion in coverage in 2014 (Damiano et al., 2013).

[7] California, Connecticut, District of Columbia, Minnesota, New Jersey, and Washington elected to enact the ACA Medicaid expansion in 2010 to 2011. However, New Jersey's early expansion only extended to 23 percent FPL while the other five states extended at least until 50 percent FPL (Sommers et al., 2013). Also, Washington's early expansion was limited to prior state plan enrollees (Sommers et al., 2013). Hence, we treat New Jersey and Washington as full 2014 expansion states.

[8] In 2008, Oregon enacted a small Medicaid expansion for low-income adults through lottery drawings from a waitlist. However, less than one-third of the 90,000 people on the waitlist were selected to apply for Medicaid in 2008 (Baicker et al., 2013) and so the 2014 expansion represented a significant increase in eligibility for low-income adults.

[9] In Hawaii, childless adults with incomes up to 100 percent FPL were eligible for the state's QUEST Medicaid managed care waiver program (Kaiser Family Foundation Report, 2016).

[10] Although Wisconsin was not an ACA expansion state, the state received federal approval to offer Medicaid to childless adults below 100 percent FPL through the BadgerCare program as of 2009 (Kaiser Family Foundation Report, 2014).

[11] In Delaware, childless adults with incomes up to 100 percent FPL were eligible for Medicaid benefits through the Diamond State Health Plan waiver (Kaiser Family Foundation Report, 2016).

[12] Massachusetts implemented reforms to expand insurance coverage to low-income adults in 2006 (Kaiser Family Foundation Report, 2016).

[13] In New York, childless adults up to 78 percent FPL were eligible for the Medicaid (Home Relief) waiver program and childless adults up to 100 percent FPL were eligible for the Family Health Plus waiver program (Kaiser Family Foundation Report, 2011).

[14] In Vermont, childless adults up to 150 percent FPL were eligible for Medicaid-equivalent coverage through the Vermont Health Access Plan waiver program (Kaiser Family Foundation Report, 2011).

**Table A2**
Event Study Estimates by Payer.

| Dependent variable: Ln (total prescriptions) | (1) Uninsured (Cash and assistance programs) | (2) Commercial | (3) Medicare |
|---|---|---|---|
| Expansion x 2013Q2 | 0.03 | -0.01 | 0.01* |
| | (0.02) | (0.01) | (0.005) |
| Expansion x 2013Q3 | 0.03 | -0.004 | 0.01* |
| | (0.03) | (0.01) | (0.01) |
| Expansion x 2013Q4 | 0.03 | -0.005 | 0.01 |
| | (0.03) | (0.02) | (0.01) |
| Expansion x 2014Q1 | 0.01 | -0.01 | 0.001 |
| | (0.03) | (0.02) | (0.01) |
| Expansion x 2014Q2 | -0.002 | -0.01 | 0.004 |
| | (0.034) | (0.02) | (0.01) |
| Expansion x 2014Q3 | 0.005 | -0.02 | 0.01 |
| | (0.03) | (0.02) | (0.02) |
| Expansion x 2014Q4 | -0.005 | -0.02 | 0.01 |
| | (0.03) | (0.02) | (0.02) |
| Expansion x 2015Q1 | -0.02 | -0.03 | 0.01 |
| | (0.03) | (0.02) | (0.02) |
| Observations | 459 | 459 | 459 |

Notes: Analysis is based on aggregated state-quarter Medicaid prescription data from 2013Q1 to 2015Q1. All models include state fixed effects, fixed effects for each quarter in the data, and unemployment rate. Robust standard errors clustered by state reported in parentheses.* Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

**Table A3**
Event Study Estimates of Prescription Drug Utilization Based on 2013 CBSA Uninsurance Rates.

| Dependent variable: Ln (total Medicaid prescriptions) | (1) All States | (2) Excl. DC, DE, MA, NY, VT |
|---|---|---|
| Pct Uninsured 2013 x Expansion x 2013Q2 | -0.0002 | 0.001 |
| | (0.001) | (0.002) |
| Pct Uninsured 2013 x Expansion x 2013Q3 | -0.001 | 0.002 |
| | (0.002) | (0.002) |
| Pct Uninsured 2013 x Expansion x 2013Q4 | -0.002 | 0.001 |
| | (0.003) | (0.003) |
| Pct Uninsured 2013 x Expansion x 2014Q1 | 0.002 | 0.005* |
| | (0.003) | (0.003) |
| Pct Uninsured 2013 x Expansion x 2014Q2 | 0.003 | 0.006** |
| | (0.003) | (0.003) |
| Pct Uninsured 2013 x Expansion x 2014Q3 | 0.006** | 0.008*** |
| | (0.003) | (0.003) |
| Pct Uninsured 2013 x Expansion x 2014Q4 | 0.004 | 0.006* |
| | (0.003) | (0.003) |
| Pct Uninsured 2013 x Expansion x 2015Q1 | 0.003 | 0.004 |
| | (0.003) | (0.003) |
| Observations | 7,029 | 6,714 |

Notes:
1. Analysis is based on aggregated CBSA-quarter Medicaid prescription data from 2013Q1 to 2015Q1. All models include CBSA fixed effects, year by quarter fixed effects, and CBSA unemployment rate. Robust standard errors clustered by CBSA reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.
2. In column (1), estimates are based on all states being categorized into expansion vs non-expansion states.
3. For the analysis corresponding to column (2), the early expansion states of DC, DE, MA, NY, and VT were dropped from the sample.

**Table A4**
Event Study Estimates of Prescription Drug Utilization Based on 2013 CBSA Minority Proportions.

| Dependent variable: Ln (total Medicaid prescriptions) | (1) All States | (2) Excl. DC, DE, MA, NY, VT |
|---|---|---|
| Pct Minority 2013 x Expansion x 2013Q2 | -0.0004 | -0.0003 |
| | (0.001) | (0.001) |
| Pct Minority 2013 x Expansion x 2013Q3 | -0.001 | -0.001 |
| | (0.001) | (0.001) |
| Pct Minority 2013 x Expansion x 2013Q4 | -0.002 | -0.002 |
| | (0.001) | (0.001) |
| Pct Minority 2013 x Expansion x 2014Q1 | 0.002 | 0.002 |
| | (0.002) | (0.002) |
| Pct Minority 2013 x Expansion x 2014Q2 | 0.002 | 0.002 |
| | (0.002) | (0.002) |

Table A4 (*Continued*)

| Dependent variable: Ln (total Medicaid prescriptions) | | |
|---|---|---|
| | (1) All States | (2) Excl. DC, DE, MA, NY, VT |
| Pct Minority 2013 x Expansion x 2014Q3 | 0.002 | 0.003 |
| | (0.002) | (0.002) |
| Pct Minority 2013x Expansion x 2014Q4 | 0.001 | 0.002 |
| | (0.002) | (0.002) |
| Pct Minority 2013 x Expansion x 2015Q1 | 0.002 | 0.003 |
| | (0.002) | (0.002) |
| Observations | 7,029 | 6,714 |

Notes:
1. Analysis is based on aggregated CBSA-quarter Medicaid prescription data from 2013Q1 to 2015Q1. All models include CBSA fixed effects, fixed effects for each quarter in the data, and unemployment rate. Robust standard errors clustered by CBSA reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.
2. In column (1), estimates are based on all states being categorized into expansion vs non-expansion states.
3. For the analysis corresponding to column (2), the early expansion states of DC, DE, MA, NY, and VT were dropped from the sample.

**Table A5**
Effect of the ACA Medicaid Expansions on Medicaid Prescription Drugs, State Specification, Restricted to data from CBSAs.

| Dependent variable: Ln (total Medicaid prescriptions) | | |
|---|---|---|
| | (1) All States | (2) Excl. DC, DE, MA, NY, VT |
| Post x Expansion | 0.22*** | 0.23*** |
| | (0.03) | (0.03) |
| Year and quarter fixed effects | Y | Y |
| State fixed effects | Y | Y |
| Observations | 441 | 405 |
| *Dependent variable means* | | |
| Expansion, Before | 13.46 | 13.48 |
| Non-expansion, Before | 13.47 | 13.47 |
| Expansion, After | 13.75 | 13.81 |
| Non-expansion, After | 13.57 | 13.57 |

Notes:
1. Analysis is based on aggregated Medicaid prescription data from 2013Q1 to 2015Q1, for all CBSAs. All models include unemployment rate. Robust standard errors clustered by state reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.
2. In column (1), estimates are based on all states being categorized into expansion vs non-expansion states.
a. Expansion states: AR, AZ, CA, CO, CT, DE, DC, HI, IL, IN, IA, IL, KY, MD, MA, MI, MN, NV, NH, NJ, NM, NY, ND, OH, OR, PA, RI, VT, WA, WV.
b. Non-expansion states: AL, AK, FL, GA, ID, KS, LA, ME, MI, MO, MT, NE, NC, OK, SC, SD, TN, TX, UT, VA, WI, WY.
3. For the analysis corresponding to column (2), the early expansion states of DC, DE, MA, NY, and VT were dropped from the sample.

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